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Nature of technology and location effects on firm performance in the US medical device industry

Rekha Rao-Nicholson*
Newcastle University London
102 Middlesex St, London E1 7EZ
Email: rekha.nicholson@ncl.ac.uk
* Corresponding author

Zaheer Khan
Kent Business School
University of Kent
Canterbury CT2 7FS
z.a.khan@kent.ac.uk

Pervaiz Akhtar
Hull University Business School
University of Hull
Hull HU6 7RX
Pervaiz.Akhtar@hull.ac.uk

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Abstract

This paper examines the location effects on firm performance (sales, employment and market value) by analyzing geographical and technological proximities in the US medical device industry. The nature of technology is introduced as a new way to scrutinize the impact of various proximities, and the findings indicate that the geographical and technological proximity in itself does not affect performance, whereas the spatially-mediated technological proximity, characterized by the technological proximity within a cluster, positively influences the performance of medical device firms. The paper addresses an important theoretical question. It consequently contributes to the effects of different proximities and nature of technology on firm performance and provides relative managerial implications interlocked with insights obtained from the medical industry.

Keywords: location, geographic and technological proximity, firm performance, medical device industry

1. Introduction

This paper addresses the question whether the nature of technology and location affect firm performance. The relative importance of geographical proximity remains an open question (e.g., Torre, 2008). We investigate this question in the context of the US medical device industry, which offers an ideal setting to gauge the nature of technology (Bobrowski, 2000) and location effect on firm performance (Chatterji, 2009). Particularly, the US medical device firms are part of a high technology (Berndt, et al., 2000; Zweifel & Manning, 2000), high growth (Okunade, 2001) and spatially clustered industry that in our case is a relevant context to disentangle the effects of both these proximities on firm performance (Chatterji, 2009; Cohen, Nelson, & Walsh, 2000). Prior work in this area has focused on the aggregate patents and has ignored the nature of technology and location effects on a particular industry (Aldieri, 2011), as in our case - the medical device industry. The location hypothesis has been suggested to play an important role in innovation and economic performance between regions (Audretsch & Feldman, 1996a; Jaffe, Trajtenberg, & Henderson, 1993; Johansson & Lööf, 2008; Lejpras, 2015), as well as new firm location decisions (Artz *et al*. 2016).

Similarly, Cooke (2002:79) notes "if the partners are co-located, the reductions in uncertainty, time lag, and transaction costs are clearly palpable." The literature discussing such location effects reveal many positive effects of agglomeration among participating firms, which can yield positive benefits in the form of knowledge transfer along with diverse spillover effects (e.g., Audretsch & Feldman, 1996a; Feldman, 1999). These positive technology transfers could be gained from intentional clustering (Alcacer & Chung, 2007). Scholars have also suggested that while clustering tends to enhance learning from other organizations (Aldieri, 2011; Lejpras, 2015), such organizations are differently exposed to the extent of these benefits associated with the location of activities and regional differences on firm performance (Chan, Makino, & Isobe, 2010). Firms can overcome these knowledge related disadvantages by imitating and vicariously learning from other firms (Kim & Miner, 2007), as well as learning organically within the boundaries of firms (de Paiva Britto, Costa Ribeiro, Araújo, da Matta Machado, & da Motta e Albuquerque, 2018).

Recently, economic geographers have tended to question the implicit assumption that competitiveness accrues from the geographic location alone (e.g., Boschma, 2005). For instance, Isaksen (2001: 110) suggests "geographical proximity only creates a potential for interaction, without necessarily leading to dense local relations." Later work, however, attempts to explain the favorable conditions generated by locations through further examination of organizational, institutional, cognitive and social proximity alongside the geographic proximity (Broekel & Boschma, 2012; Ponds, Van Oort, & Frenken, 2007).

The research activities within a cluster benefit from geographic proximity and help overcome other forms of distances such as institutional and cognitive (Ponds, et al., 2007). Some studies even noted that product related innovations were closely associated with geographic proximity (Lehmann and Menter, 2016). However, this impact was more pronounced for small firms compared to large ones (e.g., Acs, Audretsch, & Feldman, 1994).

Within the economic geography and international business literature, there is an ongoing debate as to whether meaningful knowledge transfer between co-located actors comes from cognitively proximate or more cognitively distant co-located actors (Nooteboom, Van Haverbeke, Duysters, Gilsing, & Van den Oord, 2007). Firms in the same industry have closer cognitive proximity (Boschma, 2005; Broekel & Boschma, 2012). The benefits of proximity can, therefore, be related to the types of externalities. For example, Ibrahim, Fallah, and Reilly (2009: 412) define externalities as the "useful local sources of knowledge found in a region, which was obtained beyond the recipients' organization, and that affected the innovation of the recipient."

Overall, there is a dearth of research focusing on the cognitive and organizational proximity of co-located actors as necessary conditions for effective knowledge transfer partnerships, and how these relate to geographic proximity (Ponds, et al., 2007). Additionally, the extant research is ambiguous whether different kinds of proximity (e.g., Boschma, 2005 for an overview) should be regarded as complements or substitute to each other. Despite the abundant literature on the spatial nature of knowledge spillovers in clusters (Robbins, 2006), many questions still remain underexplored, from both theoretical and empirical perspectives, for instance, the effect of geographical proximity on firm performance is unclear and, from an empirical angle, the operationalization and measurement of the mechanisms through which knowledge transfers to co-located actors thus affecting firm performance (Boschma, 2005; Massard & Mehier, 2009). The aim of this paper is to fill these gaps.

Our contributions are twofold: First, from a theoretical point of view, we disentangle different types of proximities and show that geographic proximity alone does not improve firm performance, and it is, in fact, the nature of technology - spatially-mediated technology proximity - that enhances firm performance. Second, from the empirical viewpoint, we emphasize the individual effects of geographical and technological proximities in one single industry - US medical device industry thus providing a finer view of the effects of location on firm performance. Additionally, we use many refined measures for performance such as sales, employment, and market growth and by doing so, we provide a comprehensive measure of performance.

2. Theoretical framework and hypotheses

2.1. Geographical proximity and firm performance

Much of the empirical literature seem to be mainly interested in identifying different externalities than determining how the degree of proximity may influence the effect of externalities (Phelps, 2004). Studies investigating knowledge transfer also note that knowledge is easier to transfer in a close distance to the source of the knowledge and spillovers effect seem to become weaker over a long distance from where the knowledge was originated (Audretsch

& Feldman, 1996a; Jaffe, et al., 1993). Similarly, geographic proximity has been suggested to overcome other forms of proximities such as institutional and cognitive (Ponds, et al., 2007). Geographic proximity promotes trust and helps firm performance (Broekel & Boschma, 2012). Recent research also notes that social and geographic proximity helps in the formation of inter-firm relationships compared to cognitive and institutional proximity (Molina-Morales, Belso-Martínez, Más-Verdú, & Martínez-Cháfer, 2015). Some studies, however, question the importance of geographic proximity and draw attention to the fact that some firms located outside the cluster may also benefit through non-local linkages. Hence, geographic proximity alone seems to be neither a sufficient nor a necessary condition for improving firm performance and innovation (Boschma, 2005). This argument is also in line with the research on clusters, showing that cluster related benefits are not homogenous across firms operating in a cluster (Giuliani, 2007). Some studies even noted that product related innovations were also closely associated with geographic proximity. However, this impact was more pronounced for small firms compared to large ones (e.g., Acs, et al., 1994).

Thus, we suggest:

H1: The geographical proximity will have a positive effect on firm performance.

2.2. Technological proximity and firm performance

Based on prior research, we posit nature of technology as consisting of elements that indicate the technology class, quality, and scope of technology (Buenstorf, Fritsch, & Medrano, 2015; Jaffe, 1986, 1988). The nature of technology embedded within a firm can have implications for firm-level performance, in the form of sales and employment growth (Mairesse & Hall, 1994; Merges & Nelson, 1994). This nature of technology can be proxied by patent's technological class (TC), quality indicators such as forward citations and knowledge scope indicators representing some claims (claims) (Jaffe, 1986).

The first element of the nature of technology, TC, is present *ex-ante* at the time of application for a patent and relates to main technology class that the patent sits within. The patent data and technology class indicates the technical area a firm is active in (Jaffe, 1986, 1988).

The second element of the nature of technology, forward citations, is derived *ex-post* after the patent accepted by the patenting organization. It is a cumulative process where over some years' citations are garnered by the granted patents (Jaffe, Trajtenberg, & Henderson, 1992; Murata, Nakajima, Okamoto, & Tamura, 2014; Trajtenberg, 1990) and have been used to look at firm performance (Belenzon, 2012; Hall, Jaffe, & Trajtenberg, 2005).

The third element of nature of technology is a set of claims that are mentioned in the granted patent, and this information is derived ex-ante, i.e., these claims which stipulate possible enhancements or variations that could be introduced in the patented invention are already defined in the granted patents (Merges & Nelson, 1994; Walker, 1995) which discuss the importance of patent breath[1]. Thus, a higher number of claims within a patent creates an exclusionary zone for firm's knowledge base which can be used by the inventing firm to build on its patented knowledge base (Hall, et al., 2005; Kitch, 1977; Lanjouw & Schankerman, 1997; Merges & Nelson, 1994).

Conceptually, technological proximity (or distance) is concerned with the overlap of knowledge base between firms, i.e., higher the overlap between firm's technology base (regarding quality or claims) the less distance there is between them. In extant literature, firms have been described as a series of vectors in a multi-dimensional technology space (Benner & Waldfogel, 2008; Jaffe, 1986; Olsson & Frey, 2002). Several distance measures such as the angular separation or the correlation of revealed technological advantage (RTA) have been used to measure likely spillovers between firms (Gilsing, Nooteboom, Vanhaverbeke,

[1] This concept has been widely discussed in prior research and several authors though engaging with the same idea have called this concept by different names, for example, 'patent breadth', 'patent width' or 'patent scope' (e.g., Gilbert and Shapiro, 1990, Green and Scotchmer, 1995, Klemperer, 1990, Merges and Nelson, 1994).

Duysters, & van den Oord, 2008; Griliches, 1990, 1992; Jaffe, 1986; Mohnen, 1996; Nooteboom, et al., 2007). In this research, we are interested in examining the linkages between the firm-level technological capabilities, derived from technological classes, quality of patents and number of claims in patents, compared to the whole technological base available to all firms and the subsequent impact of this relationship on firm performance. In this paper, we link nature of technology at individual firm-level to differentiate the technology levels between firms and examine how this influences technological proximity and generate spillover effects. Authors have used a similar process to capture the R&D spillover for firms within an industry (Crepon & Duguet, 1993; Crepon, Duguet, & Mairesse, 1998). Thus, irrespective of the quality of technology, scope of technology and the technological proximity at global-level, due to locational diseconomies, the firm's knowledge base might have limited positive impact on firm-level performance if we ignore the impact of geography. Hence, we argue that non location-bound technological proximity will have some positive impact on firm performance, but it can also be insignificant in some clusters where the firm's technological proximity with the global technological landscape has little or no implications for locational technological landscape. Hence, we propose:

H2: The non location-bound technological proximity will generate insignificant or weaker impact on firm performance.

2.3. Spatially-mediated technological proximity and firm performance

We also investigate the spatially-mediated knowledge transfer between firms. Cantù, (2010) explores the role of geographic proximity and spatial relationship to examine the impact on knowledge transformation. Von Hipple (1994) highlights the cost of transmitting knowledge and argues that as the knowledge becomes *sticky*, the cost of knowledge transmission goes up considerably. Thus, their study suggests that the highly contextual knowledge and uncertain technological advances are best transmitted via face-to-face interaction and through repeated interaction between different actors. Their work also links to other works which look at relational and regional proximity (Nicholson, Tsagdis, & Brennan, 2013). The authors of this paper discuss the virtues of relational isolation for firms which in competitive regions can be competitively generative, but in peripheral regions, it could lead to negative effects on firm performance.

Authors have suggested that localization in the same spatial area encourages firms to span their business environment for technology and generate rents from their innovation activities (Decarolis & Deeds, 1999). The authors have argued that firms that are co-located in clusters with other firms belonging to the same industry will have similar access to specialized suppliers and experience locational scale economies (e.g., Artz et al. 2016; Puga 2010). At the same time, these resources can interact with geographic proximity to positively impact firm performance (Liao, 2010). Also, firms in the same location might experience higher pressures of cooperation and competition and have to find a balance between these two competing activities (Park, Srivastava, & Gnyawali, 2014). This leads to location-bound technological proximity which indicates the shared knowledge base between the firms in the same region.

Jaffe et al. (1993) have found evidence of localization of knowledge spillovers. Their study shows that a patent's citations are more likely to come from the same state and standard metropolitan area than a group of firms in the same technological area of research. Also, studies have found that localization is very relevant to industries where knowledge externalities play a greater role in firm performance and firm-level innovative activities (Almeida & Kogut, 1999; Audretsch & Feldman, 1996b).

Thus, the knowledge production function is closely linked to geographic clustering of firms and individual firm's knowledge production function will be closely linked to the knowledge generated within a cluster. The extant literature has called this the geography of innovation (Feldman & Florida, 1994). Most of the studies use aggregate data at patent or R&D

level (Audretsch & Feldman, 1996b; Decarolis & Deeds, 1999; Jaffe, 1986) and few studies have focused on microstructure of patent to look at the spatial effects on process of generation of forward citations (Jaffe, 1986) and its impact on firm performance (Orlando, 2004).

A firms' higher share of local knowledge base indicates that focal firm might have resources and capabilities for leading edge and novel knowledge development. Conversely, it also implies that the focal firm might experience negative knowledge spillover since the firm generates most of the knowledge in the cluster; it might provide knowledge to other firms but might experience limited gains from knowledge spillover itself (Jaffe, 1986). Thus, we expect that spatially-mediated technological proximity will have a positive impact on firm performance, and, we also argue that this impact will be higher than the impact from just the technological proximity. Therefore, we suggest:

H3: The location-bound technological proximity, defined as a spatially-mediated technological proximity, will have a positive impact on firm performance.

3. Research context, Data, and methodology

3.1. Medical Device Industry

Across the globe, health-related costs are on the rise and governments are trying to come up with ways to offer affordable medical care and reduce health costs for their citizens. Against this backdrop, new health-related technologies and smart devices such as Computerized Axial Tomography (CAT) scan machines, pace- makers and endoscopes are being recognized as a potential way of reducing health costs and tackling quality- related issues of patient care. The medical device industry offers many innovative products that doctors can use to diagnose, prevent and cure life-threatening diseases and provide patient-oriented services at affordable cost. For example, the industry has developed state of the art products such as computer-assisted diagnostic equipment used by doctors during various medical procedures such as cardiovascular, implants and neurological procedures.

We chose the US medical device industry, which is estimated to be around $110bn in 2012 (Commerce.gov, 2012), as our context to investigate the nature of technology and location effect on firm performance, as there are some of the leading companies operating in the sectors, for instance, Boston Scientific and Abbott along with many new entrepreneurial firms and university spin-off. Thus, this is an ideal context for the empirical investigation of the location and geographic proximity effect on performance. Also, the industry is clustered around certain areas of the USA, for example, California, Minnesota, and Boston thus presenting an ideal opportunity for the investigation of location and geographic proximity effect on performance (Mukherji and Silberman, 2011).

3.2. Data

We use an original database created from NBER patent database and the Compustat file database for our study, and this section is devoted to describing the creation of the sample which we will use in our analysis. The patent data has been obtained from the NBER Database (Hall, Jaffe, & Trajtenberg, 2001). The NBER database comprises detailed information on almost all U.S. utility patents in the USPTO's TAF database granted during the period 1963 to December 2002. USPTO database has been widely used in prior studies (Aldieri, 2011; Clancy, 2018). This database also consists of all citations made to these granted patents. Also, the recent additions made to the original database provide citations till 2010 (Kogan, Papanikolaou, Seru, & Stoffman, 2012). We gather patent-level data, including citations and number of claims, from this database.

The initial universe of the US public medical device companies was obtained from the Compustat database[2]. Using prior literature which classified firms belonging to SIC 3841,

[2] Compustat has the largest set of fundamental and market data representing 90% of the world's market capitalization. Use of this database could indicate that we have oversampled the Fortune 500 firms. Being included in the Compustat database means that the number of shareholders in the firm was large enough for the firm to command sufficient investors' interest to be followed by Standard and Poors Compustat, which basically means that the firm is required to file 10-Ks to the Securities and Exchange Commission on a regular basis. It does not necessarily mean that the firm has gone through an IPO. Most of them are listed on NASDAQ or the NYSE.

3842, 3843, 3844, 3845 and 3851 as medical device firms (Coad & Rao, 2008; Cohen, et al., 2000), we collected information on the firms in these sectors. We obtained 233 firms at this stage. These firms were then matched with the firm data files from the NBER patent database, and we matched all the firms that have patents. The final sample thus contains both patenters and non-patenters. At this stage, we have 14462 patents granted to our sampled firms. After this initial match, we further matched the year-wise firm data to the year-wise patents applied by the respective firms (in the case of patenting firms). Due to limited reliability of patent and citation data in the 1960s, we focus our analysis on patent and firm data for 1970-2003, giving us a rather rich information set.

Next, using multiple methods, we developed a composite index for localization and used it to test hypothesis 1. The dummy variable, *dum(localization)*, was one if the region demonstrated a high degree of agglomeration and zero otherwise[3]. Prior literature (Audretsch & Feldman, 1996b; Dorfman, 1983; Gibson, 1970; Hekman, 1980; Scott, 1993) and recent projects like Harvard cluster mapping project and websites like Commerce.gov helped us in identifying regions that over the years were classified as clusters for medical device firms. According to the literature, the locations which show strong agglomeration in medical devices are the states of California, Minnesota, Florida and the New England regions which consist of states of Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island and Vermont. We then linked this year-wise information to firm-level data using the company address data. Regarding patent's origin, except for a small number of larger firms, we do observe a high degree of localization for medical devices firms. Most of the inventive activities and knowledge production for these firms are localized in their region of origin. The distribution of firms according to their patenting and localization activity is given in table 1. Appendix A presents

[3] For robustness checks, we created the agglomeration variable at city level. The dummy variable, dum(location(city)), was one if the city demonstrated a high degree of agglomeration and zero otherwise.

the distribution of the firms across the cities.

[Table 1 about here]

The final sample consists of 233 firms and 2,499 firm-year observations out of which we have patent information for 1,125 firm-year observations. A total of 11,210 patents for our sampled firms is included in this unbalanced panel analysis. Van Reenen (1997) asserts that the creation of longitudinal databases of technologies and firms is a major endeavor for those seriously engaged with the dynamic effect of innovation on firm growth. Thus, having created this longitudinal dataset, we feel that we will be able to methodically study whether nature of technology and spatially aggregation drives growth at the firm-level. Due to methodological issues, we are unable to extend the number of years on this dataset.

We use three dependent variables, growth in sales, growth in employment and Tobin's q (i.e., market value divided by book value of assets), in our analysis. Our choice of performance variables is derived from the extant literature. For example, Mairesse and Hall (1994) indicate that their regression results with sales as the dependent variable perform relatively well in comparison to regressions using value-added. Also, the literature on economic geography has focused on the impact of localization on firms' and regions' employment growth (De Groot, Poot, & Smit, 2009; Fritsch & Mueller, 2004). Similarly, links have been found between commitments to technology development and market value (Morck, Shleifer, & Vishny, 1988). So, we analyze if at all firms' localization and nature of technology has any impact on firms' Tobin's q.

Our main explanatory variables are the patent's forward citations (FC) and some claims. Patent's forward citations are subject to truncation issues. Hence, we calculated this measure using two alternative time windows, i.e., a fixed four-year time window from the year of the patent grant, and the full-time window from the date of the patent grant through to 2002. We use the full-time window calculations in our main model and use the forward citations created by the first method in our robustness checks. To calculate the nature of technology for individual firm-year observation, we follow a similar approach to the one adopted by Nooteboom et al. (2007) and Gilsing et al. (2008) to calculate the revealed technological advantages (RTA) of each firm relative to the other sample firms. In their study, authors calculate the RTA of a firm in a particular technological class is given by the firm's patent share in that class of the US patents granted to all companies in the study, relative to its overall share of all US patents granted to these companies.

We follow the same procedure for calculating RTA for both forward citations and number of claims. For our hypothesis 2, i.e., technological proximity, the RTA of a firm i in a particular technological class c in a particular year t is given by the firm's forward citations share in that class for that year normalized by the number of patents in that class for that year relative to forward citations of the US patents granted in that class normalized by the number of patents in that class for that year t[4].

$$RTA_{i,t,c} = (FC_{i,t,c} / \text{total patents}_{i,t,c}) / (FC_{t,c} / \text{total patents}_{t,c}) \qquad (1)$$

where, sampled firm, i = 1, …, N, t = 1970, …, 2003, technology class, c = 1, …, C. And the total RTA[5] for the firm in a year is,

$$RTA_{i,t}(forward\ citations) = \sum_{c=1}^{C} RTA_{i,t,c} \qquad (2)$$

For our hypothesis 3, i.e., spatially-mediated technological proximity, the RTA of a firm in a particular technological class *c* in a particular region *l* and in particular year *t* is given by the firm's forward citations share in that class for that region in that year normalized by the number of patents in that class for that region in that year relative to forward citations of the

[4] For calculating the RTA for claims, we use claims in each patent instead of forward citations for each patent.

[5] For example, a patent can be classified under US patent classification class – 123 – Internal Combustion Engine – in this case, say, the firm has two such patents with 10 total forward citations in a year 2001 in this class, and, if the total forward citations in this class is 1000 for total of 30 patents issued in 2001, we would calculate the RTA for this class for the firm in the following manner. RTA (class 123) = (10/2) / (1000/30) = 0.15. If the firm patented in two other classes, say classes 506 and 711 and had RTA (class 506) equal to 0.25 and RTA (class 711) equal to 0.30, then the firm's total RTA in 2001 will be calculated as, RTA total forward citations in 2001 = 0.15+0.25+0.30 = 0.7.

US patents granted in that class in that region and in that year normalized by the number of patents in that class for that region in year *t*.

$$RTA_{i,t,l,c} = (FC_{i,t,l,c} / total\ patents_{i,t,l,c}) / (FC_{t,l,c} / total\ patents_{t,l,c}) \quad (3)$$

$$RTA_{i,t}(forward\ citations) = \sum_{c=1}^{C} RTA_{i,t,l,c} \quad (4)$$

where, sampled firm, $i = 1,\ldots, N$, $t = 1970,\ldots, 2003$, technology class, $c = 1,\ldots, C$, number of regions, $l = 1,.., L$. We calculate $RTA_{i,t}(claims)$in the same way to represent the revealed technological advantages at firm-level for claims cited in the patents.

Controls

Our regression models also consist of several firm-level, location-level, and patent-level controls. We controlled for firm size, i.e., the number of its employees in year t, and firm age, i.e., the number of years elapsed from its establishment to year t. Authors have argued that larger research projects and larger firms have economies of scale for conducting research (Henderson & Cockburn, 1996). The research and patenting intensities at firm-level are controlled by using R&D to sales ratio and patent to sales ratio (RND_SALES, PAT_SALES) (Decarolis & Deeds, 1999). We control for the patenting intensity of the medical device sector in a region (LOC_PATCOUNT) by including the total count of patents by our sample firms in year t (Alcacer & Chung, 2007)[6]. Similarly, the knowledge production in the region (Alcacer & Chung, 2007), first, is calculated by measuring the number of technological classes that are patented in year t (ICL_IN_REGION), second, calculating the total number of forward citations that are generated for all patents in that region in year t (CITES_IN_REGION), and third, calculating the number of patents that are generated in that region in year t (PAT_IN_REGION)[7].

6 As a robustness check, we run the analysis using the patenting intensity of medical device sector in a region excluding the patents of our sample firm. The results of these analyses are not significantly different from those presented in this paper.

7 Due to high collinearity between forward citations and claims we do not use both these controls in our empirical model. As a robustness check we introduced claims in that region at year t instead of forward citations in that region in year t, and our results remained unchanged.

The importance of public research and the emergence of new industries has been widely studied (Buenstorf, et al., 2015; Henderson, Jaffe, & Trajtenberg, 1998). The public research organizations and universities have a tremendous impact on the science-based industries, and these institutions are also sources of powerful knowledge spillovers and providers of academic entrepreneurship (Anselin, Varga, & Acs, 1997; Feldman, 1994; Zucker, Darby, & Armstrong, 1998). We control for this geographically mediated spillovers by introducing a dummy variable for the presence of top research universities in the region (Siedschlag, Smith, Turcu, & Zhang, 2013; Zucker, Darby, Furner, Liu, & Ma, 2007). This variable (QSTOPUNIVERSITY) takes value one if the region has at least one university ranked in the world top 500 universities according to QS world university rankings, and zero otherwise. The description of variables and correlation is provided in table 2 and 3. TP_cites and TP_claims are highly correlated (correlation coefficient = 0.8697), and SMTP_cites and SMTP_claims are highly correlated as well (correlation coefficient = 0.9118). Hence, we do not use these two variables simultaneously in our regressions.

[Table 2 and 3 about here]

We also include a squared term for size, time dummies and sub-sector dummies in our empirical analysis. We use pooled ordinary least squares (OLS) and random effects (RE) panel data regressions to estimate our empirical model. Our regression models are presented below,

$$\begin{aligned} DepVar_{,t} = {} & X_{i,t-1} + SIZE_{i,t-1} + SIZE^{2}_{i,t-1} + AGE_{i,t-1} + RND\_SALES_{i,t-1} + PAT\_SALES_{i,t-1} + \\ & LOC\_PATCOUNT_{i,t-1} + QSTOPUNIVERSITY_{i,t-1} + ICL\_IN\_REGION_{i,t-1} + \\ & CITES\_IN\_REGION_{i,t-1} + PAT\_IN\_REGION_{i,t-1} + year\ dummies + sub\text{-}sector\ dummies \\ & + l + \mathrm{e}_{i} \end{aligned} \tag{5}$$

where, $DepVar_{i,t}$ is growth in sales(t,t-1), growth in employment (t,t-1) and q at time t, and, explanatory variable X is $TP\_cites_{,t-1}$ and $TP\_claims_{,t-1}$ (derived from equation 2 and represent technological proximity (TP)) and $SMTP\_cites_{i,t-1}$ and $SMTP\_claims_{,t-1}$ (derived from equation 4 and represents spatially-mediated technological proximity (SMTP)). We estimate multiple empirical models where $DepVar_{i,t}$ is one of the three above mentioned dependent variables and $X_{i,t-1}$ variable is one of the four above mentioned explanatory variable.

4. Results and discussion

The pooled OLS results for hypothesis 1 are presented in columns 2, 6, 10, and the random effects panel data regressions are presented in columns 4, 8, 12 of Table 4. We observe that localization does not affect the firm performance. Although localization has a positive impact on the growth of sales and q and a negative influence on the growth of employment, these coefficients are not statistically significant. Our results are consistent with the works of Giuliani (2007) and Boschma (2005) which suggest that geographical proximity and cluster-based localization are neither a sufficient nor a necessary condition for improving firm performance and innovation. These results can be explained by the arguments presented by prior literature which suggest that firm performance is moderated by the firm-level capabilities (Cohen & Levinthal, 1990; Folta, Cooper, & Baik, 2006; Jaffe, et al., 1993; Rosenkopf & Almeida, 2003) and costs of localization (Pouder & John, 1996; Prevezer, 1997; Shaver & Flyer, 2000; Zucker, Darby, & Brewer, 1999). Thus, we need to link the firm-level technological characteristics with the localization process of firms.

The results for hypotheses 2 and 3 are presented in tables 5 and 6. Table 5 presents the analysis of the impact of forward citations on firm performance, and table 6 presents the analysis of the impact of claims on firm performance. The pooled OLS results are presented in columns 1, 3, 5, 7, 9 and 11 of tables 5, and 6 and results of random effects panel data regressions are presented in columns 2, 4, 6, 8, 10 and 12 of tables 5 and 6[8]. We observe that

[8] As a robustness check, we also conducted similar analysis using system gmm panel data regressions and our results are not substantially different from those presented here.

size and age both have a negative impact on all our dependent firm performance variables. These results are in line with prior literature which suggests that as firms get older and bigger, the rate of growth of these companies starts stagnating (Evans, 1987; Oliveira & Fortunato, 2006). Also, it can be said that smaller and newer firms experience higher growth, and this is especially true in the high technology industry like the medical device industry.

[Table 4, 5 and 6 about here]

We find that on average the spatially-mediated technological proximity has a higher impact on our dependent variables than the technological proximity. We observe that technological proximity, proxied by forward citations, has no impact on the growth of sales, employment, and q. The spatially-mediated technological proximity proxied by forward citations, on the other hand, has a positive and significant impact on the growth of sales and q. Authors have argued that firm's nature of technology can have consequences for firm-level performance (Belenzon, 2012; Hall, et al., 2005; Mairesse & Hall, 1994; Merges & Nelson, 1994; Orlando, 2004).

Authors have suggested that firms located in a geographic area with a high degree of localization of similar firms and suppliers will have access to knowledge flows which are unavailable to similar firms in geographically isolated locations (Decarolis & Deeds, 1999). Their argument suggests that firms can build on positive externalities created for firms in the same industry co-locating to derive value from geographic clusters. Firms that are co-located in clusters with other firms belonging to the same industry will have similar access to specialized suppliers and experience locational scale economies. Hence, due to locational diseconomies, the firm's knowledge base might have a limited positive impact on firm-level performance if we ignore the impact of geography (Robbins, 2006). Thus, it can be argued that these resources can interact with geographic proximity to positively impact firm performance (Liao, 2010).

The technological proximity and spatially-mediated technological proximity, proxied by claims in patents, have limited impact on the growth of sales and employment. We observe that both these independent variables, TP_claims and SMTP_claims, have a positive and significant impact on Tobin's q. The patents with a higher number of claims can create a thicket of firm’s knowledge base that can be used by the inventing firm to block other firms from creating cumulative inventions from their proprietary technology (Hall, et al., 2005; Kitch, 1977; Lanjouw & Schankerman, 1997; Merges & Nelson, 1994).

Since, we observe the positive and significant effect for both technology proximity as well as spatially-mediated technology proximity for a number of claims within patents, to further tease out the impact of these independent variables; we perform a z-test for the difference in regression coefficients. In support of hypothesis 3, we find that SMTP_claims is significantly higher than TP_claims (*z value* = 3.98 for OLS, *z value* = 4.86 for random effects model). Also, authors have found that corporate diversification has a negative impact on firm performance and market value (Lang & Stulz, 1993). We argue that in the same manner the technological diversification and development which is not geared towards the technological necessities at the level of the cluster will have limited impact on a firm’s market value. This is especially true in the case of a number of claims presented in the patents as it represents the exclusionary zone within which the inventor can further develop their technology. These results are consistent with our arguments that localized knowledge development which can potentially leverage local embedded resources leads to a higher impact on firm performance than the pursuit of pure technology development even if it is technologically advanced to knowledge production in the cluster.

In Table 7, we present all the hypotheses together. We observe that the results of this analysis of the combined tests of hypotheses are similar to those presented in the earlier tables. In most cases, the significance of the coefficients is like those presented in other tables, and we also observe in most cases, only the spatially-mediated technology proximity coefficients are significant in our models. In terms of our results, one forward citation is worth 14 more employees in terms of employee growth and one forward citation in the same location and technology is worth $35,700.

[Table 7 about here]

5. Theoretical and Managerial contributions

Instead of dichotomy observed in cluster studies that either focus on localization or technology within clusters we add another dimension to this narrative, we look at the nature of technology. We observe that technological advancement has little implications in this industry and we find that firms that pursue an appropriate knowledge development strategy at the cluster-levels seem to derive higher returns from their innovation activities.

There are important implications for medical device business emerging from these findings. Managers need to evaluate the nature of technology within their firm and how this relates to the technology development within their cluster (Sandvig, 2000). In this article, we show that the strategy to pursue global technological dominance seems to have a lesser effect on the firms' growth of sales and market value. We recommend firms wanting to grow their sales and market value should focus on the technological development that is relevant to their cluster. Hence, managers and researchers may endeavor to generate research outputs that are of higher quality as compared to other research outputs in that cluster.

Managers and researchers should make sure that the number of claims within the patent creates not just exclusionary zones, but they also create exclusionary zones relevant to their cluster. Thus, working pro-actively at the level of patenting activities, managers can expand the technological horizon for the firm-level technology. Hence, we recommend that firms in the medical device industry may emphasize developing their technology that balances the needs of firms with those of competitors—complementary to firms in the cluster. Lastly, the paper provides important insights to managers for considering the nature of technology along with relational capital in improving sales growth in clusters.

6. Conclusion, limitations and further research

Studies investigating the effects of various proximities have produced mixed results, and this has led to more calls to study the effect of different types of proximities on firm performance (Boschma, 2005; Broekel & Boschma, 2012; Cantù, 2010). Responding to these calls, this paper has analyzed the effects of the nature of technology and location in the US medical device industry. By the pooled ordinary least squares (OLS) and random effects (RE) panel data techniques, we show that the geographical and technological proximity does not affect firm performance in the long run, whereas it is the spatially-mediated technology that has a positive influence on firm performance. Taken together, these findings demonstrate that industrial networks have an undeniable spatial element, and the way geography impacts the evolution of industrial networks is not uniform over time.

Lastly, at the level of firms' sales growth, the R&D, marketing, and production functions in an organization need to be geared to generate the spatially-mediated technological proximity. Authors have argued that firms that integrate intra- and interfirm functions will generate higher organizational performance (Ruekert & Walker, 1987), this is especially true when they have international networks (Chandrashekar & Bala Subrahmanya, 2018). Firms might have to develop informal social systems and organizational structures to achieve this cluster-level coherence and encourage knowledge transfer between co-located agents (Corsaro, Cantù, & Tunisini, 2012).

Future studies could benefit by replicating the findings of this study in a different industry and country context. For example, researchers could incorporate multiple proximity dimensions along with the nature of technology and see how these affect network dynamics or firm performance (e.g., Boshma, 2005). One of the limitations of this study is that we measure the agglomeration at the level of the city and region as a dummy variable, future studies can probably include a finer measure of agglomeration by including annual data on agglomeration as well as industry level detail on regional agglomeration. We acknowledge that some of the results lacking statistical significance might be due to the nature of the agglomeration data used in this study. Lastly, there is a scope to examine the governance-related issues and alliances formed between firms operating in a cluster and their impacts on knowledge spillovers and performance.

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Table 1. Firms classified according to their patenting activity and whether they are localized in clusters

		Localized in clusters	
		Yes	No
Innovation (proxied by R&D investment and patents) but here we just use patents to classify firms	Yes	120	72
	No	21	20

Table 2. Variables and their data sources

Construct	Variable	Data source
Dependent variables		
Growth in sales	GR_SALES	Compustat, $ Millions
Growth in employment	GR_EMP	Compustat, in thousands
Tobin's q	q	Compustat
Independent variables		
Geographical proximity	dum(localization)	Google maps, Compustat, Harvard cluster mapping project, Gibson (1970), Hekman (1980), Scott (1993), Audretsch and Feldman (1996)
Technological proximity	TP_cites TP_claims	NBER
Spatially-mediated technological proximity	SMTP_cites SMTP_claims	NBER
Firm-level controls		
R&D intensity	RND_SALES	Compustat
Patent intensity	PAT_SALES	NBER, Compustat
Firm age	AGE	Compustat
Firm size	SIZE	Compustat
Location level controls		
Top university	QSTOPUNIVERSITY	QS world university rankings
Patent stock of medical device firms in our sample in that region	LOC_PATCOUNT	NBER
Knowledge production in the region	ICL_IN_REGION CITES_IN_REGION PAT_IN_REGION	NBER

Table 3 Descriptive statistics and correlation matrix for variables

	Variable	Obs.	Mean	Std. dev.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	GR_SALES	2220	0.1578	0.5860	1.0000															
2	GR_EMP	2265	0.0866	0.3612	0.4163*	1.0000														
3	q	1176	5.9354	10.4656	0.1392*	0.1716*	1.0000													
4	dum(localization)	2499	0.5946	0.4910	0.0377*	0.0212	0.1056*	1.0000												
5	TP_cites	2499	0.6226	1.0387	0.0621*	0.0621*	0.0587*	0.0226	1.0000											
6	TP_claims	2498	0.4908	0.8134	0.0487*	0.0543*	0.0533*	-0.0247	0.8697*	1.0000										
7	SMTP_cites	2499	0.5142	0.7370	0.0477*	0.0464*	0.0811*	0.0009	0.6068*	0.5954*	1.0000									
8	SMTP_claims	2499	0.4437	0.6309	0.0454*	0.0299	0.0596*	0.0045	0.6036*	0.6530*	0.9118*	1.0000								
9	RND_SALES	2119	4.6592	74.8884	0.3540*	0.0519*	0.0645*	-0.0348	0.0165	0.0030	0.0216	0.0224	1.0000							
10	PAT_SALES	2232	2.2718	52.4090	0.2352*	0.0058	0.0947*	-0.0237	0.0765*	0.0443*	0.0519*	0.0534*	0.4878*	1.0000						
11	AGE	2499	30.8155	20.4479	-0.1227*	-0.0832*	-0.1728*	-0.2267*	0.0992*	0.1263*	0.1100*	0.1365*	-0.0413*	-0.0281	1.0000					
12	SIZE	2265	2.2159	6.2132	-0.0640*	-0.0673*	-0.1166*	-0.0142	0.1472*	0.1584*	0.1349*	0.1568*	-0.0222	-0.0151	0.4097*	1.0000				
13	QSTOPUNIVERSITY	2499	0.5878	0.4923	0.0019	0.0046	0.0601*	0.2541*	0.0170	-0.0246	0.0076	0.0103	-0.0551*	-0.0255	-0.1021*	-0.1164*	1.0000			
14	LOC_PATCOUNT	2499	4944.278	6045.042	0.0252	0.0068	0.1376*	0.3507*	0.0241	-0.0027	-0.0046	-0.0201	-0.0250	-0.0196	-0.2094*	-0.1217*	0.2871*	1.0000		
15	ICL_IN_REGION	2499	4.4737	6.1190	0.0248	0.0192	0.0347	0.1982*	0.2632*	0.2615*	0.3092*	0.2996*	-0.0226	-0.0042	0.1216*	0.3514*	0.0231	0.0868*	1.0000	
16	CITES_IN_REGION	2499	390.5658	842.0598	0.0577*	0.0338	0.2014*	0.2413*	0.2750*	0.2339*	0.2441*	0.2124*	-0.0157	0.0087	-0.0082	0.1460*	0.0672*	0.1669*	0.6322*	1.0000
17	PAT_IN_REGION	2499	16.1116	29.9936	0.0452*	0.0220	0.1430*	0.2314*	0.2263*	0.2079*	0.2480*	0.2198*	-0.0180	-0.0009	0.0265	0.2251*	0.0332*	0.1290*	0.8364*	0.8887*

* Significant at 10% level

Table 4. Analysis of the impact of localization on firm performance proxied by sales growth, employment growth, and Tobin's q

VARIABLES	(1) GR_SALES	(2) GR_SALES	(3) GR_SALES	(4) GR_SALES	(5) GR_EMP	(6) GR_EMP	(7) GR_EMP	(8) GR_EMP	(9) q	(10) q	(11) q	(12) q
H1: dum(localization)		0.00188		0.00121		-0.000991		-0.00470		0.696		0.545
		(0.0251)		(0.0259)		(0.0184)		(0.0216)		(0.753)		(1.418)
Lag.SIZE	-0.00853***	-0.00853***	-0.00913**	-0.00918**	-0.00783***	-0.00782***	-0.0101**	-0.0101**	-0.290***	-0.298***	0.00991	0.00934
	(0.00256)	(0.00257)	(0.00379)	(0.00380)	(0.00233)	(0.00234)	(0.00410)	(0.00413)	(0.0630)	(0.0630)	(0.130)	(0.132)
Lag.SIZE2	9.96e-05**	9.95e-05**	0.000101	0.000102	8.89e-05**	8.90e-05**	0.000106*	0.000106*	0.00390***	0.00390***	-0.000864	-0.000866
	(4.54e-05)	(4.54e-05)	(6.30e-05)	(6.30e-05)	(3.99e-05)	(4.00e-05)	(6.12e-05)	(6.16e-05)	(0.00107)	(0.00107)	(0.00154)	(0.00155)
Lag.AGE	-0.00201***	-0.00200***	-0.00223***	-0.00223***	-0.000953***	-0.000959***	-0.000897*	-0.000923*	-0.0111	-0.00586	-0.0651*	-0.0620
	(0.000414)	(0.000460)	(0.000563)	(0.000578)	(0.000339)	(0.000363)	(0.000534)	(0.000558)	(0.00996)	(0.0127)	(0.0333)	(0.0379)
Lag.RND_SALES	0.00112	0.00112	0.00105	0.00105	1.96e-05	1.93e-05	-2.18e-05	-2.30e-05	-0.238	-0.235	-0.280	-0.279
	(0.000936)	(0.000937)	(0.000822)	(0.000823)	(0.000236)	(0.000237)	(0.000202)	(0.000201)	(0.238)	(0.236)	(0.276)	(0.277)
Lag.PAT_SALES	0.00336	0.00336	0.00352	0.00353	0.000284	0.000284	0.000355	0.000357	0.718*	0.726**	0.418	0.418
	(0.00293)	(0.00293)	(0.00309)	(0.00309)	(0.000557)	(0.000557)	(0.000426)	(0.000424)	(0.370)	(0.368)	(0.262)	(0.262)
Lag.LOC_PATCOUNT	8.21e-07	7.73e-07	8.21e-07	7.94e-07	-1.37e-07	-1.12e-07	2.05e-07	2.99e-07	0.000137	0.000113	7.68e-05	7.07e-05
	(2.16e-06)	(2.21e-06)	(2.25e-06)	(2.36e-06)	(1.79e-06)	(1.88e-06)	(2.38e-06)	(2.48e-06)	(0.000141)	(0.000157)	(0.000258)	(0.000261)
QSTOPUNIVERSITY	0.000626	0.000339	0.00204	0.00194	9.88e-05	0.000252	-0.00130	-0.000517	0.625	0.512	0.691	0.554
	(0.0229)	(0.0229)	(0.0238)	(0.0236)	(0.0166)	(0.0165)	(0.0190)	(0.0191)	(0.445)	(0.459)	(1.188)	(1.142)
Lag.ICL_IN_REGION	0.000173	0.000164	-0.000238	-0.000271	0.00372*	0.00373*	0.00340	0.00345	-0.307***	-0.305***	-0.253	-0.255*
	(0.00398)	(0.00397)	(0.00319)	(0.00316)	(0.00214)	(0.00213)	(0.00265)	(0.00270)	(0.0897)	(0.0904)	(0.154)	(0.154)
Lag.CITES_IN_REGION	-7.44e-06	-7.48e-06	-7.98e-06	-8.01e-06	1.31e-05	1.31e-05	1.37e-05	1.37e-05	0.00299**	0.00296**	0.000890	0.000878
	(2.81e-05)	(2.81e-05)	(2.81e-05)	(2.80e-05)	(1.82e-05)	(1.83e-05)	(2.04e-05)	(2.04e-05)	(0.00120)	(0.00122)	(0.000946)	(0.000949)
Lag.PAT_IN_REGION	0.00104	0.00104	0.00112	0.00112	-0.000401	-0.000399	-0.000423	-0.000417	0.0361	0.0350	0.0780	0.0782
	(0.00136)	(0.00136)	(0.00113)	(0.00114)	(0.000737)	(0.000738)	(0.000776)	(0.000776)	(0.0326)	(0.0325)	(0.0476)	(0.0478)
Sub-industry dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.186**	0.184**	0.0455	0.0449	0.160**	0.161**	0.00790	0.0103	3.920***	2.929	1.224	0.840
	(0.0750)	(0.0797)	(0.0626)	(0.0646)	(0.0680)	(0.0704)	(0.0633)	(0.0636)	(1.325)	(1.817)	(5.389)	(5.454)
Observations	1,911	1,911	1,911	1,911	1,920	1,920	1,920	1,920	1,074	1,074	1,074	1,074
R-squared	0.093	0.093			0.039	0.039			0.154	0.154		
Number of firms			191	191			192	192			80	80
R-squared: within			0.0645	0.0646			0.0397	0.0398			0.0808	0.0809
R-squared: between			0.2038	0.2032			0.0175	0.0171			0.1909	0.1899
R-squared: overall			0.0927	0.0926			0.0377	0.0377			0.1273	0.1278
Prob > chi2			0.0000	0.0000			0.0000	0.0000			0.0000	0.0000

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5. Analysis of the impact of forward citations on firm performance proxied by sales growth, employment growth, and Tobin's q

VARIABLES	(1) GR_SALES	(2) GR_SALES	(3) GR_SALES	(4) GR_SALES	(5) GR_EMP	(6) GR_EMP	(7) GR_EMP	(8) GR_EMP	(9) q	(10) q	(11) q	(12) q
H2: Lag.TP_cites	0.0155	0.0133			0.0179**	0.0101			0.970**	0.444		
	(0.00945)	(0.0101)			(0.00701)	(0.00879)			(0.446)	(0.276)		
H3: Lag.SMTP_cites			0.0385***	0.0360**			0.0210*	0.0117			1.008**	0.481*
			(0.0139)	(0.0153)			(0.0113)	(0.0138)			(0.477)	(0.254)
Lag.SIZE	-0.00880***	-0.00918**	-0.00889***	-0.00927**	-0.00814***	-0.00991**	-0.00816***	-0.0101**	-0.292***	0.00654	-0.296***	0.00374
	(0.00255)	(0.00368)	(0.00253)	(0.00363)	(0.00232)	(0.00390)	(0.00233)	(0.00402)	(0.0617)	(0.131)	(0.0618)	(0.128)
Lag.SIZE2	0.000105**	0.000106*	0.000109**	0.000110*	9.53e-05**	0.000107*	9.55e-05**	0.000109*	0.00403***	-0.000695	0.00408***	-0.000691
	(4.54e-05)	(6.29e-05)	(4.53e-05)	(6.27e-05)	(4.00e-05)	(5.94e-05)	(4.01e-05)	(6.07e-05)	(0.00107)	(0.00156)	(0.00107)	(0.00152)
Lag.AGE	-0.00207***	-0.00221***	-0.00214***	-0.00228***	-0.00102***	-0.000948*	-0.00103***	-0.000934*	-0.0149	-0.0674**	-0.0150	-0.0665**
	(0.000415)	(0.000537)	(0.000422)	(0.000539)	(0.000338)	(0.000511)	(0.000341)	(0.000526)	(0.00960)	(0.0330)	(0.00970)	(0.0331)
Lag.RND_SALES	0.00111	0.00107	0.00114	0.00109	1.28e-05	-2.14e-05	2.22e-06	-3.05e-05	-0.203	-0.266	-0.215	-0.272
	(0.000944)	(0.000821)	(0.000934)	(0.000809)	(0.000236)	(0.000207)	(0.000242)	(0.000208)	(0.233)	(0.270)	(0.234)	(0.275)
Lag.PAT_SALES	0.00335	0.00346	0.00324	0.00336	0.000271	0.000350	0.000292	0.000363	0.683*	0.410	0.681*	0.409
	(0.00294)	(0.00310)	(0.00288)	(0.00304)	(0.000560)	(0.000442)	(0.000578)	(0.000444)	(0.353)	(0.256)	(0.355)	(0.258)
Lag.LOC_PATCOUNT	8.67e-07	8.40e-07	9.31e-07	9.07e-07	-8.71e-08	1.66e-07	-3.80e-08	2.37e-07	0.000157	9.41e-05	0.000155	9.57e-05
	(2.15e-06)	(2.20e-06)	(2.15e-06)	(2.19e-06)	(1.79e-06)	(2.33e-06)	(1.79e-06)	(2.35e-06)	(0.000142)	(0.000259)	(0.000142)	(0.000257)
QSTOPUNIVERSITY	0.00178	0.00235	0.00650	0.00725	0.00141	-0.000719	0.00259	0.000316	0.720	0.689	0.754*	0.716
	(0.0229)	(0.0232)	(0.0227)	(0.0232)	(0.0167)	(0.0185)	(0.0167)	(0.0188)	(0.446)	(1.177)	(0.445)	(1.171)
Lag.ICL_IN_REGION	-0.000749	-0.000863	-0.00148	-0.00166	0.00267	0.00288	0.00268	0.00284	-0.355***	-0.272*	-0.345***	-0.271*
	(0.00398)	(0.00318)	(0.00398)	(0.00312)	(0.00216)	(0.00264)	(0.00219)	(0.00269)	(0.0913)	(0.155)	(0.0898)	(0.154)
Lag.CITES_IN_REGION	-1.74e-05	-1.61e-05	-1.53e-05	-1.43e-05	1.55e-06	7.67e-06	4.15e-06	9.04e-06	0.00246*	0.000646	0.00262**	0.000692
	(2.86e-05)	(2.80e-05)	(2.83e-05)	(2.74e-05)	(1.83e-05)	(2.05e-05)	(1.84e-05)	(2.08e-05)	(0.00125)	(0.000926)	(0.00124)	(0.000944)
Lag.PAT_IN_REGION	0.00136	0.00136	0.00133	0.00134	-3.70e-05	-0.000239	-8.49e-05	-0.000256	0.0526	0.0854*	0.0484	0.0841*
	(0.00136)	(0.00114)	(0.00136)	(0.00113)	(0.000742)	(0.000789)	(0.000747)	(0.000805)	(0.0331)	(0.0467)	(0.0325)	(0.0473)
Sub-industry dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.190**	0.0405	0.190***	0.0435	0.164**	0.00565	0.164**	0.00408	4.223***	0.981	4.240***	0.913
	(0.0755)	(0.0601)	(0.0692)	(0.0599)	(0.0678)	(0.0601)	(0.0680)	(0.0611)	(1.340)	(5.374)	(1.344)	(5.337)
Observations	1,911	1,911	1,910	1,910	1,920	1,920	1,919	1,919	1,074	1,074	1,074	1,074
R-squared	0.094		0.097		0.041		0.041		0.161		0.159	
Number of firms		191		191		192		192		80		80
R-squared: within		0.0625		0.0638		0.0380		0.0388		0.0823		0.0821
R-squared: between		0.2207		0.2331		0.0288		0.0249		0.1993		0.1981
R-squared: overall		0.0938		0.0965		0.0400		0.0397		0.1324		0.1316
Prob > chi2		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 6. Analysis of the impact of patent scope (claims) on firm performance proxied by sales growth, employment growth, and Tobin's q

VARIABLES	(1) GR_SALES	(2) GR_SALES	(3) GR_SALES	(4) GR_SALES	(5) GR_EMP	(6) GR_EMP	(7) GR_EMP	(8) GR_EMP	(9) q	(10) q	(11) q	(12) q
H2: Lag.TP_claims	0.0141	0.0109			0.00928	-0.00183			1.413***	0.864**		
	(0.0154)	(0.0184)			(0.0106)	(0.0129)			(0.512)	(0.401)		
H3: Lag.SMTP_claims			0.0190	0.0156			0.0105	-0.00298			1.728***	1.182**
			(0.0209)	(0.0247)			(0.0147)	(0.0182)			(0.620)	(0.564)
Lag.SIZE	-0.00850***	-0.00899**	-0.00859***	-0.00903**	-0.00781***	-0.00990**	-0.00786***	-0.00988**	-0.265***	0.000164	-0.274***	-0.00221
	(0.00257)	(0.00372)	(0.00255)	(0.00368)	(0.00234)	(0.00399)	(0.00232)	(0.00395)	(0.0606)	(0.133)	(0.0604)	(0.131)
Lag.SIZE2	9.97e-05**	0.000101	0.000101**	0.000102	8.89e-05**	0.000104*	8.95e-05**	0.000104*	0.00355***	-0.000711	0.00367***	-0.000668
	(4.55e-05)	(6.27e-05)	(4.52e-05)	(6.25e-05)	(3.99e-05)	(5.96e-05)	(3.98e-05)	(5.92e-05)	(0.00104)	(0.00159)	(0.00104)	(0.00157)
Lag.AGE	-0.00206***	-0.00223***	-0.00207***	-0.00223***	-0.000988***	-0.000899*	-0.000990***	-0.000896*	-0.0172*	-0.0680**	-0.0180*	-0.0698**
	(0.000423)	(0.000561)	(0.000429)	(0.000561)	(0.000346)	(0.000538)	(0.000351)	(0.000542)	(0.00949)	(0.0328)	(0.00939)	(0.0329)
Lag.RND_SALES	0.00112	0.00106	0.00112	0.00107	1.60e-05	-1.85e-05	1.64e-05	-1.80e-05	-0.178	-0.252	-0.190	-0.255
	(0.000933)	(0.000817)	(0.000933)	(0.000816)	(0.000238)	(0.000204)	(0.000239)	(0.000203)	(0.231)	(0.268)	(0.230)	(0.270)
Lag.PAT_SALES	0.00333	0.00346	0.00332	0.00345	0.000271	0.000355	0.000269	0.000355	0.639*	0.385	0.632*	0.372
	(0.00292)	(0.00308)	(0.00292)	(0.00308)	(0.000559)	(0.000430)	(0.000561)	(0.000430)	(0.346)	(0.246)	(0.347)	(0.243)
Lag.LOC_PATCOUNT	9.61e-07	9.07e-07	9.87e-07	9.30e-07	-4.35e-08	1.78e-07	-4.33e-08	1.74e-07	0.000179	9.26e-05	0.000179	9.34e-05
	(2.15e-06)	(2.23e-06)	(2.15e-06)	(2.23e-06)	(1.78e-06)	(2.36e-06)	(1.78e-06)	(2.35e-06)	(0.000145)	(0.000261)	(0.000146)	(0.000262)
QSTOPUNIVERSITY	0.000748	0.00183	0.000620	0.00164	0.000180	-0.00123	9.52e-05	-0.00121	0.551	0.664	0.545	0.660
	(0.0229)	(0.0234)	(0.0229)	(0.0233)	(0.0166)	(0.0189)	(0.0166)	(0.0189)	(0.441)	(1.186)	(0.440)	(1.180)
Lag.ICL_IN_REGION	-0.000456	-0.000615	-0.000620	-0.000753	0.00330	0.00348	0.00328	0.00352	-0.358***	-0.276*	-0.376***	-0.289*
	(0.00407)	(0.00329)	(0.00418)	(0.00338)	(0.00215)	(0.00269)	(0.00219)	(0.00272)	(0.0954)	(0.157)	(0.0979)	(0.163)
Lag.CITES_IN_REGION	-1.17e-05	-1.10e-05	-1.23e-05	-1.16e-05	1.03e-05	1.41e-05	1.04e-05	1.43e-05	0.00252**	0.000607	0.00248**	0.000567
	(2.88e-05)	(2.84e-05)	(2.92e-05)	(2.89e-05)	(1.84e-05)	(2.07e-05)	(1.86e-05)	(2.08e-05)	(0.00119)	(0.000887)	(0.00118)	(0.000943)
Lag.PAT_IN_REGION	0.00119	0.00121	0.00124	0.00125	-0.000302	-0.000441	-0.000291	-0.000452	0.0497	0.0859*	0.0559*	0.0911*
	(0.00138)	(0.00114)	(0.00141)	(0.00117)	(0.000739)	(0.000783)	(0.000750)	(0.000791)	(0.0328)	(0.0461)	(0.0325)	(0.0492)
Sub-industry dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.187**	0.0411	0.187**	0.0401	0.160**	0.00912	0.160**	0.00939	4.163***	0.717	4.361***	0.620
	(0.0757)	(0.0612)	(0.0761)	(0.0607)	(0.0683)	(0.0623)	(0.0685)	(0.0622)	(1.367)	(5.427)	(1.350)	(5.435)
Observations	1,911	1,911	1,911	1,911	1,920	1,920	1,920	1,920	1,074	1,074	1,074	1,074
R-squared	0.093		0.094		0.039		0.039		0.163		0.164	
Number of firms		191		191		192		192		80		80
R-squared: within		0.0634		0.0632		0.0399		0.0400		0.0851		0.0867
R-squared: between		0.2137		0.2162		0.0166		0.0162		0.1970		0.1999
R-squared: overall		0.0932		0.0934		0.0377		0.0376		0.1356		0.1365
Prob > chi2		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 7. Analysis of the impact of forward citations and patent scope (claims) on firm performance proxied by sales growth, employment growth, and Tobin's q

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	GR_SALES	GR_SALES	GR_EMP	GR_EMP	q	q	GR_SALES	GR_SALES	GR_EMP	GR_EMP	q	q
H1: dum(localization)	0.00335	0.00226	-5.51e-05	-0.00431	0.891	0.626	0.00203	0.00148	-0.000594	-0.00457	0.721	0.684
	(0.0250)	(0.0257)	(0.0184)	(0.0210)	(0.776)	(1.404)	(0.0253)	(0.0257)	(0.0184)	(0.0216)	(0.750)	(1.392)
H2: Lag.TP_cites	0.00813	0.00676	0.0139**	0.00613	0.543	-0.0283						
	(0.00962)	(0.00916)	(0.00678)	(0.0133)	(0.353)	(0.352)						
H3: Lag.SMTP_cites	0.0357**	0.0337**	0.0192**	0.00616	0.887*	0.484*						
	(0.0143)	(0.0147)	(0.00929)	(0.0221)	(0.529)	(0.255)						
H2: Lag.TP_claims							-0.000748	-0.00270	0.00611	0.00146	0.736**	0.208
							(0.0264)	(0.0239)	(0.0203)	(0.0208)	(0.356)	(0.298)
H3: Lag.SMTP_claims							0.0198	0.0179	0.00418	-0.00469	1.502**	1.166**
							(0.0385)	(0.0377)	(0.0292)	(0.0321)	(0.644)	(0.552)
Lag.SIZE	-0.00900***	-0.00947***	-0.00820***	-0.00985**	-0.309***	0.00276	-0.00860***	-0.00913**	-0.00782***	-0.00991**	-0.271***	-0.00781
	(0.00254)	(0.00367)	(0.00231)	(0.00388)	(0.0618)	(0.130)	(0.00255)	(0.00370)	(0.00232)	(0.00400)	(0.0610)	(0.133)
Lag.SIZE2	0.000111**	0.000113*	9.83e-05**	0.000107*	0.00414***	-0.000697	0.000101**	0.000103	8.92e-05**	0.000105*	0.00350***	-0.000608
	(4.53e-05)	(6.32e-05)	(4.00e-05)	(5.94e-05)	(0.00107)	(0.00156)	(4.51e-05)	(6.25e-05)	(3.98e-05)	(5.99e-05)	(0.00105)	(0.00157)
Lag.AGE	-0.00214***	-0.00231***	-0.00107***	-0.000977*	-0.0100	-0.0627	-0.00206***	-0.00224***	-0.000995***	-0.000919	-0.0151	-0.0666*
	(0.000466)	(0.000549)	(0.000361)	(0.000531)	(0.0127)	(0.0383)	(0.000476)	(0.000579)	(0.000375)	(0.000567)	(0.0125)	(0.0376)
Lag.RND_SALES	0.00113	0.00107	2.48e-05	-2.49e-05	-0.188	-0.272	0.00112	0.00106	1.58e-05	-1.96e-05	-0.160	-0.246
	(0.000938)	(0.000813)	(0.000238)	(0.000209)	(0.235)	(0.276)	(0.000934)	(0.000818)	(0.000239)	(0.000202)	(0.231)	(0.266)
Lag.PAT_SALES	0.00324	0.00339	0.000194	0.000355	0.638*	0.412	0.00332	0.00346	0.000270	0.000357	0.590*	0.358
	(0.00289)	(0.00305)	(0.000550)	(0.000447)	(0.352)	(0.267)	(0.00292)	(0.00309)	(0.000560)	(0.000427)	(0.344)	(0.239)
Lag.LOC_PATCOUNT	8.64e-07	8.61e-07	-3.36e-08	2.82e-07	0.000128	8.82e-05	9.34e-07	8.87e-07	-2.32e-08	2.70e-07	0.000167	8.88e-05
	(2.20e-06)	(2.30e-06)	(1.87e-06)	(2.43e-06)	(0.000158)	(0.000265)	(2.20e-06)	(2.34e-06)	(1.87e-06)	(2.46e-06)	(0.000162)	(0.000266)
QSTOPUNIVERSITY	0.00635	0.00727	0.00463	0.000936	0.649	0.559	0.000305	0.00155	0.000243	-0.000449	0.411	0.486
	(0.0228)	(0.0231)	(0.0165)	(0.0187)	(0.454)	(1.128)	(0.0229)	(0.0232)	(0.0165)	(0.0191)	(0.450)	(1.128)
Lag.ICL_IN_REGION	-0.00188	-0.00203	0.00202	0.00280	-0.358***	-0.272*	-0.000630	-0.000785	0.00327	0.00357	-0.387***	-0.292*
	(0.00396)	(0.00319)	(0.00214)	(0.00268)	(0.0911)	(0.155)	(0.00415)	(0.00337)	(0.00218)	(0.00277)	(0.0986)	(0.164)
Lag.CITES_IN_REGION	-1.98e-05	-1.78e-05	1.06e-06	7.49e-06	0.00240*	0.000691	-1.23e-05	-1.14e-05	1.02e-05	1.43e-05	0.00226*	0.000497
	(2.88e-05)	(2.79e-05)	(1.83e-05)	(2.04e-05)	(0.00125)	(0.00101)	(2.91e-05)	(2.87e-05)	(1.85e-05)	(2.08e-05)	(0.00120)	(0.000975)
Lag.PAT_IN_REGION	0.00146	0.00145	1.18e-06	-0.000211	0.0518	0.0840*	0.00123	0.00125	-0.000291	-0.000449	0.0592*	0.0927*
	(0.00136)	(0.00117)	(0.000744)	(0.000791)	(0.0327)	(0.0493)	(0.00141)	(0.00118)	(0.000751)	(0.000791)	(0.0324)	(0.0497)
Sub-industry dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year dummies included	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.185**	0.0397	0.164**	0.00687	3.750*	0.474	0.228***	0.0397	0.118**	0.0116	3.348	0.0534
	(0.0733)	(0.0619)	(0.0667)	(0.0597)	(2.147)	(5.410)	(0.0698)	(0.0632)	(0.0562)	(0.0628)	(2.179)	(5.506)

Observations	1,910	1,910	1,919	1,919	1,074	1,074	1,911	1,911	1,920	1,920	1,074	1,074
R-squared	0.097		0.043		0.162		0.094		0.039		0.167	
Number of firms		191		192		80		191		192		80
R-squared: within		0.0636		0.0382		0.0822		0.0634		0.0401		0.0869
R-squared: between		0.2353		0.0278		0.1968		0.2145		0.0158		0.2007
R-squared: overall		0.0967		0.0402		0.1321		0.0933		0.0376		0.1385
Prob > chi2		0.0000		0.0000		0.0000		0.0000		0.0000		0.0000

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix A. Distribution of firms across the cities

City	No. of firms	City	No. of firms	City	No. of firms	City	No. of firms	City	No. of firms	City	No. of firms
Alachua	1	Chelmsford	1	Fremont	3	Marlborough	2	O'Fallon	1	San Jose	3
Allen	1	Chester	1	Fresno	1	Memphis	2	Orange	1	Santa Barbara	1
Allendale	1	Cincinnati	2	Gainesville	2	Menlo Park	2	Orangeburg	1	Santa Clara	2
Andover	1	Clear Lake	1	Golden	1	Mentor	1	Overland Park	1	Smithfield	2
Arden Hills	1	Clearwater	1	Golden Valley	1	Miami	1	Palo Alto	1	Snoqualmie	2
Atlanta	2	Cleveland	1	Great Neck	1	Midvale	1	Parsippany	1	Somerset	1
Austin	3	Colorado Springs	1	Hayward	1	Milford	1	Pembroke Pines	1	South Jordan	1
Bartlesville	1	Columbia	1	Houston	1	Milpitas	2	Philadelphia	1	Stewartville	1
Batesville	1	Columbus	1	Indianapolis	2	Minneapolis	8	Piscataway	2	Sunnyvale	4
Bedford	1	Concord	1	Irvine	9	Minnetonka	1	Pleasanton	3	Temecula	1
Bethel	1	Conshohocken	1	Jacksonville	1	Monroe	1	Plymouth	1	Tempe	1
Billerica	2	Cranberry Township	1	Kalamazoo	1	Monrovia	1	Pompano Beach	1	Tewksbury	1
Boston	1	Danvers	1	Kennesaw	1	Montgomeryville	1	Post Falls	1	Thousand Oaks	1
Bothell	2	Deerfield	1	Knoxville	1	Montvale	1	Queensbury	1	Troy	1
Boulder	1	Deerfield beach	1	Lake Forest	1	Morrisville	1	Rancho Santa Margarita	1	Utica	1
Bountiful	1	Des Plaines	1	Lakewood	1	Mount Arlington	1	Raynham	1	Vista	3
Braintree	1	Draper	1	Largo	1	Mountain View	3	Redwood City	1	Wakefield	1
Branchburg	1	Earth City	1	Lewisville	1	Mundelein	1	Ronkonkoma	2	Walnut Creek	1
Branford	1	East Windsor	1	Lilburn	1	Murray	1	Saint Louis	1	Warrendale	1
Brooklyn	1	Elkhart	1	Lincolnshire	1	Murray Hill	1	Saint Paul	8	Warsaw	2
Burlington	1	Elyria	1	Little Elm	1	Murrysville	1	Salt Lake City	3	Waukesha	2
Carlsbad	1	Ewing	1	Livingston	1	New Brighton	1	San Antonio	1	Wayland	1
Carlstadt	1	Fitchburg	1	Long Island City	1	New Jersey	1	San Clemente	1	Wayne	1
Chaska	1	Fort Worth	1	Longwood	1	New York City	1	San Diego	5	West Deptford	1
Chatsworth	1	Franklin Lakes	1	Malvern	1	Norwood	2	San Francisco	2	West Hills	1
				Westbury	2	Wilmington	1	Woodsboro	1	York	2