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The impact of external technology acquisition on enterprise innovation performance: the moderating effect of geographical distance

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ABSTRACT

Enterprises often acquire technologies from external sources which are geographically dispersed. Although previous literatures have discussed the role of external technology acquisition (ETA) in enterprises' innovation performance, how innovation is affected by the breadth and depth of ETA is less investigated, and little is known about how geographical distance (GD) is involved. Therefore, this paper first analyses the relationship between the breadth, depth of ETA and enterprises' innovation performance with patent transaction data of listed manufacturing enterprises in China. Then we further investigate how GD moderates the relationship. Results show that both the breadth and depth of ETA positively affect enterprises' innovation performance. GD has no moderating effect on the relationship between the breadth of ETA and enterprises' innovation performance, but negatively moderates the relationship between the depth of ETA and enterprises' innovation performance. Our results have implications for enterprises' ETA strategy.

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External technology acquisition; innovation performance; geographical distance; patent transaction

1. Introduction

Innovation has been defined as a process of recombining existing knowledge into new knowledge (Smith, Collins, and Clark 2005). Due to the rising complexity of innovation, it is far from sufficient for a company to develop all necessary technology and maintain competitiveness with in-house knowledge. Therefore, many enterprises apply open innovation strategy to seek external resources (Tsai, Hsieh, and Hultink 2011; Charmjuree, Badir, and Safdar 2021). Studies on open innovation have highlighted the role of external technology acquisition (ETA) in reducing the cost, cycle and risk of R&D (Ki, Gil, and Jina 2015; Jang et al. 2021). However, ETA does not always lead to expected effects as there exists considerable information asymmetry between enterprises and technology market. Therefore, enterprises must consider how to manage their relationship with their external technology suppliers (ETSs) to take full advantage of acquired resources.

Prior literature mainly studies the impact of ETA behaviour on enterprise innovation performance (Liu, Chen, and Kittilaksanawong 2013; Flor, Cooper, and Oltra 2018; Shi, Zhang, and Zheng 2019; Radicic 2021). For example, Kang, Jo, and Kang (2015) examined the role of ETA to investigate whether ETA is complementary or substitutive to internal R&D activities in creating innovation. Tsai, Hsieh, and Hultink (2011) investigated the ETA-product innovativeness relationship and examined the moderating roles of R&D investment. However, little attention has been paid to the impact

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of ETSs. Therefore, we aim to study how the configuration of ETSs can affect the follow-up innovation of enterprises. Specifically, we focus on the breadth and depth of ETA.

The breadth of ETA refers to the number of ETSs. According to the knowledge-based theory, a wide range of ETSs brings more diverse knowledge which can be recombined with enterprises' internal knowledge bases and lead to greater innovation (Chesbrough 2003; Beck and Schenker-Wicki 2014). However, collaborating with a large number of ETSs may increase the cost of management and information exchange for enterprises (Beck and Schenker-Wicki 2014). Therefore, the relationship between the breadth of ETA and enterprises' innovation performance remains unclear. Another line of query is how the depth of ETA involves in enterprises' subsequent innovation. The depth of ETA is defined as the strength of enterprises' collaborative ties with ETSs. Enterprises benefit from their relationship with ETSs because it can effectively promote tacit knowledge transfer (Jiang, Wang, and Feng 2020). However, over-embeddedness in supply network may lead to knowledge lock-in by limiting enterprises' access to more knowledge providers (Pomegbe et al. 2020). As a result, more research needs to be conducted on the linkage between the depth of ETA and enterprises' innovation performance.

In addition, geographical dimension is what has received little attention in the literature on ETA, yet research on knowledge collaboration has points in this direction (Gallié 2009; Luo et al. 2018). Geography favours the creation of economical and institutional linkages between actors, which is important to innovative activities and knowledge spillovers (Petruzzelli 2011). The main reason for these effects is that short geographical distances (GD) bring organisations together, favour interaction with a high level of information richness and facilitate the exchange of tacit knowledge between actors (Boschma 2005). However, an increasing number of studies have questioned the dominant role of local collaboration and suggested that knowledge creation takes place in a combination of both geographically close and distant settings (Bignami, Mattsson, and Hoekman 2020). External partners in different regions may have various impacts on the subsequent innovation performance because knowledge across geographical boundaries may be heterogeneous in technical fields and industries (Moaniba, Lee, and Su 2020). It can be seen that the role of GD in ETA remains unclear.

In summary, the purpose of this paper is to answer two research questions: (1) How do the breadth and depth of ETA affect enterprise innovation performance? (2) How does GD involve in the relationship? We are contributing to the existing literature in three ways. First, we introduce a categorisation that takes into account the range and strength of ties between enterprises and their ETSs. Second, we focus on the important role that GD plays in the consequence of ETA, which is still a controversial issue. Third, our study is conducted from the perspective of patent transaction while previous studies mainly focus on mergers and acquisitions (Wagner 2011; Gantumur and Stephan 2012; Han, Jo, and Kang 2018; Zhou et al. 2018), collaborative R&D (Park et al. 2020; Wu et al. 2020) and innovation alliance (Filiou and Massini 2018; Tran and Vu 2021; Zhang, Li, and Li 2022).

The rest of this paper is organised as follows. Section 2 is the theoretical analysis and hypothesis. In Section 3, we describe the research design including sample selection, data sources, variables and regression model. Then we demonstrate empirical results in Section 4. The final section sums up the major conclusion and offers managerial implications.

2. Theoretical analysis and hypotheses

When enterprises acquire external technologies from ETSs, the cooperative relationship based on technology transaction has been established. The existing literature mainly measures the cooperative relationship from the dimension of breadth and depth. For instance, Zhao and Wei (2018) measured the cooperation relationship between academic authors from the dimensions of breadth and depth. They argued that the collaborative breadth is used to reflect an author's collaboration and communication ability, and collaborative depth is the indicator of collaboration stability. Sebastian, Jutta, and Welpe (2019) analysed the cooperation modes at the project level from the perspective of breadth and depth. Collaboration breadth defines how different the knowledge and resources enterprises can obtain from external resources. Collaboration depth is the intensity of the interactions between the focal firms and their collaboration partners.

Referring to these existing studies, this paper intends to explore how ETA affects the innovation performance of focal firms in two dimensions: breadth and depth. The breadth of ETA (e.g. the number of ETSs) denotes the variety of external technology and the depth of ETA represents the intensity of the interactions between the focal firms and their ETSs. In addition, a few studies suggested that GD affects enterprises' selection of external knowledge sources. For instance, Moaniba, Lee, and Su (2020) argued that both the GD to external knowledge sources and the diversity of such sources have a strong influence on the success of the search process and the development of new drugs. Therefore, we propose that GD is also an important factor in the selection of ETSs. In other words, the GD may moderate the relationship between the breadth and depth of ETA and enterprises' innovation performance.

In general, this article will be divided into two parts. We first study the impact of the breadth and depth of ETA on the innovation performance, and then discuss the effect of GD. Figure 1 presents the theoretical framework of the paper.

2.1. ETA breadth and innovation performance

The breadth of ETA can be indicated by the number of ETSs. We argue that there are three mechanisms through which ETA breadth exerts effects on enterprises' innovation performance. Firstly, from the perspective of knowledge learning, higher ETA breadth brings new knowledge and new ideas to enterprises. With the increase of ETSs, enterprises may obtain more information and inspiration from the outside and thus have better innovation performance. Secondly, from the perspective of dynamic capability, ETA breadth may affect the knowledge search and absorption ability of enterprises. External technology is a crucial supplement to the internal knowledge base of enterprises (Larsson et al. 1998). A wide range of ETSs may bring diversified external technologies, which broadens the internal knowledge base within enterprises (Chen, Chen, and Vanhaverbeke 2011). Further, diversified internal knowledge base expands enterprises' scope of knowledge search and improves their probability of discovering new opportunities (Rui and Lyytinen 2019). In this way, enterprises can easily maintain competitive in market. In addition, diversified internal knowledge base enhances the absorptive capacity so that enterprises are able to make full use of new external knowledge. Thirdly, different suppliers offer heterogeneous technology, which is conducive to breaking the existing knowledge structure and bringing more innovative combinations to

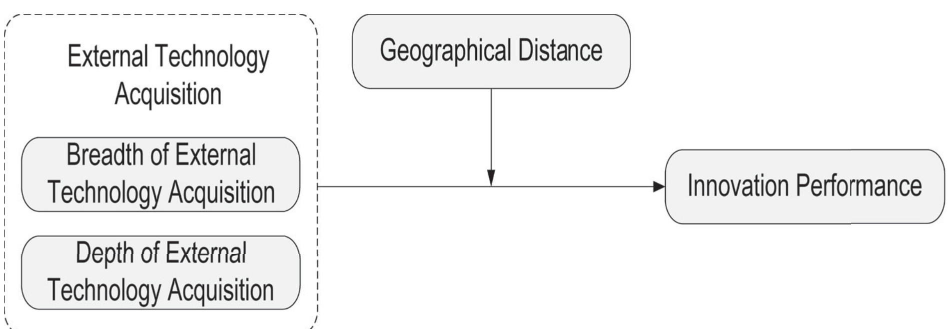

Figure 1. Research framework.

enterprises (Van Beers and Zand 2014; Ki, Gil, and Jina 2015; Kang, Jo, and Kang 2015; Bolli, Seliger, and Woerter 2020). Thus, with regards to knowledge recombination, enterprises may obtain more diverse external knowledge with the increasing number of ETSs. Based on the discussions, we propose the following hypothesis:

Hypothesis 1: The breadth of ETA has a positive effect on enterprises' innovation performance.

2.2. ETA depth and innovation performance

The depth of ETA can be indicated by the frequency of collaboration and communication between enterprises and their ETSs. The enterprises' innovation performance may be impacted in three ways. Firstly, greater depth of ETA brings more communication between enterprises and ETSs, which is conducive to building trust and stable cooperative relations between the two sides. In the long run, stable external cooperation is essential for innovation. Therefore, frequent cooperation with ETSs may provide a relatively stable and sustainable external environment for enterprises. Secondly, strong relationships with ETSs may generate intensive information exchange (Paulraj, Lado, and Chen 2008), reducing the possibility of opportunistic behaviour of ETSs effectively. Thirdly, more frequent communication and deeper trust contribute to absorptive capacity. The combination of external and internal knowledge is a process of tacit knowledge exchange, which requires enterprises to establish deep interaction with ETSs (Chen, Chen, and Vanhaverbeke 2011).

Greater depth of ETA results in more frequent tacit knowledge communication between enterprises and ETSs (Ganesan, Malter, and Rindfleisch 2005; Perez-Luno, Alegre, and Valle-Cabrera 2019; Perez-Luno, Alegre, and Valle-Cabrera 2019), which helps enterprises absorb external technology more efficiently. In this way, enterprises may have a deeper understanding of the external technology and make novel combinations with their raw knowledge base (Rowley, Behrens, and Krackhardt 2000). Accordingly, we propose our second hypothesis.

Hypothesis 2: The depth of ETA has a positive effect on enterprise innovation performance.

2.3. The moderating role of GD

2.3.1. The moderating effect of GD on the relationship between ETA breadth and innovation performance

The relationship between ETA breadth and enterprise innovation performance may be moderated by GD, which is measured by the spatial distance between enterprises and their ETSs. Many studies have highlighted the crucial role of combining knowledge from different regions in enterprises' innovation performance. Fitjar and Rodriguez-Pose (2013) found that collaboration with non-local organisations helps enterprises gain more diverse knowledge. Petruzzelli, Albino, and Carbonara (2009) argued that when external knowledge sources are limited locally, the learning ability of local actors may be weakened. This spatial constraint can be alleviated by establishing non-local linkages, as knowledge creation requires balancing or mixing local and non-local relationships. Other researchers have also reached a consensus that the combination of knowledge from different regions to promote innovation is the foundation of enterprise success. Enterprises with the ability to acquire non-local (distant) technologies can overcome the limitation of local knowledge and thus utilise diversified external knowledge to promote enterprise innovation (Frost 2001; Dervitsiotis 2010). We hence argue, enterprises can more easily overcome the limitation of local knowledge and make innovation more likely to happen with the rises of GD.

Hypothesis 3: The GD positively moderates the relationship between the breadth of ETA and enterprise innovation performance.

2.3.2. The moderating effect of GD on the relationship between ETA depth and innovation performance

GD may have effects on the relationship between the depth of ETA and enterprises' innovation performance. Firstly, the opportunistic behaviour of ETSs is affected. The frequency and depth of interaction between enterprises and ETSs gradually decrease with the increase of distance (Boschma 2005; Ponds, van Oort, and Frenken 2007) as remote cooperation is accompanied by high transmission costs, high communication costs, and planned meetings in advance. In this way, knowledge exchange over long distances becomes more difficult (Audretsch and Feldman 1996). On the contrary, enterprises can more easily interact with local collaborators through face-to-face interaction, personal contact and randomly arranged meetings (Paci and Usai 2000), contributing to the development of reciprocal relationships and reducing the opportunistic of ETSs (Barney and Hansen 1994). Secondly, the tacit knowledge exchange between enterprises and ETSs is affected. Frequent face-to-face communications are conductive to the exchange of tacit knowledge, which is stored at the individual level and difficult to be made explicit. Geographic proximity enhances regular face-to-face interactions and communication between partners and supports them to share tacit knowledge with each other, so that the external technology can be absorbed much better. In summary, we posit that the positive effect brought by the depth of ETA will be weakened if the GD between enterprises and their ETSs is large.

Hypothesis 4: The GD negatively moderates the relationship between the depth of ETA and enterprise innovation performance.

3. Data and methodology

3.1. Data sources

Patent assignment has become an important way for enterprises to acquire external technology. Therefore, we use patent assignment data to measure the ETA of enterprises. The number of patent assignments is valued as the frequency of ETA.

In terms of sample selection, we choose Chinese publicly listed manufacturing enterprises because the innovation activities of manufacturing industry depend more on external technology compared with the financial industry and service industry. In this study, we focus on the strategic behaviour of firms based on ETA, which should be stable and predictable. Therefore, we also deleted the enterprises that only purchased one patent, because purchasing only one patent is considered arbitrary and unstable (Chen and Lu 2017). The dataset in total covers samples of 240 firm-year observations on 205 enterprises.

In terms of data processing, we first use the enterprise name as the assignee to retrieve all patent assignment data of enterprises. Yearly data on patent assignments is collected from China National Intellectual Property Administration. The dataset includes the name and locations of patent assignors and assignees. We then manually exclude patents that enterprises purchased from their subsidiaries because it is hard to tell the boundary between them and parent enterprises can easily obtain technology from their subsidiaries (Kang, Jo, and Kang 2015). Finally, we supplement the dataset with financial data at the firm level through the China Stock Market and Accounting Research database.

3.2. Dependent variables

The dependent variable in the study is innovation performance. We measure innovation performance by the stocks of utility models and invention patent applications. Considering it takes a maximum of 18 months before a patent application is publicised, we limit our patent data to those applied before 31 December 2019. As enterprises may take time to learn the technology acquired from external sources, we consider 1-year lag on the dependent variable, which is able to prevent endogeneity problems caused by reverse causality.

3.3. Independent variables

The independent variables are the breadth and depth of ETA. In particular, the breadth of ETA can be measured by the stock of ETSs. Higher breadth represents more ETSs. The depth of ETA is measured by the average stock of patents a company purchases from per supplier. A larger value indicates more frequent communication and stronger ties between organisations.

3.4. Moderating variables and control variables

Geographical distance (GD) is our moderating variable. Following the practice of Jang et al. (2021), we set GD as a dummy variable, whose value is set to 0 if the enterprise and ETSs are located in the same city and 1 otherwise.

The selection of control variables depends on the following considerations. First, R&D investment is a factor directly related to a firm's innovation performance (Bronzini and Piselli 2016). Second, firm size and firm age are important variables affecting firm technological innovation, which is consistent with the Schumpeter hypothesis. Schumpeter hypothesis suggests that large firms outperform SMEs in innovation because they have significant advantages in terms of economies of scale, risk sharing, and innovation input support (Albert 1980). Besides, firms have a life cycle similar to that of an organism from birth to death. The willingness to innovate and the R&D capability of firms differ significantly in different life cycle stages (Miller and Friesen 1984). Third, state-owned enterprises in China have significant credit financing advantages compared to others (Acharya, Drechsler, and Schnabl 2014; Huang et al. 2017), resulting in state-owned enterprises having access to more working capital to support innovation. Fourth, the externally acquired technologies may vary among the different types of ETSs. The inherent nature of universities and public research institutes to provide public goods makes the technologies they provide often based on basic research, while the technologies provided by firms are more application-oriented. Such a distinction may also have implications for the subsequent innovation of the firms that acquire the technology. In summary, we select the following control variables: (1) R&D investment (RD). We use the logarithm to account for the skewness of yearly R&D investment values. (2) Total assets. (3) Age of the company. (4) Nature of ownership, which is a binary dummy variable whose value is set to 1 for state-owned enterprises and 0 otherwise. (5) Type of external ETSs. We divide the ETSs into enterprises, universities and public research institutes. The logarithm is also used here for the skew distribution of yearly total assets volume.

3.5. Model setting

As innovation performance is measured by the stocks of patent applications, which are made up of non-negative integers, we use negative binomial regression to test our hypotheses:

$$\begin{aligned}\text{Innovation performance}_{i,t} = f(&\text{Breadth}_{i,t-1}, \text{Depth}_{i,t-1}, \text{Age}_{i,t}, \text{RD}_{i,t}, \text{Ownership}_{i,t}, \text{Type}_{i,t-1},\\ &\text{Scale}_{i,t}, \text{GD}_{i,t-1}, \text{Breadth}_{i,t-1}*\text{GD}_{i,t-1}, \text{Depth}_{i,t-1}*\text{GD}_{i,t-1}, \varepsilon)\end{aligned}$$

4. Results

4.1. Descriptive statistics

Table 1 presents the descriptive statistical results and variance inflation factor (VIF) of the variables. The minimum value of innovation performance is 1 while the maximum value reaches 1208, and the standard deviation (192.9325) is greater than the average value (97.9163), indicating a high degree of disparity in data distribution. This confirms the usage of negative binomial regression. All the VIFs are smaller than 10, indicating that multi-collinearity can be neglected for the regression model. Further, we analyse the technology areas and source locations of the transacted patents, and the results are presented in Figure 2 and Figure 3, respectively. It can be seen that the technologies obtained from ETSs are mainly concentrated in the technology areas such as A61 (Medical Field), H01 (Electrical Field), G02 (Optical Field), H04 (Electrical Field) and C07 (Chemical Field). Figure 3 shows the geographical distribution of external technology sources at the provincial level. It can be found that ETA occurs more frequently in Guangdong, Jiangsu, Zhejiang, Beijing, Shanghai and Shandong.

4.2. Empirical analysis

Table 2 shows the results of our negative binomial regression analysis with the stock of patent application as the dependent variable, measures of ETSs and strength of ties as independent variables, GD as moderating variables and other control variables. We start with Model 1 which only includes control variables. Then we add the variable for the breadth and depth of ETA in Model 2 for testing hypotheses 1 and 2. We add GD in Model 3 and Model 4 includes the interaction term of the breadth of ETA and GD, and the interaction term of the depth of ETA and GD.

The results from Model 2 shows the coefficients for the breadth and depth of ETA are both significant ($p < .05$) and positive, which provide support for both hypotheses 1 and 2. The positive and significant results remain in all the following models. In Model 4, the coefficient for the interaction term between GD and the breadth of ETA is positive but insignificant, suggesting that GD does not moderate the effect of the breadth of ETA on enterprises' innovation performance. On the contrary, the positive and significant coefficient for the interaction term between GD and the depth of ETA is positive and significant ($p < .01$). The results indicate that enterprises benefit more from ETA if they are geographically close to their ETSs.

4.3. Exploratory analysis

Our results on the positive relationship between the breadth, depth of ETA and enterprises' innovation performance are different from some former studies on collaboration. Jang et al. (2021) argued that the breadth and depth of inter-organisational collaboration has a negative effect on enterprises' innovation performance because more collaborators distract managers and excess ties with homogenous collaborators limit enterprises' access to new knowledge. Thus, it is reasonable to posit that being over-embedded in the technology acquisition network weakens enterprises' innovation capability. To verify the point, we induce the quadratic terms of variables for the breadth and depth of ETA to Model 2 (Table 3). The new model is used to test whether there exists an inverted-U relationship between the breadth, depth of ETA and enterprises' innovation performance. The coefficients for both the quadratic terms of breadth and depth are not significant, which suggests there exists no inverted-U relationship between the variables. The results, as an

Table 1. Descriptive statistics and multi-collinearity test.

Variables	Mean	Min	Max	Standard Deviation	VIF
Innovation performance	97.9163	1	1208	192.9325	–
Breadth	1.5941	1	7	0.9250	1.62
Depth	3.7718	0.6667	45	4.8154	1.07
GD	0.7490	0	1	0.4345	1.09
Age	15.9456	3	36	5.5125	1.05
RD	18.8712	12.8992	22.9649	1.5454	2.97
Ownership	0.3933	0	1	0.4895	1.43
Type	1.2427	1	3	0.4487	1.53
Asset	22.3249	19.9577	26.2164	1.3188	3.49

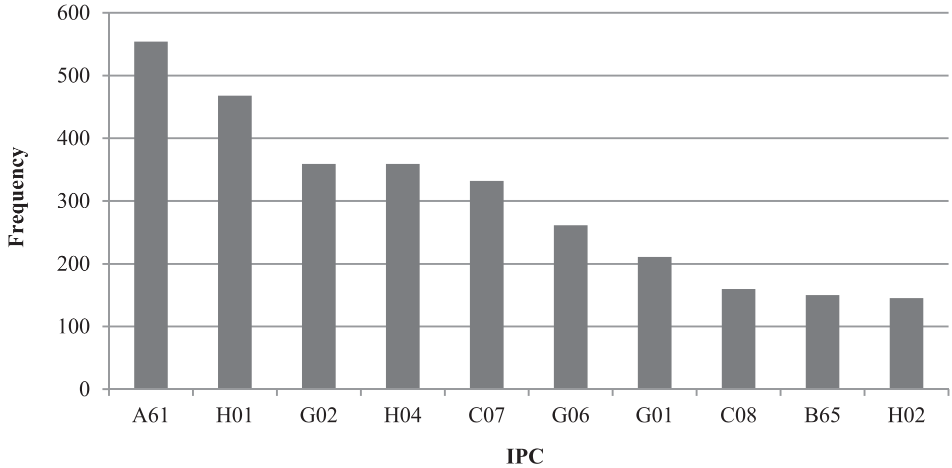

Figure 2. IPC of externally acquired technologies.

important supplement to the study of Jang et al. (2021), reinforce our opinion that the breadth and depth of ETA can strengthen enterprises' innovation capability .

4.4. Robustness check

As the results can be heterogeneous in different regression models, OLS regression is firstly used to test the robustness of the results (Table 4). Then we change the measurement of GD in Table 5 and Table 6 as different measurements can lead to heterogeneous results as well. We follow the study of Hong and Su (2013) and calculate the GD in two ways. The first way is to locate the enterprise at the prefectural level. In other words, we calculate the distances of enterprises based on the latitude and longitude of the cities they are located in:

$$\mathrm{GD}_{ij} = \{6371 * \arccos(\sin(\mathrm{lat}_i)\sin(\mathrm{lat}_j) + \cos(\mathrm{lat}_i)\cos(\mathrm{lat}_j)\cos(|\mathrm{long}_i - \mathrm{long}_j|))\}$$

where GD_{ij} represents the GD between city i and j. lat_i and lat_j, long_i and long_j denote the latitude and longitude of city i and j. 6371 (km) is the average radius of the Earth. The empirical results are presented in Table 5.

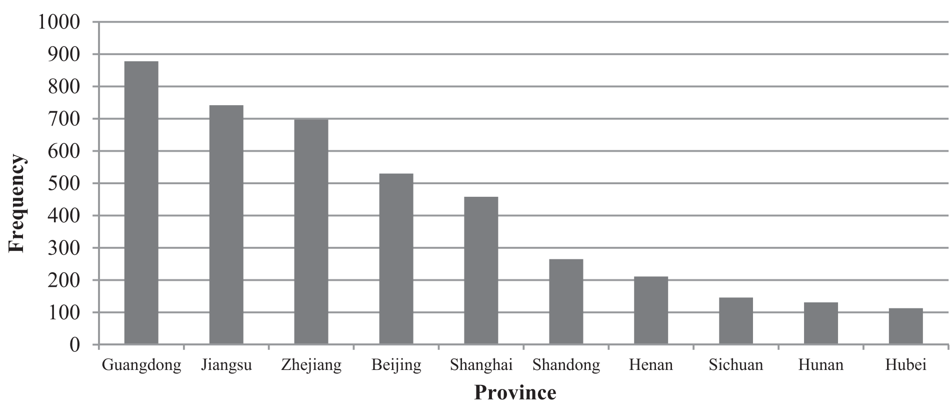

Figure 3. Source of externally acquired technologies.

Table 2. The regression results of ETA and innovation performance.

Variables	Innovation performance Model 1	Model 2	Model 3	Model 4
RD	0.5113 (0.000)***	0.4444 (0.000)***	0.4475 (0.000)***	0.4139 (0.000)***
Ownership	−0.0001 (1.000)	−0.1958 (0.269)	−0.1986 (0.264)	−0.2599 (0.138)
Age	−0.2376 (0.045)**	−0.0185 (0.113)	−0.0186 (0.110)	−0.2000 (0.078)*
Asset	0.1732 (0.057)*	0.2588 (0.008)***	0.2562 (0.010)***	0.3093 (0.002)***
Type	−0.3673 (0.018)**	−0.5826 (0.006)***	−0.5795 (0.006)***	−0.6236 (0.003)***
Breadth		0.2385 (0.015)**	0.2400 (0.015)**	0.1973 (0.531)
Depth		0.0495 (0.001)***	0.0485 (0.002)***	0.0857 (0.001)***
GD			−0.0369 (0.831)	0.3624 (0.454)
Breadth*GD				0.0265 (0.932)
Depth*GD				−0.1012 (0.002)***
Constant	−8.6331 (0.000)***	−9.6641 (0.000)***	−9.6328 (0.000)***	−10.2511 (0.000)***
Prob > Chi2	0.000***	0.000***	0.000***	0.000***

Note: ***$p < .01$, **$p < .05$, *$p < .1$.

Since the above formula cannot measure the GD between enterprises in the same city, we also use the second method to measure the GD between enterprises and ETSs. The specific method is to search for the GPS coordinates of enterprises and ETSs through Baidu Map, and then calculate the GD between different enterprises. The calculation formula is as follows:

$$\mathrm{GD}_{mn} = \{6371 * \arccos(\sin(\mathrm{lat}_m)\sin(\mathrm{lat}_n) + \cos(\mathrm{lat}_m)\cos(\mathrm{lat}_n)\cos(|\mathrm{long}_m - \mathrm{long}_n|))\}$$

where GD_{mn} represents the GD between enterprise m and$n$. lat_m and lat_n, long_m and long_n denote the latitude and longitude of enterprise m and n. 6371 (km) is the average radius of the Earth. The empirical results are presented in Table 6.

Table 4 shows the coefficients for breadth and depth remain positive and significant in OLS regression while supporting hypotheses 1 and 2 once again. It appears in Table 5 and Table 6 that the interaction term of breadth and GD stays insignificant while the interaction term of depth and GD is still significant (Model 12 and Model 16). The results are in line with what is shown in Table 2, which provides support for hypothesis 4.

5. Conclusion and implication

5.1. Conclusion

We construct a negative binomial regression model to empirically analyse how innovation is affected by the breadth and depth of ETA and further check the robustness of the results. Our study shows that (1) The breadth of ETA has a positive impact on enterprises' innovation performance, which means that enterprises with more ETSs have more technological innovation. (2) The depth of ETA

Table 3. Regression model with square term of independent variable.

Variables	Regression coefficients	Standard error	Z	$P > \|Z\|$	95% Confidence interval Lower limit	Upper limit
RD	0.4527***	0.0655	6.91	0.000	0.3243	0.5812
Ownership	−0.1733	0.1788	−0.97	0.333	−0.5238	0.1772
Age	−0.0173	0.0117	−1.48	0.138	−0.0403	0.0056
Asset	0.2448**	0.0993	2.46	0.014	0.0501	0.4395
Type	−0.5392**	0.2155	−2.50	0.012	−0.9615	−0.1168
Breadth	−0.0089	0.3040	−0.03	0.977	−0.6047	0.5869
Depth	0.0441	0.0427	1.03	0.302	−0.0397	0.1279
Breadth^2	0.0459	0.0545	0.84	0.400	−0.0610	0.1527
Depth^2	9.48e−05	0.0013	0.08	0.940	−0.0024	0.0026
Constant	−9.3348***	1.6099	−5.80	0.000	−12.4902	−6.1795

Note: ***$p < .01$, **$p < .05$, *$p < .1$.

Table 4. Robustness test results (OLS regression).

	Innovation performance			
Variables	Model 5	Model 6	Model 7	Model 8
RD	51.3266 (0.000)***	47.5743 (0.000)***	47.7633 (0.000)***	42.8703 (0.000)***
Ownership	13.3800 (0.582)	18.4933 (0.439)	17.6862 (0.463)	12.1384 (0.604)
Age	−3.5554 (0.059)*	−3.3151 (0.07)*	−3.3423 (0.069)*	−3.6643 (0.039)**
Asset	29.0289 (0.042)**	26.4412 (0.058)*	26.3491 (0.06)*	32.9475 (0.016)**
Type	−53.4703 (0.019)**	−88.6466 (0.001)***	−88.0145 (0.001)***	−95.1596 (0.000)***
Breadth		42.5875 (0.002)***	43.0749 (0.002)***	79.6545 (0.06)*
Depth		5.8393 (0.006)***	5.7963 (0.007)***	18.9604 (0.000)***
GD			−6.8167 (0.773)	128.3363 (0.049)**
Breadth*GD				−39.6455 (0.344)
Depth*GD				−19.1164 (0.000)***
Constant	−1400.869 (0.000)***	−1324.336 (0.000)***	−1321.389 (0.000)***	−1469.401 (0.000)***
Adj *R*-Squared	0.3453	0.3838	0.3813	0.4232

Note: ***$p < .01$, **$p < .05$, *$p < .1$.

Table 5. Robustness test results (GD is measured by the distance between cities).

	Innovation performance			
Variables	Model 9	Model 10	Model 11	Model 12
RD	0.5113 (0.000)***	0.4444 (0.000)***	0.4546 (0.000)***	0.4448 (0.000)***
Ownership	−0.0001 (1.000)	−0.1958 (0.269)	−0.1944 (0.271)	−0.2155 (0.221)
Age	−0.2376 (0.045)**	−0.0185 (0.113)	−0.0202 (0.083)*	−0.0211 (0.067)*
Asset	0.1732 (0.057)*	0.2588 (0.008)***	0.2482 (0.011)**	0.2685 (0.006)***
Type	−0.3673 (0.018)**	−0.5826 (0.006)***	−0.5925 (0.005)***	−0.6065 (0.004)***
Breadth		0.2385 (0.015)**	0.2383 (0.015)**	0.2812 (0.012)**
Depth		0.0495 (0.001)***	0.0465 (0.002)***	0.0542 (0.001)***
GD			−0.0001 (0.125)	0.0001 (0.531)
Breadth*GD				−0.0001 (0.359)
Depth*GD				−1.83e−05 (0.016)**
Constant	−8.6331 (0.000)***	−9.6641 (0.000)***	−9.5170 (0.000)***	−9.8337 (0.000)***
Prob > Chi2	0.000***	0.000***	0.000***	0.000***

Note: ***$p < .01$, **$p < .05$, *$p < .1$.

Table 6. Robustness test results (GD is measured by the distance between enterprises).

	Innovation performance			
Variables	Model 13	Model 14	Model 15	Model 16
RD	0.5113 (0.000)***	0.4444 (0.000)***	0.4515 (0.000)***	0.4417 (0.000)***
Ownership	−0.0001 (1.000)	−0.1958 (0.269)	−0.2087 (0.238)	−0.2332 (0.185)
Age	−0.2376 (0.045)**	−0.0185 (0.113)	−0.0189 (0.102)	−0.0199 (0.083)*
Asset	0.1732 (0.057)*	0.2588 (0.008)***	0.2539 (0.009)***	0.2749 (0.005)***
Type	−0.3673 (0.018)**	−0.5826 (0.006)***	−0.5826 (0.005)***	−0.5928 (0.004)***
Breadth		0.2385 (0.015)**	0.2390 (0.014)**	0.2695 (0.022)**
Depth		0.0495 (0.001)***	0.0471 (0.002)***	0.0548 (0.001)***
GD			−0.0001 (0.193)	0.0001 (0.666)
Breadth*GD				−3.54e−05 (0.593)
Depth*GD				−1.78e−05 (0.018)**
Constant	−8.6331 (0.000)***	−9.6641 (0.000)***	−9.6170 (0.000)***	−9.9325 (0.000)***
Prob > Chi2	0.000***	0.000***	0.000***	0.000***

Note: ***$p < .01$, **$p < .05$, *$p < .1$.

has a positive impact on enterprises' innovation performance, suggesting that enterprises developing stronger ties with their ETSs have more subsequent innovation outputs. (3) GD has no moderating effect on the relationship between the breadth of ETA and enterprises' innovation performance. (4) The GD negatively moderates the relationship between the depth of ETA and enterprises' innovation performance, indicating that enterprises keeping stronger ties with local ETSs have greater performance on innovation.

5.2. Implications

We contribute to the existing literature in three ways. First, we use patent transaction to investigate ETA while previous studies mainly focus on mergers and acquisitions (Wagner 2011), collaborative R&D (Belderbos, Carree, and Lokshin 2004) and innovation alliance (Filiou and Massini 2018). Our new dataset provides new insights for this line of study.

Secondly, we provide new empirical evidence for the relationship between ETA and firm innovation performance, which is a controversial topic. Previous studies have reached conflicting results over the effects of external technology search. Huang et al. (2015) believed that the width and depth of external knowledge search promote enterprises' innovation performance, while Jang et al. (2021) held the opposite view. Our study with evidence from listed enterprises in China supports the positive function of the breadth and depth of ETA to enterprises' innovation performance. In addition, we design an exploratory study based on the benchmark regression model and confirm that the breadth and depth of ETA only have a positive impact on enterprises' innovation performance. Our results are in line with Jin et al. (2018) and Huang et al. (2015) and are important supplements to the literature on external knowledge search.

Thirdly, we further add to the literature on the intersection of GD and innovation. We find that GD does not moderate the relationship between the breadth of ETA and enterprises' subsequent patent applications. The results suggest that there is no difference in the impact of local and non-local knowledge on enterprise innovation performance. One possible reason is that local and non-local knowledge technology is homogeneous because GD information is not the primary consideration for enterprises to choose external technology sources, which has been confirmed by Cuellar, Méndez-Morales, and Herrera (2022). Although this conclusion is different from the results of Petruzzelli, Albino, and Carbonara (2009), Fitjar and Rodriguez-Pose (2013), it is not surprising. It has been verified that both local and distant partners can provide valuable knowledge (Wang and Lin 2018; Wu 2015) and the mixture of local and non-local knowledge is crucial for innovation (Petruzzelli, Albino, and Carbonara 2009). Our conclusions support these views. Besides, our results that GD weakens the function of strong ties suggest that close and strong relationships between enterprises and their ETSs benefit enterprises more. The findings are in consistence with Ganesan, Malter, and Rindfleisch (2005) and Bolivar-Ramos (2019). We argue the reason is that enterprises can have more frequent communication with local ETSs and bring about more exchange of tacit knowledge.

Our study has implications for managers. First of all, enterprises can keep in contact with more ETSs so that they can absorb diverse knowledge. When the demand for external technology is clear, the enterprise should search for more external technology sources through the patent database, and then try to establish contact with different technology sources. Secondly, it benefits enterprises if they have strong connections with their main ETSs as it helps enterprises gain tacit knowledge. Thirdly, it is easier for tacit knowledge transfer in local regions. Therefore, enterprises should keep more interactions and strong relationships with local ETSs, and the specific measures are as follows. (1) Enterprises should identify potential local ETSs. For enterprises, they can search for local large-sized companies, universities and research institutes related to their technology fields through patent databases. These institutions generally have stronger innovation ability and apply for more patents. Therefore, they can be the main potential ETSs. (2) Enterprises should explain their ETA requirements to the main local potential suppliers as accurately as possible. For example, enterprises should hold more meetings related to technology transaction and invite local potential suppliers to participate. This kind of in-person interaction helps technology buyers and sellers know the needs of each other better. (3) Enterprises should strive to facilitate technology transactions with main local potential ETSs. Specifically, the enterprise should formulate a mutually beneficial cooperation plan to ensure that both the enterprise and local ETSs can benefit from the technology transaction. This is not only conducive to the completion of the technology transaction, but also the establishment of mutual trust, which helps develop long-term cooperative relations between the enterprises and local ETSs.

5.3. Limitations and future research

Our study is not free of limitations. As our samples are limited to listed enterprises, we expect further research on the ETA of non-listed enterprises. In addition, our study is limited to Chinese enterprises and it would be interesting to compare the results in other countries. Furthermore, we only investigate the moderating effect of GD, and other proximities such as institutional proximity and technological proximity can also be included in future studies.

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