Threshold effects, technology purchasing, and firm outcomes: An absorptive capacity perspective

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ABSTRACT

External technology purchasing is frequently adopted as a strategy to facilitate technology innovation and to enhance firm performance. However, research shows that there is considerable heterogeneity across firms with respect to innovation output and firm performance after technology purchasing. This study uses an absorptive capacity perspective in proposing the existence of an R&D employees threshold and a technology purchasing scale threshold. Using a sample of 1460 high-tech companies in China, we find support for both thresholds. We also find that the two variables are complementary with each other, jointly promoting innovation when both thresholds are crossed.

1. Introduction

Technology purchasing is adopted by many firms to get complementary technical resources with lower R&D costs, and to achieve innovation through a shorter technology R&D cycle (Tsai et al., 2011; Xie et al., 2019). For example, Google has perfected its in-flight Internet service and improved the Google Fiber blueprint by purchasing Nokia's airborne broadband system technology (Bloomberg, 2018). Alibaba has achieved a more powerful data processing capability by acquiring and expanding the Apache Flink platform technology that it purchased from Data Artisans (Tech.eu, 2019). Technology purchasing can be considered as a technology transfer mechanism that gives an enterprise external knowledge, intangible technologies, or physical facilities such as machinery and equipment (Cassiman and Veugelers, 2006).

Research shows that combining externally acquired new knowledge with existing internal knowledge may contribute to an optimal level of innovation performance (Zahra and George, 2002; Todorova and Durisin, 2007; Ferraris et al., 2017). In fact, integrating externally-acquired knowledge with internal knowledge may lead to heterogeneous bundles of resource configurations which can be further used to stimulate innovation activities in the organization. Some firms even directly produce new products through buying a new product line (Cassiman and Veugelers, 2006). It has been argued that innovation performance is maximized only if the externally acquired technology is thoroughly understood and synergized with a firm's own accumulated knowledge base (Zahra and George, 2002; Liao et al., 2007).

An organization must obviously have some existing resource base in order to successfully absorb acquired technologies (Enkel and

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Heil, 2014; Ferraris et al., 2017), and that base will affect the acquisition and assimilation of externally-acquired resources. Also, the magnitude of technology purchasing can make a difference, since small-scale purchasing might not be sufficient to create a diversified resource bundle.

Accordingly, in this study we address the following research questions: (1) what is the optimal scale threshold regarding the extent of technology purchasing and the extent of the existing knowledge-based resource base, and (2) what is the relationship between the two thresholds, i.e., are they substituting or complementary?

To answer these research questions, this study uses absorptive capacity theory to propose hypotheses and to test the existence and mutual dependence of absorptive capacity thresholds. We follow the definition of absorptive capacity proposed by Zahra and George (2002): organizational routines and processes of knowledge acquisition, assimilation, transformation, and exploitation. These routines and processes are further clustered into *potential* absorptive capacity (acquiring and assimilating knowledge) and *realized* absorptive capacity (transforming and exploiting knowledge) (Zahra and George, 2002). Specifically, a firm (1) needs enough internal knowledge to understand the new knowledge that it gains through acquisition, (2) has a capacity to integrate the new knowledge with existing internal knowledge, (3) must ensure that organization members internalize the new knowledge, and (4) must creatively find different resource combinations that generate increased innovation performance (Grant, 1996; Escribano et al., 2009; Tidd and Trewhella, 2010). We use the distinction between potential and realized absorptive capacity to propose the existence of a *potential* absorptive capacity threshold (the organizational R&D capacity to acquire and assimilate external knowledge, as measured by the number of R&D Employees), and a *realized* absorptive capacity threshold (the acquired external knowledge can be transformed and integrated with internal knowledge to exploit innovations, as measured by the Technology Purchasing Scale).

We use threshold regression models to test our hypotheses with a sample of 1460 Chinese high-tech companies that continuously operated from 2010 to 2015. The findings support the hypotheses about the existence of the threshold of R&D employees and the threshold of technology purchasing. Specifically, we found that technology purchasing can lead to increased innovation performance when a firm crosses the R&D employees threshold, or a purchased technology scale threshold. Furthermore, we found that there is a complementary effect between the number of R&D employees and the technology purchasing scale; the two variables will jointly promote innovation performance when both thresholds are crossed. There is also a substitution effect between the number of R&D employees and the technology purchasing scale; the two variables will jointly have a negative impact on innovation when neither of the thresholds are crossed. Lastly, we find that the innovation eventually results in an increased level of firm performance.

This study has both theoretical and practical implications. With regard to the former, we enrich the research literature of potential absorptive capacity with the finding about the R&D employees threshold effect. It goes beyond the traditional linear idea, and provides a non-linear aspect in exploring firms' heterogeneous innovation performance after technology purchasing. With regard to the non-linear aspect, we identify the existence of both an R&D employees threshold and a technology purchasing scale threshold. One implication of our research findings is that a firm needs a sufficient accumulation of internal R&D capacity before initiating technology purchasing.

The paper is organized as follows: Section 2 reviews the concept of absorptive capacity theory and proposes hypotheses about it. Section 3 presents our research methodology, including sample and data sources, measures, and analyses. Section 4 describes the results of our empirical tests that are based on panel threshold regressions, Tobit regressions, OLS regressions, and the Heckman two-stage model. In Section 5, we summarize our findings, note their implications, identify the limitations of our study, and make suggestions for future research.

2. Theory and hypotheses

2.1. Absorptive capacity and technology purchasing

Technology purchasing is a strategy that is used to access and absorb external knowledge with the purpose of increasing a firm's innovation performance (Basant and Fikkert, 1996; Lowe and Taylor, 1998). The term *absorptive capacity* (Cohen and Levinthal, 1990) refers to the capacity of a firm to acquire, assimilate, transform, and exploit knowledge, technology, and other tangible or intangible resources that are available externally. In this study, we use absorptive capacity theory to study the impact of technology purchasing, and to propose the existence of a R&D employees threshold (potential absorptive capacity), and a technology purchasing threshold (realized absorptive capacity).

Various studies have shown that there is considerable heterogeneity in firms' innovation performance after they acquire external knowledge-based resources (Cohen and Levinthal, 1990; Ahuja and Katila, 2001). To better understand this heterogeneity, the notion of absorptive capacity is further divided into *potential* (acquiring and assimilating knowledge) and *realized* (transforming and exploiting knowledge) capacity (Zahra and George, 2002). Potential absorptive capacity emphasizes the firm's internal capacity to identity and access the value of external resources (*knowledge acquisition*), and to accept and understand novel interpretations that are embodied in external knowledge (*knowledge assimilation*). By contrast, realized absorptive capacity emphasizes the firm's capacity to transform and exploit external knowledge-based resources. Applying potential absorptive capacity to target external resources is necessary in order to effectively combine internal and external knowledge. Potential absorptive capacity is the precondition that is necessary to realize the value of acquired technology (Zahra and George, 2002; Liao et al., 2007; Enkel and Heil, 2014).

We adopt the concepts of potential and realized absorptive capacity to study technology purchasing (Zahra and George, 2002). In particular, we argue that the potential absorptive capacity threshold is largely captured by the number of R&D employees (Huang et al., 2015), whereas the realized absorptive capacity threshold is captured by the magnitude of technology purchasing (Fig. 1). We also theorize that there is a minimum level of R&D employees (threshold effect of R&D employees), and also a minimum level of

technology purchasing scale (threshold effect of technology purchasing). Only when both have been achieved can a focal firm transform purchased technology into improved innovation performance.

We also argue that there may be mutual dependence between the two thresholds, meaning that the R&D employees threshold may either complement (or substitute for) the technology purchasing threshold. Here, complementing means a larger threshold in one is coupled with a larger magnitude of threshold in the other, while substituting means that a small threshold in one is coupled with a smaller magnitude in the other.

2.2. R&D employees threshold

A firm must have a certain amount of knowledge to identify the kinds of external technology that should be purchased (Zahra and George, 2002; Jansen et al., 2005). Since the capacity of a firm is determined by people rather than being an inevitable result of monetary resource commitment, we view R&D employees as the main subjective entity who use a firm's "stocked resources" to recognize the value of external sources (Huang et al., 2015). Some knowledge is tacit and is derived mainly from experience; it is therefore difficult to convert to explicit knowledge (Shane, 2000). R&D employees have not only the skills to use technology, but also the ability to transform technology into know-how and organizational processes (Nonaka and von Krogh, 2009). Therefore, R&D employees can be considered as the knowledge base of a firm's potential absorptive capacity (Martínez-Sánchez et al., 2020).

Because the absorption of external knowledge is based on storage and retrieval of internal knowledge (Carlile and Rebentisch, 2003), we propose that the R&D employees threshold is important for several reasons. First, R&D employees have the ability to fully recognize the value of external resources (Eisenhardt and Martin, 2000; Teece, 2007), and a firm must have a certain amount of knowledge storage to identify the kinds of external technology that should be purchased (Zahra and George, 2002; Jansen et al., 2005). Second, more technology experts and professional personnel means an increased ability to assimilate the external knowledge into forms that can be absorbed by the organization (Hu, 2001). Third, a firm needs to have enough experienced R&D employees to not only learn about external acquired knowledge (Carlile and Rebentisch, 2003), but also to combine internal and external acquired knowledge into possible novel resource bundles (Lee et al., 2010; Noori et al., 2017). Fourth, more technology experts and professional personnel imply a larger knowledge stock that can be used to search and assess various alternative resource bundles for maximizing the value of integrated internal and external knowledge (Cumming et al., 2016; Cao et al., 2020). Given the discussion above, we propose:

H1. When the number of R&D employees exceeds the minimum threshold, the firm can successfully increase its innovation performance by external technology purchasing.

2.3. Technology purchasing scale threshold

Organizations often hope that their level of innovation performance will increase as a result of external technology purchasing. But in order to achieve a superior level of synergy between internal and external knowledge, the firm's technology purchasing might need to exceed a certain threshold; again, there are several reasons for this.

First, only after exceeding some size threshold can external technology purchasing motivate the organization to transform and exploit newly acquired knowledge resources. In fact, only when the purchase goes beyond the threshold value can the acquired technologies start to supplement the lack of key technologies and increase the firm's innovation potential. Second, larger-scale technology purchasing can bring in a richer resource base which will consequently challenge the firm's current stock of knowledge, and potentially help create new organizational routines and practices (Tsai and Wang, 2008; Phene et al., 2012). Third,
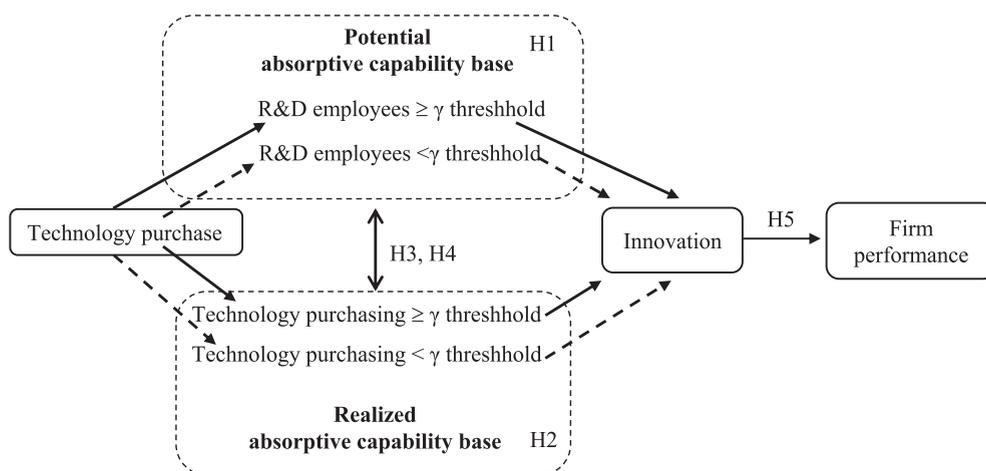

Fig. 1. Hypotheses model.
Note: Solid line means a positive effect, and dashed line means a negative or insignificant effect.

organizations that are inclined to stick to their original knowledge base will slow or even block the learning of new knowledge (Shane, 2000). The acquired knowledge allows the firm to go beyond a certain threshold in order to expand the utility of prior knowledge and stimulate the absorption of newly acquired knowledge (Zahra and George, 2002; Jansen et al., 2005). In other words, the firm needs to abandon its previous path and reconfigure new organizational routines by combining new knowledge and prior knowledge (Zhou and Li, 2012). We therefore propose:

H2. When a firm's technology purchasing scale exceeds the minimum threshold, the firm can successfully increase its innovation performance through technology purchasing.

2.4. The interaction effect of R&D employees and technology purchasing scale on innovation

As mentioned above, R&D employees represent knowledge storage, technology experts, professional personnel and learning experiences, while the technology purchasing scale represents the supplement to the required key technologies, the abandonment of the previous path, and the reconfiguration of the new organizational routines and practices, which are interdependent and mutual matching. We further argue that the impacts of purchased technology are not only driven by the number of R&D employees and purchased technology scale respectively (H1&H2), but also affected by the mutual dependency and mutual matching shown in the processes of absorptive capacity, including acquiring, assimilating, transforming and exploiting.

Specifically, combing H1&H2, there is a complementary effect between technology purchasing and R&D employees when they exceed the minimum thresholds. When both thresholds (R&D employees and technology purchasing scale) are crossed at the same time, it means that companies have enough capability and resources to benefit from increased absorptive capacity. A large number of R&D employees can efficiently acquire and assimilate the external technology because there are more internal experts, professional personnel, and experience, and that accumulated understanding allows for more interpretation and learning (Zahra and George, 2002; Zhou and Li, 2012). For example, a large number of R&D employees means an active knowledge base which can help firms to search for valuable external technology and to avoid failure in technology choice. It also means a series of effective knowledge accumulation experiences that can help firms identify the characteristics and parameters, and assimilate the tacit value of external technologies (Kim and Lee, 2021). Therefore, the stock of knowledge-based resources helps make the process after technology purchasing proceed smoothly (Cumming et al., 2016; Hartono et al., 2019; Cao et al., 2020).

When technology purchasing reaches a certain scale (which corresponds to the minimum requirement of the company's own resource base), the utility of technology purchasing can be fully achieved through the internalization, conversion, and utilization of external target technology, matching and having synergy with the existing technology reserves (Zahra and George, 2002). Only when the scale of purchased technologies is large enough it can complement the firm's existing stock of knowledge or exploit new organizational routines and practices (Tsai and Wang, 2008; Phene et al., 2012). Abundant external resources usually mean a more helpful knowledge base (mainly measured by patents, software, or physical technologies) which can transform the internal knowledge base and upgrade the absorptive capacity by R&D employees' learning and exploitation (Cassiman and Veugelers, 2006).

Therefore, when both the technology purchasing scale and the number of R&D employees cross the minimum threshold, they form an adequate absorptive capacity by promoting each other, which further improves the firm's innovation. Hence, the following hypothesis is proposed:

H3. There is a complementary effect between technology purchasing and R&D employees on innovation performance when both elements cross the minimum threshold.

By contrast, when neither threshold is crossed, there is a substitution effect between technology purchasing scale and R&D employees, and the overall effect will be a decline in innovation. There are reasons to believe that it will be difficult for companies to identify and assimilate external technology if they lack sufficient numbers of highly skilled R&D employees to identify the characteristics effectively and to make professional decisions timely (Zahra and George, 2002). Even experts can miss the opportunities to purchase valuable technologies. It will also be difficult for them to combine the necessary technical and managerial talent and experience to ensure that the technology purchasing process will be successful (Lee et al., 2010; Noori et al., 2017).

A less sophisticated R&D department with a small scale of technology purchasing cannot lead to the corresponding level that its own capability and resource foundation requires (Cao et al., 2020). That also makes it hard for the company to internalize the purchase and use the external technology well, because of the mismatch and unfitness (Zahra and George, 2002). The purchasing activity also takes up the limited funds and resources and makes it harder for the internal R&D employees to develop and use the new technology, and to acquire and assimilate new knowledge (Booyens, 2011). Thus, when both the scale of technology purchasing and R&D employees don't cross the minimum threshold value, the firms can not directly assimilate the newly purchased technologies, nor can they transform them. The lower scale of R&D employees may wrongly set target external technology to purchase, and this purchasing may lead firm to spends so excessive resources in internalizing external technology that influence firm's other research plan or even bring down the firm. Meanwhile, the purchased external technology may actually disrupt the R&D strategic direction, resource input and personnel allocation, which further damage firms' innovation because of the mutual interference of technology sources (Tsai and Wang, 2009). Hence, the following hypothesis is proposed:

H4. There is a substitution effect between technology purchasing and R&D employees on innovation performance when neither of the elements cross the minimum threshold values.

2.5. The effect of innovation on firm performance

While enterprises realize innovation through technology purchasing, innovation plays an important role in further promoting firm performance (Jansen et al., 2006; Damanpour et al., 2009; Kostopoulos et al., 2011). There are three well-founded arguments that can support the point. First, innovation can help enterprises to meet the evolving demands and preferences of customers, thereby driving enterprises to achieve greater product sales and increased market competitiveness (Srinivasan et al., 2009; Kostopoulos et al., 2011). Second, innovation helps enterprises further explore the potential demands of existing customer groups, and to dig deeply into existing segments or expand new segments with the goal of higher returns, so as to obtain strong growth in firm performance and sustainability (Bayus et al., 2003; Srinivasan et al., 2009). Third, on the basis of the above, continuous innovation will help enterprises build the ability to adapt to changes in market demand, effectively absorb and utilize innovative knowledge and resources to create value, thereby increasing profitability and competitive advantage (Bayus et al., 2003; Srinivasan et al., 2009; Kostopoulos et al., 2011; Weerawardena and Mavondo, 2011). Therefore, we propose that:

H5. There is a positive effect of innovation on firm performance.

3. Methodology

3.1. Sample and data sources

China is the world's largest emerging economy, and it has experienced rapid growth in the past three decades. Zhongguancun (ZGC), known as China's Silicon Valley, is one of China's leading industrial clusters. Most noted for its high-tech companies that include computer, semiconductor, telecommunications, and many other industries, ZGC is an ideal research context for two reasons. First, it was one of the earliest high-tech "demonstration zones" that have been established in China, and its annual revenue far exceeds that of other, less well developed demonstration zones. Second, technology purchasing is frequent, and the there is a great deal of size variation across companies. This facilitates research regarding the impact of varying resource availability on technology purchasing. Data for this study were provided by the Ministry of Science and Technology of China (MOST).

As the threshold model requires balanced panel data (Wang, 2015), this study performed a rigorous and standardized procedure using STATA's xtbalance command to convert raw unbalanced panel data to balanced panel data. Moreover, we exclude outliers and winsorize the core variables at the 1% and 99% points of the distribution, so as to ensure that the results of this study would not be disturbed by extreme values. Balanced panel data from 1460 high-tech companies from 2010 to 2015 were obtained.

3.2. Measures

Dependent variable. Following Okamuro (2007) and Schwartz et al. (2012), this study uses the logarithm of the number of patent applications as a measure of *innovation output*. The number of patent *applications* better reflects the real innovation level of enterprises because it avoids the underestimation of innovation output from technology purchasing due to the time lag between patent application and final granting (Okamuro, 2007).

To further explore the effect of innovation on *firm performance*, this study measures firm performance using the total sales revenue of enterprises (*Sales_Revenue*), as measured by the logarithm of total sales revenue of enterprises (thousands of RMB). As the income obtained by the company from selling products and related commodities, the total sales revenue of enterprises is the intuitive embodiment of the materialization and commercialization of a company's innovation achievements in products and related commodities (Cooper, 2011). Sales revenue has been widely examined as an important measure of firm performance in previous studies (Gomez et al., 2004; Thornhill, 2006; Kim and Min, 2015).

To verify the robustness of innovation effects on firm performance, this study also uses the value of Tobin's Q (*TobinQ*), as measured by the ratio of enterprise market value to total assets, as well as the price-earnings ratio (*PER*), which is measured by the logarithm of the ratio of stock price to earnings per share. Tobin's Q is a market-based measure to some degree, since the metric embodies a forecast of future cash flows produced by the firm and a market assessment of the investment opportunity set of the firm. Such market-based measures can capture future or long-term financial performance (Chung and Pruitt, 1994). Tobin's Q also has been widely examined as an important measure of firm performance in previous studies (Pucheta-Martínez and Gallego-Álvarez, 2019; Pham and Tran, 2020). In addition, the price-earnings ratio is a kind of value analysis indicator widely used by investors which reflects the future profitability of a company (Platonova et al., 2018), and it has been widely examined as an important measure of firm performance in previous studies (Platonova et al., 2018).

Core variables. Following Tsai and Wang (2008), who used the logarithm of the purchase expenditures as a measure of external technology acquisition, this study measures technology purchasing (*Tecpurch*) by using total expenditures for technology purchasing in each firm-year.

Threshold variables. In this study, two threshold variables are used. The first is the scale threshold of R&D employees (*R&D employees*). Following Huang et al. (2015), we used the logarithm of the total number of R&D personnel. Relevant studies have shown that R&D employees not only represent the scale of the existing knowledge and resources of the enterprise, but also can be the key to absorbing external technology acquisition (Teirlinck and Spithoven, 2013). The second is the scale threshold of technology purchasing (*Tecpurch*), which is represented by the core variable itself, showing the expenditure scale of technology purchasing.

Control variables. Some studies have suggested that as enterprises grow older, organizational inertia may hinder their innovation

Table 1
Variable descriptive statistics and correlation analysis.

	#	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8
1, Innovation Output	8760	0.791	1.209	0.000	5.112	1.000							
2, Tecpurch	8760	0.096	0.811	0.000	8.936	0.119$	1.000						
3, R&D employees	8760	3.287	1.666	0.000	6.956	0.463$	0.075$	1.000					
4, Age	8760	2.461	0.430	1.386	4.007	0.150$	0.034$	0.194$	1.000				
5, Type	8760	8.970	3.508	1.000	21.000	−0.068$	0.034$	−0.092$	−0.244$	1.000			
6, Lev	8760	0.467	0.458	0.000	11.275	0.027	0.002	−0.048$	0.004	−0.016	1.000		
7, Tax	8760	7.566	2.380	0.000	12.401	0.395$	0.068$	0.578$	0.294$	−0.091$	−0.079$	1.000	
8, R&D	8760	3.157	4.129	0.000	11.797	0.375$	0.088$	0.366$	0.101$	−0.030$	0.016	0.276$	1.000
9, Edu	8760	0.583	0.237	0.000	1.000	−0.017	−0.011	0.057$	−0.111$	0.000	−0.007	−0.057$	−0.134$
10,Techcat	8760	2.914	2.753	1.000	11.000	0.123$	0.022	−0.064$	0.044$	−0.076$	0.071$	0.050$	0.148$
11, Fixed Assets	8760	0.106	0.136	0.000	1.676	0.045$	−0.019	0.043$	0.002	0.016	0.011	0.023	0.107$
12, Intangible Assets	8760	0.062	0.132	−0.075	1.781	−0.100$	−0.017	−0.120$	−0.131$	0.049$	−0.099$	−0.231$	−0.077$
13, Sales_Revenue	8760	7.721	4.681	−0.183	14.628	0.279$	0.039$	0.340$	0.186$	−0.020	−0.028$	0.429$	0.240$
14, Z Score	329	2.020	0.919	0.149	5.298	−0.045	0.243$	0.011	−0.052	0.097	−0.641$	0.007	−0.162$
15, M/T Ratio	329	4.245	3.290	0.468	29.391	0.010	0.122	0.013	0.050	0.010	−0.236$	0.026	−0.282$
16, TobinQ	329	4.017	2.478	1.107	17.497	0.032	0.168$	−0.001	0.068	−0.017	−0.222$	0.058	−0.257$
17, PER	329	4.105	0.860	2.241	7.933	0.149$	−0.039	−0.037	0.010	−0.153$	−0.067	−0.229$	−0.178$

	9	10	11	12	13	14	15	16	17
9, Edu	1.000								
10, Techcat	−0.119$	1.000							
11, Fixed Assets	−0.184$	0.018	1.000						
12, Intangible Assets	0.014	−0.071$	−0.016	1.000					
13, Sales_Revenue	−0.227$	−0.017	−0.005	−0.080$	1.000				
14, Z Score	−0.031	−0.153$	0.018	−0.023	−0.016	1.000			
15, M/T Ratio	0.065	−0.135	−0.081	0.075	−0.022	0.549$	1.000		
16, TobinQ	0.021	−0.091	−0.040	0.030	0.047	0.579$	0.922$	1.000	
17, PER	−0.007	−0.179$	0.060	0.137	0.062	0.216$	0.428$	0.439$	1.000

$ $p < 0.01$; the descriptive statistics and correlation analysis of *Z Score, M/T Ratio, TobinQ* and *PER* in rows (14) to (17) are based on 329 listed companies.

(Coad et al., 2016; Petruzzelli et al., 2018). We therefore control for the age of the firm (*Age*), measured by the logarithm of the number of years since the founding of the business. Also, there is a close connection between internal R&D and innovation performance (Enkel et al., 2009). Thus, we control for the expenditure of internal R&D activities (*R&D*) by using the logarithm of total internal expenses on research and development (thousands of RMB). Studies have also suggested that there is a positive relationship between employee education and enterprise innovation performance (e.g., Østergaard et al., 2011). Thus, we control for the proportion of highly educated employees (*Edu*) by using the ratio of the number of employees with a bachelor's degree or above to the total number of employees. To avoid the impact of business operations of enterprises on innovation, we control for the debt to asset ratio (*Lev*) by using the ratio of total liabilities to total assets, and total tax paid (*Tax*) by using the logarithm of total tax paid. Lastly, we also control for the impact of firm type and technology sector on innovation, setting firm type (*Type*) by using the business registration type of enterprise. We assign values from 1 to 21 according to the registration type of the enterprise, and technology sector (*Techcat*) by using the technical field of the enterprise, and assigning values from 1 to 11 according to the technical field to which the enterprise belongs. Moreover, we control for the effect of a firm's exiting innovation ability, and the fixed effect of industry and year.

When estimating the innovation effect on firm performance, more control variables are included for their potential impact on performance. We control the proportion of fixed assets (*Fixed Assets*) by using the ratio of total fixed assets to total assets. We also control the proportion of intangible assets (*Intangible Assets*) by using the ratio of total intangible assets to total assets. In the robustness test of innovation effects on firm performance, two indicators suitable for listed enterprises are additionally controlled: the Altman-Z Score (*Z Score*) and the ratio of market value to tangible assets (*M/T Ratio*).

To make variables of different years comparable, we take price fluctuations into account and adjust all variables by the annual price index. Logarithmic processing is performed to reduce the influence of a skewed distribution. The measurements, descriptive statistical results, and correlation analyses are shown in Table 1.

3.3. Analyses

This study tests the threshold effects of R&D employees and technology purchasing, and explores the interaction effect between the two thresholds. Following Hansen (2000), the analyses include 5 steps: (1) A bootstrap method is the first step of a threshold test to determine the number of thresholds, and the threshold value based on a triple threshold regression, and then choosing the suitable threshold model accordingly. (2) Based on the chosen threshold model, the threshold regression is the second step of a threshold test; it explores the role of the core variable on the dependent variable. (3) Tobit regressions with the intersection of technology purchasing and R&D employees are used to explore the complementarity or substitution effect between the two variables. (4) The OLS regressions are used to explore the effect of innovation on firm performance. (5) Robustness tests are conducted to further examine the findings; these include Tobit regression tests for threshold effect, the alternative sample and variable measures, and the Heckman two-stage model test.

In particular, considering the characteristics of variables, the dependent variable *innovation output* contains a substantial number 0 values, taking on the value of 0 with positive probability while it is a continuous random variable over strictly positive values. Therefore, referring to the study of Wooldridge (2002), this study uses Tobit regressions to analyze such left-cornered solution models.

To verify hypotheses 1 and 2, we extend the basic model of the panel threshold test set by Hansen (2000) and Wang (2015), which not only helps control for subjectivity and potential selection bias, but also mitigates endogeneity issues. We construct the threshold test of technology purchasing scale and R&D employees based on the triple and single threshold models (Models 1 and 2). To verify hypotheses 3 and 4, Model 3 with intersection of technology purchasing and R&D employees is used to explore the complementarity and substitution between the two threshold variables. To verify hypothesis 5, Model 4 (which considers the time lag) is used to explore the effect of innovation on firm performance. Model 5 intends to verify the direction of causality by exploring the causal effect of performance on innovation.

$$Innovation_{it} = \mu + \beta_1 Tecpurch_{it} I(q_{it} \leq \gamma_1) + \beta_2 Tecpurch_{it} I(\gamma_1 < q_{it} \leq \gamma_2) + \beta_3 Tecpurch_{it} I(\gamma_2 < q_{it} \leq \gamma_3) + \beta_4 Tecpurch_{it} I(q_{it} > \gamma_3) + \alpha Controls + e_{it} \tag{1}$$

$$Innovation_{it} = \mu + \beta_5 Tecpurch_{it} I(q_{it} \leq \gamma_n) + \beta_6 Tecpurch_{it} I(q_{it} > \gamma_n) + \alpha Controls + e_{it} \tag{2}$$

$$Innovation_{it} = \mu + \beta_7 Tecpurch_{it} + \beta_8 R\&D\ employees_{it} + \beta_9 Tecpurch_{it} \times R\&D\ employees_{it} +$$

$$\alpha Controls + e_{it} \tag{3}$$

$$Performance_{it+1} = \mu + \beta_{10} Innovation_{it} + \beta_{11} Performance_{it} + \alpha Controls + e_{it} \tag{4}$$

$$Innovation_{it+1} = \mu + \beta_{12} Performance_{it} + \beta_{13} Innovation_{it} + \alpha Controls + e_{it} \tag{5}$$

where i represents the individual enterprise; t is the year identification; *Innovation* represents the dependent variable of innovation output. *Tecpurch* represents the core variable as well as the threshold variable, technology purchasing; *R&D employees* represents the threshold variable, R&D employees; q and γ constitute the threshold conditions in different situations, where q represents the technology purchasing scale and the number of R&D employees, γ represents the threshold corresponding to the n-th threshold ($n = 1, 2, 3$); I represents the condition function, and takes the value of 1 if the conditions in the brackets are fulfilled, and 0 otherwise; *Tecpurch × R*

& D employees* is the intersection of technology purchasing and R&D employees, representing the complementary and substitution relationship between the two thresholds; *Performance* represents firm performance; *e* represents the random perturbation term. In addition, control variables are added to the models.

4. Results

4.1. The threshold effects of R&D employees and technology purchasing scale

The threshold test is based on the research of Hansen (2000) and Wang (2015). First, the triple threshold model is used to calculate the number of thresholds and the threshold value by 100 bootstrap replications for each threshold. The results of regression provide the number of thresholds and the significance of each threshold, so that, from the significance of each threshold, we can know how many thresholds exist in this model. Second, based on the results of the triple threshold regressions, the single threshold model is chosen and used to observe the impact of technology purchasing above and below the threshold. Finally, Tobit regressions with the intersection of technology purchasing and R&D employees are used to explore the interaction effect between the two thresholds. The results of thresholds and their interaction effect are shown in Table 3.

4.1.1. Threshold effect of R&D employees
As shown in Table 2, when technology purchasing is used as a core variable and R&D employees is used as a threshold variable, the F-value corresponding to the single threshold model is 5.550* ($p = 0.090$), which is significant at the 10% level. The threshold value is 4.1744. However, the F-values corresponding to the double and triple thresholds are 4.800 and 1.740, respectively, and the *p*-values are not significant, indicating that there is a single threshold of R&D employees regarding the impact of technology purchasing on innovation.

The single threshold model is therefore employed. According to the results of Model (1) in Table 3, the corresponding p-value of technology purchasing on innovation is significant at the 1% level when R&D employees exceeds the threshold value; this shows that the larger the company, the greater the positive impact of technology purchasing on innovation performance. The resource base of large enterprises represents the accumulation of technical and managerial capabilities (Eisenhardt and Martin, 2000; Teece, 2007), and the accompanying realized absorptive capacity enables large enterprises to achieve better internalization and utilization of the purchased technology (Zahra and George, 2002). Thus, technology purchasing can lead to significantly higher innovation performance. When R&D employees fails to exceed the threshold, the coefficient of technology purchasing on innovation is 0.021 and the p-value is not significant, indicating that there is no significant relationship between technology purchasing and innovation. Therefore, hypothesis H1 is supported.

4.1.2. Threshold effect of technology purchasing scale
As shown in Table 2, when technology purchasing is used as both a core variable and a threshold variable, the F-value corresponding to the single threshold model is 3.717* (p = 0.090), which is significant at the 10% level. The threshold value is 4.6627. However, the F-values corresponding to the double and triple thresholds are 2.693 and 3.504, respectively, and the p-values are not significant. This indicates that there is a single threshold of technology purchasing scale regarding the impact of technology purchasing on innovation.

Subsequently, the single threshold model is used to determine the specific threshold value and to observe the impact of technology purchasing above and below the threshold. According to the regression results of Model (2), the corresponding p-values of technology purchasing on innovation are significant at the 1% level when technology purchasing scale exceeds the threshold value. This means that purchasing technology can have a positive impact on innovation performance only in companies which have reached the minimum thresholds of R&D employees and technology purchasing. When the technology purchasing scale fails to exceed the threshold, the coefficient of technology purchasing on innovation is −0.024 and the p-value is not significant, indicating that there is no significant relationship between technology purchasing and innovation. Therefore, hypothesis H2 is supported.

Table 2
Results of triple threshold model.

Threshold variables	Threshold	Threshold value	Interval	F-value	P-value	Crit10	Crit5	Crit1
R&D employees (*R&D employees*)	Single	4.1744	[3.892, 4.489]	5.550	0.090*	5.473	7.438	8.394
	Double	4.1744, 3.6636	[3.647, 4.489] [3.401, 3.892]	4.800	0.170	5.670	7.980	12.370
	Triple	3.8918	[3.401, 4.489]	1.740	0.660	8.894	10.205	15.966
Technology Purchasing Scale (*Tecpurch*)	Single	4.6627	[1.485, 8.480]	3.717	0.090*	3.424	4.773	8.537
	Double	8.4447, 4.6627	[1.485, 8.445] [1.485, 7.329]	2.693	0.170	3.051	4.245	6.308
	Triple	6.8763	[1.485, 7.327]	3.504	0.110	3.878	5.203	8.078

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

4.1.3. Mutual dependence between technology purchasing and R&D employees

To explore the interactive relationship between the two thresholds, we generate the intersection of technology purchasing and R&D employees, and employ Tobit regressions to explore the complementarity and substitution relationship between the two variables.

From the results of Models (3) and (4) in Table 3, we can see that when both the thresholds of R&D employees and technology purchasing scale are crossed, the coefficient of the intersection of technology purchasing and R&D employees on innovation is positive and significant, showing that there is a complementary effect between the technology purchasing scale and R&D employees ($\beta = 0.200^*$). Hypothesis H3 is therefore supported. This finding demonstrated that both the number of R&D employees capacity and technology purchasing scale were equally essential and that they constitute an effective absorptive capacity for innovation after crossing their thresholds. A firm's superior innovation driven by technology purchase is evident because of the synergy between internal and external effective technology sources that the source itself is good for innovation. If only one factor develops well, it is challenging to ensure expected creation when a firm purchases external technologies.

However, when neither of the thresholds are crossed, the coefficient of the intersection of technology purchasing and R&D employees on innovation is negative and significant ($\beta = -0.153^*$), showing that there is a substitution effect between technology purchasing scale and R&D employees. Therefore, hypothesis H4 is supported. Indeed, an inappropriate technology purchase will not

Table 3
Effect of R&D employees and technology purchasing scale on innovation.

	Single Threshold Regression		Tobit Regressions					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample			R&D Emp >4.174 & Tecpurch>4.663	R&D Emp ≤4.174 & Tecpurch≤4.663	R&D Emp >4.174	R&D Emp ≤4.174	Tecpurch >4.663	Tecpurch ≤4.663
Tecpurch$_t$ (R&D employees >4.174)	0.069*** (0.017)							
Tecpurch$_t$ (R&D employees ≤4.174)	0.021 (0.015)							
Tecpurch$_t$ (Tecpurch>4.663)		0.048*** (0.012)						
Tecpurch$_t$ (Tecpurch≤4.663)		−0.024 (0.040)						
Tecpurch$_t$*R&D employees$_t$			0.200* (0.103)	−0.153* (0.091)				
Tecpurch$_t$			−0.761 (0.587)	0.510* (0.306)	0.061*** (0.017)	0.013 (0.013)	0.264*** (0.091)	−0.021 (0.039)
R&D employees$_t$	0.128*** (0.010)	0.128*** (0.010)	−0.964 (0.739)	0.077*** (0.008)	0.148*** (0.030)	0.077*** (0.008)	0.355*** (0.108)	0.115*** (0.008)
Innovation Output$_{t-1}$	0.144*** (0.011)	0.144*** (0.011)	0.337*** (0.103)	0.419*** (0.018)	0.703*** (0.014)	0.411*** (0.018)	0.433*** (0.095)	0.511*** (0.020)
Age$_t$	−0.385*** (0.126)	−0.386*** (0.126)	−0.049 (0.165)	−.106*** (0.031)	0.012 (0.044)	−0.107*** (0.032)	−0.015 (0.170)	−0.033 (0.029)
Type$_t$		−0.005 (0.006)	−0.005 (0.036)	−0.004 (0.003)	−0.001 (0.005)	−0.005 (0.003)	−0.021 (0.020)	−0.003 (0.003)
Lev$_t$	−0.054* (0.031)	−0.050 (0.031)	−0.046 (0.396)	−0.001 (0.019)	0.149** (0.067)	0.001 (0.019)	0.064 (0.310)	0.032 (0.021)
Tax$_t$	0.046*** (0.008)	0.046*** (0.008)	−0.060 (0.077)	0.032*** (0.005)	0.040*** (0.014)	0.033*** (0.005)	0.053 (0.063)	0.043*** (0.005)
R&D$_t$	0.010*** (0.003)	0.010*** (0.003)	−0.008 (0.038)	0.023*** (0.003)	0.027*** (0.005)	0.023*** (0.003)	0.029 (0.028)	0.025*** (0.003)
Edu$_t$	−0.021 (0.070)	−0.023 (0.070)	0.765 (0.476)	0.025 (0.046)	0.174* (0.095)	0.026 (0.046)	−0.160 (0.427)	0.081* (0.047)
Techcat$_t$	0.004 (0.007)	0.004 (0.007)	−0.009 (0.029)	0.015*** (0.004)	0.029*** (0.007)	0.015*** (0.004)	−0.034 (0.031)	0.022*** (0.004)
Industry	Included	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included	Included
Constant	0.729** (0.303)	0.729** (0.303)	5.835 (4.423)	0.005 (0.093)	−1.025*** (0.195)	0.017 (0.094)	−2.656*** (1.028)	−0.433*** (0.090)
Threshold-value	4.174	4.663	–	–	–	–	–	–
P-value	0.090	0.000	–	–	–	–	–	–
R^2 (within)	0.079	0.079	–	–	–	–	–	–
F-value	29.770	29.690	–	–	–	–	–	–
Wald chi2	–	–	418.520	1416.580	4612.810	1367.590	547.190	3535.020
Prob > chi2	–	–	0.000	0.000	0.000	0.000	0.000	0.000
Log likelihood	–	–	−25.617	−5975.089	−3459.099	−6052.730	−115.461	−9767.487
Observations	8760	8760	49	6111	2594	6166	104	8656
# of enterprises	1460	1460	27	1182	585	1183	70	1458

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

trigger, but will damage the firm's innovation performance. Both technology purchasing scale and R&D employees constitute a reduction in absorptive capacity when neither of the elements crosses the minimum threshold values. In fact, if a firm makes a large investment in technology purchasing but only with a limited number of R&D professionals, it might fail to accumulate sufficient knowledge in identifying promising opportunity associated with the technology, and might fail to develop strong capabilities to exploit the opportunity. Similarly, when the scale of purchased external is limited, R&D personnel may choose to commit resources to other research projects.

4.1.4. Robustness test of the threshold effects of R&D employees and technology purchasing scale

We use Tobit regressions, the alternative sample and variable measures, and the Heckman two-stage model to test the robustness of the results. For the robustness test of hypotheses 1 and 2, we use the Tobit regressions to verify the effect of technology purchasing on innovation in different sample groups divided by enterprises crossing the threshold or not. As shown in Models (5) to (8) of Table 3, when enterprises cross the threshold of R&D employees or technology purchasing scale, technology purchasing has a positive effect on innovation ($\beta = 0.061^{***}$ and $\beta = 0.264^{***}$). However, when enterprises fail to cross the threshold of R&D employees or technology purchasing scale, technology purchasing has no significant effect on innovation ($\beta = 0.013$ and $\beta = -0.021$). Therefore, hypotheses 1 and 2 are robust.

For the robustness test of hypotheses 3 and 4, we use the Heckman two-stage model to verify the interaction effect of the two

Table 4
Heckman two-stage model.

DV	Tecpurch 0–1$_t$	Innovation Output$_t$					
	1st Stage: Probit Regression	2ed Stage: Tobit Regression					
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample		R&D Emp > 4.174 & Tecpurch >4.663	R&D Emp ≤ 4.174& Tecpurch ≤4.663	R&D Emp > 4.174	R&D Emp ≤ 4.174	Tecpurch > 4.663	Tecpurch ≤ 4.663
R&D employees _Margin$_t$	0.073** (0.035)						
Tecpurch$_t$*R&D employees$_t$		0.209* (0.110)	−0.156* (0.091)				
Tecpurch$_t$		−0.803 (0.619)	0.516* (0.306)	0.059*** (0.017)	0.011 (0.013)	0.271*** (0.088)	−0.019 (0.039)
R&D employees$_t$		−1.254 (1.551)	0.667*** (0.209)	0.491* (0.258)	0.527** (0.207)	2.310*** (0.777)	1.230*** (0.136)
Innovation Output$_{t-1}$	0.045 (0.031)	0.184 (0.731)	0.776*** (0.127)	0.915*** (0.148)	0.683*** (0.126)	1.576*** (0.460)	1.181*** (0.081)
Age$_t$	0.140 (0.090)	−0.510 (2.183)	1.007** (0.395)	0.683 (0.484)	0.741* (0.391)	3.787** (1.507)	2.070*** (0.256)
Type$_t$	0.049*** (0.009)	−0.161 (0.738)	0.384*** (0.137)	0.230 (0.166)	0.291** (0.136)	1.271** (0.509)	0.728*** (0.089)
Lev$_t$	0.053 (0.063)	−0.222 (0.918)	0.423*** (0.151)	0.390** (0.198)	0.324** (0.150)	1.402** (0.607)	0.831*** (0.099)
Tax$_t$	0.015 (0.022)	−0.106 (0.230)	0.152*** (0.043)	0.112** (0.054)	0.124*** (0.042)	0.473*** (0.176)	0.268*** (0.028)
R&D$_t$	0.035*** (0.011)	−0.126 (0.558)	0.298*** (0.097)	0.192 (0.119)	0.233** (0.096)	0.953*** (0.365)	0.544*** (0.063)
Edu$_t$	0.068 (0.182)	0.572 (1.027)	0.571*** (0.199)	0.502** (0.254)	0.442** (0.197)	1.685** (0.837)	1.119*** (0.134)
Techcat$_t$	0.015 (0.014)	−0.054 (0.216)	0.135*** (0.043)	0.101* (0.053)	0.106** (0.042)	0.354** (0.156)	0.248*** (0.028)
IMR		−3.750 (17.690)	8.818*** (3.123)	5.377 (3.873)	6.723** (3.089)	30.010**−30.010** (11.820)	16.770*** (2.030)
Industry	Included	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included	Included
Constant	−3.145*** (0.331)	19.740 (65.710)	−32.480*** (11.500)	−20.670 (14.180)	−24.750** (11.380)	−113.000*** (43.470)	−62.080*** (7.461)
LR chi2	118.050	–	–	–	–	–	–
Wald chi2	–	418.950	1430.460	2214.840	1376.160	587.530	3893.800
Prob > chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Log Likelihood	−625.537	−25.595	−5968.734	−3445.420	−6047.977	−112.335	−9716.186
Observations	8747	49	6106	2586	6161	104	8643
# of Enterprises	1460	27	1182	583	1183	70	1458

Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 5
OLS regressions.

DV	Sales_Revenue$_{t+1}$	PER$_{t+1}$	TobinQ$_{t+1}$	Innovation Output$_{t+1}$		
Model	(1)	(2)	(3)	(4)	(5)	(6)
Innovation Output$_t$	0.097**	0.124**	0.281*	0.089***	−0.136	−0.151*
	(0.038)	(0.050)	(0.148)	(0.013)	(0.085)	(0.084)
Sales_Revenue$_t$	0.198***			0.002		
	(0.013)			(0.005)		
PER$_t$		−0.0460			−0.002	
		(0.102)			(0.174)	
TobinQ$_t$			−0.176			−0.286
			(0.361)			(0.204)
Tecpurch$_t$	0.038	−0.030	0.010	0.030**	0.074	0.070
	(0.036)	(0.044)	(0.133)	(0.012)	(0.076)	(0.075)
R&D employees$_t$	0.187***	0.0606	0.318	0.065***	0.106	0.124
	(0.034)	(0.096)	(0.287)	(0.012)	(0.163)	(0.163)
Innovation Output$_{t-1}$	−0.023	0.031	−0.082	−0.119***	−0.248***	−0.252***
	(0.037)	(0.050)	(0.148)	(0.013)	(0.085)	(0.084)
Age$_t$	1.238***	−0.762	−6.109	−0.300**	4.410	4.541
	(0.443)	(1.673)	(4.985)	(0.153)	(2.862)	(2.818)
Type$_t$	0.016	−0.044	0.149	0.007	−0.082	−0.086
	(0.022)	(0.084)	(0.251)	(0.007)	(0.144)	(0.142)
Lev$_t$	−0.062	0.859	4.225**	−0.051	1.889	1.436
	(0.100)	(0.681)	(2.119)	(0.035)	(1.164)	(1.198)
Tax$_t$	0.035	−0.126*	−0.503**	0.043***	−0.009	0.002
	(0.028)	(0.069)	(0.207)	(0.010)	(0.118)	(0.117)
R&D$_t$	0.011	−0.001	0.008	0.007**	0.053**	0.057**
	(0.010)	(0.016)	(0.047)	(0.003)	(0.027)	(0.027)
Edu$_t$	0.207	−1.021*	−0.115	−0.058	2.296**	2.284**
	(0.237)	(0.579)	(1.737)	(0.082)	(0.990)	(0.982)
Techcat$_t$	0.019	0.179	0.027	−0.006	−0.167	−0.169
	(0.021)	(0.146)	(0.437)	(0.007)	(0.250)	(0.247)
Fixed Assets$_t$	−0.188	1.214	0.634	0.212*	1.833	1.887
	(0.338)	(0.971)	(2.865)	(0.116)	(1.661)	(1.619)
Intangible Assets$_t$	−0.835**	−0.441	−0.997	−0.095	6.585**	5.905*
	(0.324)	(1.788)	(5.415)	(0.112)	(3.058)	(3.061)
Z Score$_t$		−0.010	−0.072		0.195	0.143
		(0.133)	(0.404)		(0.228)	(0.229)
M/T Ratio$_t$		0.066	0.429		−0.109	0.146
		(0.041)	(0.341)		(0.070)	(0.193)
Industry	Included	Included	Included	Included	Included	Included
Year	Included	Included	Included	Included	Included	Included
Constant	2.659**	6.578	18.860	0.844**	−12.220	−12.320
	(1.055)	(4.827)	(14.190)	(0.363)	(8.256)	(8.024)
R^2 (within)	0.064	0.549	0.478	0.044	0.246	0.257
F-value	17.400	7.540	5.680	11.620	2.020	2.140
Observations	7300	216	216	7300	216	216
Number of enterprises	1460	65	65	1460	65	65

Standard errors in parentheses.
*** p < 0.01, ** p < 0.05, * p < 0.1.

thresholds on innovation. This can effectively correct for any sample selection bias (Heckman, 1979; Wang and Qian, 2011), avoids the endogeneity problem, and also ensures comparability with some of the previous research in this area (Escribano et al., 2009). In the first stage, we establish the selection equation for whether the enterprise purchases technology (Tecpurch0–1), and then choose the margin of R&D employees (*R&D employees_Margin*) as the instrumental variable. The margin of R&D employees (*R&D employees_Margin*) is measured by the difference between the actual size of the firm minus the threshold value. We use the Probit regression model to estimate the probability that each enterprise will purchase the external technology and to get the Inverse Mills Ratio (IMR). The result in Model (1) of Table 4 shows that the coefficient of the instrumental variable *R&D employees_Margin* on the technology purchasing decision (Tecpurch0–1) is 0.073 and is significant at the 5% level, which also reflects that crossing the R&D employees threshold significantly affects the technology purchasing decision in a positive way.

In the second stage, we use the selected sample of the first stage and add the IMR as a correction variable to the regression equation. The results show that part of the coefficients of the IMRs are significant, indicating that there exists sample selection bias. However, the regression results of Tobit regressions in Models (2) and (7) of Table 4 show that the results are consistent with the previous hypothesis tests. Therefore, hypotheses 1–4 are robust.

The results of the Heckman two-stage model also show the sequence of crossing two thresholds. The results of the first stage show

that firms that exceed the scale threshold have a higher probability of making technology purchase decisions, and in the second stage sample selection, there are more samples that exceed the scale threshold. Therefore, once an enterprise crosses the R&D employees threshold, it will be more likely to cross the threshold of technology purchasing scale and finally realize the significant impact of technology purchase on innovation. This sequence perfectly matches the sequence of potential and realized absorptive capacity mentioned in Zahra and George's (2002) research.

4.2. The effect of innovation on firm performance

To further explore the effect of innovation on firm performance, as mentioned above, this study uses three indicators measuring firm performance and two theory models (Models 4 and 5) to test the positive impact of innovation on firm performance. They verified the robustness of the results with each other. As shown in Table 5, the three performance indicators are: total sales revenue (*Sales_Revenue*), the price-earnings ratio (PER), and the value of Tobin's Q (*TobinQ*), to test the effect of innovation on firm performance by using an OLS regression test. Moreover, to examine the causal relationship between innovation and performance, following Sims (1972) and Chow (1987), this study lags the performance by one period and controls for the impact of current period performance. This study also tests the effect of performance on lagged innovation with the impact of current period innovation controlled.

Since only a small part of the sample in this study are listed enterprises, the test in this part is divided into two sets of samples. The test with total sales revenue (*Sales_Revenue*) as the dependent variable is done with the full sample, while the tests with the price-earnings ratio (PER) and Tobin's Q (*TobinQ*) as the dependent variables are done with the sample of listed enterprises. The results of the regressions are shown in Table 5. As shown in Models (1) to (3), innovation has a positive effect on firm performance ($\beta = 0.097^{**}$, $\beta = 0.124^{**}$, and $\beta = 0.281^{*}$), while in Models (4) to (6), firm performance has no significant effect on innovation ($\beta = 0.002$, $\beta = -0.002$, and $\beta = -0.286$). Therefore, hypothesis 5 is supported.

5. Conclusion and discussion

5.1. Conclusion

The threshold of internal stock knowledge is ignored when researchers stress the acquisition of external knowledge when studying the absorptive capacity of firms. In this study, we answer the call for threshold studying both the potential and realized aspects of absorptive capacity. We adopt a panel threshold model to analyze 1460 Chinese high-tech companies from 2010 to 2015, and confirm the threshold effect of R&D employees and technology purchasing scale in influencing firm innovation performance.

Specifically, there are threshold effects of R&D employees and technology purchasing scale for innovation driven by technology purchasing. When enterprises reach a certain level of resource base, they have enough capability to identify, interpret, and understand the value of external technology, so that they can assimilate the external heterogeneous technology knowledge well. For the technology purchasing scale threshold effect, our findings suggest that enough external technology has to be purchased to cross the threshold, and once that level is reached, the firm can realize the potential of its own core technology. This will increase synergy, integrate internal and acquired external knowledge, promote core competitiveness, and improve innovation performance.

This study also explores the interaction effect between technology purchasing scale and R&D employees. The results show that their interaction positively affects innovation, which implies a complementary effect between the two variables. Innovation performance increases when both the technology purchasing scale and R&D employees exceed the minimum threshold value. Interestingly, in the robustness test using the Heckman two-stage model, the results further show that the threshold of R&D employees can be a precondition for technology purchasing (i.e., crossing the threshold of technology purchasing scale positively affects the innovation process driven by technology purchasing). These results are in line with the order of potential and realized absorptive capacity proposed by Zahra and George (2002).

5.2. Theory contributions and managerial implications

This study offers several theoretical and practical contributions. First, this study responds to calls to study the proportionality of potential and realized absorptive capacity by drawing attention to an enterprise's own capacity. This helps us to explore and understand the heterogeneous findings about firm innovation performance after technology purchasing has occurred. Accordingly, this study enriches the research on both potential and realized absorptive capacity, and explores thresholds of technology purchasing scale and R&D employees for innovation. It means that a firm must accumulate enough resources to raise absorptive capacity, so that it can generate innovation through technology purchasing.

Second, this study reveals the existence of an R&D employees threshold and a technology purchasing scale threshold. The empirical results show that if R&D employees has not reached a minimum required level, the firm will not have enough capability to identify, acquire, and effectively use external technology. They will also not be able to build the routines and processes that allow enterprises to analyze, process, interpret, and understand the information that is obtained from external sources. If the purchased technology scale does not complement the firm's existing internal knowledge, or if the purchased technology does not add enough value to the existing internal resource base scale, the firm will not be able to maximize its innovation performance.

This study has several practical implications. First, before purchasing external technology, a company's own technology and capability base must reach a certain level. Specifically, a company must have enough capability to identify, interpret, and understand the value of the external technology it is purchasing, so that it can transform the purchased external technology into increased

innovation performance. Second, firms should strive to achieve the appropriate level of R&D employees and technology purchasing scale at the same time. This will create complementarity with internal and external technical resources and will result in higher innovation performance.

5.3. Limitations and recommendations

Along with its contributions, this study also has some limitations, and these suggest some issues for further research. First, this study focuses on absorptive capacity and emphasizes the point that research on absorptive capacity is based on Zahra and George (2002). However, it does not open the black box of absorptive capacity construction mechanisms. Considering that the absorptive capacity acts as an organizational routine and process, more qualitative research (e.g., case studies) are needed to reveal the micro-foundation of absorptive capacity and further open the black box of the absorptive capacity construction process (e.g., absorptive capacity grows nonlinearly with the different life cycles of the enterprise).

Second, although our study illustrates the importance of identifying thresholds, it does not explore the factors that affect the magnitude of the thresholds. In future research, the fsQCA method, which focuses on the conditional configuration of factors (Pappas et al., 2016), can be used to determine the combination of variables and core conditions that affect the threshold, by comparing the relationship between conditional variable configurations.

Third, this study uses high-tech companies as a sample. These firms usually locate in high value-added industries and have relatively high technology thresholds, and the thresholds of R&D employees and technology purchasing are significant. Future research is needed to determine if the two thresholds of R&D employees and technology purchasing scale have an impact in other industries as well.

Author statement

Data availability

The authors do not have permission to share data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ememar.2022.100973.

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