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TRADE-OFF EXPLORATION AND EXPLOITATION AS MODERATORS: HOW DOES TECHNOLOGICAL HETEROGENEITY AMONG COOPERATORS AFFECT FIRMS' FINANCIAL PERFORMANCE?

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ABSTRACT

Drawing on a resource-based view, this study focused on the relationship between technological heterogeneity among cooperators and the firm's financial performance. An important influence mechanism was that technological heterogeneity among cooperators makes the firm's knowledge recombination more diversified so that the firm can create more products to capture market demands and make a profit. In particular, the intra-firm learning strategies, namely exploratory learning, exploitative learning or ambidexterity, have a strong influence on the absorption of external heterogeneous knowledge. Thus, technological heterogeneity among cooperators and the intra-firm learning strategies may have an interactive impact on the firm's financial performance. Based on the patent data and financial data of 31 Chinese innovative firms from 2000 to 2016, we found that technological heterogeneity among cooperators positively affected the firm's financial performance. The firm's exploitative learning negatively moderated the relationship between technological heterogeneity among cooperators and the firm's financial performance. The firm's ambidexterity positively moderated the relationship between technological heterogeneity among cooperators and the firm's financial performance. Finally, the suggestions about organizational learning and sustainable profitability are discussed.

Contribution/ Originality: The paper's primary contribution is finding that technological heterogeneity among cooperators benefits the firm's financial performance. Our study introduced exploratory learning, exploitative learning and ambidexterity as the moderator variables, and suggested that a firm's internal ability to balance exploratory learning and exploitative learning is critically important.

1. INTRODUCTION

Recently, firms gradually seek inter-organizational R&D cooperation (Chesbrough, 2003b; Enkel, Gassmann, & Chesbrough, 2009; Martinez-Noya & Narula, 2018; Powell, Koput, & Smith-Doerr, 1996) to acquire external heterogeneous knowledge (Ming-Yeu, 2012; Muller & Penin, 2006). For instance, Haier Group, a Chinese firm who engaged in collective multinational consumer electronics and home appliances, has established the Haier Open Partnership Ecosystem (HOPE) to obtained external heterogeneous technologies from universities, research centers and innovative firms, and finally achieves the market breakthroughs. Similarly, Sany Heavy Industry opened many international equipment plants to gain advanced technologies from international counterparts through external cooperation and M&A, and thus profits from sustainable growth. Meanwhile, Neusoft Corporation maintains close strategic cooperation with more than twenty renowned global firms in the field of marketing, human resources, operations management and finance, especially for diverse IT technology and solutions to make the firm develop vigorously.

Drawing on the resource-based theory (Barney, Ketchen, & Wright, 2011) external technology sourcing is critical for organizational sustainable growth in the era of open innovation. Firms purse external technological cooperation to access heterogeneous knowledge and gain a competitive advantage in the market (Kim & Choi, 2014). Technological heterogeneity among cooperators makes the firm's knowledge recombination more diversified so that the firm can create more products to fully meet market demands (Carnabuci & Operti, 2013). Prior studies have explored R&D cooperation to access external heterogenous technology (Lavie & Rosenkopf, 2006; Ye, Hao, & Patel, 2016).

However, extant research that links the intra-firm ambidextrous learning strategies with heterogenous technology among cooperators is scarce. Indeed, a comprehensive picture of how a firm deals with exploitative learning and exploratory learning is missing. Since March (1991) first proposed the concept of ambidexterity for organizational learning, organizational learning scholars have widely discussed exploratory learning, exploitative learning and ambidexterity as internal learning drivers recently (He & Wong, 2004).

Exploitative learning is based on intensive search, and it means experimentation along existing knowledge; exploration is rooted in extensive search that pursues potential new knowledge (March, 1991). However, exploratory learning is risky and uncertain. The unfamiliar and even useless insights will generate inefficiencies in problem solving and increase coordination costs (Yan & Guan, 2018). Separate exploitative learning will lock firms in the original technological trajectory, and they are not willing to change the existing rules, routines and norms, ultimately facing the risk of being eliminated (Levinthal & March, 1993). Therefore, if technological heterogeneity among cooperators is high, separate exploratory learning will increase the coordination cost and separate exploitative learning will inhibit the identification of external heterogeneous technology. Separating exploration and exploitation might not be a good choice (Kauppila, 2010).

As a result, one stream of literature focuses on the simultaneous pursuit of exploitation and exploration, namely ambidexterity, which proposes that exploitative learning and exploratory learning are fundamentally incompatible (Smith & Tushman, 2005; Wei, Yi, & Guo, 2014). The interest in ambidexterity is warranted (Kauppila, 2010) and it gives deep insight into the knowledge being rationally utilized under limited resource (He & Wong, 2004). Ambidexterity encourages firms to experiment along their existing technologies and explore external new technologies, so that firms can fully absorb and integrate external heterogeneous knowledge for organizational learning (Cohen. & Levinthal, 1990; He & Wong, 2004; Katila & Ahuja, 2002). Taken together, the co-effect of technological heterogeneity among cooperators and the intra-firm ambidextrous learning strategy on the firm's financial performance should be taken into consideration. Thus, the aim of this study was to determine the interactive effects on the firm's financial performance by doing an empirical study.

Extant studies have explored the antecedents of exploratory learning, exploitative learning and ambidexterity (Yan & Guan, 2018) or the mediating role (Xie & Gao, 2018) or examined their influence on the organizational outcomes, such as profitability and growth (Ellen, Heil, Hengstler, & Wirth, 2017; He & Wong, 2004; Jansen, Van Den Bosch, & Volberda, 2006; Uotila, Maula, Keil, & Zahra, 2009) but few empirical studies have taken them as moderator variables. Exploratory learning, exploitative learning and ambidexterity as important intra-firm learning strategies might affect the relationship between technological heterogeneity among cooperators and the firm's financial performance.

Based on organizational learning research (Levinthal & March, 1993) we tested a set of hypotheses about how technological heterogeneity among cooperators and the intra-firm ambidextrous learning strategy influence the firm's financial performance. Social network analysis was applied to establish the cooperative network by using data of co-invention (Wang, Rodan, Fruin, & Xu, 2014) and thus, help us understand the technological heterogeneity among cooperators. However, this kind of "one-mode" network couldn't describe the characteristics of technological heterogeneity among cooperators clearly. To handle this gap, we adopted a two-mode network (Wasserman & Faust, 1994) to describe the relationship between cooperators and knowledge they possessed. Our empirical study selected 31 Chinese innovative firms and their cooperators as samples. The conclusions of this study will provide suggestions to organizational learning strategy and sustainable development.

2. LITERATURE REVIEW AND HYPOTHESES

2.1. Technological Heterogeneity among Cooperators and the Firm's Financial Performance

Technological heterogeneity among cooperators refers to the degree of technological differentiation among the firm's external R&D partners, which increases the amount of technology and cognitive variation that internal R&D lacks (Heimeriks, Duysters, & Vanhaverbeke, 2007). Based on the resource-based theory (Barney et al., 2011) the firm needs external heterogeneous technology for organizational sustainable growth.

Technological heterogeneity among cooperators brings more diverse knowledge, which makes the knowledge recombination more diversified (Carnabuci & Operti, 2013; Ye et al., 2016). The cognitive differences generated by the external technological heterogeneity could also make the firm break the stereotype and overcome the core rigidity of technological innovation to prevent a negative lock-in effect in one particular technology field (Garcia-Vega, 2006).

However, technological heterogeneity among cooperators improves the firm's competitive advantages. The stronger the technological heterogeneity among cooperators, the wider the technological field that the firm pays attention to, so that the firm can quickly grasp the market demands and make a profit (Wang., Chen, & Fang, 2018). Cohen and Caner (2016) proposed that alliance partners with heterogeneous knowledge provide the firm new methods to solve the problem using familiar technologies, and thus discover the hidden market demands. Fang, Wang, and Chen (2017) and Chen (2017) showed that diversified knowledge enables the firm to gain competitive advantages in competing with their rivals.

Based on the above discussion, the following hypothesis was proposed:

Hypothesis 1: Technological heterogeneity among cooperators will improve the firm's financial performance.

2.2. Technological Heterogeneity among Cooperators, Exploratory Learning, Exploitative Learning and the Firm's Financial Performance

Exploratory learning and exploitative learning are two different intra-firm learning strategies (Ellen et al., 2017). In strategy and organization research, the conventional resolution to the exploration-exploitation paradox is to separate the two learning activities. As Ebben and Johnson (2005) and Giarratana and Fosfuri (2007) pointed out that firms pursuing either exploratory learning or exploitative learning generally outperform those adopting a mixed strategy.

Exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation (March, 1991) which encourages the firm to pursue new knowledge, developing new technologies and new products by going beyond local search and exploring new areas of opportunity (Guan & Liu, 2016). However, exploratory learning is risky and uncertain. The unfamiliar or useless insights can lead to inefficiencies in problem solving and difficulties in member coordination (Yan & Guan, 2018). These unfavorable factors not only squeeze the firm's efforts to integrate and absorb external heterogeneous technological knowledge, but also increase the cost of organizational learning, thus inhibiting the positive influence of technological heterogeneity among cooperators on the firm's financial performance. Failed exploratory learning activities would lead to existing business losses, and also undermine the firm's successful practices in extant areas (Mitchell & Singh, 1993). Therefore, separate exploratory learning would hinder the positive effect of technological heterogeneity among cooperators on the firm's financial performance.

Exploitation includes such things as refinement, choice, production, efficiency, selection, implementation, execution (March, 1991). Exploitative learning is in-depth search of existing rules and practices, which can deepen the firm's knowledge base without changing the technological trajectory (Yan & Guan, 2018). Although the firm adopts exploitative learning strategy can reduce the risk of innovation, it tends to make the firm form technological overlaps and organizational inertia. Separate exploitative learning also locks the firm in the original technological path, thereby reducing the ability of the firm to adapt to the environmental changes, and ultimately facing the risk of being eliminated (Levinthal & March, 1993). On the condition that technological heterogeneity among cooperators is high, separate exploitative learning will affect the firm's identification of external heterogeneous technologies, and thus the firm losses the chance to grasp new technologies and seize the market.

Thus, we proposed the hypotheses as follows:

Hypothesis 2: The firm's exploratory learning negatively moderates the relationship between technological heterogeneity among cooperators and the firm's financial performance so that when the firm's exploratory learning is high, the positive effect of technological heterogeneity among cooperators on the firm's financial performance will be weakened.

Hypothesis 3: The firm's exploitative learning negatively moderates the relationship between technological heterogeneity among cooperators and the firm's financial performance so that when the firm's exploitative learning is high, the positive effect of technological heterogeneity among cooperators on the firm's financial performance will be weakened.

2.3. Technological Heterogeneity among Cooperators, Ambidexterity and the Firm's Financial Performance

The trade-off between exploratory learning and exploitative learning is inevitable (He & Wong, 2004). In recent years, many scholars have emphasized that firms need to balance exploratory learning and exploitative learning activities in response to fierce market competition (Luger, Raisch, & Schimmer, 2018; O'Reilly & Tushman, 2013). The exploratory learning and exploitative learning promote and complement each other (March, 1991). The exploratory learning will deepen the use of existing technologies and experimenting with existing technologies will promote the firm's exploration of new technology areas. The firm's sustainable growth relies on exploratory learning to create new knowledge and exploitative learning to mine existing technologies (March, 1991). In this study, ambidexterity was defined as a firm's pursing simultaneously high levels of exploratory learning and exploitative learning in a balanced manner (Cao, Gedajlovic, & Zhang, 2009; Kauppila, 2010).

Maintaining a balance between exploration and exploitation, namely, ambidexterity is a key factor for firms' survival and prosperity (Uotila et al., 2009). Ambidexterity improves the firm's absorption capacity, which makes the firm fully absorb and integrate external heterogeneous knowledge for organizational learning (Cohen. & Levinthal, 1990).

However, ambidexterity improves the firms' dynamic capabilities and reduces the risk of instability and high cost (Cao et al., 2009). Ambidexterity flexibly explores new technologies while efficiently exploit the existing knowledge, which avoids the firms' core rigidity (Quintana-García & Benavides-Velasco, 2008) and promotes knowledge sharing (Im & Rai, 2008).

Taken together, ambidexterity enables the firm to identify and absorb external heterogeneous technologies and reduce the firms' innovation risks and operating costs. Therefore, ambidexterity has a positive moderating effect on the relationship between technological heterogeneity among cooperators and the firm's financial performance.

Therefore, we proposed the following hypothesis:

Hypothesis 4: The firm's ambidexterity positively moderates the relationship between technological heterogeneity among cooperators and the firm's financial performance so that when the firm's ambidexterity is high, the positive effect of technological heterogeneity among cooperators on the firm's financial performance will be strengthened.

3. DATA AND METHODOLOGY

3.1. Sample

According to the China Innovative Firms Development Report Editorial Board (2015)[1], Chinese innovative firms are clustered in some industries, including computers, telecommunication and other electronic equipment manufacturing, software and information technology services, automobile, equipment manufacturing, steel and mining, chemistry, electrical machinery. We tested our model based on the data of 41 Chinese innovative public firms which were listed as a Top 100 Firm in the Industry Report and Top 100 Firm in Income Ranking Report.

The patent data used in this study was derived from the Derwent Innovation Index database (DII), which covers patents issued by more than 100 countries and 40 patent authorities. The basic information and financial data used in this research were from the WIND database, which is the leading financial data, information and software services database in China.

Data collection and cleaning steps were as follows:

1) Patent data retrieval. In order to collect patents affiliated with each firm precisely and promptly, we spent effort verifying the transformation of the name of each firm. We used the name of 41 firms as the assignee words to search patents among 2000 and 2016 one by one in DII[2]. We performed the retrieval on another 40 firms in February 2017.

2) Patent data cleaning. Screening of all cooperative patents to keep the patents belonging to two or more assignees. At the same time, we cleaned the assignee name to the same form, in order to avoid double-counting, eventually we got 2604 cooperative patents from31 firms to establish the two-model external cooperative network.

3) We collected the data including firm age, ownership type, region, industry, and R&D input of 31 firms from WIND database.

4) We established the two-model external cooperative network by Organization Risk Analyzer (ORA), which is a dynamic network analyzation software. We established the firm's two-model (Agent-Knowledge) external cooperative network with firms (assignees) as Agent node and IPC as Knowledge node. All the cooperative networks were established with the patent data in the three years prior to the t period as a time window (i.e. t-3 to t-1). Due to the difference in the starting time of the firms' cooperative patent, the networks were established in accordance with the beginning year of the firms' cooperative patents. Finally, there were 186 two-model external cooperative networks of 31 firms. This study included the invention patents registered between 2000 to 2016 of 31 Chinese innovative firms, which are shown in Table 1. There were nineteen firms with more than 1000 invention patents, and FOTON, Haier, Inspur, Midea, XCMG, ZTE, and GREE had more than 5000 patents.

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[1]Board, China Innovative Enterprises Development Report Editorial, 2015. China Innovative Enterprise Development Report (2013–2014) (Chinese Edition). Economic Management Publishing House, Beijing.

[2] For example, to search patents belonging to ZTE Group, we used a fuzzy term "ZTE or ZHONGXING" in the first step. We extracted the assignee information of the patents and got a list of whose name included the term "ZTE" or "ZHONGXING". By checking these assignees and judging each term whether it was the transformation or wrong spelling of the name of the focal firm, we excluded those entering the list but not the focal firm we aimed to research. Finally, we adopt the searching term as follows: ZTE VAST SKY INFORMATION TECHNOLOGY CO, ZTE Corp, ZET COMMUNICATION CO LTD, ZTE ITS CO LTD, ZTE INSTR SHENZHEN CO LTD, ZTE IOT TECHNOLOGY PARK CO LTD, ZTE INC, ZTE TELECOM CO LTD, ZHONGXING COMMUNICATION CO LTD, ZHONGXING TELECOM CO LTD.

Table-1. Number of patents in sample firms.

S	Patent Year	Patent count
1. JAC	2000-2014	2873
2. Beijing Xinwei	2000-2016	13
3. BYD	2003-2016	4961
4. Neusoft	2003-2016	815
5. FOTON	2002-2016	5877
6. Guangxi Liugong	2010-2016	664
7. Haier	2004-2016	8790
8. Hanvon	2008-2011	385
9. Xiamen Hongfa	2008-2014	190
10. Inspur	2004-2016	9057
11. Midea	2007-2016	14346
12. Sany heavy	2009-2016	4204
13. Xiamen Jinlong	2011-2015	112
14. Baoxin Software	2009-2013	142
15. SAIC	2004-2016	4392
16. Shougang Group	2002-2015	2690
17. Sugon	2009-2016	1119
18. TAIJI	2001-2015	123
19. TISCO	2005-2015	1798
20. TBEA	2006-2015	311
21. Tongfang	2001-2016	1102
22. Wanhua Chemical	2002-2014	165
23. West mining	2007-2015	34
24. Goldwind	2012-2016	577
25. XCMG	2010-2016	5352
26. CHINT	2009-2016	1515
27. FAW	2007-2016	3028
28. Zoomlion	2011-2016	4121
29. ZTE	2005-2016	41375
30. Chongqing Changan	2007-2016	4787
31. GREE	2013-2016	9896

Source: Derwent Innovation Index database (DII).

3.2. Variables

3.2.1. Dependent Variable

Our dependent variable was *the firm's financial performance*. We measured a firm's financial performance using net income. This was based on past accounting literature, which suggested net income as a reliable indicator of the firm's financial performance.

3.2.2. Independent Variables

Our independent variable was *technological heterogeneity among cooperators*. The cooperation networks or knowledge networks couldn't depict the relationship between the firm's external cooperators and knowledge clearly, thus, we introduced the firm's two-model external cooperative network. The technological heterogeneity among cooperators was described by knowledge diversity of firms' two-model external cooperative network. The variable refers to the extent to which external R&D cooperators have heterogeneous technologies with each other. It is a Herfindahl-Hirschman Index calculated according to the column of the A-K matrix. The calculation method was as the following (Carley, 2002):

$$w_k = \sum_{i=1}^{|A|} AK(i,k),\ 1 \le k \le |K|$$

$$W = \sum_{k=1}^{|K|} w_k$$

$$TH = 1 - \sum_{k=1}^{|K|} \left(\frac{w_k}{W}\right)^2$$

TH represents the technological heterogeneity among cooperators, *AK (i,k)* values 1 or 0, which represents the relationship between firm *i* and knowledge *k* in the network, w_k refers to the number of firms possess knowledge *k*, and *W* refers to the total number of firms possessed each knowledge.

3.2.3. Moderator Variables

Our moderator variable was a measure of *exploratory learning and exploitative learning*. Following the previous method of Katila and Ahuja (2002) we used the IPC classification code as the proxy variable of the knowledge element. According to previous studies (Wang et al., 2014) we first extracted the four code numbers of IPC classification for each patent, then compared them with all IPC classifications of the firm's previous patents. The new IPC classification number was a measure of the exploratory learning, and the old IPC classification number of the patent was the exploitative learning.

Another moderator variable was a measure of *ambidexterity*. This variable described the balance between exploratory learning and exploitative learning. Because the gap between the exploratory learning and exploitative learning in Chinese innovative firms was big, this research adopted the "relative organizational ambidexterity" (Uotila et al., 2009; Wei et al., 2014) to calculate the firm's ambidexterity. Corresponding to the window period of the two-mode external cooperative network (t-3 period to t-1 period), the firm's ambidexterity was calculated respectively in t period as the following:

Exploratory learning / (Exploratory learning + Exploitative learning)

3.2.4. Control Variables

In addition to the independent variable and moderator variables, we controlled for a variety of organizational factors in our models.

Patent count. The number of previous t-1 period patents before the given period t was used as the accumulation of firms' technological knowledge, which may affect their financial performance in the year of observation t. Thus, we chose previous t-1 period patents as the control variable for unobserved heterogeneity.

Industry dummies. Variation in the organizational ambidexterity might be associated with the industrial branch where the firms involved because different industries have different technology development and patent strategy. Therefore, we included four industry dummies: 1) computers, telecommunication and other electronic equipment manufacturing, software and information technology services; 2) equipment manufacturing, steel and mining, and chemistry; 3) electrical machinery; 4) automobile. Therefore, we included three dummy variables and the default value was automobile.

Ownership type dummies. Ownership type had been empirically confirmed as important factors in innovation performance (Aghion, Van Reenen, & Zingales, 2013). Firms in this study were classified into four types of ownership: Central state-owned firms, local state-owned firms, private firms and collective firms. Therefore, we included three dummy variables and the default value was collective firms.

Region dummies. Firms located in different regions may have different propensities to apply for patents (Arundel & Kabla, 1998). Adopting common practice, we classified regions for firms into East China, South China, Middle China, North China, Northwest, Southwest, and Northeast and introduced six dummy variables. The default value was Northeast.

Firm age. It was the difference value between the year of the firm establishment and the year of data collection. The older the firm was, the more knowledge was accumulated. Firms may tend to rely more on their existing competencies and pay less attention to learning new competencies so it was controlled.

R&D input. As R&D input was an important antecedent for the firm's financial performance, it was controlled in this study. Because of the lack of disclosure of R&D expenditure in the annual report of the sample firms in the earlier year, we adopted the ratio of R&D employees of the total number of employees as the measurement of R&D input.

Asset-liability ratio. The asset-liability ratio will have great influence on the firm's diversification expansion and financial performance (Chen. & Ho, 2000; Singh. & Davidson, 2003) so it was controlled.

3.3. Methodology

Our dependent variable, the firm's financial performance, was a continuous variable. It was dealt with in a Generalized Least Square (GLS) Regression model. The random effects models were adopted for our panel data because the fixed effects models would have biased estimates when the period is short (Greene, 1997). Thus, we used the Random-Effect Generalized Least Square (GLS) Regression to test our hypothesis. In order to alleviate concerns of reverse causality and avoid simultaneity (Singh, Kryscynski, Li, & Gopal, 2016) we used the longitudinal design. The dependent variable was measured in the period of t by lagged one year with independent variables in the prior period of t-3 to t-1. Formally, these relationships are expressed in Model 1.

Model 1.

$$
\begin{aligned}
&Firm's\ \text{financial performance}_t = \beta_0 + \beta_1 \times TH_{(t-3-t-1)} \\
&+\beta_2 \times Exploratorylearning_{(t-3-t-1)} + \beta_3 \times Exploitativelearning_{(t-3-t-1)} \\
&+\beta_4 \times Ambidexterity_{(t-3-t-1)} + \beta_5 \times Exploratorylearning_{(t-3-t-1)} \times TH_{(t-3-t-1)} \\
&+\beta_6 \times Exploitativelearning_{(t-3-t-1)} \times TH_{(t-3-t-1)} + \beta_7 \times Ambidexterity \times TH_{(t-3-t-1)} + \beta_8 \times Control\ varibles_{(t-1)} + \varepsilon
\end{aligned}
$$

4. RESULTS

Table 2 shows descriptive statistics and a correlation matrix for all the variables employed in our models. The technological heterogeneity among cooperators was positively related to the firm's financial performance ($r = 0.394$, $p < 0.01$). The mean and S.D. of firm's exploratory learning was lower than firm's exploitative learning.

Table 3 reports the results of our tests of hypotheses. Model 1 was the basic model, which included only the control variables (patent count, industry dummies, ownership type dummies, region dummies, firm age, R&D input, asset-liability ratio). In Model 2, the independent variables were entered. Finally, the moderating variables and interaction terms were individually entered in Model 3, Model 4 and Model 5.

As expected, the results indicated that the technological heterogeneity among cooperators positively affected the firm's financial performance (see Model 2, $\beta = 1.293$, $p < 0.05$). Thus, Hypothesis 1 was accepted.

The result of Model 3 showed that the firm's exploratory learning had no significant moderating effect on the relationship between technological heterogeneity among cooperators and the firm's financial performance (see Model 3, $\beta = -0.005$, $p > 0.05$). However, the interaction between the firm's exploitative learning and the technological heterogeneity among cooperators had a significant negative effect on the firm's financial performance (see Model 4, $\beta = -0.001$, $p < 0.05$). Hence, Hypothesis 2 was rejected and Hypothesis 3 was accepted.

The interaction between the firm's ambidexterity and the technological heterogeneity among cooperators had a significant positive effect on the firm's financial performance (see Model 5, $\beta = 7.666$, $p < 0.01$). Thus, Hypothesis 4 was accepted.

To show the interaction effect briefly, it is shown in Figure 1 and Figure 2. As shown, when the exploitative learning was at a high level, the positive effect of technological heterogeneity among cooperators on the firm's financial performance were weakened. When the firm's ambidexterity was at a high level, the positive effect of technological heterogeneity among cooperators on the firm's financial performance were strengthened. Thus, Hypothesis 3 and 4 were verified.

4.1. Robust Tests

We provided additional analysis to confirm the robustness of the results. We recalculated the exploratory learning, exploitative learning and ambidexterity (t period to t+2 period).

Table 4 reports the Random-Effect GLS regression results. The main effect was confirmed (see Model 2, $\beta = 1.293, p < 0.05$). The negative moderating effect of the firm's exploitative learning was corroborated (see Model 4, $\beta = -0.001, p < 0.05$). The firm's ambidexterity positively moderated the relationship between technological heterogeneity among cooperators and the firm's financial performance (see Model 5, $\beta = 8.176, p < 0.01$).

However, we measured the firm's financial performance using ROA and Table 5 reports the Random-Effect GLS regression results. All the results of GLS regression were also consistent with previous findings.

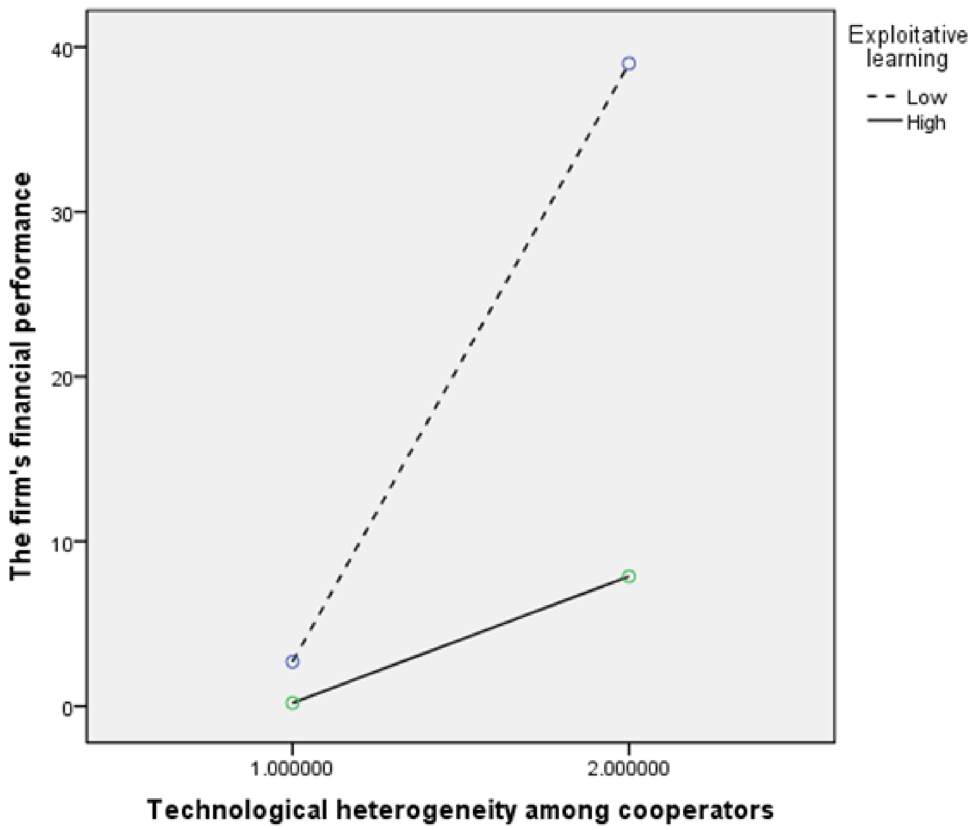

Figure-1. The moderating effect of the firm's exploitative learning.

Table-2. Descriptive statistics and correlation matrix.

Variable	Mean	S.D.	1	2	3	4	5	6	7	8	9
1. Firm's financial performance	0.094	1.739	1								
2. Technological heterogeneity among cooperators	0.688	0.216	0.394**	1							
3. Exploratory learning	22.20	26.16	0.133	-0.070	1						
4. Exploitative learning	849.5	1791	0.259**	0.078	0.330**	1					
5. Firm's ambidexterity	0.122	0.179	-0.228**	-0.300*	0.124	-0.267**	1				
6. Patent count$_{t-1}$	654.4	1217	0.256**	0.117	0.083	0.644**	-0.297**	1			
7. Firm age	25.65	26.32	0.202*	0.166*	-0.030	-0.006	-0.122	-0.005	1		
8. R&D input	0.267	0.211	-0.182*	-0.040	-0.142	-0.004	-0.025	-0.048	-0.180*	1	
9. Asset-liability ratio	0.507	0.225	0.404**	0.054	0.056	0.267**	-0.037	0.027	-0.083	0.040	1

Notes: *p < 0.05 **p < 0.01.

Table-3. Random-effects generalized least square regression results.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5
Technological heterogeneity among cooperators(TH)		1.293*	1.374**	1.212**	0.716
		(0.534)	(0.524)	(0.521)	(0.553)
Exploratory learning			0.004		
			(0.003)		
Exploitative learning				0.0002*	
				(0.0001)	
Ambidexterity					-0.238
					(0.644)
TH * Exploratory learning			-0.005		
			(0.013)		
TH * Exploitative learning				-0.001*	
				(0.0003)	
TH * Ambidexterity					7.666**
					(2.816)
Patent count $_{t-1}$	0.0002	0.0001	0.0001	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Industry 1	-2.632**	-2.531**	-2.330*	-2.308**	-2.391*
	(0.875)	(0.852)	(0.987)	(0.906)	(0.943)
Industry 2	-0.880	-0.878	-0.853	-0.718	-0.727
	(0.957)	(0.929)	(1.085)	(0.990)	(1.023)
Industry 3	-1.393	-1.540	-1.494	-1.282	-1.375
	(0.820)	(0.799)	(0.921)	(0.849)	(0.869)
Central state-owned firms	-0.151	-0.076	-0.052	0.013	-0.016
	(0.554)	(0.543)	(0.553)	(0.546)	(0.530)

Local state-owned firms	-0.614	-0.412	-0.335	-0.422	-0.410
	(0.530)	(0.526)	(0.539)	(0.530)	(0.516)
Private firms	-0.025	0.013	0.316	0.128	0.159
	(0.607)	(0.593)	(0.624)	(0.603)	(0.595)
Firm age	0.005	-0.004	-0.011	-0.004	0.016
	(0.074)	(0.072)	(0.085)	(0.077)	(0.080)
East China	0.135	-0.866	-1.862	-0.854	1.66
	(10.08)	(9.789)	(11.56)	(10.43)	(10.85)
South China	0.445	-0.50	-1.672	-0.869	2.087
	(10.19)	(9.90)	(11.7)	(10.55)	(10.97)
Middle China	-1.302	-2.161	-3.084	-2.090	0.370
	(10.07)	(9.780)	(11.57)	(10.43)	(10.86)
North China	-0.281	-1.330	-2.237	-1.336	1.364
	(10.26)	(9.965)	(11.80)	(10.630)	(11.07)
Northwest	-0.443	-1.313	-2.220	-1.163	1.369
	(10.22)	(9.926)	(11.74)	(10.585)	(11.02)
Northeast	-0.504	-1.548	-2.536	-1.516	0.939
	(9.897)	(9.614)	(11.37)	(10.25)	(10.67)
R&D input	1.136	1.009	1.315	0.880	1.143
	(0.726)	(0.716)	(0.694)	(0.694)	(0.703)
Asset-liability ratio	3.669***	3.689***	3.909***	3.274***	3.730***
	(0.978)	(0.961)	(0.923)	(0.942)	(0.884)
Constant	1.211	1.466	2.076	1.458	-1.258
	(11.99)	(11.64)	(13.71)	(12.395)	(12.87)
Observations	146	146	145	146	145
Wald chi²	51.83***	60.53***	53.18***	64.69***	67.90***

Notes: *p < 0.05 **p < 0.01 ***p < 0.001.

Table-4. Robust test results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological heterogeneity among cooperators(TH)		1.293*	1.368*	1.275*	0.837
		(0.534)	(0.549)	(0.522)	(0.554)
Exploratory learning			0.005		
			(0.003)		
Exploitative learning				0.000179*	
				(7.53e-05)	
Ambidexterity					0.0416
					(0.628)
TH * Exploratory learning			-0.005		

			(0.014)		
TH * Exploitative learning				-0.000758*	
				(0.000387)	
TH * Ambidexterity					8.176**
					(2.747)
Patent count $_{t-1}$	0.0001	0.0001	0.0002	6.93e-05	0.000102
	(0.0001)	(0.0001)	(0.0001)	(0.000109)	(0.000101)
Industry 1	-2.632**	-2.531**	-2.357**	-2.310*	-2.462**
	(0.875)	(0.852)	(0.882)	(0.905)	(0.928)
Industry 2	-0.880	-0.878	-0.849	-0.717	-0.735
	(0.957)	(0.929)	(0.957)	(0.988)	(1.008)
Industry 3	-1.393	-1.540*	-1.444	-1.283	-1.386
	(0.820)	(0.799)	(0.822)	(0.848)	(0.857)
Central state-owned firms	-0.151	-0.076	-0.025	0.0117	-0.0228
	(0.554)	(0.543)	(0.548)	(0.546)	(0.528)
Local state-owned firms	-0.614	-0.412	-0.350	-0.423	-0.391
	(0.530)	(0.526)	(0.533)	(0.530)	(0.515)
Private firms	-0.025	0.013	0.176	0.127	0.143
	(0.607)	(0.593)	(0.609)	(0.603)	(0.590)
Firm age	0.005	-0.004	-0.013	-0.00406	0.0168
	(0.074)	(0.072)	(0.074)	(0.0764)	(0.0787)
East China	0.135	-0.866	-2.076	-0.831	1.758
	(10.08)	(9.789)	(10.10)	(10.41)	(10.71)
South China	0.445	-0.500	-1.952	-0.843	2.181
	(10.19)	(9.900)	(10.23)	(10.53)	(10.82)
Middle China	-1.302	-2.161	-3.270	-2.067	0.487
	(10.07)	(9.778)	(10.09)	(10.41)	(10.71)
North China	-0.281	-1.330	-2.611	-1.312	1.434
	(10.26)	(9.965)	(10.29)	(10.61)	(10.92)
Northwest	-0.443	-1.313	-2.463	-1.141	1.500
	(10.22)	(9.926)	(10.24)	(10.56)	(10.87)
Northeast	-0.504	-1.548	-2.667	-1.494	1.034
	(9.897)	(9.614)	(9.920)	(10.23)	(10.53)
R&D input	1.136	1.009	0.967	0.883	1.271
	(0.726)	(0.716)	(0.715)	(0.694)	(0.697)
Asset-liability ratio	3.669***	3.689***	3.844***	3.276***	3.751***
	(0.978)	(0.961)	(0.965)	(0.942)	(0.884)
Constant	1.211	1.466	2.447	1.389	-1.503
	(11.99)	(11.64)	(11.99)	(12.37)	(12.69)

Observations	146	146	146	146	145
Wald chi²	51.83***	60.53***	60.79***	64.80***	69.14***

Notes: *p < 0.05 **p < 0.01 ***p < 0.001.

Table-5. Robust test results.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Technological heterogeneity among cooperators(TH)		0.083**	0.078**	0.093***	0.084**
		(0.028)	(0.029)	(0.028)	(0.028)
Exploratory learning			-0.0001		
			(0.0002)		
Exploitative learning				0.0004	
				(0.0004)	
Ambidexterity					-0.011
					(0.006)
TH * Exploratory learning			0.001		
			(0.001)		
TH * Exploitative learning				-0.0004*	
				(0.00002)	
TH * Ambidexterity					0.043*
					(0.017)
Patent count $_{t-1}$	-0.004	-0.008*	-0.008*	-0.011**	-0.017***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.005)
Industry 1	-0.095*	-0.084**	-0.088**	-0.079*	-0.092**
	(0.033)	(0.031)	(0.032)	(0.032)	(0.032)
Industry 2	-0.076*	-0.072*	-0.073*	-0.065*	-0.0643
	(0.034)	(0.032)	(0.031)	(0.032)	(0.033)
Industry 3	-0.071*	-0.076**	-0.077**	-0.070*	-0.072*
	(0.030)	(0.028)	(0.028)	(0.028)	(0.030)
Central state-owned firms	0.015	0.0101	0.009	0.006	0.012
	(0.024)	(0.022)	(0.022)	(0.023)	(0.023)
Local state-owned firms	-0.016	-0.006	-0.006	-0.012	-0.010
	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)
Private firms	-0.036	-0.030	-0.031	-0.031	-0.0380
	(0.025)	(0.023)	(0.024)	(0.023)	(0.024)
Firm age	-0.004	-0.005	-0.004	-0.004	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
East China	0.024	0.025	0.025	0.028	0.033
	(0.030)	(0.027)	(0.027)	(0.027)	(0.029)
South China	0.008	0.014	0.017	0.016	0.035

	(0.037)	(0.034)	(0.035)	(0.037)	(0.037)
Middle China	-0.034	-0.027	-0.028	-0.023	-0.024
	(0.039)	(0.036)	(0.035)	(0.036)	(0.038)
North China	-0.024	-0.028	-0.025	-0.026	-0.014
	(0.031)	(0.029)	(0.029)	(0.029)	(0.031)
Northwest	-0.026	-0.023	-0.024	-0.019	-0.006
	(0.040)	(0.037)	(0.036)	(0.037)	(0.040)
Northeast	0.548	0.632	0.622	0.629	0.461
	(0.348)	(0.325)	(0.324)	(0.324)	(0.346)
R&D input	-0.002	-0.004	-0.002	-0.005	-0.004
	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
Asset-liability ratio	-0.050*	-0.047*	-0.047*	-0.052**	-0.056**
	(0.020)	(0.019)	(0.020)	(0.019)	(0.019)
Constant	0.187*	0.156	0.163	0.151	0.130
	(0.091)	(0.086)	(0.086)	(0.086)	(0.089)
Observations	166	166	165	166	164
Wald chi^2	32.59***	45.25***	46.54***	49.90***	52.97***

Notes: *$p < 0.05$ **$p < 0.01$ ***$p < 0.001$.

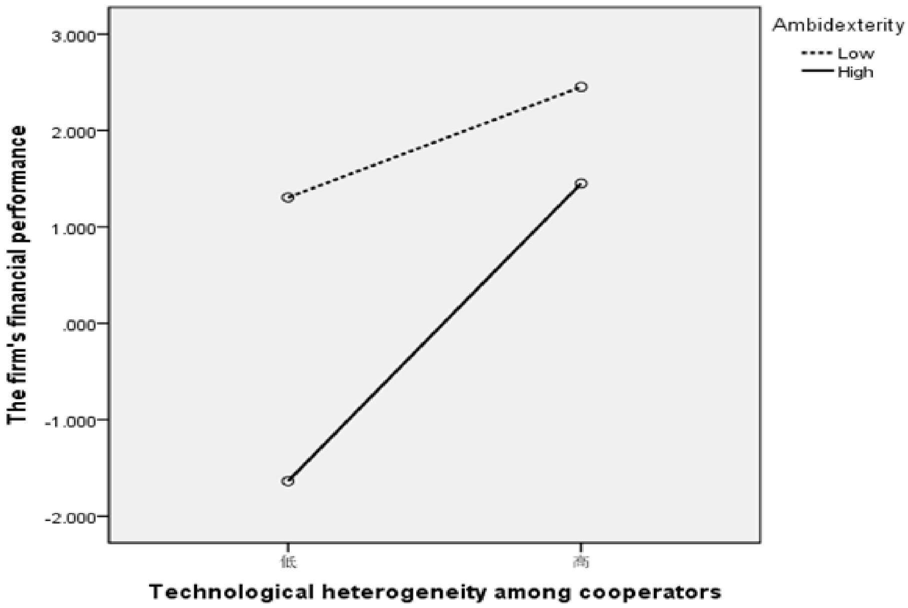

Figure-2. The moderating effect of the firm's ambidexterity.

5. DISCUSSIONS AND CONCLUSIONS

5.1. Main Findings

Referring to strategic decisions about organizational learning, the firms easily fall into two traps: one was separate exploitative learning to access short-term benefits, which makes the firm fall into the "success trap"; another was separate exploratory learning to seek future technological opportunities, whereby firms finally fall into the "failure trap" (Levinthal & March, 1993). Our study focused on the influence of technological heterogeneity among cooperators on the firm's financial performance, considering the moderating effect of exploratory learning, exploitative learning and ambidexterity. The main findings are as follows:

First, our results revealed that technological heterogeneity among cooperators positively influenced the firm's financial performance. Our explanation is that technological heterogeneity among cooperators provides more opportunities for the firm to acquire complementary technologies from external R&D cooperators and knowledge recombination is more diversified (Carnabuci & Operti, 2013; Ye et al., 2016) which makes up for the lack of internal knowledge. External heterogeneous technology is a source of new ideas, which enables the firm to gain insight into market demands and gain competitive advantages (Cohen & Caner, 2016; Fang et al., 2017; Wang. et al., 2018). Thus, technological heterogeneity among cooperators benefits the firm's financial performance.

Second, the firm's exploitative learning negatively moderated the relationship between technological heterogeneity among cooperators and the firm's financial performance. This phenomenon shows that adopting separate exploitative learning strategies leaves the firm locked in the original technology development path and falling into technological overlap, ultimately facing the risk of being eliminated (Levinthal & March, 1993). If the technological heterogeneity among external R&D partners is high, the firm might not be able to effectively identify external diverse technologies so the efficiency of the firms' technology reorganization decreases. It may also make the firms lose the opportunity to grasp new technology and loss market share, which is not conducive to the firms' sustainable profitability.

Third, the firm's ambidexterity positively moderated the relationship between technological heterogeneity among cooperators and the firm's financial performance so that when the firm's ambidexterity was high, the positive effect of technological heterogeneity among cooperators on the firm's financial performance was strengthened. Our explanation is that ambidexterity improves the firm's absorption capacity, which makes the firm fully absorb and integrate external heterogeneous knowledge for organizational learning (Cohen. & Levinthal, 1990). The firm can maintain ambidexterity by adopting exploratory learning and exploitative learning, which promotes knowledge sharing (Im & Rai, 2008) and reduce the risk of instability and high cost (Cao et al., 2009). Therefore, the firm's ambidexterity has a positive moderating effect. Nevertheless, we failed to find that the firm's exploratory learning negatively moderates the relationship between technological heterogeneity among cooperators and the firm's financial performance. Our understanding is that although separate exploratory learning increases the risk and uncertainty of innovation, exploratory learning encourages the firm to pursue new technologies. In the era of open innovation, technological heterogeneity among cooperators is high and the adverse effects of exploratory learning are weakened. In addition, a large amount of Chinese innovative firms engaged in exploitative learning, and the exploratory learning is insufficient, which may affect the moderating effect of the firm's exploratory learning. Therefore, the moderating effect of the firm's exploratory learning was not significant.

5.2. Theoretical Contributions

The main theoretical contributions of this study include:

Firstly, on the basis of previous studies on the influence of inter-firm technological heterogeneity on the firm's innovation performance (Phelps, 2010) this study further analyzed the impact of technological heterogeneity among external R&D cooperators on the firm's financial performance under open innovation. Based on resource-based view (Barney et al., 2011) technological heterogeneity among cooperators benefits the firm's financial performance by promoting diversified knowledge and mining the market demands.

The findings will enrich the extant literature on the relationship between inter-firm technological heterogeneity and the firm's sustainable profitability. We broaden the network analysis in innovation studies by introducing the two-mode network analytical method. Technological heterogeneity among cooperators was extracted from cooperator-technology network and corresponds to correlation distinctiveness across each pair of the firm's external cooperators. The results depict a more comprehensive picture of social network analysis.

Secondly, extant studies have placed emphasis on the antecedents of exploratory learning, exploitative learning and ambidexterity (Yan & Guan, 2018) or the mediating role (Xie & Gao, 2018) or explored their influence on the organizational outcomes, such as profitability and growth (Ellen et al., 2017; He & Wong, 2004; Jansen et al., 2006; Uotila et al., 2009) but few empirical studies have used them as moderator variables. In contrast to Ebben and Johnson (2005) and Giarratana and Fosfuri (2007) who advocated for the separation of exploratory learning and exploitative learning, our study introduced exploratory learning, exploitative learning and ambidexterity as the moderator variables, and suggested that a firm's internal ability to balance exploratory learning and exploitative learning was critically important for acquiring and absorbing external heterogeneous technology. Our studies inspire researchers to explore the role of organizational ambidextrous learning from different perspectives.

5.3. Practical Suggestions

Based on the findings above, we provide the following practical suggestions for R&D management and organizational learning: Firms should engage in inter-organizational R&D cooperation to access more external heterogeneous knowledge. It is necessary to focus on the technical characteristics of their cooperators when they are engaged in R&D cooperation for acquiring external technologies and to select firms with heterogeneous technical backgrounds. Concentrating on different technological fields makes the firm obtain more diverse knowledge from cooperators. However, firms also need to trade off the relationship between exploratory learning and exploitative learning. It is inefficient to adopt separate exploratory learning or separate exploitative learning. For Chinese innovative firms, firms need to access heterogeneous knowledge from cooperators to do more exploratory learning to achieve organizational ambidexterity. Due to the firms' resource constraints, exploratory learning and exploitative learning are bound to compete for scarce resources (Smith & Tushman, 2005; Uotila et al., 2009). Managers should be cautious and effectively coordinate the allocation of resources to internally balance exploratory learning and exploitative learning, thus increasing the firm's sustainable profits.

5.4. Limitations and Future Work

Despite the above theoretical contributions and practical implications, this study still has some limitations.

Firstly, we measured the exploratory learning and exploitative learning based on nonexistent or existing IPC code of patents. Although the method has been applied in previous studies (Wei et al., 2014) this operational definition of organizational learning narrowly reflects the whole meaning of exploratory and exploitative learning.

In addition, we only adopted the relative dimension of firms' ambidexterity. There are two ways to calculate the relative dimension and the interactive dimension of ambidexterity (Cao et al., 2009).

Future work could also use questionnaires to measure the ambidexterity flexibly and calculate the interactive dimension of ambidexterity to make a robust conclusion. Secondly, the sample firms came from China and from specific industries. Chinese firms lack exploratory learning, and the firms' ambidexterity will highlight the necessity of the exploratory learning. This might not be the case for firms in developed countries and in typical research-oriented industries. In future studies, we can consider expanding the sample, for example, by including global innovative firms. Thus, more empirical studies are needed in order to provide more robust conclusions and comprehensive management suggestions.

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