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Article

How innovation alliances promote technological innovation—Evidence from China’s new research & development institutes

Huidong Peng

School of Marxism Studies, South China Business College of Guangdong University of Foreign Studies, Guangzhou 510545, China; huidong.peng@outlook.com

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Abstract: Applied research institutes are crucial to technological progress. New Research & Development Institutes (NRDIs) are such a type of organization with Chinese styles. NRDIs participate in innovation alliances to promote technological innovation. Extant literature rarely explores innovation alliances’ influence on NRDIs. Based on social network theories, this research explains how innovation alliances affect NRDIs’ innovation performance. The analysis based on the panel data of 138 NRDIs in China’s Guangdong Province during 2017–2022 finds that innovation alliances’ number and diversity positively affect applied research institutes’ innovation performance. Also, internal financial resources negatively moderate the relationship between innovation alliances’ diversity and alliance members’ innovation performance.

Keywords: new research & development institute; applied research institute; innovation alliance; innovation performance

1. Introduction

Technological innovation is important for a country’s competitiveness and sustainable development. Applied research institutes (which bridge the gap between scientific research and commercial application) play an important role in promoting technological innovation. Great examples are Germany’s Fraunhofer Society and the US-based Federally Funded Research and Development Centers. These institutes narrow the gap between research in the laboratory and industrial products and become an engine for economic growth and social prosperity.

In developing countries like China, similar institutes are emerging. New Research & Development Institutes (NRDIs) are the Chinese-style applied research institutes. In the late 1990s and early 2000s, China’s NRDIs grew against the backdrop of the lack of interaction between scientific research and economic development [1]. In recent years, NRDIs have developed rapidly. In 2019, the Chinese central government issued the “Guiding Opinions on Promoting the Development of NRDIs”, further boosting NRDIs’ growth. According to the NRDIs Report 2022 released by the Ministry of Science and Technology, China had 2412 NRDIs in 2022. These institutes have employed over 200,000 employees and undertaken 35,000 research projects. NRDIs have become an emerging force driving technological innovation in China. NRDIs are new in terms of institutions and functions. From an institutional perspective, traditional research institutes are mostly public institutes with unitary ownership. By contrast, the institutional forms of NRDIs are diverse, including public institutes, state-owned/private enterprises, social organizations, etc. In terms of function, traditional research institutes usually only have one function (i.e., research), while NRDIs play multiple roles, including basic research, applied research and development, incubation, investment, and training. NRDIs are committed to integrating all innovative elements and building a micro-innovation system.

A well-functioning NRDI can improve innovation's quality and accelerate the speed of innovation. Exploring the factors affecting NRDIs' innovative performance is of great significance to understand the operating mechanism of applied research institutes and lay a solid foundation for innovation policy making.

There is little research on factors affecting NRDIs' performance. As for the limited relevant literature, the analysis of how innovation alliances affect NRDIs' technological innovation is particularly rare. Innovation alliances are contractual cooperative organizations and innovation networks aiming to improve technological innovation and are usually formed by multiple innovation actors such as enterprises, universities, research institutes, and financial organizations [2]. Innovation alliances can effectively integrate innovation networks, optimize resource allocation, and promote technological innovation. Inspired by social network theories, this article examines how the number and diversity of innovation alliances, as well as the duration of being embedded in an alliance, promote technological innovation. The remaining part of the article is organized as follows: The first part reviews the literature and proposes theoretical hypotheses; the second part introduces the research design; the third part analyzes the empirical results; the last part is the conclusion and discussion.

2. Literature review and theoretical hypotheses

2.1. Research on applied research institutes

The recent literature on applied research institutes can be classified into four groups (**Table 1**). The first group of literature analyzes the applied research institutes' current situation. Scholars investigate applied research institutes' organizational models [3], resource commitment [4], innovation process [5], technology transfer [6], management systems [7,8], spatial distribution [9], development modes [10–12], and operating mechanisms related to financing, employee incentives, and management decision-making [13–15]. The second group of literature provides suggestions for applied research institutes' further development. They advocate that applied research institutes need to improve and enhance their talent development, market-oriented reform, strategic management, and digital collaborative management along certain paths [16–19].

The third group of literature focuses on applied research institutes' performance evaluation. In order to accurately evaluate the performance of applied research institutes, researchers have constructed performance indexes according to investments, scientific research output, technology transfer, business incubation, talent development, and social impact [20–22]. At the same time, they use sophisticated statistical methods to assess these institutes' exact performance at the city or firm level [23,24]. The fourth group of literature explores factors affecting applied research institutes' performance, including technological innovation performance and technology transfer performance [1,25–28]. In terms of technological innovation performance, researchers examine the influence of major factors such as research and development investment, government support, infrastructure, institutional background, regional environment, and operating mechanism [1,25,27]. However, few scholars have studied the effect of innovation alliances on applied research institutes' technological innovation performance. This article attempts to fill this gap.

Table 1. Research on applied research institutes.

	First group	Second group	Third group	Fourth group
Author	J. Zhou et al., 2021; Kang, 2021; Y. Zhang et al., 2018 and others	Wei et al., 2021; Wu & Xu, 2022; Borsi, 2021; Zhi et al., 2021	Deng et al., 2023; B. Yang & Tu, 2018; G. Zhang et al., 2021 and others	C. Jiang et al., 2023; Mao et al., 2022; Y. Zhang et al., 2022, 2022; E. Zhou & Liu, 2018; J. Zhou et al., 2023
Focus	Current situation	Suggestions for development	Performance evaluation	Factors affecting performance

2.2. Research on innovation alliances and innovation performance

Probably because of the fact that many innovation alliances have been built to promote firms' innovation, there is abundant literature on the relationship between innovation alliances and firms' innovation performance. In this literature, one group of studies focuses on the effects of alliances' overall characteristics on members' innovation performance. They argue that focal firms' innovation performance is influenced by alliances' quantity [29–32], configuration (e.g., vertical or horizontal in the industry chain) [33,34], value chain position (e.g., upstream or downstream) [35], inner industry cognitive distance [36], and overall diversity (e.g., geographic, functional, cultural, and sectoral diversity) [37–42]. The other group of research draws attention to the attributes of partners within the alliance. They claim that alliance partners' quantity [43], experience [44], size [44,45], and type diversity [45,46] have significant effects on focal firms' innovation performance.

Although this firm-centric literature's discussion on innovation alliance and innovation performance is insightful, little is known about the relationship between innovation alliance and NRDIs' innovation performance. NRDI is a new type of applied research institute. Compared to most firms, they focus more on research. Different from pure research institutes, they have a predilection for commercialization. Whether the previous findings related to alliance and firms' innovation performance can be applied to NRDIs is still unknown. Therefore, it is necessary to investigate this new type of organization's performance from an alliance-based perspective.

2.2.1. Social network theory and hypotheses

Among current studies on innovation alliance and innovation performance, social network theory provides a coherent and convincing argument about the relationship between innovation alliances and an organization's innovation performance. I draw insights from this theory and put forward several hypotheses.

A technology innovation alliance can be seen as an innovation network composed of numerous innovation actors. Innovation networks play an important role in NRDIs' performance. Social network theory provides an insightful perspective to understand how alliance networks might improve NRDIs' innovation performance (**Figure 1**).

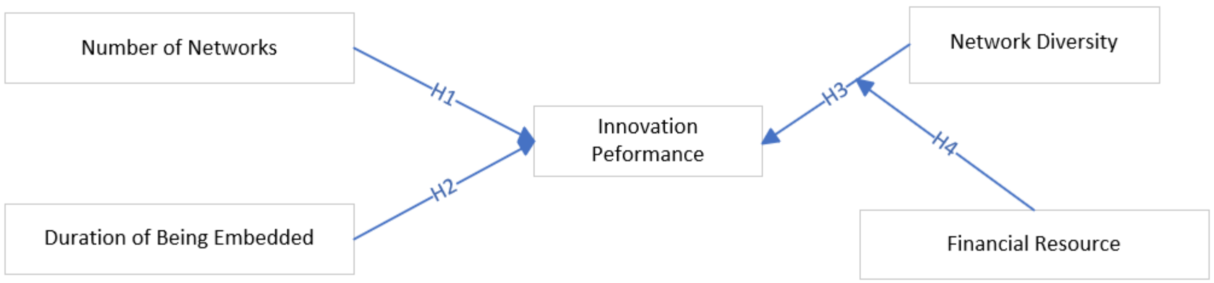

Figure 1. Theoretical model.

2.2.2. Number of innovation networks

Alliance networks can strengthen interaction, cultivate trust, enhance cooperation, and promote joint innovation among enterprises, universities, research institutes, and other innovation actors [47,48]. More importantly, innovation actors can gain resources through alliance networks [47,48]. For example, enterprises can share technology patents, research talent, and equipment with universities and research institutes; NRDIs can also utilize market information provided by enterprises to develop products that meet market demand; and NRDIs can gain help from financing organizations to alleviate financial pressure in research and development activities. The resource-sharing channels provided by the alliance network can help NRDIs improve the efficiency of technological innovation. The more innovation alliances NRDIs participate in, the more likely they are to obtain resources.

Therefore, I propose hypothesis 1: The number of alliance networks positively affects NRDIs' innovation performance.

2.2.3. Duration of being embedded in an alliance network

The duration of being embedded in the alliance (i.e., becoming a member of the alliance) also has an impact on an organization's innovation performance [49]. For one thing, the longer the actors are embedded in the alliance, the more likely they are to fully absorb resources. For another, the longer the time of being embedded in an alliance, the more frequent the interaction between the actor and other alliance members, and the more possible it is to cultivate trust, avoid opportunism, and promote collaborative innovation.

Based on this, I put forward hypothesis 2: The time of being embedded in an alliance network positively affects the innovation performance of NRDIs.

2.2.4. Diversity of innovation networks

Scholars have further pointed out that when members in an alliance are different types of organizations, alliance networks can provide heterogeneous resources, including scientific knowledge, start-up funds, equipment, and product markets that are crucial for technological innovation [37,39,42]. These resources help NRDIs improve their innovation performance. When the number of participants in the alliance is the same, the higher the degree of diversity within the alliance, the more conducive it is to the technological innovation activities of NRDIs.

Therefore, I formulate hypothesis 3: The diversity of alliance networks positively affects NRDIs' innovation performance.

2.2.5. Internal financial resources' moderating effects on the relationship between innovation alliance diversity and alliance members' innovation performance

Although innovation alliances have an impact on alliance members' innovation performance, the relationship between the two is not straightforward. Some scholars argue that several factors moderate innovation alliances' effects. Among these studies, innovation alliance's diversity draws much attention. Research finds that firms' absorptive capacity, the uncertainty of technology per se, market uncertainty, and competition intensity [50,42] regulate the relationship between alliances' diversity and firms' innovation performance. For example, market uncertainty has a negative moderating effect. This indicates that when the market uncertainty level is low, innovation alliances' diversity has more significant effects on firms' innovation performance compared to the situation when the market uncertainty level is high.

These studies on moderating effects are enlightening. But they do not pay enough attention to the role of internal financial resources in moderating alliance diversity's effects on innovation performance. I argue that organizations' internal financial resources have negative effects on the linkage between alliances' functional diversity and innovation performance. When an organization has abundant financial resources, it can create or acquire other organizations with functions different from its own. For example, a manufacturing company can establish or acquire a private college, a bank, or a research institute and incorporate them into an alliance to increase this alliance's functional diversity. By contrast, an organization lacking financial resources is less likely to do so. Therefore, diverse functions provided by an alliance are less important to an organization with ample funds compared to an organization lacking financial resources because the latter needs the alliance more to have access to diverse resources. When the diversity of innovation alliance is the same, NRDIs with insufficient resources are more likely to perform efficiently in technological innovation than those with abundant resources.

Based on this, I propose hypothesis 4: NRDIs' internal financial resources weaken the positive impact of alliance network diversity on NRDIs' technological innovation.

3. Research design

3.1. Sample and data

This study uses NRDIs in China's Guangdong Province as the sample and collects relevant data to test the above-mentioned hypotheses. Guangdong Province is the earliest provincial region to establish NRDIs, and the NRDIs in this area have rich experience and mature operating mechanisms. Many other provinces emulate Guangdong and have begun to set up their own NRDIs since the 2000s. From this perspective, one can argue that Guangdong Province's NRDIs are typical in China [51].

Considering the availability of data, the sample is NRDIs certified by the Guangdong Provincial Government during 2015–2017. Data is collected from local governments' official websites, NRDIs' official websites, local newspapers, Tianyancha (a widely used online business database), the official website of the China National Intellectual Property Administration, the Soopat patent database, etc. After removing NRDIs with missing or abnormal data, the final sample size is 138. I constructed a balanced panel data set from 2017 to 2022 based on these 138 NRDIs.

3.2. Measurement of variables

Since our dependent variable and key independent variables are related to innovation alliance, it is important to clarify what an innovation alliance is before introducing variables' measurement. As mentioned before, an innovation alliance is a contractual cooperative coalition composed of multiple organizations with the aim to improve innovation performance [2]. I take at least three ways to find out whether an NRDI has participated in an innovation alliance. Firstly, I check its official website. For example, the official website of Guangdong HUST Industrial Technology Research Institute (http://www.hustmei.com/index.htm) shows that it has participated in three innovation alliances. Secondly, I search local electronic newspapers (e.g., Guangzhou Daily, Shenzhen Daily) for information related to the alliance that an NRDI has joined. The key words I use for search are: NRDI's name + innovation alliance. Thirdly, I search local governments' official websites for relevant information by inputting keywords, just like searching the electronic newspapers. After identifying the innovation alliances a NRDI has joined, I check whether this alliance is the "alliance" I am looking for by utilizing information from alliances' official websites (e.g., Guangdong Virtual Reality Industry Technology Innovation Alliance's official website is http://topiavr.cn), local newspapers, and local governments' official websites. I would accept it as an innovation alliance to be included in our research if it has the following characteristics: 1) having agreements/contracts among members; 2) having more than two members; 3) aiming to improve technological innovation.

Based on the information related to the innovation alliance, I then attempt to measure variables. The dependent variable of this research is NRDIs' innovation performance. In line with other scholars [1], I measure NRDIs' innovation performance by the number of patent applications. Considering the lag effect of relevant factors on technological innovation, the study uses data lagged one year.

The first independent variable—the number of innovation networks—is measured by the number of innovation alliances joined by NRDIs. The second independent variable (i.e., duration of being embedded in an alliance network) refers to years of membership by the year of interest (i.e., 2017, 2018, 2019, 2020, 2021). For the third independent variable, network diversity, the paper draws on relevant literature on enterprise research and measures it as a diversity index (also known as the Blau index) [52]. The diversity index ranges from 0 to 1. An index score of 0 means a completely homogeneous group, while an index score of 1 suggests a perfectly heterogeneous group. The formula for calculation is diversity index = $1-\sum(P_i^2)$[52]. P refers to the proportion of group members belonging to a certain category, while i means the number of categories. Following business management scholars [53], I divide alliance members into four categories: manufacturing firms (the first category), universities (the second category), research institutes (the third category), and others (the fourth category). For example, if an alliance consists of two manufacturing firms, two universities, four research institutes, and two financial organizations, then the diversity index for this alliance is $1 - (2/10)^2 - (2/10)^2 - (4/10)^2 - (2/10)^2 = 0.72$. If an NRDI participates in multiple alliances in a given year, then the final value on the variable network diversity is the average of these alliances' diversity index scores. It is common in social sciences to use the average value to measure variables [54]. The moderating variable—NRDI's internal financial resource—is measured as NRDI's registered capital (the unit is 10,000 RMB). This information is from the Tianyancha database.

The study also controls for organizational-level variables, including type of organization (i.e., enterprises or others), age, and size. The data comes from Tianyancha and NRDIs' official websites. Also, since patenting activities might vary across different fields in technologies, I also control for technology fields each NRDI belongs to. According to the World Intellectual Property Organization and the China National Intellectual Property Administration [55,56], there are eight technology fields for all patents: a = human necessities (agriculture & medicine & other light industries), b = performing operation & transportation, c = chemistry & metallurgy, d = textiles & papers, e = fixed constructions, f = mechanical engineering, g = physics, and h = electricity. I divide NRDIs in terms of their main technology fields based on this classification. Since there is no NRDI whose main technology field is d, the NRDIs in this study can be classified into seven technology fields: a, b, c, e, f, g, and h. In the Soopat patent database, each NRDI's technology field is reported. Based on this, I create seven dummy variables to control for the effect of technology fields. If an NRID's main technology field is a, then it is coded as 1 on the dummy variable tech_a. Similarly, other dummy variables are coded according to the technology category an NRDI falls into. **Table 2** summarizes the measurement and data sources of variables.

Table 2. Measurement of independent and dependent variables and data sources.

Variables	Measurement	Source
Innovation performance	Number of patent applications	China National Intellectual Property Administration, Soopat patent database
Number of networks	Number of alliances joined by an NRDI	local governments' official websites, NRDI's official websites, local newspapers
Duration of being embedded	Years of being a member in the alliance joined in the earliest year	NRDI's official websites, local newspapers
Network diversity	Alliance's diversity index (Blau index) = $1 - \sum(P_i)^2$; for an NRDI participating in multiple alliances, the value is the average.	local governments' official websites, NRDI's official websites, local newspapers
Internal financial resource	Registered capital	NRDI's official websites, local newspapers; Tianyancha, recruitment websites
Type	Whether it is enterprise or not	NRDI's official websites, local newspapers, Tianyancha
Size	Number of employees	NRDI's official websites, local newspapers, Tianyancha
Age	Years of existence	NRDI's official websites, local newspapers, Tianyancha
Tech_a, b, c, e, f, g, h	Whether an NRDI belongs to a technology field	China National Intellectual Property Administration, Soopat patent database

3.3. Descriptive analysis and statistical models

This article uses the negative binomial regression model to test the above hypothesis. The dependent variable in this study is non-negative count data. This means that conventional linear regression models are not applicable, and I should use nonlinear regression models. In nonlinear regression models, I consider Poisson regression models and negative binomial regression models. Since the standard deviation and mean of the dependent variable are not equal, using the Poisson regression model may misjudge the root-mean-square error and the significance level. Therefore, I use the negative binomial panel regression model for the data analysis. **Table 3** reports the descriptive statistics of variables and each independent variable's variance inflation factor (VIF). Most variance inflation factors are smaller than 5 (VIF related to the dependent variable and the dummy variable tech_a using as a reference for other technology field variables are not available). This indicates that there is no serious multicollinearity problem [57], and effective regression analysis can be conducted. I carry out a Hausman test on each model, and the results show that the negative binomial regression model with fixed effects should be rejected (the results are not significant at the 0.00 level). Therefore, this study chooses a random effects negative binomial regression model and reports the results.

Table 3. Descriptive statistics of variables and variance inflation factor (VIF).

	Obs	Mean	Std. Dev.	Min	Max	VIF
Innovation performance	690	14.0812	50.5677	0.0000	743.0000	Not available
Number of networks	690	0.7319	1.2056	0.0000	9.0000	3.2900
Duration of being embedded	690	1.8464	2.8797	0.0000	14.0000	3.3600
Network diversity	690	0.2265	0.2859	0.0000	0.7439	2.7500
Internal financial resource	690	3853.9816	6869.8721	1.0000	41408	1.2300
Type	690	0.4348	0.4961	0.0000	1.0000	1.2400
Size	690	197.8333	410.4908	5.0000	3000.0000	1.5800
Age	690	9.5739	7.1121	0.0000	39.0000	1.3400
Tech_a	690	0.1522	0.3594	0.0000	1.0000	Not available
Tech_b	690	0.1232	0.3289	0.0000	1.0000	1.6400
Tech_c	690	0.2319	0.4223	0.0000	1.0000	2.0800
Tech_e	690	0.0072	0.0849	0.0000	1.0000	1.0600
Tech_f	690	0.0145	0.1196	0.0000	1.0000	1.1000
Tech_g	690	0.3551	0.4789	0.0000	1.0000	2.4300
Tech_h	690	0.1159	0.3204	0.0000	1.0000	1.7300

4. Statistical analysis and robustness check

4.1. Analysis of regression results

Models 1–4 test (**Table 4**) the hypotheses mentioned above. The chi-square test showed that all four models have some explanatory power (significant at the 0.00 level). Models 1–3 examine the effects of number of networks, duration of being embedded, and network diversity on innovation performance, respectively. The results of Model 1 indicate that the number of innovation networks has a significant positive impact on innovation performance (the regression coefficient is significant at the 0.01 level). The calculation of the incidence rate ratio suggests that for an additional innovation alliance joined by an NRDI, the number of patent applications increases by approximately 16.5780%.

Table 4. Regression analysis results.

DV = innovation performance				
	Model 1	**Model 2**	**Model 3**	**Model 4**
IVs				
Number of networks	0.15339***			
Duration of being embedded		0.01666		
Network diversity			1.24580***	1.90412***
Internal Financial resource				0.00007***
Internal Financial Resource * network diversity				−0.00016***
Type	−0.59608***	−0.64260***	−0.64564***	−0.58257***
Size	0.00107***	0.00095***	0.00075***	0.00074***
Age	−0.02433**	−0.01338	−0.01768	−0.01810*
Tech_b	−0.35505	−0.33934	−0.38163	−0.40772
Tech_c	0.46145*	0.46601*	0.45157*	0.35796
Tech_e	−1.05867	−0.74503	−0.71694	−0.89087
Tech_f	−1.04840*	−0.87930	−0.94528	−0.97193
Tech_g	0.58611**	0.59002**	0.59327**	0.38253
Tech_h	−0.49994	−0.45185	−0.48727	−0.49196
Number of observations	690	690	690	690
	Wald chi2(10) = 170.59	Wald chi2(10) = 116.88	Wald chi2(10) = 148.56	Wald chi2(12) = 167.89

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Hypothesis 1 passes the test. In practice, the case of Shenzhen Advanced Technology Institute (hereafter SATI) illustrates this point well [58]. During 2017–2022, this institute participated in ten innovation alliances (i.e., Supercomputing Innovation Alliance, Civil Aviation Flight Industry Technology Innovation Alliance, Brain Cognitive & Brain Disease Innovation Alliance, CAS Investment & Innovation Alliance, China Health Engineering Technology Innovation Strategic Alliance, Gene Industry Innovation Alliance, Infectious Disease Diagnostic Reagent Industry Technology Innovation Alliance, Shenzhen Metamaterials Industry Alliance, Shenzhen Big Data Innovation Alliance, and New Material Innovation Alliance). Being involved in these ten innovation alliances enables SATI to gain trust from other alliance members and cooperate to jointly apply for patents as well as develop new products. Also, being a member of several alliances allows SATI to exploit resources from other members because, according to some policies formulated by alliances, members can share resources such as talent, markets, and equipment, etc. Although SATI may have these resources, the increased quantity of resources from the alliance considerably increased its innovation capability. During 2017–2022, this institute made 553 patent applications annually, much higher than the average (about 14 patent applications per year) [59]. In sum, the alliances can improve SATI's innovation performance by encouraging cooperation and sharing of resources. Joining more alliances can lead to more cooperation opportunities and more resources and thus promote innovation performance.

The regression coefficient of duration of being embedded in a network in Model 2 is not significant at the level of 0.1, indicating that being an alliance member for a long time does not help enhance innovation performance. Hypothesis 2 fails the test. One possible explanation is that the development of emerging technologies requires a continuous stream of new heterogeneous resources, and being embedded in one network for too long may isolate NRDIs from the external environment. It might limit the flow of emerging diverse resources into NRDIs and hinder NRDIs' technological innovation under the rapidly changing conditions. This can be seen as the negative effect of over-embeddedness [47]. The case of Guangdong Electronics Industry Corporation (hereafter GEIC) sheds light on this point [60]. As early as 2009, GEIC became a member of the Guangdong Internet of Things Innovation Alliance (hereafter IOT Alliance), composed of nine members, including firms, universities, and research institutes. As the only alliance that GEIC took part in, the IOT alliance has become an important channel for GEIC to exploit external resources. The IOT alliance provided a platform for GEIC and other members to cultivate trust and promote cooperation. During the early years, the IOT alliance brought abundant and various resources (e.g., wireless communication technology, information technology talent) to GEIC, and GEIC cooperated with alliance members to apply for patents successfully and develop new products. However, as time went on, resources provided by the IOT alliance could not meet GEIC's demand for advanced intelligent electronics products. As a result, the cooperation between GEIC and IOT Alliance members decreased, and at the same time, GEICs' innovation activities declined. In fact, during the late 2010s and early 2020s, GEIC's technological patent applications were zero [59] after being embedded in an alliance for more than 10 years.

The results of Model 3 show that innovation networks' diversity positively affects innovation performance (the regression coefficient is significant at the 0.05 level). Hypothesis 3 passes the test. An example related to this hypothesis is the Guangzhou Advanced Technology Research Institute (hereafter GATRI) [61]. This is a relatively small institute with a registered capital of 30 million RMB (lower than the average of all NRDIs, which is about 38 million RMB). During 2017–2022, GATRI joined four innovation alliances with an overall diversity score of 0.6100, much higher than the average score of 0.2265 [59]. These diverse alliances provided GATRI numerous resources, such as talent training, market information, and special lab facilities. These diverse resources are what GATRI desperately needed for technological innovation, but it was difficult to create or buy as a small research institute. Innovation alliances with high-level diversity help solve these problems and enable GATRI to operate in a highly innovative way (its annual patent applications are about 39, much higher than the average score of 14) [59].

Model 4 tests the moderating effect of financial resources on the positive impact of network diversity. The regression coefficients of the main independent variable, moderating variable, and interaction term are significant at the 0.01 level. The regression coefficients of the main independent variable and the moderating variable are positive, while the regression coefficients of the interaction term are negative. This suggests that financial resources weaken network diversity's positive impact on technological innovation and that financial resources and network diversity interact as substitutes in improving innovation performance. In other words, the positive effects of network diversity on innovation performance are more significant when NRDIs' financial resources are insufficient. Compared to large NRDIs with abundant resources, small NRDIs with fewer resources are more capable of fully utilizing the heterogeneous resources of alliance networks and promoting technological innovation.

As for the control variables, it is interesting to notice that NRDIs in different technological fields have different innovation performance. For example, compared to the reference group—NRDIs in the technology field a (human necessities including agriculture & medicine), NRDIs in technology field c (chemistry & metallurgy) and technology field g (physics) are more likely to be innovative. These dummy variables are statistically significant in all three models without the interaction term.

4.2. Robustness check

Table 5. Robustness check results.

DV = innovation performance				
	Model 1	**Model 2**	**Model 3**	**Model 4**
IVs				
Number of networks	0.15273***			
Duration of being embedded		0.01712		
Network diversity			1.24703***	1.90672***
Internal financial resource				0.00007***
Internal financial resource * network diversity				−0.00016***
Enterprise	−0.58936***	−0.63655***	−0.64148***	−0.57847***
Size	0.00110***	0.00097***	0.00075***	0.00074***
Age	−0.02439**	−0.01327	−0.01761	−0.01803
Tech_b	−0.35161	−0.33633	−0.38043	−0.40702
Tech_c	0.46410*	0.46708*	0.45272*	0.35888
Tech_e	−1.07271	−0.75442	−0.72052	−0.89498
Tech_f	−1.04183*	−0.87667	−0.94384	−0.97060
Tech_g	0.59015**	0.59445**	0.59764**	0.38633
Tech_h	−0.49434	−0.44762	−0.48492	−0.48989
Number of observations	690	690	690	690
	Wald chi2(10) = 171.50	Wald chi2(10) = 116.90	Wald chi2(10) = 147.87	Wald chi2(12) = 167.13

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

In line with existing research [62], I winsorize data (i.e., transform extreme values) to conduct the robustness check. Considering that there are some outliers in organizational size, I winsorize the data at the 1% percentile based on size and use the transformed data to do regression analysis. The results (**Table 5**) indicate that, except for differences in specific coefficients, the number of networks and network diversity still have a significant impact on innovation performance. At the same time, the moderating effect of financial resources remains significant. Similarly, I winsorize the data at the 1% percentile based on capital and then use the data to do statistical analysis. The results show that the main regression coefficients are still significant. This analysis suggests that the previous results are robust.

5. Conclusion and discussion

5.1. Conclusion

The paper explores the impact of innovation alliances on innovation performance based on the data of NRDIs in China's Guangdong Province from 2017 to 2022. It finds that innovation alliances can bring resources to NRDIs. The number of embedded alliance networks positively affects NRDIs' innovation performance. Secondly, diverse members within the alliance network can bring NRDIs heterogeneous resources. The degree of network diversity has a positive impact on NRDIs' innovation performance. Finally, NRDIs' internal resources moderate network diversity's effects on innovation performance. NRDIs' internal financial resources weaken network diversity's positive effects on innovation performance.

5.2. Comparison: NRDIs and the Fraunhofer society

This research's main findings seem to be consistent with insights provided by the experience of some sophisticated applied research institutes in advanced countries. For example, the Fraunhofer Society in Germany has participated in alliances with high-level internal diversity to promote technological innovation. Firstly, the Fraunhofer Society participates in numerous alliances to exploit external resources. It has joined at least 24 innovation alliances (which are contract-based, having multiple members and aiming to promote technological innovation), such as the European Energy Research Alliance and the European Solar PV Industry Alliance [63], during 2017–2022. Secondly, the Fraunhofer Society also pays attention to the level of diversity within the alliance. For example, in the European Solar PV Industry Alliance, joined by the Fraunhofer Society, there are various members, including manufacturing firms, universities, research institutes, investors, consultancies, and even local authorities. This relatively high level of functional diversity enables the Fraunhofer Society to have access to heterogeneous resources and utilize them as driving forces for innovation [63].

However, there are also differences between the Fraunhofer Society and China's NRDIs. Two of them are noticeable. Firstly, the Fraunhofer Society is much larger than most NRDIs in China in terms of employees' numbers. In 2022, the Fraunhofer Society had 30,800 employees, while a typical Chinese NRDI has no more than 200 employees (see the descriptive analysis). Generally speaking, larger applied research institutes have higher innovation capability (see the regression results). Developing large applied research institutes is still a challenge for China. Secondly, the Fraunhofer Society is more internationalized than its Chinese counterparts. It is rare to find an

NRDI involved in an alliance with members from different countries, while the Fraunhofer Society has participated in multiple transnational alliances [59,63]. To exploit resources efficiently, it is necessary for Chinese NRDIs to build international ties via alliances.

5.3. Contribution

Compared to previous studies on NRDIs, this research mainly makes two contributions. Firstly, this paper contributes to the applied research institutes literature. Previous literature rarely investigates factors influencing applied research institutes' innovation performance from an alliance-based perspective. This research fills this gap by examining innovation alliances' influence on applied research institutes' innovation performance in the context of NRDIs in China—the largest emerging economy. Secondly, it contributes to the innovation alliance literature. Extant studies pay little attention to financial resources' moderating effects on the linkage between alliance diversity and organizations' innovation performance. This paper bridges this gap by revealing the nuanced relationship and finds that internal financial resources can negatively moderate alliance diversity's effects on alliance members' innovation performance.

5.4. Policy implication

The findings in this research yield several policy suggestions. Firstly, NRDIs may consider joining innovation alliances rather than striving to be successful on their own. Numerous resources shared by alliance members help improve innovation efficiency, while the cooperation platforms provided by alliances can cultivate trust and promote joint innovations. Secondly, it is better for NRDIs to enter or form alliances with different types of organizations (such as universities, public sectors, and financial institutions). These heterogeneous alliance members can improve resource diversity, which is beneficial to technological innovation. Thirdly, NRDIs with insufficient financial resources may consider putting more emphasis on the diversity within an alliance rather than blindly joining numerous alliances with a low degree of network diversity. Internal financial resources' moderating effects on alliance diversity's influence on innovation performance suggest that internal financial resources and alliance diversity are substitutable. Diverse resources can either be bought with NRDIs' financial resources or provided by alliances. NRDIs can utilize alliance diversity to overcome the problem of lacking financial resources.

5.5. Limitation

This research also has some limitations. Firstly, the data used in the study is based on south China, and whether the findings can be applied to other regions (e.g., north China) and other developing countries (e.g., India, Vietnam, and Indonesia) remains unknown. In addition, using patents to measure innovation is not completely accurate. The reason is that in order for patents to become innovation results (e.g., new industrial products on the market), technology transfer from research institutes to industrial firms or co-patenting is needed [64]. Further research will try to overcome these shortcomings.

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