

Whether the Innovation Policy Will Really Improve Enterprise's Innovation Performance—Mediating Role of Ambidextrous Learning

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Received: July 25, 2018

Accepted: August 22, 2018

Online Published: August 27, 2018

doi:10.5539/ibr.v11n9p96

URL: <https://doi.org/10.5539/ibr.v11n9p96>

Abstract

As the scope embodiment of public policy in specific fields, the government innovation policy is essentially a system arrangement and rule design and it plays an external guidance and incentive effect on the enterprises' innovation activities. Whether the innovation policy will really promote the improvement of enterprises' innovation performance and how it is realized have not reached the conclusion among theorists. As such the aim of this research is to test the relationships between innovation policy and enterprises' innovation performance with the aim of contributing to help the government adjust policies and improve the innovation performance of enterprises. Based on the data of high-tech enterprises in Shandong Province in 2017, this paper studied the impact mechanism of innovation policy on enterprise innovation performance through regression analysis. The paper found that the innovation policy has a significant impact on enterprise innovation performance, and the ambidextrous learning plays a mediating role in this process.

Keywords: Innovation policy, ambidextrous learning, innovation performance

1. Introduction

Appropriate policy support may have an important impact on enterprise innovation. In the newly industrialized and developing countries, the impact of innovation policy on enterprise innovation is much more significant. For this reason, it has become a common concern of theorists and governments for encouraging enterprises to carry out innovative activities through applying the innovation policy. However, whether the innovation policy will really promote the improvement of enterprises' innovation performance and how it is realized have not reached the conclusion among theorists (Fagerberg, 2017). More importantly, most theoretical researches have been concerned about the impact of government innovation policy on enterprise innovation behaviors for a long time and it lacked the consideration on enterprise innovation performance. In recent years, although the impact of innovation policy on enterprise innovation performance has gradually become the focus of researches, the related researches ignored the transmission mechanism between innovation policy and enterprise innovation performance, and it cannot explain the micro mechanism of the innovation policy working.

Fu and Mu (2014) demonstrated the mechanism process where the technology innovation policy acts on the innovation behavior of enterprises and further improves the mechanism of innovation performance through the sampling survey of the samples of small and medium enterprises in Guangdong. Eickelpasch and Fritsch (2005) studied German innovation policy and showed that German innovation policy system put more emphasis on the construction of competition mechanism among enterprises compared with the traditional innovation policy system, and the "Picking the winner" policy orientation also stresses the flexibility and effectiveness of management. Ketels (2016) conducted a research based on the sample of Spanish enterprises and it showed that although the R&D subsidy policy would encourage private enterprises to invest in innovative resources as a whole, there might also be the Crowding Out Effect for a small number of enterprises samples (30% test samples). Mazzucato (2016) verified the relationship between innovation policy synergy and economic performance by the method of policy measurement and empirical study and the results showed that there was a significant directional difference in the impact of innovation policy synergy on economic performance, which is not the stronger, the better. Chen and Ping (2004) took the medium and small enterprises board of Shenzhen stock exchange in China as a sample to evaluate the performance of China's innovation policy, and the results showed that innovation policy had a positive impact on enterprise innovation performance, but its influence is

not homogeneous.

To sum up, the research conclusions on the mechanism of the role of innovation policy still have the inadequacy of explanatory power and consistency, which is reflected in the relationship between innovation policy and enterprise innovation performance. On the one hand, the innovation performance of different enterprises may have great differences in the context of similar innovation policy (Laranja, Uyarra, & Flanagan, 2008); on the other hand, different innovation policy situations may lead to similar enterprise innovation performance. In addition, most studies regard the intermediate process from “government innovation policy” to “enterprise innovation performance” as black box, and ignore the influence of innovation policy on the process of enterprise innovation, which is not conducive to understanding the working mechanism of innovation policy in depth.

According to the study of March (1991), ambidextrous learning refers to the explorative and exploitative learning. The explorative learning emphasizes the ability of new knowledge that is different from the accumulated existing knowledge accumulation, while the exploitative learning emphasizes the gradual change and reform in the field of the existing products or knowledge. Different type of learning methods will lead to different performance results. Innovation policy is an important factor of the external environment affecting the ambidextrous learning, such as policy put forward by Lavie (2006) and so on which can have an influence on the ambidextrous learning. Innovation policy will directly affect the ability of enterprises to explore and exploit knowledge. When enterprises are supported by government policies or funded, enterprises will show more capable of exploring knowledge and be willing and dare to take risks to innovate. If enterprises can't get policy support, they may prefer to adopt a conservative attitude rather than explore new knowledge. Therefore, it can be started from ambidextrous learning to study the generative mechanism of the impact of innovation policy on innovation performance, and discuss the influence of different type of learning methods on innovation performance under the innovation policy.

Based on the above logic framework, this paper tries to conduct the analysis from the perspective of ambidextrous learning, and considers the organization of ambidextrous learning as the intermediary mechanism of innovation policy affecting innovation performance, and discusses the transmission mechanism between the innovation policy and the innovation performance. The integrated framework of innovation policy, ambidextrous learning and innovation performance is constructed to reveal the important role of innovation policy for the development of enterprises, and provide the basis for enterprises to improve their organizational learning ability and then improve the innovation performance through the innovation policy.

2. Hypothesis

As the external guidance and incentive approach of enterprise innovation activities, innovation policy can guide organizational learning through influencing resource integration, utilization and reconstruction (Naqshbandi & Tabche, 2018), and thereby affect the innovation performance. Enterprises supported by the innovation policy can often improve their innovation performance by changing learning behaviors (more exploration and stronger mining and utilization of existing knowledge) (Mohnen & Röller, 2005).

2.1 Impaction of Innovation Policy on Innovation Performance

Tax policy and direct subsidy policy have always been the two most common and most significant innovative policies applied by governments (Eisner, 1969), policy cultural issues can make or mar the open innovation process (Naqshbandi, Kaur, & Ma, 2014). Financial subsidy refers to a certain amount of financial support and allowances granted to specific enterprises in a given period according to the political and economic situation. Financial subsidy can provide additional resources for the enterprises to deal with the uncertainty during the innovation, which reduces the risk of innovation. So it will encourage enterprises to increase innovation investment, and thus achieve better innovation performance (Toivanen, 2012). Due to lack of funds and resources for enterprises, their innovation results may have strong uncertainty and the technological values are faced with the risk of invisible loss. These are the main reasons for restraining the innovation of enterprises. If the government can provide certain financial support for the enterprises, and help them out of the "valley of death" at the beginning of the innovation, it will promote the enterprises to increase innovation and achieve better innovation performance. Based on the above analysis, this paper holds that the financial subsidy policy of government has positive impact on innovation activities of enterprises. In terms of tax policy, it is the universal innovation policy tool to guide and encourage enterprises to increase investment in science and technology through preferential tax policies (Gale & Brown, 2013). By providing tax preferences for enterprises, the government reduces the tax cost undertaken by enterprises to alleviate the shortage of R & D funds in enterprises, which thereby indirectly reduces the R & D risk of enterprises, encourages enterprises to increase effort on the R & D of innovation and achieves better innovation performance (Mansfield, 1982). For those projects with high

risk, long R & D cycle, and large social income and small private income, enterprises are often reluctant to invest too much, but a certain degree of tax preferences will reduce the burden of enterprises, stimulate their enthusiasm for innovation and encourage them to increase R & D investment so as to achieve the improvement of innovation performance.

H1: Innovation policy positively impact on innovation performance.

2.2 Impact of Innovation Policy on Ambidextrous Learning

There is little research on the impact of policy climate on the organizational learning of enterprises. In particular, empirical research on the impact of policy climate on the organizational learning of enterprises on specific industries in China is lacking. Most scholars believe that the government plays an important role in encouraging and nurturing innovation, which will make the activities of enterprises more innovative (Yang, Zhou, & Zhang, 2015). Zhang and Chen (2014) finds that cooperation with government agencies has a direct impact on the promotion of cooperative learning in small and medium-sized enterprises (SMEs). Wang, Chen, and Hu (2011) point out that the government support is the most external influence of organizational learning, government funding, tax incentives and purchase behavior of enterprises to promote independent organizational learning have a positive effect. Khan, Yong, and Akhtar (2016) found that there is a significant correlation between the government policy and the performance of cooperative innovation through the investigation and research on the cooperative innovation of Chongqing Municipality. The government formulates the relevant supporting policies, strengthens the guidance of scientific and technological achievements transformation work and strengthens the macro-Guidance can effectively promote the performance of cooperative innovation. Therefore, this paper proposes the following assumptions:

H2: Innovation policy positively impact on ambidextrous learning

H2a: Innovation policy positively impact on explorative learning.

H2b: Innovation policy positively impact on exploitative learning.

2.3 Impact of Ambidextrous Learning on Innovation Performance

Naqshbandi and Kaur (2014) develop a model to explain how leadership interacts with absorptive capacity and organizational learning culture to influence open innovation outcomes. Explorative learning is related to new and differentiated new product ideas and product concepts. Explorative learning can lead to breakthrough product changes and develop new products that lead the market. Customer demand diversification and differentiation are becoming higher and higher. In this case, leading products with differentiated performance are more likely to create user requirements and be accepted by customers. Explorative learning can integrate new ideas and new knowledge into product design, and therefore design new products with new characteristics and utility (Westerlund, Peters, & Rajala, 2010). Explorative learning in addition to be able to promote breakthrough new product development, more importantly, explorative learning with self-enhancing effect. The self-reinforcing effect of exploratory learning can bring the new product development into the track of the virtuous circle. Explorative learning can also encourage team members to incorporate new knowledge and experience into their knowledge reserves, thereby increasing team members' knowledge accumulation and learning ability.

According to the resource-based theory, internal knowledge is more likely to be a sustainable competitive advantage, and internal knowledge is path dependent. In the process of exploitative learning, the use of new knowledge will face smaller conflicts and resistance than the use of new external knowledge (March, 1991), The knowledge produced by the exploitative learning can create higher value for the enterprise and is difficult to learn and imitate by competitors. In view of this, the following hypothesizes are proposed

H3: Ambidextrous learning positively impact on innovation performance.

H3a: Explorative learning positively impact on innovation performance.

H3b: Exploitative learning positively impact on innovation performance.

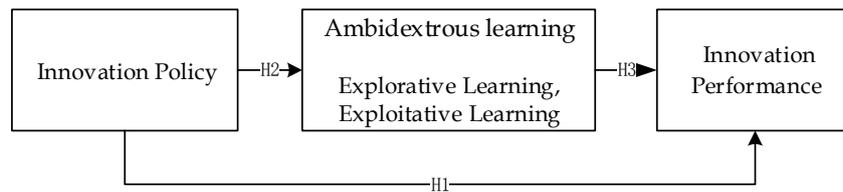


Figure 1. Theoretical Model

3. Method

This study collects data in the form of questionnaire survey, and carries out statistical analysis for the collected questionnaires, like reliability and validity validation, multiple regression analysis, etc. This research uses statistical analysis software - SPSS and AMOS, where SPSS software is used for the measurement of variable reliability and verification of proposed assumption, AMOS software is used for confirmatory factor analysis and model fitting degree analysis.

3.1 Data Collection

The core topic of this paper is to explore the relationship between innovation climate and performance, so the research object must have high intensity of R & D activities and innovative practice. The innovative team in high-tech enterprises, as high-intensive economic entity of knowledge, technology and investment, is capable of continuing the new technology and product development, with product high-tech, and on behalf of the most advanced and cutting-edge development direction in the technological field of enterprise. Compared with other general organizations, high-tech enterprises need to carry out innovative activities to construct core innovation ability (Schilling, Jones, Gareth, Hill, & Charles, 2001) in order to handle internal and external environment change. Therefore, high-tech enterprises match with this research issues. At the same time, the technological innovative activities of high-tech enterprises are of great strategic significance to the construction of an innovative country, promote the industrial transformation and upgrading whose results can also bring beneficial practical enlightenment to the enterprises and regional development.

Benefit from the development of high-tech enterprises, Shandong Province ranks the third in GDP in 2015. Taking the convenience of information collection, research costs and data aggregation problems into account, this study choose high-tech manufacturing enterprises in Shandong Province as a research object. There are a total of 1516 high-tech enterprises in Shandong Province (Source: Science and Technology Department of Shandong Province) with 1374 manufacturing among them. In this study, stratified random sampling was used to sample 1374 high-tech manufacturing industries. One of the main problems of this study focuses on the impact of the external innovation climate on the innovation performance of enterprises. In order to ensure that the research results can fully reflect the influence of different external environment, this study proceed sampling according to the administrative region division of Shandong Province, which divided into 17 layers and sampled in accordance with 20% proportion in each layer to reduce the influence of data variability in every sampling layer, so as to make sure the extracted samples with sufficient representation.

In this study, 275 questionnaires are distributed in total, and 215 questionnaires are returned in fact, with the return rate of 78%. Besides, 45 invalid or poor-quality questionnaires are removed in accordance with the questionnaire screening standard in Chapter IV. The final number of valid questionnaires is 170, with the valid questionnaire return rate of 61.8%. The results of sample descriptive statistics in this study are shown as follows.

Table 1. Sample Descriptive Statistics

Variable	Categories	Frequency	Percentage
Number Of Employees	Below 5 0	58	34.2
	50-150	9	5.3
	150-300	18	10.5
	More Than	85	50
	Sum	170	100
Enterprise Type	State-Owned Enterprise	45	26.3
	Private Enterprise	4	2.6
	International Joint Ventures	89	52.6
	Foreign Enterprise	13	7.9
	Others	18	10.5
	Sum	170	100
Enterprise Development Stage	Establishment Stage	27	15.8
	Growth Stage	49	28.9
	Mature Stage	72	42.1
	Decline Stage	13	7.9
	Second Undertaking Stage	9	5.3
	Sum	170	100
Time	1-5 Years	27	15.8
	5-10 Years	22	13.2
	10-15 Years	13	7.9
	More Than 15 Years	58	63.2
	Sum	170	100
Post	Grass-Roots Managers	40	23.68
	Middle Manager	128	75
	Top Management	2	1.32
	Sum	170	100
Respondent's length of service	1-2 Years	27	15.8
	3-5 Years	22	13.2
	5-8 Years	13	7.9
	8-10 Years	72	42.1
	More Than 10 Years	36	21
	Sum	170	100

Seen from the data in Table 1, state-owned and joint venture enterprises account for about 89%; the enterprises with more than 300 employees approximately account for 50% of the total number of enterprises; 63.2% of enterprises have a development period of over 15 years, and the large-scale enterprises with high resource accumulation account for above 50% of the samples. 77% of respondents hold medium/senior management posts, and 56% of respondents have more than 5 years of work experience in respective enterprises. Thus, they have a better understanding of their enterprise status, and can provide better help for this study to obtain valid data. To sum up, the data in the table can meet the data requirements for the research issue, and can be analyzed.

3.2 Measurement of Variables

In order to ensure the reliability and validity of the variables of this study, the scale used in this study is derived from the mature scale developed by the previous scholars. This study used the Likert 5 point scale to measure these items.

Independent Variable: Innovation policy is the behavior of the government to encourage enterprises to participate in innovative activities, including relevant laws, regulations and administrative rules and regulations (Vermeulen, 2005). The innovation policy measurement mainly draws lessons from the research results of Mohnen and Röller (2000). The innovation policy is measured by the following four items: Enterprises get local government financial support; the enterprise get the local government tax policy support; Implementation procedures of innovation policy; Efficiency of government in implementing innovation policy;

Mediation Variables: Based on the research of March (1996), this paper divides ambidextrous learning into exploitative learning and explorative learning. Exploitative learning and explorative learning were measured using the scale of Chung, Yang, and Huang (2015). Explorative learning were measured by five items: The company obtains new technologies and skills for itself within three years; The company learn the new product development technology and development process for industry; The company get new management and organizational skills that are important to innovation; The company have access to new technologies in investing, R & D deployment, R & D, training and development of engineer and so on; The company strengthens innovative skills in previously inexperienced areas. Exploitative learning were measured by five items: Upgrade the existing knowledge and skills in familiar products and technology field; Enhance skill investment to improve

productivity when using mature technology; Enhanced the ability to find solutions to customer problems that are not new but resemble existing methods; Enhance your skills further in new product development processes that already have some experience; Strengthen project knowledge and experience to improve the efficiency of existing innovative activities.

Dependent Variable: Based on Gemunden (1996) innovation performance scale, Ritter (1999) measured innovation performance from product innovation and technological innovation. This scale is convenient and concise in the process of use, and has more outstanding characteristics of subjective evaluation of respondents. Therefore, this study uses this scale to measure innovation performance. The measure item of process innovation includes: we have very advanced production equipment; compared with our competitors, our production equipment is more advanced; our production equipment embodies the first class technology. Product innovation items include: Compared to our competitors, the improvement and innovation of our products have a better market reaction; compared with our competitors, we have a higher rate of success in product innovation; Our products are first class in technical content.

Control Variable: The economic nature of firms has an impact on innovation performance. Compared with state-owned enterprises and foreign-funded enterprises, private enterprises are more likely to develop high innovation performance because their small-scale organization has flexibility in responding to the changing competitive environment. Longer-established enterprises can accumulate the necessary innovation experience, which has a positive impact on innovation activities, but such enterprises do not focus too much on situation outside enterprise or even ignore information from customers (Sorensen & Stuart, 2000). Scale is closely related to innovation activities of enterprise. Scale has influence on the adoption of managerial innovation and a strong relationship with explorative learning (Dewar & Dutton, 1986). Therefore, this paper places the industry attributes, economic nature, the year of establishment, team scale into the control variable category. This paper carries out the dummy variable treatment to the control variable in order to make a more rigorous study. During dummy variable treatment, first, segment study variables, take K-1 dummy variable if divided into K section, omit variables such as (0, 0), which can largely simplify the analysis process. Show as below.

Table 2. Control Variable Setting and Measurement

Control variable	Variable segment	D1	D2	D3	D4
Economic nature	State-owned enterprise	0	0	0	0
	Private enterprise	0	1	0	0
	Sino-foreign joint venture	0	0	1	0
	Foreign-funded enterprise	0	0	0	1
Years	between 1 and 3 years	0	0	0	0
	Between 3 and 5 years	0	1	0	0
	Between 6 and 10 years	0	0	1	0
	Over 10 years	0	0	0	1
Scale	Over 300 people	0	0	0	0
	Between 150 and 300 people	0	1	0	0
	Between 50 and 150 people	0	0	1	0
	Under 50 people	0	0	0	1

3.3 Common Method Bias Test

In this study, Harman single factor test was used to test the common method bias. By the Harman single factor test, 4 factors were analyzed (characteristic root > 1). The rate of variance of the greatest common factor before rotation was 39.265% (< 40%). As shown in table 3, so there is no common method bias problem in this study data.

Table 3. Result of Harman Single Factor Test

Factor	Characteristic Root	Variance Interpretation Rate Before Rotation
1	9.031	39.265
2	3.848	16.731
3	1.205	5.237
4	1.021	4.439

4. Result Analysis

4.1 Reliability Analysis

In this study, Cronbach's α is used to test the internal consistency of scales. Nunnally (1978) indicated that the estimated Cronbach's α should be above 0.7 as a high reliability value of a construct. Melchers (1987) indicated that the coefficient of internal consistency at the lowest level should be above 0.5, preferably above 0.6, and the lowest coefficient of internal consistency of the entire scale should be above 0.7, preferably above 0.8.

As shown in table 4, the Cronbach's α values of innovation policy is respectively 0.865. The Cronbach's α values of explorative learning and exploitative learning are respectively 0.876 and 0.795. The Cronbach's α values of innovation performance are respectively 0.813. It shows that the reliability of each scale is within an acceptable range, with good internal consistency.

Table 4. Questionnaire Reliability Analysis Results

Variable	No.	Cronbach's α
Innovation Policy	4	.865
Explorative Learning.	5	.876
Exploitative Learning.	5	.795
Innovation Performance	6	.813

4.2 Confirmatory Factor Analysis

To test the discriminant validity among key variables and the corresponding measurement parameters of each measurement scale, AMOS17.0 is adopted in this study to carry out confirmatory factor analyses (CFA) on key variables, and the model comparison method is used to investigate the discriminant validity and convergent validity of each scale (Gatignon, 2010).

AMOS is tested on the basis of chi-square statistic value (X^2). In general, the chi-square value $P > 0.05$ is deemed as a criterion to judge that a model has a good fit effect (Rong, Scholz, & Martin, 2009). However, the chi-square statistic is susceptible to the sample size. Thus, in addition to chi-square statistic, other fit indexes need to be considered as well (Fox, 1983). The judgment criteria for fit indexes are listed in tables 5 (Gatignon, 2010).

Table 5. Goodness of Fit Analysis of Model

Index	χ^2	χ^2/df	GFI	AGFI	RMSEA	NFI	CFI
Standard Value	>0.5	<5	>0.9	>0.9	<0.1	>0.9	>0.9
Model	264.972	2.038	0.867	0.963	0.095	0.980	0.987

According to the judgment criteria for fit indexes (Gatignon, 2010) listed in tables 5 a confirmatory factory analysis on model is carried out. The results show that the verification indexes such as X^2/df , RMSEA, NFI and CFI in the model basically reach the acceptable level, indicating that model has good fit.

Table 6. CFA of Model

	Route		λ	C.R.	AVE
Z1	<---	Z	0.682		
Z2	<---	Z	0.806	0.761	0.772
Z3	<---	Z	0.946		
Z4	<---	Z	0.763		
S11	<---	S1	0.801		
S12	<---	S1	0.841		
S13	<---	S1	0.835	0.918	0.799
S14	<---	S1	0.894		
S15	<---	S1	0.893		
S21	<---	S2	0.868		
S22	<---	S2	0.899		
S23	<---	S2	0.755	0.927	0.802
S24	<---	S2	0.917		
S25	<---	S2	0.883		
C1	<---	C	0.987		
C2	<---	C	0.94		
C3	<---	C	0.776	0.906	0.766
C4	<---	C	0.833		
C5	<---	C	0.717		
C6	<---	C	0.871		

Note. Z, S1, S2 and C stand for innovation policy, explorative learning, exploitative learning and innovation performance.

For the convergent validity of each dimension, the average variance extraction (AVE value) is adopted to reflect the value, and generally used to reflect the convergent validity of scales, which can directly display how much variance explained by latent variables comes from measurement errors. The bigger the AVE value is, the larger the variation percentage of the measured variable explained by latent variables will be. Accordingly, the measurement error will be smaller. The average variance extraction values all conform to the criterion of 0.50+ suggested by Fornell and Larcker (1981). The above data show that the model is within an acceptable range.

Composite reliability (CR) as one of the judgment criteria for intrinsic quality of the model reflects whether the observation item in each latent variable consistently explains the latent variable. Seen from Table 6, CR is above 0.7, which is above the criterion of more than 0.60 suggested by Fornell and Larcker (1981), with good internal consistency.

4.3 Regression Analysis Results and Discussion

Main effect test: The regression analysis in this study is based on 170 samples, and the multiple regression method is adopted to analyze the causal relationship between factors. For the regression, stepwise regression is adopted. As independent variables enter the regression equation, the statistical probability of the default variable coefficient F entering the regression equation according to SPSS is 0.05. In the analysis, such values as R^2 , F and Sig.(p) are mainly used to analyze the regression effect (Draper & Smith, 2014). R^2 refers to the coefficient of determination, which reflects a good or bad regression effect, the closer to 1, the better. The F-test of regression effect has to undergo the T-test, the bigger the T value, the better. The Sig.(p) value reflects the significance between independent and dependent variables. Bounded by 0.05, the smaller the value is, the higher the significance level will be.

Model 1 and Model 2 mainly verify the effect of innovation policy on innovation performance. In model 1, only control variables are added, including the founding time, scale, number of employees and development stage of an enterprise; Based on model 1, model 2 is added with innovation policy to verify the affection of innovation policy on innovation performance, and the affection of innovation policy on innovation performance. The regression results (Table 7) show that in the regression of innovation policy on innovation performance, R^2 values are significantly increased to 0.668 respectively; the F-test values are respectively 20.883, passing the F-test ($p=0.000<0.001$); The regression coefficients are respectively 0.822 ($p=0.000<0.001$), which show a positive effect and zero significant difference, thereby, passing the T-test ($p=0.000<0.001$). Innovation policy has a significantly positive effect on innovation performance.

Table 7. The Effect of Innovation Policy on Innovation Performance

Independent Variable	Dependent Variable	
	Innovation Performance	
Control Variable	Model1	Model 2
Nature	-.110	-.200
Number Of Employees	-.264	-.017
Stage Of Development	.133	-.060
Founding Time	-.013	.033
Independent Variable		
Innovation Policy		.822***
F	1.016	20.883***
R^2	.071	.668
ΔR^2	.071	.597
Adj R^2	.001	.636

Note. * $p<0.05$; ** $p<0.01$; *** $p<0.001$

Mediating Effect Test: This paper uses the bootstrap method (Hayes, 2013) to examine the mediating effect. The sample size was 5000 and the confidence interval was 95%.

It can be seen from the test results of intermediary effect of explorative learning. Without considering the mediating role of explorative learning, the independent variable has a significant positive effect on the mediator variable. The result is contrary to the previous conclusion. The reason is that this result is obtained by a simple linear regression on the data of 5,000 samples randomly retrieved from the original sample without considering the panel data. Seen from regression results from dependent variables and mediator variables, government innovation policy has a significant positive impact on enterprise innovation performance. This result is consistent with the previous research findings, H1 is verified too, and meanwhile explorative learning has a significant positive impact on enterprise innovation performance. It can be seen from the results of direct and indirect effects. The results of explorative learning intermediary test did not contain 0 (LLCI=-0.0192,ULCI=-0.0041), It indicates that the mediating effect of explorative learning is significant, and the coefficient of mediating effect is -0.0103. When controlling the variable of explorative learning, The interval of direct effect does not contain 0 (LLCI=0.0405,ULCI=0.1658), The direct impact is still significant when government innovation policies affect innovation performance. It shows that explorative learning plays a mediating role in the impact of government innovation policy on firm performance, but it is not the only mediating variable.

Table 8. the Results of Mediating Effect Test

Control Intermediary(Yes/No)	Path	coeff	effect	se	95% confidence interval		P
					LLCI	ULCI	
No	Z-S ₁	.0966	-	.0292	.0393	.0154	.0001
	S ₁ -C	.1065	-	.0301	-.1657	-.0474	.0004
	Z-C	.1032	-	.0319	.0405	.1658	.1658
Yes	Direct Effect	-	.1032	.0319	.0405	.1658	.0013
	Mediation Effect	-	.0103	.0038	.0192	.0041	-

It can be seen from the test results of intermediary effect of exploitative learning. Without considering the mediating role of exploitative learning, the independent variable has a significant positive effect on the mediator variable. The result is contrary to the previous conclusion. The reason is that this result is obtained by a simple linear regression on the data of 5,000 samples randomly retrieved from the original sample without considering the panel data. Seen from regression results from dependent variables and mediator variables, government innovation policy has a significant positive impact on enterprise innovation performance. This result is consistent with the previous research findings, H1 is verified too, and meanwhile exploitative learning has a significant positive impact on enterprise innovation performance. It can be seen from the results of direct and indirect effects. The results of exploitative learning intermediary test did not contain 0 (LLCI=-0.0029,ULCI=0.0187), It indicates that the mediating effect of exploitative learning is significant, and the coefficient of mediating effect is 0.0029. When controlling the variable of exploitative learning, The interval of direct effect does not contain 0 (LLCI=0.0212,ULCI=0.1462), The direct impact is still significant when government innovation policies affect innovation performance. It shows that exploitative learning plays a mediating role in the impact of government innovation policy on firm performance, but it is not the only mediating variable.

Table 9. the Results of Mediating Effect Test

Control Intermediary(Yes/No)	Path	coeff	effect	se	95% confidence interval		P
					LLCI	ULCI	
No	Z-S ₂	.0236	-	.0084	-.0400	-.0400	-.0072
	S ₂ -C	.3890	-	.1052	-.5953	-.1826	.0002
	Z-C	.0837	-	.0319	.0212	.1462	.0087
Yes	Direct Effect	-	.0837	.0319	.0212	.1462	.0087
	Mediation Effect	-	.0092	.0040	.0029	.0187	-

5. Conclusions

Based on the empirical study, this paper analyzes the mechanism of the impact of government innovation policy on enterprise innovation performance. The conclusions are as follows:

5.1 Conclusions

First, this paper provides empirical evidence for the debate on “whether the innovation policy is really effective”. The empirical study results show that the impact of innovation policy on enterprise innovation performance is significantly positive. This shows that the government innovation policy has a significant support for the independent innovation of the enterprise. The policy preferences given by the government can help enterprises get rid of certain resource constraints, effectively reduce the financial risks of enterprises’ independent innovation, and make them get more recognizable innovation opportunities and allocate their own limited resources better to improve the innovation performance. This is consistent with the study of Nceie et al. (2005). Jaffe and Palmer (1997) present that flexible policy regimes give firms greater incentive to innovate than prescriptive regulations, such as technology-based standards. The results are inconsistent with this paper, the reason is that the division of innovation policy is different. In subsequent studies, we further discussed the impact of different types of innovation policies on innovation performance.

Second, the theorists pay more attention to the direct impact of government innovation policy on enterprise innovation performance, but regard the impact process as black box. In fact, when enterprises accept different innovation policies, their organizational learning behavior will be changed, and it is the change of these behaviors that leads to the change of final innovation performance. This paper deeply explores the impact mechanism of innovation policy on innovation performance, and finds that the organizational ambidextrous learning plays a significant mediating role in the whole process. This is consistent with the study of Alzuod, Isa, and Othman (2017). The innovation policy encourages enterprises to choose organizational learning way which is more suitable for enterprise innovation, and the more deeply and extensive organizational learning can promote the improvement of innovation performance in turn (Radzi, 2014). This finding makes up for the deficiency that the explanatory power of the existing model is inadequate caused by the lack of intermediate variable, deepens

the understanding of the innovation policy, and lays a preliminary theoretical foundation for further exploring the mechanism of the action of the innovation policy from the micro level.

Third, under the rapid development of technology environment, enterprises should lay emphasis on the importance of organizational learning. Enterprises can solve problems of enterprise vitality through explorative learning and exploitative learning, and expand the depth and breadth of information exchange with the outside world so as to promote the innovation performance of enterprises.

5.2 Policy Suggestions

The study in this paper put forward the following policy suggestions for the government: Firstly, continue to increase investment in innovation policies. Considering the significant promotion impact of the government's innovation policy on enterprise innovation performance, it's reasonable to support the government to continue to increase the investment in innovation policy, especially for the enterprises in the early stage of development which should be given stronger policy support to reduce the cost and risk pressure encourage their independent innovation, and achieve better innovation performance.

Secondly, promote enterprises to carry out cooperative innovation better through innovation policy. By means of the guidance of the innovation policy, the government should encourage the establishment of cooperative innovation organizations between enterprises and enterprises, enterprises and institutions of higher learning and scientific research institutes such as the national engineering laboratory or industry R & D center to carry out more deeply innovation and cooperation. This will enable enterprises to actively share information with partners, and help enterprises to further conduct the organizational learning and achieve better innovation performance.

Finally, enhance the pertinence of policy implementation and improve the review and supervision mechanism before the implementation of policy. Considering the impact of enterprise heterogeneity on the implementation effect of innovation policy, it is particularly important to appropriately implement different innovation policies supports for different types of enterprises.

5.3 Limitations

The limitations of this study are as follow: first, this paper conducts the study only based on the data of Shandong Province in 2017, so the research results may have some limitations. For future researches, it's necessary to adopt data with longer time span and wider geographical scope to supplement and develop the results of this study. Second, this study uses the cross sectional data, which can't reflect the dynamic impact of innovation policy on ambidextrous learning and innovation performance. Therefore, dynamic analysis can be tried in the future. Third, this paper analyzes the intermediary role of innovation policy on ambidextrous learning and innovation performance, but it may also be regulated by other factors during the process, such as environmental dynamics and redundant resources etc. Further studies on these aspects can be conducted in the future.

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