Heterogeneity effects of science and technology innovation policy mix

Yujun Lin[1,a], Meirong Zhou[1,b], Chaoshun Li[1,c], Yusi Li[1,d], Xinyi Luo[1,e], Ge Chen[1,f,*]

[1]Business School, Guangdong Ocean University, Yangjiang, 529500, China

[a]lyj@gdou.edu.cn, [b]1953275607@qq.com, [c]lcs@gdou.edu.cn, [d]lys@gdou.edu.cn, [e]919335109@qq.com, [f]chenge@gdou.edu.cn

*Corresponding author

Keywords: Policy mix, Innovation effect, System simulation, Kruskal-Wallis test

Abstract: Against the backdrop of science and technology innovation (STI) becoming a core driving factor for a country's comprehensive national strength and an enterprise's competitiveness, existing studies mostly focus on the effects of individual STI policies, with insufficient exploration into the differences in the effects of policy mixes. This study innovatively adopts a hybrid method combining system simulation experiments and Kruskal-Wallis test to systematically explore the similarities and differences in the innovation effects of different STI policy mixes. The findings are as follows: First, different combinations of policy tools exhibit significantly heterogeneous effects in promoting STI, challenging the traditional assumption of simple linear superposition of policy effects and confirming that the synergetic effect of policy mixes is the key to improving innovation performance. Second, the differences in the effects of policy mixes stem not only from the absolute level of individual policies but, more importantly, from the synergetic logic between policy types and the adaptability of policy levels. The research results hold significant theoretical and practical implications. Theoretically, it breaks through the limitations of individual policy research, constructs an analytical framework of "policy type - policy level - innovation effect", verifies the synergetic and differential characteristics of policy mixes, and provides new support for policy evaluation theory. Practically, it offers specific guidance for policymakers to optimize the STI policy system, including prioritizing the promotion of positive synergetic combinations of environmental, demand-side, and supply-side policies, avoiding contradictory configurations of negative policy mixes, and implementing differentiated dynamic adjustments based on the sensitivity of different policy effects.

1. Introduction

The strategy of science and technology innovation (STI) and innovation-driven development has become a core engine for countries to enhance their comprehensive national strength and for enterprises to strengthen their market competitiveness. As a key force driving global development, STI not only has an in-depth effect of promoting sustainable economic growth but also provides solutions to global challenges such as energy security supply, food security system construction, and climate change response [1]. It is not only an important pillar for improving people's well-being and achieving sustainable development goals but also the fundamental driving force for the development of the modern economy. Currently, policymakers are increasingly recognizing that STI plays an irreplaceable core role in promoting inclusive growth and sustainable economic prosperity [2], and this field has gradually evolved into a key focus of economic policy formulation [3]. There is a broad international consensus that STI policies can empower innovation activities [4]. Faced with the accelerating evolution of the global competitive landscape, STI capability has become a core factor determining a country's development status, which requires all countries to systematically plan and dynamically optimize their STI policy systems from a strategic perspective.

A detailed analysis of the similarities and differences in the effects of policy mixes can not only systematically reveal the internal mechanism of the synergetic effect of different policy tools but also provide scientific decision-making basis for researchers and policymakers. Policymakers can clarify

  DOI: 10.25236/icfmhss.2025.014

the priority policy objectives at different development stages and accurately determine the optimal policy intensity and combination configuration required to achieve these objectives. This kind of analysis can also provide policymakers with diversified policy path options when policy objectives are fixed, including the priority ranking of different policy tools, dynamic adjustment strategies of policy intensity, and timing matching schemes of policy mixes, thereby significantly improving the accuracy, effectiveness, and flexibility of policy formulation. Whether from the perspective of expanding the selection scope of policy objectives or enriching the implementation plans of policy tools, this research can provide important ideas for solving the "optimal solution" problem in policy formulation.

In view of this, this study innovatively adopts a hybrid method combining system simulation experiments and Kruskal-Wallis test to effectively identify the differential performance of various STI policy mixes in improving innovation performance and their statistical laws, and systematically explore the similarities and differences in the innovation effects of STI policy mixes.

2. Literature review

At present, academic research on the effects of STI policies mostly focuses on the analysis of the effects of individual types of policies, specifically including the discussion on the effects of individual policies in the field of STI, such as tax policies, R&D subsidy policies, and government procurement policies.

In terms of research on the effects of STI tax policies, a number of achievements have formed rich research conclusions. Alvarez-Ayuso et al. conducted a study on the impact of tax policies on R&D activities and proposed that tax incentives can effectively promote the growth of R&D investment [5]. However, Mukherjee et al. drew a different conclusion when studying the interaction between taxation and innovation, proposing that taxation may have a hindering effect on innovation [6]. In the field of research on the effects of R&D subsidy policies, relevant scholars have also carried out targeted explorations. Raffaello and Paolo took the northern region of Italy as the research object and specifically analyzed the actual impact of local R&D subsidy policies on innovation. In terms of research on the effects of government procurement policies, existing achievements also show a variety of research perspectives [7]. Guerzoni and Raiteri explored the impact of government procurement on R&D investment and innovation output through empirical analysis, and the results showed that government procurement can have a positive impact on both [8].

To sum up, current academic research on the effects of STI policies mainly focuses on the analysis of the effects of individual policies, that is, most studies focus on exploring the independent impact of a specific type of policy (such as tax policies, R&D subsidy policies, government procurement policies, etc.) on STI. However, from the perspective of actual policy implementation scenarios, the final effect of STI is often not the result of a single policy but a comprehensive effect formed by the cooperation and joint efforts of multiple policies. There are still obvious deficiencies in existing research on the effects of STI policy mixes, especially in the exploration of "differences in the effects between different STI policy mixes". The depth, breadth, and richness of the research results all need to be further expanded and improved to better meet the needs of the practical application of policy mixes.

3. Analysis of similarities and differences in the innovation effects of policy mixes

Rothwell and Zegveld believed that policy effects come from different levels, and based on this, STI policies can be divided into three categories: one is environmental policies (P1), and the other two are demand-side policies (P2) and supply-side policies (P3) [9]. In this study, three levels are set for each type of policy. Since there are three types of policies and each type has three levels, this study designs $3^3 = 27$ simulation experiments, as shown in Table 1.

Table 1. Simulation experiments of policy mixes

Number	P1	P2	P3	Number	P1	P2	P3
1	-	-	-	15	+3%	+10%	-10%
2	-	-	+10%	16	+3%	-10%	-
3	-	-	-10%	17	+3%	-10%	+10%
4	-	+10%	-	18	+3%	-10%	-10%
5	-	+10%	+10%	19	-3%	-	-
6	-	+10%	-10%	20	-3%	-	+10%
7	-	-10%	-	21	-3%	-	-10%
8	-	-10%	+10%	22	-3%	+10%	-
9	-	-10%	-10%	23	-3%	+10%	+10%
10	+3%	-	-	24	-3%	+10%	-10%
11	+3%	-	+10%	25	-3%	-10%	-
12	+3%	-	-10%	26	-3%	-10%	+10%
13	+3%	+10%	-	27	-3%	-10%	-10%
14	+3%	+10%	+10%				

3.1 Normality test

Generally speaking, when conducting hypothesis testing, parametric methods should be considered first, and non-parametric methods should be used only when parametric methods are not applicable. Therefore, before using the Kruskal-Wallis test method, it is necessary to conduct a normality test. If the sample data meets the normality requirement, the one-way analysis of variance method should be preferred for analysis. It can be seen from Table 2 that for the Kolmogorov-Smirnov test, not all significance values (p-values) are greater than 0.05; while for the Shapiro-Wilk test, all significance values (p-values) are greater than 0.05. For small samples (usually considered as samples with a size less than 30), the result of the Shapiro-Wilk test is usually preferred; otherwise, the result of the Kolmogorov-Smirnov test is usually preferred. It can be concluded that the sample data in this study does not meet the normality requirement. Therefore, the Kruskal-Wallis test method should be used in the analysis of the similarities and differences in the innovation effects of policy mixes.

Table 2. Normality test

	Number	Kolmogorov-Sminov (V)[a]			Shapiro-Wilk		
		Statistics	df	Significance	Statistics	df	Significance
Patent application acceptance	1	.080	50	.200*	.983	50	.699
	2	.057	50	.200*	.986	50	.822
	3	.128	50	.039	.973	50	.308
	4	.079	50	.200*	.984	50	.743
	5	.063	50	.200*	.987	50	.835
	6	.123	50	.056	.974	50	.338
	7	.080	50	.200*	.982	50	.641
	8	.057	50	.200*	.986	50	.804
	9	.123	50	.057	.972	50	.283
	10	.079	50	.200*	.985	50	.766
	11	.059	50	.200*	.987	50	.851
	12	.110	50	.177	.975	50	.349
	13	.080	50	.200*	.986	50	.823
	14	.063	50	.200*	.987	50	.853
	15	.105	50	.200*	.976	50	.399
	16	.084	50	.200*	.984	50	.712
	17	.060	50	.200*	.987	50	.847
	18	.116	50	.092	.973	50	.303
	19	.083	50	.200*	.981	50	.586
	20	.062	50	.200*	.985	50	.783
	21	.121	50	.064	.973	50	.293
	22	.080	50	.200*	.982	50	.651
	23	.057	50	.200*	.986	50	.808
	24	.122	50	.059	.973	50	.309
	25	.090	50	.200*	.979	50	.511
	26	.060	50	.200*	.985	50	.750
	27	.129	50	.036	.972	50	.277

*. This is the lower limit of true significance.
a. Lili's significance correction.

3.2 Kruskal-Wallis test for similarities and differences in innovation effects

As can be seen from Table 3, the results of the Kruskal-Wallis test show that the significance level (p-value) is less than 0.05, indicating that there are significant differences in the innovation effects of different STI policy mixes. It is important to note that this "significant difference" refers to an overall significant difference. At this stage, it is not possible to determine which specific STI policy mixes have significant differences in their innovation effects and which ones do not. To identify the pairs with significant differences and those without, it is necessary to adopt a multiple comparison method. Through multiple comparisons, we can clearly determine which policy mixes have significant differences in their innovation effects and which ones do not.

Table 3. Kruskal-Wallis test

Hypothesis test summary				
	Null hypothesis	Test	Significance	Decision
1	The distribution of the number of accepted patent applications is the same across experimental categories	Independent samples Kruskal-Wallis test	.000	Reject the null hypothesis

Asymptotic significance is shown. Significance level = .050.

From the results of multiple comparisons in Table 4 (abbreviated due to space constraints), when a significance level of 0.05 is adopted, the innovation effect of the policy mix corresponding to Experiment 18 shows no significant difference from that of the policy mixes corresponding to Experiments 3, 6, 9, 12, 15, 21, 24, and 27. However, it exhibits significant differences from the innovation effects of the policy mixes corresponding to all other simulation experiments. Similar analyses of similarities and differences in innovation effects can be conducted for the policy mixes corresponding to other simulation experiments (beyond the one in Experiment 18), which are not elaborated here.

Table 4. Multiple comparisons

Pairwise comparisons of experiments					
Sample 1-Sample 2	Test statistic	Std. error	Std. test statistic	Significance	Adj. significance
18-9	25.860	77.971	.332	.740	1.000
18-27	-34.120	77.971	-.438	.662	1.000
18-12	110.620	77.971	1.419	.156	1.000
18-3	138.260	77.971	1.773	.076	1.000
18-21	-142.840	77.971	-1.832	.067	1.000
18-15	234.760	77.971	3.011	.003	.914
18-24	-253.100	77.971	-3.246	.001	.411
18-6	255.780	77.971	3.280	.001	.364
18-16	453.560	77.971	5.817	.000	.000
18-25	-456.540	77.971	-5.855	.000	.000
18-7	468.580	77.971	6.010	.000	.000
18-19	-564.980	77.971	-7.246	.000	.000
18-10	577.840	77.971	7.411	.000	.000
18-1	585.600	77.971	7.510	.000	.000
18-22	-671.620	77.971	-8.614	.000	.000
18-4	697.140	77.971	8.941	.000	.000
18-13	697.700	77.971	8.948	.000	.000
18-26	-892.020	77.971	-11.440	.000	.000
18-8	929.360	77.971	11.919	.000	.000
18-17	940.160	77.971	12.058	.000	.000
18-20	-988.820	77.971	-12.682	.000	.000
18-2	1033.820	77.971	13.259	.000	.000
18-11	1052.160	77.971	13.494	.000	.000
18-23	-1083.440	77.971	-13.895	.000	.000
18-5	1127.540	77.971	14.461	.000	.000
18-14	1146.040	77.971	14.698	.000	.000
…	…	…	…	…	…

Each row tests the null hypothesis that "the distribution of Sample 1 is the same as that of Sample 2". Asymptotic significance (two-tailed test) is shown. Significance level = .05.

a. Significance values have been adjusted for multiple tests using the Bonferroni correction method.

4. Conclusions

By adopting a hybrid method combining system simulation experiments and the Kruskal-Wallis test, this study deeply explores the similarities and differences in the innovation effects of different

STI policy mixes, and draws the following main conclusions.

First, this study strongly confirms that different combinations of policy tools have heterogeneous effects in promoting STI. This conclusion challenges the traditional assumption of simple linear superposition of policy effects in policy research, and emphasizes the importance of the synergistic effect of policy mixes.

Second, the study reveals the complexity and nonlinear characteristics of policy mix effects. The differences in policy mix effects are not only reflected in the absolute level of policy tools, but more importantly, in the synergy and balance between different policy tools.

Third, this study provides a systematic decision-making basis for the formulation of STI policies. The research results offer scientific references for policymakers to select priority policy objectives and determine the optimal policy intensity and combination configuration at different development stages.

Acknowledgement

This research was financially supported by the Guangdong Philosophy and Social Sciences Planning Project (Grant NO. GD25YDXZYJ04) and the Guangdong Ocean University Research Project (Grant NO. YJR23015).

References

[1] G. Ozkaya, M. Timor, and C. Erdin, Science, Technology and Innovation Policy Indicators and Comparisons of Countries through a Hybrid Model of Data Mining and MCDM Methods, *Sustainability*, vol. 13, pp. 1-52, 2021.

[2] R. Padilla-Perez and Y. Gaudin, Science, technology and innovation policies in small and developing economies: The case of Central America, *Research Policy*, vol. 43, pp. 749-759, 2014.

[3] L. Soete, Science, technology and innovation studies at a crossroad: SPRU as case study, *Research Policy*, vol. 48, pp. 849-857, 2019.

[4] J. Edler and J. Fagerberg, Innovation policy: what, why, and how, *Oxford Review of Economic Policy*, vol. 33, pp. 2-23, 2017.

[5] I. C. Alvarez-Ayuso, C. Kao, and D. Romero-Jordan, Long run effect of public grants on the R&D investment: A non-stationary panel data approach, *Economic Modelling*, vol. 75, pp. 93-104, 2018.

[6] A. Mukherjee, M. Singh, and A. Zaldokas, Do corporate taxes hinder innovation? *Journal of Financial Economics*, vol. 124, pp. 195-221, 2017.

[7] B. Raffaello and P. Paolo, The impact of R&D subsidies on firm innovation, *Research Policy*, vol. 45, pp. 442-457, 2016.

[8] M. Guerzoni and E. Raiteri, Demand-side vs. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix, *Research Policy*, vol. 44, pp. 726-747, 2015.

[9] R. Rothwell and W. Zegveld, Industrial Innovation and Public Policy: Preparing for the 1980s and the 1990s, London: Greenwood Publishing Group, 1981.