Analysis of the Inverted U-Shaped Relationship Between Population Aging and Technological Innovation from an Openness Perspective

—Based on Provincial Panel Data

Hui Xue, Zixuan Jiang*

Business School, Sun Yat-sen University, Shenzhen, 518107, Guangdong, China

xueh8@mail2.sysu.edu.cn, *3094608884@qq.com

Abstract. This study explores the inverted U-shaped relationship between the level of aging and the level of technological innovation, and further validates this relationship through grouping studies based on different levels of openness. The research data covers Chinese provincial panel data from 2006 to 2022. First, we used the U-test to verify the inverted U-shaped relationship between the level of aging and the level of technological innovation, and conducted robustness tests by replacing core explanatory variables and using instrumental variable methods. The results show that the inverted U-shaped relationship is significant and robust in the overall sample. Then, we divided the sample into 3 groups and found that in regions with high openness, the inverted U-shaped relationship is significant. In regions with medium openness, the U-shaped relationship is not significant, but the linear relationship is significant, suggesting that the impact of aging on technological innovation in this group is primarily linear. In regions with low openness, neither the inverted U-shaped relationship nor the linear relationship is significant. The conclusions of this study provide new insights into understanding the relationship between aging and technological development, offering important reference value for policy formulation, especially in the context of increasing aging and globalization.

Keywords: Aging; Technological Innovation; Openness.

1 Introduction

Since the beginning of the 21st century, China's demographic landscape has undergone significant changes. Due to the combined effects of a significant increase in life expectancy and a rapid decline in fertility rates, the proportion of the population aged 65 and above reached 7% in 2000, marking the official entry of China into an aging society. By 2021, this proportion had risen to 14%[1], indicating that China has officially entered the "deep aging" society as defined by the World Bank. This speed also reflects that China's aging process is faster than that of other developed economies and the global average. China's entry into a "deep aging" society occurred four years earlier

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than the projection in the 2019 edition of the World Population Prospects. Nowadays, technological innovation has become the core driving force for high-quality economic development. With the acceleration of population aging, the structure of China's labor market is undergoing profound changes, and the traditional economic growth model relying on demographic dividends is no longer sustainable. Therefore, an analysis of the mechanisms through which population aging affects technological innovation is of great theoretical and practical significance for accurately formulating strategies to promote economic development and addressing the challenges of population aging.

2 Literature Review

In recent years, as many countries around the world have entered aging societies, the academic community has increasingly focused on the relationship between population aging and technological innovation.

From the perspective of human capital theory, as population aging intensifies, the proportion of middle-aged and elderly employees in enterprises will increase, while the proportion of young employees will decrease. This may undermine the innovation vitality of enterprises[2]. At the same time, the retirement of middle-aged and elderly employees can easily cause the loss of key knowledge and skills, further hindering technological innovation[3]. However, the trend of an aging workforce, which brings about labor shortages and rising employment costs, may also force enterprises to pursue technological upgrades. For instance, enterprises may choose to adopt technologies such as intelligent robots to reduce labor demand[4]. When it comes to social resource allocation and economic growth, the rise in the elderly population will force governments to increase fiscal expenditures in fields like elderly care and healthcare. This will crowd out spending on scientific research, thereby inhibiting technological progress. However, if the government can effectively expand fiscal revenue, it may cut off the negative transmission path[5]. On the other hand, the aging also brings new economic growth points, such as the "silver economy"[6].

Therefore, whether from the perspective of enterprises or society, population aging may have both positive and negative effects on technological innovation[7]. The mechanisms through which population aging affects technological innovation are complex and multi-dimensional, and empirical research findings have not yet reached a consensus. Some studies suggest that population aging inhibits corporate innovation[8], while others, such as Yang Jie and colleagues, argue that the impact of may not be significant[9]. Cai Xing observed non-linear patterns between demographic changes and innovation outcomes[10]. Research by Shen Ke and Sun Huilin shows that the relationship between population aging and technological innovation not only presents an inverted U-shape locally but also shows a U-shaped spatial spillover effect in neighboring regions[11]. Our study adds the U-test to this inverted U-shaped relationship, using panel data from 31 Chinese provinces from 2006 to 2022, more rigorously verifying the inverted U-shaped relationship between the level of aging and the level of technological innovation. Moreover, existing research indicates that population aging exerts a significant negative impact on technological innovation by inhibiting human capital accumulation, with heterogeneous characteristics observed in economically developed regions and across different types of innovation[12]. We divide the sample into high, medium, and low openness groups to study the relationship between aging and technological innovation under different openness conditions, revealing the different impacts of population aging on technological innovation in regions with different levels of openness. This not only fills the gaps in current research in this field but also provides more precise decision-making references for policymakers.

3 Research Design

3.1 Data Sources and Variable Selection

The dependent variable in this study is technological innovation. Patent-related indicators are commonly used to measure technological innovation[11]. This study uses the logarithm of the number of patent applications per 10,000 residents in each Chinese province as the measurement indicator. Data on patent applications in each province come from the National Bureau of Statistics(NBS), covering the period from 2006 to 2022. The reasons for choosing this time range are twofold: first, in August 2000, to meet the needs of China's accession to the World Trade Organization, China revised its patent law. Therefore, patent data before this period may be biased due to the influence of different patent laws rather than population aging. Second, data before 2005 and after 2023 are missing, such as the year-end resident population data, which was not distinguished between urban and rural areas before 2005.

The independent variable in this study is the level of aging. The population aged 65 and above is generally considered to have exited the labor market. Therefore, we use the proportion of the population aged 65 and above (from population sampling surveys) to the total population (from population sampling surveys) to represent the level of aging. The data source is the NBS. Zhou Mao and others suggest that the proportion of the tertiary industry is suitable for representing changes in industrial structure[13]. So we use the proportion of the tertiary industry's added value relative to provincial GDP as a metric for measuring industrial structure.

We control for a series of variables that may affect technological innovation, including provincial GDP per capita, year-end resident population, industrial structure (proportion of the added value of the tertiary industry to provincial GDP), urbanization level (proportion of urban population to total population at year-end), and investment level (growth percentage of fixed asset investment). Among these, provincial GDP per capita reflects the level of economic development, which is related to the resources available for technological innovation and the total demand for new technologies in the province[14]. As industrial structure upgrades, the demand for new technologies will increase, so industrial structure needs to be controlled[15]. The urbanization process has a positive effect on level of technological innovation, but the urbanization levels varies across regions, so urbanization level needs to be controlled[16]. The increase in fixed asset investment means the expansion of enterprise scale or the tendency to invest in the region, which in turn affects the development of technological levels, so we control for investment level.

For missing values in the above variables, we filled them with the mean of the data from the years before and after the missing values. The final sample contains 527 observations. Table 1 shows the basic statistical characteristics of all variables.

Table 1. Descriptive Statistics of Variables.

variables	N	Unit	Mean	Standard Deviation	Minimum	Maximum
Technological Innovation	527		0.880	1.360	-2.610	4.460
Aging	527	%	0.100	0.0300	0.0500	0.200
Average GDP	527	10k￥	4.800	3.080	0.610	19.02
Urbanization	527	%	0.560	0.140	0.210	0.900
Industrial Structure	527	%	0.480	0.0900	0.300	0.840
Investment	527	%	13.22	11.49	-56.60	41.30
Population	527	10k persons	4407	2849	285	12684

3.2 Models and Estimation Methods

First, this study examines the impact of the level of aging on the level of technological innovation based on provincial panel data. The F-test shows that both individual fixed effects and time fixed effects are significant, so a double fixed effects model is used for analysis. The following econometric model is established:

$$ltech_{it} = \alpha + \beta_1 \bullet aging_{it} + \beta_2 \bullet aging2_{it} + control_{it} + \sigma_i + \lambda_t + \varepsilon_{it} \quad (1)$$

In *Model(1)*, *i* denotes the province, *t* denotes the year, *ltech* represents the logarithm of the level of technological innovation, *aging* indicates the level of population aging, *aging2* is the quadratic term of the aging level, and $control_{it}$ refers to a series of control variables. Additionally, we control for province fixed effects (δ_i) and time fixed effects (λ_t).

When the error term of the linear regression model has heteroskedasticity, ordinary standard errors are no longer valid because they are derived under the assumption of homoskedasticity. In this case, using heteroskedasticity-robust standard errors can provide more accurate statistical inference[17]. Cross-sectional data usually involve multiple different individuals, and these individuals often have heteroskedasticity problems. So, for cross-sectional data, using heteroskedasticity-robust standard errors is a relatively effective and common practice. We use the heteroskedasticity-robust standard errors proposed by White, which do not rely on the assumption of homoskedasticity.

Then, we conduct robustness tests. First, we replace the core explanatory variable. We use the old-age dependency ratio instead of the level of aging and establish *model(2)* for regression:

$$ltech_{it} = \alpha + \beta_1 \bullet old\_ratio_{it} + \beta_2 \bullet old\_ratio2_{it} + control_{it} + \sigma_i + \lambda_t + \varepsilon_{it} \quad (2)$$

Among them, *old_ratio* represents the old-age dependency ratio, and *old_ratio2* is the quadratic term of the old-age dependency ratio.

Due to potential endogeneity between the level of aging and the level of technological innovation, we use an instrumental variable(IV) model. Considering the lagging effect, we use the lagged level of aging as the IV and establish *model(3)*:

$$ltech_{it} = \alpha + \beta_1 \bullet aging\_lag_{it} + \beta_2 \bullet aging\_lag2_{it} + control_{it} + \sigma_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Among them, *aging_lag* represents the lagged term of the aging level, and *aging_lag2* is the quadratic term of the lagged aging level.

Considering the endogeneity caused by two-way causality, we use the number of retirees participating in pension insurance as the IV and establish *model(4)*:

$$aging_{it} = \alpha + \varphi_1 \bullet leaveretire_{it} + \varphi_2 \bullet leaveretire2_{it} + control_{it} + \sigma_i + \lambda_t + \varepsilon_{it} \quad (4)$$

Leaveretire represents the number of retirees participating in the pension insurance by province, and leaveretire2 denotes the quadratic term of the number of retirees participating in the pension insurance by province.

Finally, we conduct group regressions for regions with different levels of openness to test the heterogeneity of the conclusions.

4 Empirical Analysis of the Level of Aging and Technological Innovation

4.1 Baseline Regression Analysis

The baseline regression results are shown in Table 1. We used a double fixed effects model for a series of regression analyses. In model 1, we only added the level of aging and its quadratic term as core explanatory variables. The results show that the coefficient of the linear term of the level of aging is significantly positive, and the coefficient of the quadratic term is significantly negative, showing a clear inverted U-shaped relationship. Considering the significant differences in economic level, urbanization level, industrial structure, investment level, and population size among different provinces, these factors may all affect technological innovation. We added relevant control variables in models 2 and 3.The results of models 2 and 3 show that the coefficient of the level of aging is significantly positive at the 1% level, and the regression coefficient of the quadratic term of the level of aging is significantly negative at the 1% level, manifest a clear "inverted U-shaped" relationship between the level of aging and technological innovation. This suggests that with the intensification of population aging, the impact of population aging on technological innovation is to promote firstly and then to inhibit.

According to the coefficients of the linear and quadratic terms of population aging in model 3, the inflection point of the inverted U-shaped curve between population aging and technological innovation is that the level of population aging is 12.45%. By the end of 2023, the proportion of the elderly population aged 65 and above in China had risen to 15.4%, indicating that China has entered a stage where population aging may have an inhibitory effect on technological innovation. As aging further intensifies, its potential negative impact on technological innovation may become more significant.

To explore the potential linear relationship , we built a linear model. Model 4 in Table 2, without fixed time or province effects, shows a significantly positive regression coefficient at the 1% level, indicating a possible positive linear link. However, in Model 5 with double fixed effects, the coefficient turned insignificantly negative, suggesting the simple linear assumption might not hold. Moreover, in Model 6 with added control variables, the coefficient stayed negative and insignificant. These results show there's no simple linear relationship between aging levels and technological innovation, solidly supporting the inverted U-shaped relationship hypothesis.

Table 2. Analysis of the Impact of Population Aging on Technological Innovation Levels.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
The level of	18.904***	42.451***	9.969**	29.49***	-1.754	-0.299
aging	(3.78)	(7.21)	(2.12)	(1.589)	(1.436)	(1.299)
Quadratic	-79.067***	-163.120***	-40.031**			
term of aging	(-4.32)	(-6.53)	(-2.30)			
level						
Economic		0.155***	0.055***			0.0471***
level		(9.47)	(3.06)			(0.0152)
Urbanization		3.563***	5.818***			5.950***
level		(11.71)	(8.84)			(0.550)
Industrial		1.736***	-1.838***			-2.036***
structure		(4.33)	(-3.63)			(0.455)
Investment		-0.009***	-0.001			-0.00104
level		(-3.52)	(-0.50)			(0.00148)
Population		0.000***	-0.000**			-0.000107**
		(8.60)	(-2.01)			(0.0000451)
Constant	-0.169	-5.476***	-1.802***			-1.188***
term	(-0.52)	(-15.15)	(-2.92)			(0.445)
Time effect	Yes	No	Yes	No	Yes	Yes
Province effect	Yes	No	Yes	No	Yes	Yes
Sample size (N)	527	527	527	527	527	527
R-sqUared	0.957	0.842	0.966	0.371	0.955	0.965

Note: Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.2 U-Test

Lind and Mehlum[18]argue that when the true relationship is convex and monotonic, model estimation will incorrectly produce an extreme point and a U-shaped relationship. Lind and Mehlum (2010) draw on the general framework invented by Sasabuchi (1980) to test whether there is a U-shaped or inverted U-shaped relationship between two variables and use this test principle to write the U-test command. To make the regression results more rigorous, we added the U-test to the model based on previous research on the inverted U-shaped relationship. The results are presented in Table 3. According to the test results, we found that models 1, 2, and 3 can reject the null hypothesis at the 1%, 1%, and 5% statistical levels, respectively, and the slope interval coefficients have opposite signs, indicating that the extreme points fitted by the models are within the data range. The inverted U-shaped relationships in models 1, 2, and 3 are all valid.

Table 3. U-Test for the Inverted U-Shaped Relationship Between Aging Level and Technological Innovation Level

U-test	Model 1	Model 2	Model 3
Aging Level Data Range	[0.048,0.200]	[0.048,0.200]	[0.048,0.200]
Critical Value	0.120	0.130	0.126
t-value	3.37	5.25	1.95
P>|t|	0.000	0.000	0.026
Passed?	Yes	Yes	Yes

4.3 Robustness Tests

The article uses a double fixed effects model to examine the impact of the level of aging on the level of technological innovation, but it cannot avoid potential endogeneity problems between variables. Therefore, the article verifies the robustness of the model through different methods. First, we replace the core explanatory variable. The level of aging reflects the proportion of the elderly population, while the old-age dependency ratio is defined as the ratio of the population aged 65 and above to the working-age population aged 15 to 64, which can also reflect the level of aging. Therefore, the article uses the old-age dependency ratio as a substitute variable for double fixed effects analysis. The results are shown in model 7 of Table 4. The coefficient of the linear term of the level of aging is still significantly positive, and the coefficient of the quadratic term is still significantly negative. The U-test result has a p-value less than 0.05, indicating that the inverted U-shaped relationship between the level of aging and the level of technological innovation is robust.

Second, we consider endogeneity issues. Using instrumental variable methods to address endogeneity is a effective approach. Endogeneity may be caused by different reasons. First, the impact of the population aging process on the level of technological innovation may have a lagging effect because technological research and innovation usually require a long time cycle, and the application of technology from invention to implementation also takes time. Therefore, we use the lagged term of the core explanatory variable as the instrumental variable for model testing. The results are shown in models 8 and 9 of Table 4. The coefficients are significant, the linear term coefficient is positive, and the quadratic term coefficient is negative. The U-test passes, and the model is still robust. Second, there may be a two-way causal relationship between the level of aging and the level of technological innovation. Technologies such as online education, and social media can help the elderly maintain social connections and health status. We use instrumental variable methods for analysis. The number of retirees participating in pension insurance is related to the level of aging but has almost no correlation with the level of technological innovation. We test the validity of the selected instrumental variable: the Hausman test based on the two-stage least squares regression finds that $p=0.00<0.05$, indicating that the level of aging is an endogenous variable. The weak instrumental variable test using the number of retirees participating in pension insurance as the instrumental variable finds that $F=34.61>10$, rejecting the null hypothesis that the instrumental variable is weak, meaning the selected instrumental variable is valid. Therefore, we use the number of retirees participating in pension insurance as the instrumental variable for the level of aging for model testing. The results are shown in model 11 of Table 4. The direction of the coefficients of the level of aging and the level of technological innovation does not change, the results are still significant, the U-test passes, and the model is significant.

In summary, we have fully demonstrated that the inverted U-shaped relationship between population aging and technological innovation is significant and robust. As for the reasons why population aging and technological innovation show an inverted U-shaped relationship, according to previous research, the reasons can be summarized as follows: in the early stages of population aging, the increase in the proportion of the elderly population may encourage society to invest more in human capital, thereby improving the quality and skills of the labor force and providing higher-quality human capital for technological innovation, promoting the development of innovation activities. However, as the level of population aging deepens, the social burden of pension and healthcare expenditures increases, which may squeeze investments in education and other areas by families and governments, leading to a slowdown or even decline in the accumulation of human capital, thereby inhibiting technological innovation.

Table 4. Robustness Tests for the Inverted U-Shaped Relationship.

Variables	Model 7	Model 8	Model 9	Model 10	Model 11
Aging level		14.36**	24.03***		222.7***
		(6.073)	(8.167)		(67.11)
Quadratic term of aging level		-50.87**	-73.85***		-739.6***
		(20.71)	(25.61)		(215.4)
Old-age dependency ratio	5.820**				
	(2.338)				
Quadratic term of old-age depend-	-18.20***				

ency ratio					
	(6.333)				
Economic level	0.0561***	0.0565***	0.0593***	-0.000546	0.0444
	(0.0149)	(0.0182)	(0.0186)	(0.000612)	(0.0512)

Continued Table 4: Robustness Tests for the Inverted U-Shaped Relationship.

Variables	Model 7	Model 8	Model 9	Model 10	Model 11
Urbanization level	6.087***	5.757***	5.621***	-0.0323	2.089
	(0.541)	(0.661)	(0.677)	(0.0223)	(2.822)
Industrial structure	-1.670***	-1.944***	-2.207***	0.0262	-4.027**
	(0.502)	(0.515)	(0.543)	(0.0184)	(2.014)
Investment level	-0.000725	-0.00105	-0.00159	0.000124**	-0.000297
	(0.00148)	(0.00166)	(0.00171)	(0.0000521)	(0.00499)
Population	-0.000121***	-0.000101*	-0.0000594	-0.0000197***	0.000494*
	(0.0000423)	(0.0000605)	(0.0000651)	(0.00000218)	(0.000287)
Retirees				0.00678***	
				(0.000583)	
Constant term	-1.886***				
	(0.544)				
Time effect	Yes	Yes	Yes		No
Province effect	Yes	Yes	Yes		Yes
Sample size (N)	527	527	527	527	527

Note: Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.4 Heterogeneous Impact of the Level of Aging on Technological Innovation Under Different Levels of Openness

To explore the impact of different levels of openness on the inverted U-shaped relationship between the level of aging and technological innovation, we divide the sample into three groups based on the level of openness. The results are presented in Table 5. In model 12, the results show that in the group with low openness, the regression coefficients are not significant, and the U-test does not pass. In model 13 with medium openness, the coefficient of the linear term of the level of aging is significantly negative, and the coefficient of the quadratic term is significantly positive, but the U-test still does not pass, indicating that the U-shaped relationship between the two may not hold. We further exclude the quadratic term of the level of aging and construct model 14, finding that the coefficient of the linear term of the level of aging is significantly negative. Therefore, we believe that when the level of openness is medium, the level of aging and the level of technological innovation show a linear relationship with a negative coefficient. In the group with high openness, the coefficient of the level of aging is significantly positive at the 1% level, and the regression coefficient of the quadratic term is significantly negative at the 1% level, and the U-test passes, indicating that when the level of openness is high, there is a clear "inverted U-shaped" relationship between the level of aging and technological innovation.

The reasons, we speculate, are that in environments with low openness, due to limited communication with the outside world, the impact of aging on technological innovation is more direct and can't form a complex inverted U-shaped relationship. As the level of openness increases to medium, the inflow of external resources brings vitality to technological innovation, but internal constraints still exist, leading to the inability of aging to bring positive effects to technological innovation in the early stages, and the relationship tends to be linear. When the level of openness further increases, extensive international exchanges make the ecosystem of technological innovation more complex. Moderate aging can provide higher-quality human capital for technological innovation. However, excessive aging will lead to fiscal burdens and a decline in innovation vitality. These factors together form the inverted U-shaped relationship between population aging and technological innovation.

Table 5. Analysis of the Impact of Aging Level on Technological Innovation Level

Variables	Model 12	Model 13	Model 14	Model 15
	Low Openness	Medium Openness		High Openness
Aging level	4.837	-43.087***	-11.168***	26.705***
	(0.67)	(-3.12)	(-2.77)	(3.89)
Quadratic term of aging level	-8.617	125.437**		-104.629***
	(-0.28)	(2.42)		(-4.01)
Economic level	-0.012	-0.016	0.004	0.083***
	(-0.19)	(-0.24)	(0.06)	(4.00)
Urbanization level	2.241	12.502***	12.654***	6.024***
	(1.36)	(5.70)	(5.67)	(8.09)
Industrial structure	-3.328***	-0.912	-0.622	-0.746
	(-3.90)	(-0.69)	(-0.46)	(-0.83)
Investment level	-0.002	-0.010**	-0.010**	0.003
	(-1.07)	(-2.02)	(-2.04)	(1.43)
Population	-0.000	-0.002***	-0.002***	0.000
	(-0.20)	(-5.28)	(-5.41)	(0.32)
Constant term	0.414	7.170***	5.322***	-4.160***
	(0.50)	(3.83)	(3.06)	(-4.41)
Time effect	Yes	Yes	Yes	Yes
Province effect	Yes	Yes	Yes	Yes
Sample size	175	174	174	174
R-squared	0.967	0.953	0.951	0.978
The U test				
Data Range	[0.048,0.200]	[0.048,0.200]		[0.048,0.200]
Critical Value	0.280	0.172		0.128
P>|t|		0.203		0.000
Passed?	No	No		Yes

Note: Robust standard errors are in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

5 Conclusion

Based on China's provincial panel data from 2006 to 2022, this study examines the relationship between aging and technological innovation. Through U-tests and robustness checks, we confirm the inverted U-shaped relationship found in previous studies.The results show this inverted U-curve only holds in highly open regions, where moderate aging supports innovation through quality human capital, while excessive aging hinders it by shrinking labor markets and reducing innovation vitality. In moderately open areas, aging shows a linear negative effect on innovation, while in low-openness regions the impact is insignificant.Our findings offer two policy implications. First, given China's aging population (15.4% aged 65+ in 2023) will continue growing rapidly, policies should carefully manage aging to harness its benefits while mitigating risks[19]. Second, region-specific approaches are needed: highly open areas should optimize innovation ecosystems; moderately open regions should increase openness and provide innovation subsidies; low-openness areas need comprehensive improvements in openness, education, technology investment and infrastructure.

References

1. National Bureau of Statistics: China Statistical Yearbook—2022, Beijing: China Statistics Press, 2022, p. 33.
2. Cheng Qian, Lu Jiehua. "How Does Workforce Aging Affect Labor Productivity?—An Analysis Based on China’s Urban Panel Data." Population & Economics, 2024, (01): 34-46.
3. Ashworth M J. Preserving knowledge legacies: workforce aging, turnover and human resource issues in the US electric power industry[J]. The International Journal of Human Resource Management, 2006, 17(9): 1659-1688.
4. Acemoglu D, Restrepo P. Demographics and automation[J]. The Review of Economic Studies, 2022, 89(1): 1-44.
5. Zhai Zhenwu, Jin Guangzhao, Zhang Yiyang. "Will Population Aging Hinder Technological Innovation?" Dongyue Tribune, 2021, 11: 24-35.
6. Mao R, Xu J. Population aging, consumption budget allocation and sectoral growth[J]. China Economic Review, 2014, 30: 44-65.
7. Chang Zhongze, Jiang Ke, Wei Shiyao. "Research on the Impact of Population Aging on Technological Innovation." Finance and Trade Research, 2022, 33(11): 55-68.
8. Zhang B, Zhou R, Yang L, et al. Population aging and corporate innovation: Evidence from China[J]. Asia-Pacific Journal of Accounting & Economics, 2023, 30(4): 986-1007.
9. Yang Jie, Luo Yun. "Dynamic Impact Analysis of Population Aging, Technological Innovation, and Economic Growth in China." Science & Technology and Economy, 2015, 28(3): 20-25.
10. Cai Xing. "Population Aging, Urbanization, and Technological Innovation." Statistics & Decision, 2021, 37(23): 76-80.
11. Shen Ke, Sun Huilin. The Spatial Effects and Heterogeneous Impacts of Population Aging on Technological Innovation: An Analysis Based on Panel Data from Prefecture-level Cities in China[J]. Population Research, 2024, 48(02): 90-103.,
12. Yao Dongmin, Ning Jing, Wei Shiyan. "How Does Aging Affect Technological Innovation?" The Journal of World Economy, 2017 (4): 105-128.

13. Zhou Mao, Lu Yi, Li Yunong. "Regional Industrial Upgrading and Labor Income Share: Estimation Based on Synthetic Instrumental Variables." Economic Research Journal, 2018, 53(11): 132-147.
14. He Jingtong, Li Feng. "Factors Influencing Independent Innovation—An Analysis of China's Provincial Data Based on the BACE Method." Nankai Economic Studies, 2007 (3): 68-79.
15. Deng Xiang, Zhang Wei. "Will Population Aging Hinder Technological Progress?—Empirical Evidence from China 2000-2014." Journal of Huazhong University of Science and Technology (Social Science Edition), 2018, 3: 28-38.
16. Tian Yipiao, Liu Mingyue, Zhang Weiguo. "The Impact of Urbanization on Regional Technological Innovation Levels." Urban Problems, 2018, (04): 4-11.
17. White H. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity[J]. Econometrica: journal of the Econometric Society, 1980: 817-838.
18. Lind J T, Mehlum H. With or without U? The appropriate test for a U-shaped relationship[J]. Oxford bulletin of economics and statistics, 2010, 72(1): 109-118.
19. Lu Jiehua, Wei Xiaodan. "The Impact Mechanism of Workforce Aging on Economic Development and Strategic Responses." Studies on Socialism with Chinese Characteristics, 2022, (03): 18-30.