Universe Scientific Publishing

Exploring the Relationship Between Technological Innovation Input and Economic Growth in China

Yixuan Yan

Queen's University, Department of Economics, K7L 3N6, 99 University Ave, Kingston ON, Canada,17yy57@queensu.ca

Abstract: A report of the 19th National Congress of Communist Party of China (2017) stated that the core of innovation-driven development is technological innovation. For finding future economic development strategies in China, based on national time-series data from 2000 to 2019, this study mainly focuses on how technological innovation input affects economic growth. A multiple linear regression model was constructed; the results showed that both research and development (R&D) fund input and personnel input play a positive role in influencing economic growth in China, and the impact of R&D expenditure is more significant than that of R&D personnel. On this basis, we found the long-term stationary equilibrium relationship between technological innovation input and economic growth by applying the unit root test and cointegration analysis. Finally, two-stage least square specification was used to eliminate issues caused by endogeneity. Based on the above conclusions, the paper proposed policy suggestions for economic growth.

Keywords: Technological Innovation; Economic Growth; China

1. Introduction and Literature Review

In the present era, China is currently in a crucial period of experiencing high-quality economic growth under the international economic uncertainty and competitiveness. After four decades of fast economic development, the population of China currently still faces the problem of "aging before getting rich" due to the rapid and considerable expansion in the demographic structure[1]. Meanwhile, wide-range development depending on cheap resources is not sustainable because of the overcapacity of low-end products and the constraints related to the environment. Under these circumstances, it is necessary for China to make strategic changes. In 2017, the report of the 19th National Congress of the Communist Party of China highlighted that "innovation is the first driving force of development and the strategic support for building a modern economic system"[1].In 2020, China also proposed five development concepts, and innovation ranked first among the five.

The promotion of technological innovation needs strong financial support. The government can make investments in basic research effectively because it can distribute funds, make direct investments, and support firms via administrative means. Hence, it is worthwhile to explore how the technological innovation input affects economic growth in the process of China's modernization. The findings of this exploration can provide some meaningful predictions and suggestions for future high-quality economic growth, moderate adjustments related to the economic gap, and supply-side structural reform[2].

The Solow growth model has been applied in many studies with the aim to reveal the relationship between technological growth and economic growth and by regarding technological progress as the exogenous factor in promoting growth. Nevertheless, the Solow growth model ignores the technical growth induced by investment in research, improvement of learning, and capital accumulation. According to Romer's research in 1990[3], an economy can achieve continuous self-growth, which is known as endogenous growth. Romer also stated that endogenous growth is the driving force of long-term economic growth. Therefore, the assumed exogeneity in the Solow model is not effective enough to explain the phenomenon of long-run economic development. To find a long-term stable equilibrium relationship, Pan and Liu (2005) used cointegration analysis through the Engle–Granger two-step method and Jahnhansen maximum likelihood method[4]. The series data most likely converge over time, and the distance between them is stationary. Hence, cointegration analysis can be an effective way to explore the long-run relationship for time-series data.

The technological innovation input can be classified into technological innovation fund input and technological innovation personnel input. The previous literature explored that the impact of technological innovation input on economic growth in China is relatively mature and adequate. Zhang (2013) found that both research and development (R&D) personnel and R&D expenditure positively impact the economic growth in China, and the final result was statistically significant, as found by analyzing data from 1995 to 2009[5] Wu (2020) applied an autoregression (AR) model to find the different types of R&D investment that can influence economic growth distinctively[6]. Li and Yong (2019) found how technological innovation input promotes regional economic growth based on spatial panel data[7]. Based on previous research findings, we found the following issues: first, researchers usually consider a single factor when exploring the relationship between technological innovation input and economic growth. Moreover, the studies do not include more variables that could affect economic growth, such as education, policy, and demographic structure. Second, previous literature mainly targeted the results of the model instead of performing more statistical and economical inference tests, which may have resulted in inaccuracy of estimation. Third, most papers do not consider the endogeneity problem between technological input and economic growth as they can simultaneously influence each other. Last, the datasets used in the previous studies were usually taken from 1990 to 2015, which is relatively old for the present research.

To this end, we used time-series data from 2000 to 2019, discussing how the technological innovation input affects economic growth in China, and which input would have the most considerable effect. We also explored whether there is a long-term stable relationship between explanatory variables and explained variables. Meanwhile, the study showed how to deal with problems caused by endogeneity. Eventually, the results of our paper reflect that there is a positive long-run relationship between technological innovation input and economic growth in China.

2. Data and Model

2.1 Indicator Chosen

The study aimed to explore the technological innovation input and economic growth in China by constructing a regression model. The explained variable is economic growth ("GDP"). The gross domestic product (GDP) per capita is a widely used indicator in developmental economics studies, which is used to measure the national economic growth. Hence, our study used the 20-year GDP per capita as an indicator of economic growth.

The explanatory variables are the technological innovation inputs, which are divided into personnel input ("Rdfte") and fund input ("Rdexp"). The indicator for personnel input is the full-time equivalent (FTE) of R&D personnel, which is the sum of the workload of full-time working personnel and the converted workload of part-time working personnel. The indicator for fund input is R&D expenditure, which involves the funds that research institutions spent on research projects and indirectly spent on management and service of R&D activities; basic constructions related to R&D; outsourcing processing charges; etc. However, the R&D expenditure excludes expenditures on productive activities, on loan repayment, and on cooperation with outside units or transfer to others.

Weng in 2020[8] and Zhang and Yue in 2019[9] added control variables to the model rather than merely including input variables. Therefore, we also chose the control variables to enhance the internal validity of our study: 1. Level of human capital ("graduation"), which is measured by the number of graduations from higher education institutions. Higher education includes both general institutes of higher education and the institutes of higher education for adults. 2. Stock of human capital ("inschool"), which is a proxy variable indicating the number of student enrollments in higher-education schools among 100,000 people in a given year. 3. Net export level of goods in a given year ("export"). According to the expenditure approach to GDP, the export and import would impact the GDP. The rising exports can increase the aggregate demand, and in turn, lead to higher economic growth. 4. Consumption level ("consumption"). Consumption is one of the most important factors in promoting economic growth; it is also an embodiment of the level of economic development. Therefore, the consumption level is measured by the annual consumption amount per capita at each year's price level from 2000 to 2019.

2.2 Data

The indicators of economic growth and control variables that are related to economic growth in the study were taken from the Chinese Statistical Yearbook from 2001 to 2020 at the National Bureau of Statistics of China (NBS). In addition, the data for indicators of technological innovation input were taken from the Communique on the R&D in 1996–2020 China Statistical Yearbook on Science and Technology. Because of the inconsistency of dimensions among variables, it is hard to obtain a reasonable and accurate result because the different ranges may affect analysis. In that case, the initial sample data were standardized through the Z-score standardization formula. The descriptive statistics after standardization are shown in Table 1. According to Table 1, 20 observations were available for each variable, which indicates data for each year from 2000 to 2019. After standardization, the mean value for consumption, export, and the stock of human capital take the approximate value of zero. The minimum values for GDP, R&D expenditure, FTE, and graduation are standardized to the negative because these values are originally less than the mean values. The standard deviation for each variable is close to 1, which also shows standard normal distribution of our sample.

Table 1. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
GDP	20	0.433	0.965	-0.711	2.261
Rdexp	20	0.396	1.015	-0.71	2.454
fteRD	20	0.441	0.954	-0.751	2.107
graduation	20	0.502	0.855	-0.939	1.521
consumption	20	0	1.026	-1.137	2.042
export	20	0	1.026	-1.631	1.52
inschool	20	0	1.026	-2.179	1.452

2.3 Statistical Test

2.3.1 Unit Root Test

Our study used time-series datasets; however, most time-series data are not stable. Therefore, the unit root test must be performed before performing further analysis so that we can select stable variables for running the regression and avoid the spurious regression problem. The study used the augmented Dickey–Fuller test (ADF test) to estimate the stationarity of each series, including the data for dependent variable and for the independent variables. During operation in Eviews, the most suitable test form was chosen from the "intercept", "trend and intercept", and "none" options using the method of finding the minimum value of AIC, SC, and HQ1. In this case, we can obtain the ADF results from each feasible test form.

1 AIC is Akaike info criterion, SC is Schwarz criterion, and HQ is Hannan–Quinn criterion.

According to the ADF test results (Table 2), none of the variables is stationary for the unit root in the original level except the stock level of human capital, since their p-values are larger than 0.05. However, when we test the series of dependent variables and independent variables for the unit root in the second difference, the ADF test statistics mostly become more negative. Therefore, this strongly indicates that the null hypothesis of a unit root must be rejected. The p-values are close to zero for "DGDP", "Dgraduation", "Dconsumption", "Dexport", and "Dinschool", and the null hypothesis that there is a unit root at the significance level of 5% can be rejected. The p-values for the technological innovation input "DRdexp" and "DfteRD" are in the range between 0.1 to 0.05; thus, we can reject the null hypothesis at the 10% significance level. The results shown in the table at the second difference are statistically significant at either 5% or 10% and all of them are stationary. In this context, we can leave both explanatory variables and the explained variable for further analysis.

Table 2. Unit-root test (ADF) results

Variables	Test Form (C, T, K)	ADF Test	Test at 5% Significance Level	P-value	Test Result
GDP	(C, T, 4)	-2.422243	-3.759743	0.3551	Not Stationary
Rdexp	(C, T, 4)	-0.802444	-3.733200	0.9432	Not Stationary
fteRD	(C, T, 4)	-2.633330	-3.690814	0.2714	Not Stationary
graduation	(0, 0, 4)	-1.380368	-1.961409	0.1498	Not Stationary
consumption	(C, T, 4)	-0.659416	-3.673616	0.9617	Not Stationary
export	(C, T, 4)	-2.158133	-3.673616	0.4838	Not Stationary
inschool	(C, 0, 4)	-3.703538	-3.029970	0.0130	Stationary***
DGDP	(C, 0, 4)	-5.498020	-3.065585	0.0005	Stationary***
DRdexp	(0, 0, 4)	-1.899980	-1.962813	0.0567	Stationary**
DfteRD	(0, 0, 4)	-1.876047	-1.966270	0.0597	Stationary**
Dgraduation	(0, 0, 4)	-4.495285	-1.962813	0.0002	Stationary***
Dconsumption	(C, 0, 4)	-5.516749	-3.065585	0.0005	Stationary***
Dexport	(0, 0, 4)	-5.296534	-1.964418	0.0000	Stationary***
Dinschool	(C, T, 4)	-4.705144	-3.297799	0.0085	Stationary***

Note: D: 2nd difference; ***: rejecting the null hypothesis at the 5% significance level; **: rejecting the null hypothesis at the 10% significance level. No "*" mark means we failed to reject the null hypothesis. In the test form, C stands for constant, T is Trend, and K is the maximum lagged value based on SIC.

2.3.2 Pearson Correlation Test

For testing the correlation among variables, the study used the Pearson correlation test. The Pearson correlation test measures the linear relationship between two sets of data, which is calculated by the covariance of two variables and divided by the product of their standard deviation. Through covariance analysis, the study showed that the economic growth (GDP) is correlated to "Rdexp", "fteRD", "graduation", "consumption", "export", and "inschool" with correlation coefficients of 0.9976, 0.9911, 0.9233, 0.9975, 0.9469, and 0.9125. All correlation coefficients are above 0.90, so it can be explained that there is a fairly strong positive correlation between GDP and R&D expenditure, FTE(R&D), graduations from higher education, the annual consumption per capita, the net export, and student enrollments in higher-education institutions. Moreover, there might be a problem of multicollinearity among the independent variables as the correlation coefficients of "Rdexp", "fteRD", and "graduation" with the remaining variables are large.

Table 3. Pearson Correlation test results

	GDP	Rdexp	fteRD	grad	consum	export	inschool
GDP	1.0000						
Rdexp	0.9976*	1.0000					
fteRD	0.9911*	0.9843*	1.0000				
graduation	0.9233*	0.8967*	0.9473*	1.0000			
consumption	0.9975*	0.9993*	0.9813*	0.8975*	1.0000		
export	0.9469*	0.9261*	0.9648*	0.9820*	0.9246*	1.0000	
inschool	0.9125*	0.8882*	0.9357*	0.9874*	0.8885*	0.9738*	1.0000

Note: *represents the result is significant at 0.05 (two-tailed).

2.4 Model

The results of the unit root test and Pearson correlation test show that time-series data of the explained variable and the explanatory variables are stationary, and there is a relationship between economic growth and technological innovation input. To explore how technological innovation input affects the GDP and by how much, we need to construct a regression model.

The study used the stepwise regression method, which is a combination of forward selection and backward elimination and involves adding and removing the controlled variables for each step. The procedure of adding and elimination is ended when the results of the model are statistically significant. The study used two separate multiple linear regression models to explore the impacts of technological innovation inputs on economic growth:

$$GDP = \beta_0 + \beta_1 Rdexp + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t (1)$$

$$GDP = \beta_0 + \beta_1 fteRD + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t (2)$$

In the regression model, β_0 is a constant; β_1,β_2,β_3,β_4,and β_5 are the coefficients; is the random error; and t represents time. The first regression model focuses on the fund input, aiming to find the impact of R&D expenditure on economic growth. The second regression model mainly targets personnel input to find how the FTE of R&D personnel affects GDP. As predicted before the estimation, the technological innovation input promotes economic growth. The more the input, the more developed technological innovation, and this can increase the productivity and output to boost economic growth.

3. Empirical Analysis and Result

3.1 Multiple Linear Regression Results

The estimation results of the model are shown in Table 4. Similar to the result predicted in the designing model part, the technological innovation input can promote economic growth. Column (1) shows the effect of R&D expenditure on the GDP considering the data from 20 years. The R&D expenditure positively affects the economic growth. More specifically, a one unit increase in the R&D expenditure is estimated to increase the GDP per capita by 0.949 units. The null hypothesis can be rejected at the significance level of 0.01. The finding here is statistically significant. In column (2), the controlled variables “graduation”, “consumption”, “export”, and “inschool” are added. The effect of R&D expenditure on GDP is less than that in column (1), decreasing from 0.949 to 0.473, which means that these control variables also play roles in impacting economic growth. However, the estimated effect of R&D expenditure in column (2) is still statistically significant at 0.01. For control variables, “graduation”, “consumption”, and “export” positively affect the GDP. An increasing number of graduations from higher education would increase the GDP, and the finding is statistically significant at 0.01. According to Hanushek’s study (2016), in the micro-aspect, higher education can generate substantial rewards for individuals in terms of individual incomes; in the macro-aspect, higher education affects productivity and economic growth[10]. For consumption and export, one additional increase in consumption per capita in the given year is estimated to increase the GDP by 0.335 units, and one higher unit of export would increase the GDP by 0.065. Student enrollments in higher-education institutes would negatively impact the GDP at the significance level of 0.05. The coefficient of “inschool” can be interpreted as follows: for an increase of one unit in the student enrollments in the higher-education institutes, the GDP is estimated to decrease by about 0.065. This effect is different from the findings from previous research in the field of human capital stocks and economic growth. Benhabib and Spiegel (1994) found that the higher is the human capital stock, the higher is the economic growth because human capital stocks are trained to increase productivity[11]. One explanation for our finding is that the human capital stock in the higher-education institutions is not the labour force in the labour market at a given year, and the stock cannot generate additional benefits until they graduate from higher education and get into the labour force.

Column (3) shows the pure effect of the FTE of personnel on economic growth. A one unit increase of FTE personnel in R&D is estimated to increase the GDP by 1.002 units. The result is also statistically significant at 0.01. In column (4), the same control variables are added to the model. The variables “consumption” and “export” are significant at the level of 0.01. Similar with the result of fund input, consumption (coefficient = 0.707) affects GDP more than export (coefficient = 0.073). The variable “graduation” is less significant compared with the case in column (2), but it is still statistically significant (at 0.05). Lastly, the human capital stock indicator “inschool” still negatively affects GDP, as observed in column (2). In contrast, the result of “inschool” is less statistically significant in column (4) than in column (2).

A comparison of the effect of R&D expenditure and FTE personnel in R&D in columns (2) and (4) shows that both these explanatory variables positively affect economic growth by 0.473 and 0.319, respectively, and both results are statistically significant at 0.01. However, the R&D expenditure contributes more in promoting economic development than FTE personnel in R&D. Even though the difference between those two effects is not large, it is enough to show that the government’s direct fund input to technological innovation is more effective.

Table 4. Regression Results

	(1)	(2)	(3)	(4)
	GDP	GDP	GDP	GDP
Rdexp	0.949***	0.473***		
	(0.015)	(0.11)		
graduation		0.179***		0.095**
		(0.035)		(0.034)
consumption		0.335***		0.707***
		(0.107)		(0.022)
export		0.065**		0.073***
		(0.025)		(0.023)
inschool		-0.065**		-0.049*
		(0.023)		(0.023)
fteRD			1.002***	0.149***

			(0.032)	(0.034)
_cons	0.057***	0.156***	-0.009	0.319***
	(0.016)	(0.052)	(0.033)	(0.02)
Observations	20	20	20	20
R-squared	0.99	0.98	0.98	0.98

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

3.2 The Engle and Granger Method of Cointegration

In the beginning of section 3, the results of multiple linear regression models also indicate the impact of technological input on economic growth. However, we need also explore whether the effect found in section 3.1 is a long-term stable effect or not, which would help in identifying long-term trends and making the results more meaningful for current and future research.

A cointegration relationship is one way to highlight the long-term relationship. The study analyzed the cointegration relationship of different series at the same order by estimating the regression coefficients and residuals. Because the paper did not adopt the VAR model, the Engle and Granger method of cointegration was applied here. Based on the multiple regression model in Section 3.1, the first step of the Engle-Granger methodology is to generate residuals of the regression model. The generated residuals based on the two models are given by and . In the second step, the generated residuals must be applied to measure the regression of the first-differenced residuals on the lagged residuals. At this stage, the study simply tests for the unit root of the residual series to check whether the residual series is stationary. As the results in Table 5 show, the result of the ADF test shows that the p-values of residuals for personnel input regression and fund input regression are both less than 0.05 and close to zero, which means there is no unit root in the residual series. The stationary residual series also indicate that there is a cointegration relationship between the dependent and independent variables in both multiple linear regression models. In summary, the effect of technological innovation input on economic growth is both stationary and exists in the long term.

Table 5. Unit-root test (ADF) results for input residual

Residual	Test Form	ADF Test	Test at 5% Significant Level	P-value	Test Result
	(None)	- 3.631866	- 1.964418	0.0013	Stationary***
	(None)	- 3.844104	- 1.964418	0.0008	Stationary***

Note: *** means the null hypothesis was rejected at the 5% significance level, ** means that the null hypothesis was rejected at the 10% significance level. No “*” means we failed to reject the null hypothesis.

4. Potential Issues

4.1 Endogeneity

In the study, the problem of endogeneity caused by simultaneity also exists, because not only can the technological innovation input affect economic growth but the economic growth can also affect the technological innovation input. With a higher economic growth level, there will be more funds to support technological innovation by spending more on R&D.

Table 6. Descriptive statistics for instrument variables

Variable	Obs	Mean	Std. Dev.	Min	Max
activities	19	0	1.027	-1.135	1.929
visit	20	0	1.026	-1.895	2.419

To deal with endogeneity and ensure unbiased estimation of parameters, we employed the instrument variables and applied the two-stage least square estimation (2SLS) for each multiple linear regression model. The instrument variable for the regression model about fund input is "activities", which represents the number of activities related to science popularization in each year. In Table 6, the descriptive statistics show that there are only 19 observations for "activities" because there is a missing value in 2005. As the more activities related to science popularization are held, the public would come to know about the importance of scientific and technological innovation. As a result, technological innovation would raise the public's attention so that the government, authorities, and enterprises engaged in technology can increase funding; for example, increase the expenditure on R&D. In the first stage, we regress the R&D expenditure on activities and other control variables, as shown in equation (3). In the second stage, we run the regression of "GDP" on the value of R&D expenditure obtained in the first stage as well as on other control variables. The results of the second stage are reported in column (1) of Table 7. After estimating the 2SLS specification, the coefficient of R&D expenditure decreases from 0.473 to 0.44, which indicates a slight change compared with the original regression model. The result is still statistically significant at the 0.01 level. As the multiple linear regression estimate is very close to the IV estimates, the endogeneity between "GDP" and "Rdexp" is not very serious, and our findings do not distort the estimations we found in the previous regression. We can conclude that the R&D expenditure is not endogenous, and "activities" is a valid instrument variable after applying the 2SLS method.

$$1st\ Stage: Rdexp = \beta_0 + \beta_1 activ + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t \quad (3)$$

$$2nd\ Stage: GDP = \beta_0 + \beta_1 Rdexp + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t \quad (4)$$

Similarly, for personnel input, the instrument variable is "visit", which represents the number of researchers dispatched abroad to advance their research. The opportunity of learning abroad and exchanging ideas works as an incentive for people to get involved in R&D. Therefore, we assumed that the larger number of researchers learned abroad, the more FTE R&D personnel would be present. Equation (5) indicates the first stage where we regress FTE personnel in R&D on the number of visits to foreign countries and other control variables. Moreover, in the second stage (equation (6)), we run the regression of "GDP" on the value of the FTE R&D personnel that we got from the first stage and other control variables. The result of the second stage is shown in column (2) of Table 7; there is a small decrease for the FTE of R&D personnel from 0.149 to 0.143, and the result is still statistically significant at 0.01. For the same reason, endogeneity between "GDP" and "fteRD" is not very serious as well.

$$1st\ Stage: fteRD = \beta_0 + \beta_1 visit + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t \quad (5)$$

$$2nd\ Stage: GDP = \beta_0 + \beta_1 fteRD + \beta_2 grad + \beta_3 consum + \beta_4 export + \beta_5 inschool + \mu_t \quad (6)$$

Table 7. The second stage regression result

	(1) GDP	(2) GDP
Rdexp	0.44***	
	(0.161)	
graduation	0.167***	0.096***
	(0.031)	(0.029)
consumption	0.365**	0.709***
	(0.156)	(0.022)
export	0.07***	0.074***
	(0.023)	(0.02)
inschool	-0.059***	-0.049**
	(0.019)	(0.019)
fteRD		0.146***
		(0.036)
_cons	0.176**	0.32***

	(0.073)	(0.018)
Observations	19	20
R-squared	0.99	0.99

Standard errors are in parentheses
**** p<.01, ** p<.05, * p<.1*

5.Conclusion

We can conclude that there is a long-run stationary equilibrium relationship between technological innovation input and economic growth in China. Both R&D expenditure and the FTE of R&D personnel promote economic growth in China. However, the effect of increasing personnel input on the economic growth is not evident when we compare it with fund input. Hence, the Chinese government should focus more on strengthening the efficiency of increasing personnel input, optimizing the team structure of the scientific and technical personnel, and creating a more rational administrative system to enhance the working efficiency. Consequently, China could achieve the goal of increasing the economic growth effectively by increasing both R&D fund input and talent input. Our result is opposite to the findings of Zhang's (2012), but it is consistent with the results of Weng's research (2020). The reason for this circumstance is that China considerably expanded R&D expenditure since 2015 after the announcement of several plans, such as the "Made in China 2015" and "the Report of the 19th National Congress of the Communist Party of China". Hence, there has been a significant increase in the fund input to technological innovation compared with personnel input after 2015, but Zhang's research does not account for those remarkable changes because of the time constraint. Our finding is also based on more updated data compared with the data from 2000 to 2017 in Weng's study, which shows the timeliness of the study, and the study has more reference for current research and future explorations. The paper also highlights the problem of endogeneity, which is mainly caused by simultaneity between GDP and R&D inputs. By employing instrument variables in the two-stage least square specification, the endogeneity issues can be fixed, and we can prove that our final findings are exogenous.

There is still abundant room for further progress in exploring how geographical factors would impact the final findings and in expanding the topic. Our paper used time-series data to explore the overall impact of technological innovation input on economic growth. Future researchers are suggested to use the panel data to consider the heterogeneity of different regions. More specifically, future studies can analyze the relationship between technological innovation input and regional economic growth by adding national provincial data. Moreover, future researchers can also use the fixed effect model in their empirical analysis to estimate the effect in the west, east, north, and south of China. The development rank of each city can also be applied to classify regions, such as "first-tier city", "second-tier city", and "third-tier city". In addition, future researchers do not need to limit themselves to the topic of "technological innovation input", and they are encouraged to expand the topic broadly. For instance, they can attempt to find how technological innovation affects economic growth by considering both the input side and output side. For the technological innovation output, the patent application numbers, high-tech industry scale, and contract amount in the technical market can be used.

On this basis, we provided some policy suggestions for future improvement: First, the government should increase financial investments in science and technology, encouraging enterprises to transform and upgrade to technological and intelligent production. Enterprises can increase their productivity through applying more advanced technology. Second, it is also a main goal to cultivate innovative talents through boosting the high-quality development of education. China should break through the traditional concept of education, and it is necessary to guide schools to cultivate students' innovative thinking, independent thinking, and questioning ability.

Reference

[1] Long, X. (2019). Scientific and technological innovation related to real economic growth. China Political Economy,

2(1), 108–122. https://doi.org/10.1108/cpe-04-2019-0012

[2] Boulter, J. (2018). China's Supply-side Structural Reform. Global Economy, 19, 1–19. https://www.rba.gov.au/publications/bulletin/2018/dec/chinas-supply-side-structural-reform.html

[3] Endogenous Technological Change. (1991). National Bureau of Economic Research.

[4] Pan, X.& Liu, F. (2005). Cointegration Analysis on Technical Market Development and Economic Growth in China. Studies in Science of Science, 1–4. https://www.ixueshu.com/document/c538e839d5755f34.html

[5] Zhang, J. (2019). Science and Technology Input and Economic Growth of the Innovation of Association Studies. CNKI, 1–5. https://oversea.cnki.net/kcms/detail/detail.aspx?filename=KJCK201911003&dbcode=CJFQ&dbname=CJFDTEMP&v=

[6] Wu, M. (2020). Research on the Relationship between R&D Investment, Technological Innovation and Economic Growth in China. INTERNAL AUDITING IN CHINA, 9, 81–89. https://www.cnki.com.cn/Article/CJFDTotal-ZJYL202012024.htm

[7] Liu, L., & Zhang, Y. (2019). An Analysis on the Spillover Effect of Science and Technology Innovation Input on Regional Economic Growth. East China Economic Management, 33(1), 62–66. https://doi.org/10.19629/j.cnki.341014-1014/f.170802008

[8] Weng, C. (2020). Research on the Influence of Science and Technology Innovation Input on Regional Economic Growth. Research on the Influence of Science and Technology Innovation Input on Regional Economic Growth, 75–87. https://doi.org/10.19374/j.cnki.14-1145/f.2020.08.018

[9] Zhang, H., & Yue, H. (2019). Scientific and technological innovation investment, financial development and economic growth. Guizhou Social Sciences, 351(3), 133–139. https://doi.org/10.13713/j.cnki.cssci.2019.03.020

[10] Hanushek, E. A. (2016). Will more higher education improve economic growth? Oxford Review of Economic Policy, 32(4), 538–552. https://doi.org/10.1093/oxrep/grw025

[11] Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. Journal of Monetary economics, 34(2), 143-173.