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Provincial Factor Inputs and Economic Growth in China: Evidence from Panel Granger Non-Causality Tests

Yanyan Fu, Pei-Tha Gan*, Norimah Ramli, Norasibah Abdul Jalil

Department of Economics, Faculty of Management and Economics, Universiti Pendidikan Sultan Idris (Sultan Idris Education University), 35900 Tanjong Malim, Perak. Malaysia

*Corresponding Authors Email: gan.pt@fpe.upsi.edu.my

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Abstract

This study examines the causal relationships between economic growth and factor inputs, namely physical capital, labour, human capital, and research and development in China's top six economic powerhouses, including Guangdong, Jiangsu, Shandong, Zhejiang, Henan and Sichuan provinces with annual data over the period from 1996 to 2022 with Dumitrescu and Hurlin (2012) and Juodis et al. (2021) Granger non-causality tests. Both Dumitrescu and Hurlin (2012) and Juodis et al. (2021) test suggest that there are causal relationships from physical capital, labour, human capital, and R&D to economic growth. Additionally, the observed bidirectional causality, in some instances, highlights the dynamic interaction between factor inputs and economic performance. The implication of the findings is that (i) the identification of factor inputs such as physical capital, labour, human capital, and research and development causation may help policymakers infer precise economic growth by identifying the correct causation of factor inputs; (ii) identifying the correct causality can provide valuable insights for policymakers aiming to make optimal decision-making on resource allocation to enhance long term economic performance.

Keywords: Economic Growth, Factor Inputs, Panel Granger Non-Causality

Introduction

Having implemented market-oriented economic reforms since 1978, China has become a global production leader due to its export-oriented approach and low input costs (United Nations, 2022). With this strategic shift, China joined the ranks of rapidly growing economies (Liu, 2023), consistently achieving annual real gross domestic product (GDP) growth of approximately 9 per cent through 2023, according to World Bank Data. However, as China's economy matured, its growth rates moderated significantly, decreasing from 14.2 per cent in 2007 to 5.2 per cent in 2023. This slowdown signifies a shift towards what the Chinese government terms the "new normal," an era anticipating growth rates of around 7 per cent in the foreseeable future (Saggu & Anukoonwattaka, 2015). The government has prioritized innovation through its industrial policies in response to this changing economic landscape by stabilizing and moderating the growth over the medium to long term (Morrison, 2019). Consequently, the economic focus is shifting from secondary activities, such as manufacturing and processing, to tertiary activities, such as innovation and services (Xu, 2020). The outcomes of this strategic transformation may remain ambiguous as they are intertwined with the forces driving innovation-driven growth. As a result, it remains an open question whether more research in this field might contribute to a deeper understanding of economic growth sources and implications for future policy directions. Since China plays a pivotal role in global production, insights into these factor inputs are not only crucial for shaping China's domestic policies but also hold significant implications for global economic stability (World Trade Organization, 2022).

This study is motivated by the crucial role that factor inputs play in propelling economic growth in China's leading provinces, which are vitally important to the country's overall economy. As a result of reforms and globalization, China has achieved remarkable growth over the last four decades, becoming the world's leading manufacturing powerhouse (World Bank, 2019; United Nations, 2022). However, the global financial crisis in 2008 emphasized the necessity of more sustainable economic strategies by revealing vulnerabilities in China's growth model. Investigating the role factor inputs have in influencing economic performance in China’s leading provinces is necessary as the country transitions into a "new normal" economy characterized by slower but more balanced growth. Understanding how these factors drive regional growth is crucial since these provinces contribute significantly to China's GDP and global economic standing. Even though theoretical frameworks emphasize the importance of these factors (Barro, 1991; Lucas, 1988; Romer, 1990; Solow, 1957), empirical evidence is inconsistent, highlighting gaps in understanding their role in China's economic landscape. In addition, achieving uniform growth is complicated by persistent regional disparities, challenges in resource allocation, and overcapacity. World Bank (2022) underscores these gaps that must be addressed to clarify regional growth dynamics and optimize factor inputs, making this research crucial for policy and economic planning.

The objective of this study is to examine the causal relationship between economic growth and factor inputs, namely, physical capital, labour, human capital, and research and development (R&D), such that the identified causal relationships can help policymakers to infer the projected economic growth by identifying the correct causation of factor inputs. In doing so, the identified causality should help promote the best macroeconomic outcomes. The present study uses a sample comprising 6 selected economic powerhouses: Guangdong, Jiangsu, Shandong, Zhejiang, Henan and Sichuan provinces. The notable feature of this study is the use of Romer's (1990) model extension, which illustrates that a set of factor inputs explains the output in economic growth. This study estimates the causality nexus by Dumitrescu and Hurlin (2012) and Juodis et al. (2021) Granger non-causality techniques. The results can be used to support the soundness of the indicators further.

Literature Review

The empirical research into the forces of China's economic performance in an innovation-driven economy is limited to focus on whether the traditional reliance on factor inputs has been undermined by technical change. These factor inputs serve as essential components of the economy. In China, such inputs generally comprise physical capital, labour, human capital, and R&D, while technical advancements may focus on improving R&D, driving innovation, and efficiency improvement (Brandt et al., 2020; Brandt & Rawski, 2008).

Physical Capital

Concerning physical capital, Pomi et al. (2021) analysed how physical capital influenced the economic growth of Bangladesh from 2000 to 2019 with the vector autoregression model. The Granger causality test concludes that physical capital is a two-way Granger factor for economic growth. Pasara and Garidzirai (2020) also evaluate the causality between physical capital and growth performance in South Africa from 1980 to 2018 within the vector autoregression framework. The findings further confirm that economic growth causes physical capital. However, some empirical studies found the opposite result between physical capital and economic growth. Selvamani and Muthusamy (2021) assessed the relationship between GDP and physical capital in India from 2016 to 2019. The test outcomes indicate no relationship between GDP and physical capital. Etokakpan et al. (2020) analysed the Granger causality technique to identify the predictability power of data from 1980 to 2014. The findings showed that physical capital does not Granger-cause economic growth in Malaysia.

Labour

Concerning labour, Yakubu et al. (2020) explored the causal relationship in Nigeria from 1990 to 2017 using the vector error correction model, concluding that labour Granger-cause real GDP. Similarly, Turyareeba et al. (2020) employed the Engel-Granger error correction method to evaluate the causal relationship in Uganda from 2001 to 2018. The analysis discovered that while there was no causal nexus between labour and growth performance in the short run, there was a positive and statistically significant causal link between variables in the long run. Sinha (2023) investigates the dynamics of economic growth and labour in India from 1990 to 2020, underpinned by the vector error correction mode framework. The findings reveal that a bidirectional causality exists between labour and economic growth. In contrast, Ahmed et al. (2016) explored the relationships between variables in Iran between 1965 and 2011. Using the Cobb-Douglas production function, the results identify a one-way causal relationship between labour and economic output.

Human Capital

Concerning human capital, Ngepah et al. (2021) explored the causal link between human capital and economic growth in South Africa from 1993 to 2016. The results indicated a bidirectional causal relationship between output and human capital, as tested using Dumitrescu and Hurlin (2012) Granger non-causality test. Jaber et al. (2022) found a similar bidirectional relationship in Morocco from 1990 to 2019, employing the Toda-Yamamoto causality test. However, the connection between economic growth and human capital remains ambiguous in other empirical studies. For instance, Islam (2020) analysed South Asian economies from 2000 to 2017. The empirical investigation found a unidirectional causal relationship between economic growth rates and human capital. Meanwhile, Olopade et al. (2020) examined the causal relationship between human capital and economic growth in Nigeria from 1981 to 2017. Their results revealed no evidence of Granger causality between human capital and real output growth.

Research and Development (R&D)
Concerning R&D, Adedoyin et al. (2020) investigated the impact of R&D on economic growth in EU countries during the period 1997 to 2015. Using the Dumitrescu and Hurlin (2012) non-causality test, they discovered a bidirectional causal link between R&D and output. Similarly, Kose et al. (2020) assessed the influence of R&D on sustainable growth across EU nations from 1997 to 2014 with the panel Granger causality test, as outlined by Emirmahmutoglu and Kose (2011), revealed a significant causal effect of R&D on economic growth. In contrast, Mtar and Belazreg (2021) studied the relationship between R&D and growth in 27 OECD countries from 2001 to 2016, applying a panel vector autoregression model. Their results indicate that R&D may not be a direct driver of productivity, as no evidence was found between R&D and growth. Xiang (2022) investigated the causal relationship between R&D and growth using panel data in China from 2007 to 2017, applying the Granger non-causality test of Juodis et al. (2021). The results indicated that R&D Granger-cause economic growth, but no evidence of reverse causality was found.

Theoretical Model and Methodology
Model Specifications
This study uses a modified endogenous growth model from Romer (1990). Romer's premise postulates that technological change is the driving force behind growth. This change resulted from deliberate actions that individuals have taken in response to market incentives, which suggests that a knowledge-based economy has positive externalities and spillover effects that will lead to economic growth. The designs used to create new products are non-rival; they can be duplicated without additional costs.

Initially, Romer (1990) endogenous growth model incorporates four basic inputs: capital, labour, human capital and technology. This model in the Cobb-Douglas production function is given by

$$y = Ak^{\alpha}L^{\beta}H^{\delta} \quad (1)$$

Where y denotes real output, A represents technology, and k, L, H, r represent real physical capital, labour, and human capital, respectively. The coefficients α, β and δ represent the output elasticity of k, L and H, respectively. Eq. (1) in log-linear function can be given by

$$\log y_t = \log A_t + \alpha \log k_t + \beta \log L_t + \delta \log H_t \quad (2)$$

In this study, a modified version of Romer's (1990) model is employed, as represented by Eq. (1), where the technology variable is replaced by real R&D (Omar, 2019; Sulaiman et al., 2015). This explicit inclusion of R&D allows for a deeper understanding of its two "faces". In addition to its traditional function of driving innovation, R&D also enhances technology transfer by improving industries or firms' capacity to absorb and implement advancements in the leading edge (Griffith et al., 2004). Also, R&D represents intentional decisions in innovation, aligning directly with Romer's argument that technological change results from deliberate economic activities Romer (1990). This replacement emphasizes the idea that innovation is not an exogenous shock but the outcome of deliberate R&D efforts. Therefore, the modified model in log-linear is

$$\log y_t = \varepsilon \log r_t + \alpha \log k_t + \beta \log L_t + \delta \log H_t \qquad (3)$$

Theoretically, all factor inputs have positive impacts on growth, the coefficients are expected to have positive signs, i.e., $\varepsilon > 0, \alpha > 0, \beta > 0, \delta > 0$ (Khatun & Afroze, 2016).

Methodology

Granger causality refers to the ability to predict the future values of one variable by leveraging past information from another variable. As previously noted, panel data techniques offer more comprehensive information and statistically robust outcomes compared to time-series methods (Chang et al., 2014). Therefore, this study employs the panel Granger non-causality test developed by Dumitrescu and Hurlin (2012) and Juodis et al. (2021) to investigate the causal relationships between factor inputs and economic growth. The first method is the Dumitrescu and Hurlin (2012) Granger non-causality test, which evaluates the null hypothesis of homogeneous non-causality against the alternative of heterogeneous non-causality. This test is utilized due to its ability to handle non-causality in heterogeneous panel data with fixed coefficients. Fuethermore, it addresses cross-sectional dependence by incorporating a bootstrap procedure to adjust the empirical critical values. The Dumitrescu and Hurlin (2012) test exhibits robust finite sample performance, even in the presence of cross-sectional dependence (Albaladejo et al., 2023). Following Ayomitunde et al. (2019) and Woldu and Kanó (2024), The Granger non-causality relationship between real output and real physical capital, labour, human capital and real R&D is estimated as follows:

$$y_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} y_{i,t-m} + \sum_{m=1}^{M} k_{i,t-m} + \tau_{it} \qquad (4a)$$

$$k_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} k_{i,t-m} + \sum_{m=1}^{M} y_{i,t-m} + \tau_{it} \qquad (4b)$$

$$y_{it} = \alpha_i + \textstyle\sum_{m=1}^{M} \varphi_{im} y_{i,t-m} + \sum_{m=1}^{M} L_{i,t-m} + \tau_{it} \qquad (5a)$$

$$L_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} L_{i,t-m} + \sum_{m=1}^{M} y_{i,t-m} + \tau_{it} \qquad (5b)$$

$$y_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} y_{i,t-m} + \sum_{m=1}^{M} H_{i,t-m} + \tau_{it} \qquad (6a)$$

$$H_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} H_{i,t-m} + \sum_{m=1}^{M} y_{i,t-m} + \tau_{it} \qquad (6b)$$

$$y_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} y_{i,t-m} + \sum_{m=1}^{M} r_{i,t-m} + \tau_{it} \qquad (7a)$$

$$r_{it} = \sigma_i + \textstyle\sum_{m=1}^{M} \varphi_{im} r_{i,t-m} + \sum_{m=1}^{M} y_{i,t-m} + \tau_{it} \qquad (7b)$$

Where M is lag order, which is identical for all individuals, the appropriate lag length is chosen based on Bayesian information criteria (BIC). σ_i is a dimensional vector referring to constant time individual fixed effects.

An alternative test, namely Juodis et al. (2021) Granger non-causality test, can be applied to detect the null hypothesis of no Granger causality. This method exhibits strong power against both homogeneous and heterogeneous alternatives and enables the consideration of cross-sectional dependence and cross-section heteroskedasticity (Xiao et al., 2023). Juodis et al. (2021) calculate the Wald test statistic and its corresponding p-value, present the null and alternative hypotheses and show regression findings for the half-panel jackknife (HPJ) bias-corrected pooling estimator. The lag order can be selected using the BIC information criterion.

Data and Empirical Results

Data

This study includes six economic powerhouses in China: Guangdong, Jiangsu, Shandong, Zhejiang Henan and Sichuan. The data is collected annually from 1996 to 2022. This data source is from the China Statistical Yearbook, the Provincial Statistical Yearbook and the data from the World Bank. The variables are explained as follows.

(i) Real output (y): Real output is proxied by real gross domestic product (RGDP), which is calculated by dividing nominal gross domestic product by the consumer price index (CPI).

(ii) Physical capital (k): Physical capital is proxied by real fixed asset investment, which is derived by dividing nominal fixed asset investment by the CPI. To estimate the stock of physical capital, this study employs the perpetual inventory method (Arya et al., 2019; Bailliu et al., 2019).

$$k_t = k_{t-1}(1-\delta) + i_t \qquad (8)$$

k_t is the physical capital stock, δ is the depreciation rate and i_t represents real fixed asset investment in the current year, the initial year of physical capital stock is computed as:

$$k_0 = i_0/(g+\delta) \qquad (9)$$

Where i_0 is the initial year of real fixed asset investment. Following Zhang (2008), the depreciation rate δ in China is taken by 9.6 per cent, and g is the growth rate of fixed asset investment. The formula of g is calculated by

$$g = \left(\sqrt[T]{\frac{i_t}{i_0}} - 1\right) \times 100\% \qquad (10)$$

T is the number of interval years.

(iii) Labour (L): Labour is proxied by the numbers of working age population aged 16 and above each year.

(iv) Human capital (H): Human capital is proxied by the average years of schooling. As China's schooling years of different levels are 0, 6, 9, 12 and 16 for illiteracy, primary, junior secondary, senior secondary schools, and tertiary education, respectively. Following Zhang and Zhuang (2011), the stock of H can be calculated as

$$H = (0 \times L_0 + 6 \times L_6 + 9 \times L_9 + 12 \times L_{12} + 16 \times L_{16})/pop \qquad (11)$$

Where L_i refers to the number of people with educated years (i=0, 6, 9, 12, 16) and pop is the numbers of population.

(v) R&D (r): R&D is proxied by real R&D expenditure. Real R&D expenditures can be obtained by deflating the annual R&D expenditures using the GDP deflator index to exclude price changes (Guellec & Bruno, 2002; Hall, 2007). Following Griliches (1980) and Goto and Suzuki (1989), this study uses the perpetual inventory method to estimate the stock of R&D expenditure, i.e., R&D stock, to consider the effect of past R&D inputs. The R&D stock is calculated as the sum of the present value of R&D expenditures from all previous periods and the current value of the R&D capital in time $t-1$.

$$r_t = \sum_{i=1}^{n} \mu_i e_{t-1} + (1-\delta) r_{t-1} \qquad (12)$$

Where r_t is the R&D stock in time t, μ_i is the lag operator connects past real R&D expenditure e_{t-i} to the current increase in technological knowledge, δ is the depression rate of the R&D capital. However, as the lag structure is challenging to specify by obtaining the information, Goto and Suzuki (1989) simply used average lag, and assumed $\mu_i = 1$ and $n = 1$ respectively, that is, the average lag is one year. Therefore, the Eq. (12) is simplified by

$$r_t = e_{t-1} + (1-\delta) r_{t-1} \qquad (13)$$

Goto and Suzuki (1989) assume that the growth rate of e is equal to the growth rate r, the initial R&D stock R_0 are estimated by $R_0 = E_0/(g+\delta)$, where g is the growth rate of real R&D expenditure. The depreciation rate is set at 15 per cent in R&D stocks, which is a common practice in the literature (Griliches & Lichtenberg, 1984; Hu et al., 2005).

All variables, i.e., y, k, L, H, and r, are expressed in log form.

Results and Discussion

Before carrying out the panel Granger non-causality test, cross-sectional dependence and homogeneity tests need to be applied since Dumitrescu and Hurlin's (2012) Granger non-causality test can consider both cross-sectional dependence and heterogeneity. Cross-sectional dependence is a critical issue in identifying causal relationships between variables. Ignoring the potential spillover effect may lead to misleading inferences (Fahimi et al., 2021). This study implements a series of tests such as Breusch and Pagan (1980) Lagrange multiplier (LM) test, Pesaran (2004) Scaled LM test, Pesaran (2004) cross section dependence (CD) test, and Pesaran et al. (2008) bias-adjusted LM test. Table 1 overwhelmingly demonstrates that the null hypothesis of cross-section independence is rejected at a 1 per cent significant value. The findings suggest that cross-sectional dependence exists among panel variables.

Table 1
Results of cross-sectional dependence test

cross-sectional dependence Test	y_t	k_t	L_t	H_t	r_t
LM test	328.4*** (0.000)	261.5*** (0.000)	142.9*** (0.000)	271.4*** (0.000)	299.1*** (0.000)
Scaled LM test	18.01*** (0.000)	15.86*** (0.000)	10.33*** (0.000)	16.43*** (0.000)	17.23*** (0.000)
CD test	20.070*** (0.000)	20.077*** (0.000)	8.014*** (0.000)	19.424*** (0.000)	20.044*** (0.000)
Bias-adjusted LM test	162.0*** (0.000)	127.3*** (0.000)	65.73*** (0.000)	132.4*** (0.000)	146.8*** (0.000)

Notes: ( ) denotes probability. ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively.

Another critical issue in examining causal relationships is whether panel estimates consider country-specific heterogeneity (Pesaran & Yamagata, 2008). The assumption of slope homogeneity is often unrealistic, as countries tend to have distinct economic features. As a result, applying uniform slope coefficients across the entire panel may overlook these country-specific differences (Fahimi et al., 2021). This study implements the standardized form of the Swamy (1970) homogeneity test (delta tests) developed by Pesaran and Yamagata (2008). Table 2 summarizes the results that the null hypothesis of slope homogeneity is also rejected at a 5 per cent significance level, thereby confirming slope heterogeneity within the panel.

Table 2
Results of the homogeneity test

Homogeneity Tests	y_t	k_t	L_t	H_t	r_t
delta	-2.612*** (0.009)	2.371** (0.018)	9.619*** (0.000)	-2.188** (0.029)	6.736*** (0.000)
$\text{delta}_{\text{adj.}}$	-3.455*** (0.001)	2.560*** (0.010)	10.390*** (0.000)	-2.895*** (0.004)	7.276*** (0.000)

Notes: ( ) denotes probability. ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively.

Considering the existence of cross-sectional dependence, traditional panel unit root tests become ineffective. It is necessary to use second-generation panel unit root testing that can address cross-sectional dependence.Therefore, this study applied the cross-sectional augmented Dickey-Fuller (CADF) and cross-sectional augmented Im-Pesaran-Shin (CIPS) panel unit root tests (Mitra, 2019). The outcomes are presented in Table 3. CIPS and CADF tests are conducted on the variables at the level and first difference. The results indicate that y_t, along with k_t, L_t, H_t, and r_t are not integrated of the same order, revealing a mix of I(0) and I(1) process.

Table 3
Results of panel unit root test

Variables	Tests	CIPS	CADF
y_t	Level	-2.016	-2.016
	First Difference	-3.623***	-3.623***
	Decision	I(1)	I(1)
k_t	Level	-3.296***	-3.230***
	First Difference	-2.899***	-3.065***
	Decision	I(0)	I(0)
L_t	Level	-1.878	-1.259
	First Difference	-2.946***	-2.419**
	Decision	I(1)	I(1)
H_t	Level	-3.399***	-2.482**
	First Difference	-5.007***	-4.258***
	Decision	I(0)	I(0)
r_t	Level	-1.852	-1.903
	First Difference	-3.757***	-3.423***
	Decision	I(1)	I(1)

Notes: ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively.

In order to examine the causal relationship between real output and its determinants: real physical capital, labour, human capital, and real R&D, this study applied the Dumitrescu and Hurlin (2012) and Juodis et al. (2021) Granger non-causality test. Both tests are performed in the first difference value of the variable pairs. From Table 4, the shaded area is the interest that addresses the hypothesis in this study. The Dumitrescu and Hurlin (2012) Granger non-causality test provides evidence against the null hypothesis of no Granger causality from k_t to y_t at 5 per cent significant value, from L_t to y_t at 10 per cent significant value, from H_t to y_t at 5 per cent significant value, and from r_t to y_t at 1 per cent significant value. However, the non-shaded area provides evidence against the null hypothesis of no Granger causality from y_t to k_t is also provided at 10 per cent significant value.

Table 4
Results of the Dumitrescu and Hurlin (2012) Granger non-causality test

Null Hypothesis	Optimal lags	*W*-bar	*Z*-bar	*Z*-bar tilde
$\Delta k_t \neq> \Delta y_t$	1	3.8224	4.8886** (0.0400)	3.9687** (0.0400)
$\Delta y_t \neq> \Delta k_t$	2	5.8338	4.6955* (0.0600)	3.5038* (0.0600)
$\Delta L_t \neq> \Delta y_t$	1	2.4654	2.5382* (0.0900)	1.9905* (0.0900)
$\Delta y_t \neq> \Delta L_t$	1	0.7575	-0.4200 (0.7100)	-0.4993 (0.6600)
$\Delta H_t \neq> \Delta y_t$	1	0.8301	-0.2942** (0.0500)	-0.3934** (0.0500)
$\Delta y_t \neq> \Delta H_t$	1	0.1700	-1.4376 (0.2200)	-1.3557 (0.1700)
$\Delta r_t \neq> \Delta y_t$	1	6.2890	9.1608*** (0.0000)	7.5645*** (0.0000)
$\Delta y_t \neq> \Delta r_t$	1	0.7977	-0.3503 (0.8400)	-0.4406 (0.7600)

Notes: ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively. Δ denotes the first difference. $\neq>$ denotes does not Granger-cause. The bootstrap replication is 100. The lag length selection is based on BIC criteria.

As expected, there are causal relationships from real physical capital, labour, human capital, and real R&D to real output. Specifically, the results also indicate that there is a unidirectional causality running from labour, human capital, and real R&D to real output, indicating that economic growth did not Granger-cause labour, human capital and R&D, though these factor inputs influence economic growth in a unidirectional manner. Empirical research supports labour-induced economic growth as opined by Yakubu et al. (2020) and Ahmed et al. (2016); human capital-induced economic growth agreed by Islam (2020) and Ozturk and Suluk (2020); R&D-induced economic growth suggested by Kose et al. (2020), and Xiang (2022). Also, there is bidirectional causality between real physical capital and real output, implying that economic growth increases physical capital, and physical capital drives economic growth. The findings align with the study of Haque et al. (2019) and Pomi et al. (2021) in the case of Bangladesh.

In addition, an alternative panel Granger non-causality test developed by Juodis et al. (2021) begins by testing whether the pair of real physical capital, labour, human capital and real R&D Granger-cause real output. After that, univariate testing is conducted, modelling real output as a function of real physical capital, labour, human capital, and real R&D separately. As shown in Table 5, the null hypothesis that k_t, L_t, H_t, and r_t do not jointly Granger-cause real output is rejected at the 1 per cent significance level. The standard errors of each variable reveal that the priority of factor inputs is ranked in the following order, i.e., H_t, r_t, k_t, and L_t. The coefficient of each variable has a positive sign except H_t. The Juodis et al. (2021) Granger non-causality covariates test thus indicates that the past values of selected variables also contribute to forecasting real output in addition to its own past values. The BIC criteria identify one lag as optimal, and the regression results show that all covariates drive the test outcomes.

Table 5
Results of Juodis et al. (2021) Granger non-causality test (covariates test)

HPJ Wald test	Optimal lag	HPJ *p-value*	Remark
597.0489***	1	0.000	Selected covariates Granger-cause Δy
Results of HPJ estimator			
Variables	Coefficient		Standard errors
Δk_t	0.2992***		0.0698
ΔL_t	0.5408***		0.0995
ΔH_t	-0.1415***		0.0179
Δr_t	0.4401***		0.0556

Notes: ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively. Δ denotes the first difference. In this estimation procedure, the maximum lag of the dependent variable and covariates is 3.

Subsequently, this study considers Juodis et al. (2021) univariate testing approach to test the Granger non-causality for each variable separately to ensure that these results are robust. The result is presented in Table 6, the shaded area is the interest that in line with the objectives of the study, the result reveals that the null hypothesis, i.e., k_t, L_t, H_t, and r_t do not Granger-cause real output y_t, is rejected. On the other hand, the non-shaded area showed that there is feedback causality between real output and real physical capital, labour, human capital, and real R&D, respectively. In addition, the same patterns can be observed as those displayed at Table 5. The standard errors in each set of null hypotheses find that there is an orderly priority of factor inputs, ranging from the top to the bottom, H_t, r_t, k_t, and L_t. Although the results imply that H_t causes y_t, no conclusion can be drawn from the negative H_t coefficient. This may be due to the data insufficiency (Lütkepohl, 2005; Mullet, 1976). Undoubtedly, r_t is the most important source of country's growth factor, which is in line with the fact that R&D investment has become a driver of China's economic shift toward innovation-led growth (World Bank, 2019). The priority of k_t is lower than that of H_t and r_t, but higher than L_t. This highlights that the influence of real physical capital is comparatively weaker than that of human capital and real R&D. The results reflect the diminishing returns to real physical capital under China's innovation-driven strategy (Morrison, 2019). L_t ranks the lowest in terms of standard errors. This result may be related to structural changes in China's labour market, as the shrinking demographic dividend has exerted pressure on China's economic growth potential (Dollar et al., 2020).

The above discussions suggest that the Chinese government's growth strategy is well aligned with the projected sources of growth from the pre- and the post-new normal of the economy (Garnaut et al., 2018; Nishimura, 2020). For better and sustainable economic growth in the future, the current strategy should be aligned with the government authorities, emphasizing the critical role of scientific and technological innovation and higher quality of human capital, particularly in R&D sectors. Coupled with deepening structural reforms and domestic competition, these efforts are poised to drive further productivity gains (IMF, 2024). Thus, the univariate test implies that the past values of real physical capital, labour, human capital, and real R&D contribute to forecasting the real output. Incorporating the past values of these variables can help in the prediction of real output.

Table 6
Results of Juodis et al. (2021) Granger non-causality test (univariate test)

Null hypothesis	Optimal lag	HPJ Wald test	*p-value*	HPJ estimator		
				Variable	Coefficient	Standard errors
$\Delta k_t \neq> \Delta y_t$	1	82.3391***	0.0000	Δk_t	0.5005***	0.0552
$\Delta y_t \neq> \Delta k_t$	1	57.8122***	0.0000	Δy_t	0.2068***	0.0272
$\Delta L_t \neq> \Delta y_t$	1	19.0051***	0.0000	ΔL_t	0.8351***	0.1916
$\Delta y_t \neq> \Delta L_t$	1	28.4331***	0.0000	Δy_t	0.1105***	0.0207
$\Delta H_t \neq> \Delta y_t$	1	220.4503***	0.0000	ΔH_t	-0.1831***	0.0123
$\Delta y_t \neq> \Delta H_t$	1	14.3805***	0.0001	Δy_t	0.1412***	0.0372
$\Delta r_t \neq> \Delta y_t$	1	42.5418***	0.0000	Δr_t	0.3462***	0.0531
$\Delta y_t \neq> \Delta r_t$	1	27.6617***	0.0000	Δy_t	0.2789***	0.0530

Notes: ***, **, and * indicate significance at 1, 5, and 10 per cent, respectively. Δ denotes the first difference. $\neq>$ denotes does not Granger-cause. The lag length selection is based on BIC criteria.

Several important policy implications arise from this study. The existence of cross-sectional dependence suggests that a shock in one of China's leading provinces is likely to have a ripple effect, triggering shocks in the economies of the others. Additionally, the strong link between economic growth and its determinants in China's top six economic powerhouses suggests that the identification of factor inputs, i.e., physical capital, labour, human capital, and R&D causation, may help policymakers infer precise economic growth. This causal relationship means that when formulating economic policies and growth strategies, it is essential to take a comprehensive approach to the interaction and influence of these factors to sustain economic growth. At the same time, it is necessary to strengthen policy coordination and be innovation-driven to fully leverage the potential to stimulate economic growth.

Conclusions

This study examines the causal relationship between economic growth and factor inputs, namely physical capital, labour, human capital, and R&D. China's top six economic powerhouses, i.e., Guangdong, Jiangsu, Shandong, Zhejiang, Henan and Sichuan provinces are included in this study. The estimation period is from 1996 to 2022. For causal relationships examination, this study uses Dumitrescu and Hurlin (2012) and Juodis et al. (2021) Granger non-causality test, to support the hypothesis that the factor inputs, namely physical capital, labour, human capital, and R&D do cause the economic growth. Additionally, the observed bidirectional causality, in some instances, highlights the dynamic interaction between factor inputs and economic performance. Thus, the findings from the results suggest that (i) the identification of factor inputs such as physical capital, labour, human capital, and research and development causation may help policymakers infer the projected economic growth by identifying the correct causation of factor inputs; (ii) identifying the correct causality can provide valuable insights for policymakers aiming to make optimal decision-making on resource allocation to enhance long term economic performance. Overall, the identified causality should help promote the best macroeconomic outcomes. These insights are crucial for policymakers, as identified causality between factor inputs and economic growth can aid in designing strategies that effectively leverage these inputs to foster the best macroeconomic outcomes.

This study has some limitations. First, the study includes only six provinces and four factor input variables (physical capital, labour, human capital, and R&D). For future research, one can include more countries and other prominent factor inputs (e.g., institutional quality) via the existing methodologies to improve the credibility and reliability of the existing inferences or outcomes. Second, data limitations due to reliance on secondary sources and the short time frame also restrict the study. Furthermore, the findings may not apply universally across China due to regional disparities in industrial structures and policies.

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References

Adedoyin, F. F., Bekun, F. V., & Alola, A. A. (2020). Growth impact of transition from non-renewable to renewable energy in the EU: The role of research and development expenditure. *Renewable Energy*, *159*, 1139-1145.

Ahmed, K., Mahalik, M. K., & Shahbaz, M. (2016). Dynamics between economic growth, labor, capital and natural resource abundance in Iran: An application of the combined cointegration approach. *Resources Policy*, *49*, 213-221.

Albaladejo, I. P., Brida, J. G., González-Martínez, M. I., & Segarra, V. (2023). A new look to the tourism and economic growth nexus: A clustering and panel causality analysis. *The World Economy*, *46*(9), 2835-2856.

Arya, V., Banerjee, R., & Cavoli, T. (2019). Capital flows to Asia and Latin America: Does institutional quality matter? *The World Economy*, *42*(7), 2039-2069.

Ayomitunde, A. T., Omotayo, O. H., Adejumo, A. V., & Abolore, Y. F. (2019). Panel cointegration and granger causality approach to foreign direct investment and economic growth in some selected emerging economies. *European Financial and Accounting Journal*, *14*(2), 27-42.

Bailliu, J., Kruger, M., Toktamyssov, A., & Welbourn, W. (2019). How fast can China grow? The Middle Kingdom's prospects to 2030. *Pacific Economic Review*, *24*(2), 373-399.

Barro, R. J. (1991). Economic growth in a cross section of countries. *The Quarterly Journal of Economics*, *106*(2), 407-443.

Brandt, L., Litwack, J., Mileva, E., Wang, L., Zhang, Y., & Zhao, L. (2020). China's productivity slowdown and future growth potential. *The World Bank.*

Brandt, L., & Rawski, T. G. (2008). *China's great economic transformation*. Cambridge University Press.

Breusch, T. S., & Pagan, A. R. (1980). The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, *47*(1), 239-253.

Chang, T., Lee, C. C., & Chang, C. H. (2014). Does insurance activity promote economic growth? Further evidence based on bootstrap panel Granger causality test. *The European Journal of Finance*, *20*(12), 1187-1210.

Dollar, D., Huang, Y., & Yao, Y. (2020). *China 2049: Economic Challenges of a Rising Global Power*. Brookings Institution Press.

Dumitrescu, E. I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic Modelling*, *29*(4), 1450-1460.

Emirmahmutoglu, F., & Kose, N. (2011). Testing for Granger causality in heterogeneous mixed panels. *Economic Modelling*, *28*(3), 870-876.

Etokakpan, M. U., Solarin, S. A., Yorucu, V., Bekun, F. V., & Sarkodie, S. A. (2020). Modeling natural gas consumption, capital formation, globalization, CO2 emissions and economic growth nexus in Malaysia: Fresh evidence from combined cointegration and causality analysis. *Energy Strategy Reviews*, *31*, 100526.

Fahimi, A., Olasehinde-Williams, G., & Akadiri, S. S. (2021). Examining the causal relationship between globalization and energy consumption in MINT countries: evidence from bootstrap panel Granger causality. *International Journal of Finance & Economics*, *26*(2), 1886-1896.

Garnaut, R., Song, L., & Fang, C. (2018). *China's 40 years of reform and development: 1978–2018*. Australian National University Press.

Goto, A., & Suzuki, K. (1989). R&D capital, rate of return on R&D investment and spillover of R&D in Japanese manufacturing industries. *The Review of Economics and Statistics*, 555-564.

Griffith, R., Redding, S., & Reenen, J. V. (2004). Mapping the two faces of R&D: Productivity growth in a panel of OECD industries. *Review of Economics and Statistics*, *86*(4), 883-895.

Griliches, Z. (1980). R&D and the productivity slowdown. *NBER Working Papers No. 434*.

Griliches, Z., & Lichtenberg, F. (1984). Interindustry technology flows and productivity growth: A reexamination. *The Review of Economics and Statistics, 66(*2*), 324-329.*

Guellec, D., & Bruno, V. P. d. l. P. (2002). R&D and productivity growth: panel data analysis of 16 OECD countries. *OECD Economic Studies*, *2001*(2), 103-126.

Hall, B. H. (2007). Measuring the returns to R&D: The depreciation problem. *National Bureau of Economic Research*.

Haque, A. U., Kibria, G., Selim, M. I., & Smrity, D. Y. (2019). Labor force participation rate and economic growth: Observations for Bangladesh. *International Journal of Economics and Financial Research*, *5*(9), 209-213.

Hu, A. G. Z., Jefferson, G. H., & Jinchang, Q. (2005). R&D and technology transfer: Firm-level evidence from Chinese industry. *Review of Economics and Statistics*, *87*(4), 780-786.

International Monetary Fund. (2024). *People's Republic of China: 2024 Article IV Consultation-Press Release; Staff Report; and Statement by the Executive Director for the People's Republic of China* (IMF Country Report No. 24/258). Washington, DC: International Monetary Fund.

Islam, M. S. (2020). Human capital formation and economic growth in South Asia: Heterogeneous dynamic panel cointegration. *International Journal of Education Economics and Development*, *11*(4), 335-350.

Jaber, J., Kabouri, I., Bouzahzah, M., Ibourk, A., & Karim, M. (2022). Economic growth and education in Morocco: Cointegration and Toda Yamamoto Granger causality. *International Journal of Accounting, Finance, Auditing, Management and Economics*, *3*(4-1), 1-20.

Juodis, A., Karavias, Y., & Sarafidis, V. (2021). A homogeneous approach to testing for Granger non-causality in heterogeneous panels. *Empirical Economics*, *60*(1), 93-112.

Khatun, T., & Afroze, S. (2016). Relationship between real GDP and labour and capital by applying the Cobb-Douglas production function: A comparative analysis among selected Asian countries. *Journal of Business Studies*, *37*(1), 113-129.

Kose, N., Bekun, F. V., & Alola, A. A. (2020). Criticality of sustainable research and development-led growth in EU: The role of renewable and non-renewable energy. *Environmental Science and Pollution Research*, *27*(11), 12683-12691.

Liu, Z. Z. (2023). *Sovereign funds: How the Communist Party of China finances its global ambitions*. Harvard University Press.

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, *22*(1), 3-42.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Mitra, S. K. (2019). Is tourism-led growth hypothesis still valid? *International Journal of Tourism Research*, *21*(5), 615-624.

Morrison, W. M. (2019). China's economic rise: History, trends, challenges, and implications for the United States. *Congressional Research Service (CRS) Report, RL33534*.

Mtar, K., & Belazreg, W. (2021). Causal nexus between innovation, financial development, and economic growth: The case of OECD countries. *Journal of the Knowledge Economy*, *12*(1), 310-341.

Mullet, G. M. (1976). Why regression coefficients have the wrong sign. *Journal of Quality Technology*, *8*(3), 121-126.

Ngepah, N., Saba, C. S., & Mabindisa, N. G. (2021). Human capital and economic growth in South Africa: A cross-municipality panel data analysis. *South African Journal of Economic and Management Sciences*, *24*(1), 1-11.

Nishimura, Y. (2020). New normal and new economy: A new growth engine for China. *International Journal of Economic Policy Studies*, *14*(2), 301-312.

Olopade, B. C., Okodua, H., Oladosun, M., Matthew, O., Urhie, E., Osabohien, R., Adediran, O., & Johnson, O. H. (2020). Economic growth, energy consumption and human capital formation: Implication for knowledge-based economy. *International Journal of Energy Economics and Policy*, *10*(1), 37-43.

Organization for Economic Cooperation and Development (OECD). (2015). *The impact of R&D investment on economic performance: A review of the econometric evidence*. OECD Publishing, Paris

Omar, N. S. (2019). Innovation and economic performance in MENA region. *Review of Economics and Political Science*, *4*(2), 158-175.

Ozturk, S., & Suluk, S. (2020). The granger causality relationship between human development and economic growth: The case of Norway. *International Journal of Research in Business and Social Science*, *9*(6), 143-153.

Pasara, M. T., & Garidzirai, R. (2020). Causality effects among gross capital formation, unemployment and economic growth in South Africa. *Economies*, *8*(2), 1-12.

Pesaran, M. H. (2004). General diagnostic tests for cross section dependence in panels. Cambridge Working Papers. *Economics*, *1240*(1), 1.

Pesaran, M. H., Ullah, A., & Yamagata, T. (2008). A bias-adjusted LM test of error cross-section independence. *The Econometrics Journal*, *11*(1), 105-127.

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50-93.

Pomi, S. S., Sarkar, S. M., & Dhar, B. K. (2021). Human or physical capital, which influences sustainable economic growth most? A study on Bangladesh. *Canadian Journal of Business and Information Studies*, *3*(5), 101-108.

Romer, P. M. (1990). Endogenous technological change. *Journal of Political Economy*, *98*(5), 71-102.

Saggu, A., & Anukoonwattaka, W. (2015). China's 'new normal': Challenges ahead for Asia-Pacific trade. *ESCAP Trade Insights, 7*(11), 1-11. United Nations

Selvamani, K., & Muthusamy, A. (2021). Relationships among exports, imports, physical capital and economic growth in India: An econometric analysis. *Strad Research*, *8*(8), 657-668.

Sinha, J. K. (2023). Dynamics of investment, economic growth, and employment in contemporary India: Analyzing patterns and future potential. *Political Science International*, *1*(1), 52-60.

Solow, R. M. (1957). Technical change and the aggregate production function. *The Review of Economics and Statistics*, *39*(3), 312-320.

Sulaiman, C., Bala, U., Tijani, B. A., Waziri, S. I., & Maji, I. K. (2015). Human capital, technology, and economic growth: Evidence from Nigeria. *Sage Open*, *5*(4), 2158244015615166.

Swamy, P. A. V. B. (1970). Efficient inference in a random coefficient regression model. *Econometrica*, *38*(2), 311-323.

Turyareeba, D., Ainomugisha, P., Mbabazize, R., Ssebbaale, E. M., Mulema, S., Wemesa, R., Wagima, C., & Bakaki, I. (2020). Employment–growth nexus in Uganda: Analysis with error correction modelling. *Archives of Business Review*, *8*(7), 39-57.

United Nations. (2022). *China's structural transformation: What can developing countries learn?* United Nations Conference on Trade and Development. United Nations Publications.

Woldu, G. T., & Kanó, I. S. (2024). Primary surplus dynamics and fiscal sustainability in sub-Saharan African countries. *Economia Politica*, *41*(2), 499-519.

World Bank. (2019). *Innovative China: New drivers of growth*. World Bank.

World Bank. (2022). *Global Economic Prospects*. World Bank.

World Trade Organization. (2022). *World trade statistical review*. World Trade Organization.

Xiang, P. (2022). Using Stata software to study the impact of technological innovation on economic growth. In *2022 International Conference on Mathematical Statistics and Economic Analysis (MSEA 2022)*, Atlantis Press.

Xiao, J., Karavias, Y., Juodis, A., Sarafidis, V., & Ditzen, J. (2023). Improved tests for Granger noncausality in panel data. *The Stata Journal*, *23*(1), 230-242.

Xu, Y. (2020). *Environmental policy and air pollution in China: Governance and strategy*. New York: Routledge.

Yakubu, M. M., Akanegbu, B. N., & Jelilov, G. (2020). Labour force participation and economic growth in Nigeria. *Advances in Management and Applied Economics*, *10*(1), 1-14.

Zhang, C., & Zhuang, L. (2011). The composition of human capital and economic growth: Evidence from China using dynamic panel data analysis. *China Economic Review*, *22*(1), 165-171.

Zhang, J. (2008). Estimation of China's provincial capital stock (1952–2004) with applications. *Journal of Chinese Economic and Business Studies*, *6*(2), 177-196.