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Provincial Factor Inputs and Economic Growth in China: A Panel Autoregressive Distributed Lag Model Method

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ABSTRACT

A notable feature of empirical research into the forces of China's economic growth in an innovation-driven economy is the limited focus on whether the traditional reliance on factor inputs has been undermined by technical change. To address this shortfall, this study uses the endogenous growth model to measure the roles of factor inputs. It examines empirical validity based on a sample of China's top six economic powerhouses, namely, Guangdong, Jiangsu, Shandong, Zhejiang, Henan, and Sichuan Province. Using panel autoregressive distributed lag method, the findings suggest that policymakers should not ignore the explanatory power of factor inputs, namely, physical capital, labor, human capital, and research and development on economic growth in navigating economic evolution by relying on increasing quantities of inputs to focus on improving the efficiency and quality of those inputs. Through their accumulation and utilization in production processes, these factor inputs may collectively enhance an economy's production capabilities and growth potential.

Keywords: Dynamic Heterogeneous Panel Autoregressive Distributed Lag, Economic Growth, Factor Inputs
JEL Classifications: C23, O4, O47

1. INTRODUCTION

Since initiating investment and implementing free-market reforms in 1978, China has emerged as a global production leader through its export-oriented approach and low input costs (United Nations, 2022). This strategic shift has catapulted China into the ranks of rapidly growing economies (Liu, 2023), consistently achieving an average annual real gross domestic product (GDP) growth of approximately 9% through 2023, underscoring its economic ascension (World Bank Open Data). However, as China's economy has matured, its growth rates have moderated significantly, decreasing from a peak of 14.2% in 2007 to 5.2% in 2023. This slowdown signifies a shift towards what the Chinese government terms the "new normal," an era anticipating growth rates of approximately 7% in the foreseeable future (Saggu and Anukoonwattaka, 2015). In response to this changing economic landscape, the government has prioritized innovation through its industrial policies, aiming to stabilize and moderate economic growth over the medium to long-run (Morrison, 2019). Consequently, the economic focus is shifting from secondary activities, such as manufacturing and processing, to tertiary sectors, including innovation and services (Xu, 2020). Despite this strategic transformation, the outcomes may remain ambiguous and intertwined with the forces behind innovation-driven growth.

Understanding the impact of factor inputs on economic growth in China's leading provinces is crucial due to the country's shift towards quality-driven growth and innovation, moving beyond traditional input reliance. Therefore, it remains an open question whether further investigations in this area could enhance better understanding of the sources of economic growth and their implications for future policy directions. Given China's pivotal role as a major contributor to global output and its capacity to meet world demand, exploring how specific inputs contribute to sustainable growth in these key provinces is vital, especially given China's regional economic disparities and global economic influence. Insights into these factor inputs are not only crucial for shaping China's domestic policies but also have significant implications for the global economy, influencing international trade dynamics and economic stability (World Trade Organization, 2022).

Considering the pivotal role of factor inputs in China's economic model, especially physical capital, labor, human capital, and research and development (R&D), this study offers a valuable reassessment of these factors within the context of sustainable and balanced growth. Over the past four decades, China has achieved remarkable growth by leveraging reform and globalization, becoming a leader in global manufacturing (World Bank, 2019; United Nations, 2022). However, the global financial crisis of 2008 exposed vulnerabilities in China's growth model, emphasizing the need for more sustainable economic strategies. As China transitions into a "new normal" economy characterized by slower but more balanced growth, understanding the role of factor inputs in economic performance across its leading provinces, i.e., Guangdong, Jiangsu, Shandong, Zhejiang, Henan, and Sichuan Province become essential. These provinces are significant contributors to China's GDP and global economic standing, underscoring the importance of studying how these factors drive regional growth. Insights from this analysis help to bridge a critical gap in the literature, offering empirical evidence that can guide policymakers in designing strategies tailored to regional needs, optimizing resource allocation, and fostering economic resilience. Despite theoretical frameworks that emphasize the importance of factor inputs (Barro, 1991; Lucas, 1988; Romer, 1990; Solow, 1957), empirical evidence remains inconsistent, highlighting gaps in understanding their roles in China's economic landscape. Furthermore, persistent regional disparities and challenges in resource allocation and overcapacity complicate efforts to achieve uniform growth. The World Bank (2022) emphasizes the need to address these disparities, pointing to the importance of clarifying regional growth dynamics and enhancing the effective use of factor inputs in economically critical areas, making this research essential for informing policy and strategic planning.

A notable feature of empirical investigation into the forces of China's economic growth in an innovation-driven economy is the limited focus on whether the traditional reliance on factor inputs has been undermined by technical change. These factor inputs are fundamental building blocks of the economy. In the context of China, the typical factor inputs may include physical capital, labor, human capital, whereas technical changes may include enhancing R&D, fostering innovation, and improving efficiency (Brandt et al., 2020; Brandt and Rawski, 2008). With respect to physical capital, Li et al. (2015) argue that physical capital makes a significant contribution to China's swift economic expansion, mainly through large-scale investments in infrastructure and industrial capacity. However, they opine that future growth may face diminishing returns from physical capital, necessitating a shift towards more sustainable and quality-focused investment strategies. Guo et al. (2023) provide evidence that there was a correlation between physical capital and the expansion of the regional economies of China. The empirical research findings indicate that physical capital has the potential to successfully drive China's growth performance. Yang (2023) demonstrates that China's economic output relies heavily on physical capital. The insufficient supply of factor inputs hinders sustained rapid economic expansion since China adopted an investment-driven growth strategy that heavily relies on physical capital for economic expansion. Wu et al. (2019) state that the Chinese economy is currently experiencing a "new normal" phase characterized by slower growth and structure optimization. The empirical findings suggest that China's economic growth mainly depends on physical capital.

With respect to labor, Li et al. (2017) state that China's remarkable economic expansion can be attributed to the rise in the size of labor, i.e., the increasing working-age population may contribute to labor productivity. In turn, efficiency in labor productivity facilitates the redistribution of workers to more productive industries. Ciuriak (2022) demonstrates that the persistent deceleration in the growth of labor, i.e., the working-age population, triggered pressure on China's economic growth potential since China's population growth fell steeply over the past three decades. Additionally, the rapidly aging population results in a growing burden on labor. Yang (2020) reports that much of the economic growth in China was fuelled by the demographic structure of the country in the first decade of the twenty-first century. Having an abundant supply of labor allowed China to conduct large-scale labor-intensive exports. A significant expansion occurred simultaneously, and the surplus labor supply was greatly diminished. Depletion occurred simultaneously with a decrease in China's demographic dividends beginning in 2009. Undoubtedly, this has contributed to the recent slowdown in China's economy. Lam et al. (2015) indicate that China's economy has recently entered a "new normal" state. As China has implemented structural reforms, maintaining stability in the labor market has become crucial. Despite the economic slowdown, the labor market has remained relatively stable. However, there is evidence of increased labor hoarding in industries with surplus capacity.

With respect to human capital, Wang et al. (2022) employ a panel threshold model to analyze the dynamic nexus between human capital and China's growth. From the preceding findings, human capital emerges as a vital foster for economic growth. Human capital yields a positive external effect that accelerates the innovation process, especially considering the demographic trend of an aging population. Ahmed et al. (2016) suggest that the level of human capital is positively related to growth performance. It is necessary to increase the average level of education and improve the perspective quality of education for the working-age population. Whalley and Zhao (2013) provide empirical evidence of the significant impact of human capital on China's growth. The research reveals that human capital accounts for 38.1% of the overall increase in total GDP between 1978 and 2008. The findings suggest that there may have been a decline in the effectiveness of resource utilization in China or a deterioration in the allocation of human capital in recent years. Ma et al. (2023) state that human capital accumulation accelerates economic growth in China. Greater levels of human capital leads to improved technical innovation, which in turn enhances overall high-quality economic growth. Human capital has spillover effects and enhances the pace of innovation, particularly in the context of an ageing population.

With respect to R&D, Liu and Xia (2018) suggest that effective R&D expenditures can stimulate technological innovation, which is ultimately beneficial to economic growth. As a result of increased R&D expenditures, innovation activities involve more resources and optimized production conditions, thus promoting the output of technological innovation in China. Song et al. (2019) provide evidence that R&D activities served as catalysts behind technological advancement. An increase in R&D yields beneficial outcomes for China's sustained economic growth. Lin and Zhu (2019) suggest that R&D inputs help accelerate growth productivity in China by facilitating activities that contribute to technological advancement. Wang et al. (2021) suggest that the long-run expansion of China's economy is contingent on the country's investments in R&D as well as technological innovation. In addition, it has been discovered that greater R&D expenditures make a favorable contribution to economic growth. Morrison (2019) suggested that China must develop a "new normal" that promotes sustainable economic growth by prioritizing R&D as the primary catalyst for the Chinese economy. Without significant economic reforms, China may experience a period of stagnating economic growth and living standards.

The objective of this study is to examine the relationships between economic growth and factor inputs, namely, physical capital, labor, human capital, and R&D. The implications of the study offer an insightful perspective on how these inputs contribute to both the efficiency and quality of economic output, moving beyond a traditional reliance on quantity alone. Through their accumulation and utilization in production processes, these factor inputs may collectively enhance an economy's production capabilities and growth potential. This study may be particularly useful for stakeholders (i.e., government policymakers, investors, business owners and academic scholars) interested in economic growth, as it provides an in-depth understanding of how different inputs interact within China's diverse provincial economies. This study employs a sample comprising six selected leading provinces, i.e., Guangdong, Jiangsu, Shandong, Zhejiang, Henan and Sichuan Province. The important feature of this study is the use of the modified Romer (1990) model, which illustrates the theoretical framework for this study. This modified function expresses that a set of factor inputs can illustrate the output in growth. This study uses the Pesaran et al. (1999) panel autoregressive distributed lag (ARDL) method to estimate those dynamic relationships in short-run and long-run settings. In doing so, it can make the findings relevant for both immediate and sustained growth analysis.

2. MODEL SPECIFICATIONS

This study focuses on the empirical investigation of the dynamic relationship between real output and factor inputs, namely labor, physical capital, human capital and R&D. Follow Fu et al. (2025), a modified endogenous growth model i.e., a modified version of Romer (1990) model, is used in this study (Note that 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 lead to economic growth. The blueprints (designs) used to create new products are non-rivals, that is, they can be duplicated without additional costs).

Initially, Romer (1990) model incorporates key variables, i.e., physical capital, labor, human capital, and technology in the function. This model in the Cobb-Douglas (C-D) production function is given by:

$$y = Ak^{\alpha} L^{\beta} H^{\delta} \tag{1}$$

In the general form above, y denotes real output (representing economic growth). A represents technology, and k, L and H are used to denote physical capital, labor, and human capital, respectively. The coefficients of α, β and δ represent the output elasticities of K, L and, H, respectively.

R&D plays an important role in measuring the extent of a region's input into technology. Thus, building on the empirical work of Sulaiman et al. (2015) and Omar (2019), Model (1) can be modified by replacing the technology with R&D. This adjustment aims to better capture the role of innovation and technological progress in driving economic growth. By focusing on R&D, the model emphasizes the importance of investments in research, innovation, and knowledge creation as key drivers of productivity and long-term economic growth. Considering the consensus of the empirical literature, the C-D production function is adopted for evaluating the impact of R&D expenditure on output or productivity growth (Akoum, 2016; Inekwe, 2015; Ulku, 2004; Van Elk et al., 2015). One can undertake a regression analysis of economic performance measures against conventional production inputs, namely, physical capital, labor, and human capital in addition to R&D. This study modifies Model (1) as follows in the log-linear production function:

$$\ln y_{it} = \alpha \ln k_{it} + \beta \ln L_{it} + \delta \ln H_{it} + \varepsilon \ln r_{it} + \mu_{it} \tag{2}$$

Where i and t denote the province and the year of panel data, respectively. y stands for real output, proxy by real GDP; k stands for physical capital, proxy by fixed asset investment; L denotes labor, proxy by the working-age population; H refers to human capital, proxy by average years of schooling; r is R&D, proxy by R&D expenditures, and μ stands for the statistical error term.

The modified Romer's (1990) model in forms of Eq. (2) illustrates that the output in economic growth is illustrated by a set of factor inputs, i.e., k, L, H and r. The sum of the exponents of factors in C-D production measures the aggregate proportionate change in output for a given proportionate change in physical capital, labor, human capital and R&D. Theoretically, all factor inputs are expected to have positive relationships with GDP. The coefficients are expected to have positive signs, i.e., $\alpha > 0$, $\beta > 0$, $\delta > 0$, and $\varepsilon > 0$ (Khatun and Afroze, 2016). With respect to physical capital investment is a significant factor in the acceleration of economic growth. Greater capital investment in production may increase output and induce economic growth (Sakamoto, 2018). With respect to labor, population growth increases labor. Increasing labor productivity increases output and induces economic growth (Flabbi and Gatti, 2018). With respect to human capital, workers with more education or better skills help develop an economy and boost economic growth (Arshad and Malik, 2015). With respect to R&D, an increase in R&D expenditure increases output, stimulates innovation and induces economic growth (OECD, 2015).

3. METHODOLOGY

In the analysis of panel datasets, improper assumptions of cross-sectional dependence (CSD), slope homogeneity, and the issues of nonstationary frequently occur. Therefore, the panel ARDL method proposed by Pesaran et al. (1999) is adopted to estimate the long-run and short-run dynamic relationships between economic growth and its determinants, namely physical capital, human capital and R&D. Finally, the long-run association between variables is revalidated via alternative co-integration tests. The following section explains the panel ARDL dynamic heterogeneous panel method.

Following Gan (2019), Kim et al. (2010) and Lee and Wang (2015), the ARDL dynamic heterogeneous panel is specified in the panel error-correction model as follows:

$$\Delta \ln y_{it} = \phi_i(\ln y_{i,t-1} - \lambda_{1i} \ln k_{it} - \lambda_{2i} \ln L_{it} - \lambda_{3i} \ln H_{it} - \lambda_{4i} \ln r_{it}) + \sum_{f=1}^{h-1} \delta_{if}^{'} \Delta \ln y_{i,t-f} + \sum_{f=0}^{v-1} \delta_{1if} \Delta \ln k_{i,t-f} + \sum_{f=0}^{v-1} \delta_{2if} \Delta \ln L_{i,t-f} + \sum_{f=0}^{v-1} \delta_{3if} \Delta \ln H_{i,t-f} + \sum_{f=0}^{v-1} \delta_{4if} \Delta \ln r_{i,t-f} + \mu_i + \varepsilon_{it} \tag{3}$$

Where λ is the coefficient used to capture long-run effects, δ is the coefficient of average short-run, φ_i is the coefficient of error correction, μ_i is the province-specific effect, and the symbol Δ indicates the first difference. The model spans i provinces, where $i = 1, 2.,Z$, and year $t = 1, 2.,T$. All the variables are expressed in log form.

For Eq. (3), the mean-group (MG) and pooled mean-group (PMG) estimators are outlined as follows:

$$\phi_{MG} = \frac{1}{Z}\sum_{i=1}^{Z}\phi_i, \quad \lambda_{MG} = \frac{1}{Z}\sum_{i=1}^{Z}\lambda_i, \quad \delta_{MG} = \frac{1}{Z}\sum_{i=1}^{Z}\delta \tag{4}$$

$$\phi_{PMG} = \frac{1}{Z}\sum_{i=1}^{Z}\phi_i, \quad \lambda_{PMG} = \lambda\forall_i,$$

$$\delta_{PMG} = \frac{1}{Z}\sum_{i=1}^{Z}\delta; \quad \forall_i = 1,2,...,Z \tag{5}$$

The MG estimator is contingent upon the estimation of time series regression for each province and the average of the coefficients of the long-run within the panel ARDL framework. In comparison, the PMG estimator employs a method that averages the individual coefficient for short-run dynamics while pooling coefficients for the long-run to reflect relationships across provinces. The dynamic fixed effects (DFE) estimator is an alternative estimator established under the assumption of a homogeneous slope. In this estimator, the intercepts are permitted to vary across provinces while the slopes are fixed.

Finally, the error-correction coefficient φ_i is crucial for measuring the speed of adjustment of y_{it} reverts to long-run equilibrium after adjustments in associated variables such as k_{it}, L_{it}, H_{it}, r_{it}. A significant and negative value of φ_i is regarded as evidence of co-integration between y_{it} and k_{it}, L_{it}, H_{it} and r_{it}. In addition, this study performs a Hausman test to examine the efficiency of the PMG, MG, and DFE estimators.

4. DATA DESCRIPTION

This study focuses on six leading provinces in China, including Guangdong, Jiangsu, Shandong, Zhejiang Henan and Sichuan. Annual data are collected from 1996 to 2022, with sources including the China Statistical Yearbook, the Provincial Statistical Yearbook, and the World Bank. Follow Fu et al. (2025), the variables are defined as follows.

i. Real output (y): Real gross domestic product (RGDP) serves as a measure of real output. It is calculated by dividing the nominal gross domestic product (NGDP) by the consumer price index (CPI) for each year.
ii. Physical capital (k): Real fixed asset investment is employed to assess physical capital through the perpetual inventory method (Arya et al., 2019; Bailliu et al., 2019; Wu et al., 2019).

$$k_t = k_{t-1}(1-\delta) + I_t \tag{6}$$

Where k_t is the capital stock in year t, δ is the depreciation rate, I_t represents real fixed asset investment, which is calculated by dividing nominal fixed asset investment by the CPI. The initial year of physical capital stock is computed as:

$$k_0 = \frac{I_0}{g+\delta} \tag{7}$$

Where I_0 is the initial year of fixed asset investment. Following Zhang (2008), the assumed depreciation rate for physical capital in China is 9.6%. g is the average growth rate of fixed asset investment. The formula is calculated by:

$$g = \left(\sqrt[T]{\frac{I_t}{I_0}} - 1\right) \times 100\% \tag{8}$$

T is the number of interval years.

iii. Labor (L): The numbers of the working-age population are directly used to measure labor.
iv. Human capital (H): Average years of schooling are used as a measure of human capital. The corresponding years of schooling for different education levels are 0 for illiteracy,

6 for primary school, 9 for junior secondary, 12 for senior secondary, and 16 for tertiary education. Following Zhang and Zhuang (2011), the stock of human capital H is given by

$$H = \frac{0 \times L_0 + 6 \times L_6 + 9 \times L_9 + 12 \times L_{12} + 16 \times L_{16}}{pop} \tag{9}$$

Where L_i refers to the number of people with specific years of education (i = 0, 6, 9, 12, 16) and *pop* represents the population.

v. R&D (r): Real R&D expenditure is used as a proxy for R&D. Real R&D expenditures are calculated by adjusting annual R&D expenditures using the GDP deflator index (Guellec and Bruno, 2002; Hall, 2007). Following Griliches (1980), Goto and Suzuki (1989), this study uses the perpetual inventory method to estimate the R&D stock. The R&D stock at a given time t is calculated by summing the current value of R&D expenditures from previous periods along with the current value of the R&D capital from period t–1.

$$r_t = \sum_{i=1}^{n} \mu_i e_{t-i} + (1-\delta) r_{t-1} \tag{10}$$

Where r_t and r_{t-1} represent the R&D stock in the current and proceeding periods, respectively. e_{t-i} captures the R&D inputs in the period t–i, with i serving as the lag operator that links to past R&D expenditure levels. μ_i functions as the lag for the discount coefficient apply to those expenditures, while δ represents the depression rate of R&D capital. Due to the complexity of obtaining the necessary information to define the lag structure in the model, Goto and Suzuki (1989) assume $\mu_i = 1$ and $n = 1$ for simplification. Therefore, the formula is simplified by:

$$r_t = e_{t\text{-}1} + (1-\delta) r_{t-1} \tag{11}$$

Goto and Suzuki (1989) assume that the growth rate of e is equal to the growth rate of r, the initial R&D stock r_0 are estimated by:

$$r_0 = \frac{e_0}{g + \delta} \tag{12}$$

Where g is the growth rate of real R&D expenditure. The depreciation rate δ is typically set at 15%, as frequently employed in the literature (Griliches and Lichtenberg, 1984; Hu et al., 2005). All variables, i.e., y, k, L, H and r are expressed in log form.

5. RESULTS AND DISCUSSION

Typically, panel data models assume that the series is CSD. This assumption fails to account for the CSD present in the panel data analysis. As a result, the outcomes may exhibit significant bias and size distortion. The present study implements a series of tests to detect the presence of CSD, such as the Lagrange multiplier (LM) test (Breusch and Pagan, 1980), the scaled LM test (Pesaran, 2004), the cross-section dependence (CD) test (Pesaran, 2004) and the bias-adjusted LM test (Pesaran et al., 2008). Table 1 overwhelmingly demonstrates that the null hypothesis of cross-sectional independence is rejected at the $P < 0.01$ significance level. These findings indicate the presence of CSD among the panel variables.

Another critical issue in panel ARDL methods is whether panel estimates consider heterogeneous data. To determine whether slope coefficients are heterogeneous, this study employs the standardized version of the Swamy (1970) homogeneity test developed by Pesaran and Yamagata (2008), known as the delta test. The test results reject the null hypothesis of a homogeneous slope at a significance level of 5%, thereby confirming slope heterogeneity in the panel datasets. This finding highlights the need to consider individual variations in econometric modelling within panel data analyses to ensure the accuracy and relevance of the results.

Considering the existence of CSD in the panel, conventional panel unit root tests are invalid. Therefore, it is necessary to utilize second-generation panel unit root tests, i.e., cross-sectional augmented Dickey Fuller (CADF) and cross-sectional augmented Im-Pesaran-Shin (CIPS) tests, which yield valid estimations in the case of CSD. Table 2 shows that y, k, L, H and r are not integrated in the same order, i.e., the variables indicate a blend of I(0) and I(1). It has been argued by Pesaran et al. (1999) that the dynamic heterogeneous panel co-integration technique of ARDL is applicable whether the variables are I (0) or I (1).

To explore the long-term and short-term relationships between economic growth and factor inputs in six selected provinces, this study employs heterogeneous panel regression using an error correction model based on the Pesaran et al. (1999) panel ARDL method. The lag order for this model was selected according to the BIC and HQIC criteria, as presented in Table 3. The results of

Table 1: CSD test and homogeneity test results

CSD 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)
Homogeneity tests					
$\tilde{\Delta}$	−2.612*** (0.009)	2.371** (0.018)	9.619*** (0.000)	−2.188** (0.029)	6.736*** (0.000)
? ? adj	−3.455*** (0.001)	2.560*** (0.010)	10.390*** (0.000)	−2.895*** (0.004)	7.276*** (0.000)

( ) denotes probability. ***, **, and * denote 1%, 5% and 10% levels of significance, respectively. ? ? denotes "delta"

Table 2: Panel unit root test results

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

***, **, and * denote 1%, 5% and 10% levels of significance, respectively

Table 3: Lag selection

Lag	AIC	BIC	HQIC
1	−22.9441	−20.8098*	−21.4832*
2	−22.0954*	−20.3984	−21.4058
3	−22.0177	−19.7245	−21.0858

the estimators MG, PMG, and DFE are shown in Table 4, which outlines the long-term and short-term coefficients between the dependent variables and independent variables, as well as the speed of adjustment for each estimation. Additionally, a Hausman test is employed to evaluate the efficiency of the PMG, MG, and DFE estimators.

In Table 4, the results of PMG indicate that the coefficients of k, H and r are not only statistically significant but also present the expected positive signs. The results indicate that physical capital, human capital, and R&D positively and significantly impact economic growth in the long-run at the 1% significance level. Specifically, a 1% rise in physical capital typically results in an approximately 0.19% upshift in economic growth. Similarly, an increase of 1% in human capital is likely to boost economic growth by approximately 0.85%. Similarly, a 1% increase in R&D expenditure leads to an approximately 0.28% increase in economic growth. The short-term coefficients for physical capital and human capital are also statistically significant and signed properly. Furthermore, the error correction term, i.e., the speed of adjustment, is negative and statistically significant at the 1% level, suggesting that the variables return to long-term equilibrium. The coefficient of the error correction term of −0.2188 indicates that 75% of any deviation from long-run equilibrium is corrected within 1 year. Thus, the study concludes that long-run relationships exist between real output and physical capital, human capital, and R&D. In contrast, physical capital and human capital also positively impact economic performance in the short term. The short-run dynamics are determined by how much the current value deviates from the long-run value.

Table 5 presents the outcomes of the Hausman test, which assesses the relative efficiency of the PMG, MG, and DFE estimators. The findings indicate a preference for the PMG over the MG and DFE. Consequently, the conclusion of this study relies on the outcomes of the PMG estimator.

The selected findings of the PMG estimator fully support long-run co-integration between economic growth and determinants such as physical capital, human capital, and R&D. Moreover, labor does not appear to follow this trend. Additionally, physical and human capital significantly and positively affect economic performance in the short term. In line with these results, the short-run dynamics of the variables are influenced by the deviations of the current value from the long-run values.

The findings also show that physical capital positively impacts growth performance in the short term and the long term. Physical capital significantly affects growth at the 1% significance level in both the short and long-term. This finding aligns with the Harrod-Domar growth model, which suggests that an increase in physical capital investment results in physical capital accumulation, thereby fostering economic growth. The model implies that higher savings and investment contribute to robust GDP growth. However, the long-run coefficient for physical capital is less than that in the short-run. This finding is consistent with the Solow (1957) model, which argues that physical capital alone cannot sustain long-term growth due to diminishing returns. This model indicates that while economic growth increases with greater physical capital, the potential growth rate decreases over time. These findings align with those of empirical studies by Bal et al. (2016), Bunyamin (2022) and Ding et al. (2021) but contradict the empirical results of Haldar and Mallik (2010), Mehrara and Musai (2013) and Pomi et al. (2021).

Second, the findings reveal that the coefficient of human capital is positive and significant at the 1% level in the short-run and long-run. A greater long-run coefficient indicates that human capital becomes more significant over time, promoting sustained economic growth. This finding is consistent with Romer (1986; 1990) and Lucas (1988), who suggest that investing in human capital drives long-term economic growth, especially in leading provinces. Human capital enhances worker productivity through education, training, health improvements, and skills and knowledge (Schultz, 1961). Although intangible, human capital is vital for boosting productivity and increasing national income. Barro and Sala-i-Martin (1995) further argue that education increases the marginal productivity of skilled workers, indirectly benefiting other workers. The findings concerning human capital in this study are consistent with the empirical results of Sharma and Sahni (2015), Parika and Singh (2020), Uddin et al. (2021) and Bunyamin (2022). However, they differ from the findings of Johnson (2016), Muhamad et al. (2018) and Alhassan et al. (2021).

Third, R&D is positively associated with growth performance in the long term at a significant level of 1%, although the overall effect of R&D remains relatively moderate. This weaker effect may be attributed to relatively low R&D investment levels in China's leading provinces. R&D also has a positive effect in the short term; but it is not statistically significant. The endogenous growth model framework has been most frequently used in empirical research on this relationship, as these theories illustrate the knowledge accumulation process directly through human capital accumulation or indirectly via R&D (Lucas, 1988; Romer, 1986). Romer (1986; 1990) and Grossman and Helpman (1991)

Table 4: Panel ARDL model results (PMG, MG and DFE estimator)

Variable	PMG				MG				DFE			
	Coefficient	Standard error	z	P-value	Coefficient	Standard error	z	P-value	Coef.	Standard error	z	P-value
Long-run effects (LR)												
k_t	0.1902***	0.0722	2.63	0.008	0.4868	0.4738	1.03	0.304	0.3141**	0.1466	2.14	0.032
L_t	0.2619	0.2228	1.18	0.240	−0.0597	1.3637	−0.04	0.965	−0.1471	0.4645	−0.32	0.752
H_t	0.8537***	0.3033	2.81	0.005	1.0441	0.9915	1.05	0.292	0.6662	0.6981	0.95	0.340
r_t	0.2847***	0.0483	5.89	0.000	0.0596	0.4599	0.13	0.897	0.2239*	0.1181	1.90	0.058
Short-run effects (SR)												
ECT	−0.2188***	0.0753	−2.90	0.004	−0.4789***	0.1135	−4.22	0.000	−0.1218***	0.3787	−3.22	0.001
Δk_t	0.8425***	0.2721	3.10	0.002	0.9452***	0.1890	5.00	0.000	0.6606***	0.0849	7.78	0.000
ΔL_t	−0.1818	0.5205	−0.35	0.727	−0.2526	0.7263	−0.35	0.728	0.1370	0.1551	0.88	0.377
ΔH_t	0.2173***	0.0526	4.13	0.000	0.2199***	0.6846	3.21	0.001	0.1682***	0.0591	2.85	0.004
Δr_t	0.0635	0.0795	0.80	0.424	0.0077	0.1381	0.06	0.955	0.1130	0.0721	1.57	0.117
_cons	0.3816***	0.1308	2.92	0.004	−0.7118	2.9995	−0.24	0.812	0.5571	0.4229	1.32	0.188

***, **, and * denote 1%, 5% and 10% levels of significance, respectively. ECT is an error correction term. The lag length selection of panel ARDL (1, 1, 1, 1) is based on BIC criteria

Table 5: Hausman test for an efficient estimator

Coefficient	k_t	L_t	H_t	r_t
Hausman test 1: PMG versus MG				
PMG	0.1902	0.2619	0.8537	0.2847
MG	0.4867	−0.0596	1.0441	0.0596
Difference	−0.2965	0.3215	−0.1903	0.2251
chi^2 (4) = 1.41				
Probability>chi^2=0.8428 P value is>5%, indicating that PMG is preferred to MG				
Hausman test 2: PMG versus DFE				
PMG	0.1902	0.2619	0.8537	0.2847
DFE	0.3140	−0.1470	0.6662	0.2239
Difference	−0.1237	0.4089	0.1874	0.0607
chi^2 (4) = 0.01				

Probability >chi^2=1.0000 P-value is >5%, indicating that PMG is preferred to DFE

emphasize that R&D acts as a growth engine, with optimal levels of R&D activities stimulating innovation and inducing the growth process. In accordance with endogenous growth theories, this study also reveals a strong and significant positive association between R&D and economic growth in the long-run, whereas the short-run relationship remains insignificant. Empirical studies, such as Blanco et al. (2016), Khan and Khattak (2014), and Haseeb et al. (2019), support the positive impact of R&D on long-run productivity growth, while Saidi and Mongi (2018), and Gumus and Celikay (2015) also reflect this relationship in the short-run. Conversely, Tuna et al. (2015) suggest that there is no association between R&D and economic growth, and Alhassan et al. (2021) report that investment in R&D adversely influences growth performance in the short-run. In addition, new products undergo a time-consuming process of R&D. Breakthroughs in basic research may take time to be converted into new products, processes, or services. Likewise, applied research also requires time to develop prototype products and launch new products on the market. It is necessary to account for such time lags by defining the law of motion of the technological knowledge stock (Jones, 2019).

Finally, the coefficient of labor is statistically insignificant in the long-run and short-run, with values of 0.2619 in the long-run and −0.1818 in the short-run. The population growth rate is frequently employed as a proxy for labor growth. According to Solow (1957) neoclassical growth model, population growth negatively correlates with growth in per capita output. In contrast, Romer's endogenous growth theory suggests that population growth might increase per capita income by increasing the workforce in R&D sectors, thus expediting the process of technological advancement (Zhao, 2019). In this study, the results of labor align with those of Ahmed et al. (2016), Cruz and Ahmed (2018). However, numerous studies, such as Khatun and Afroze (2016), identify a strong positive relationship between labor and real GDP. Shahid (2014) states that labor positively affects economic growth in the long-run, whereas it has a negative effect in the short-run. These findings are opposite to the empirical study by Haque et al. (2019). Moreover, Young (2018) observed that labor dynamics significantly affect growth performance in the short-run and long-run. With a shrinking working-age population, China may reach a demographic shift, which might hinder potential economic growth in the short term. In the long-run, average labor productivity is likely to rise because incoming cohorts have more years of schooling than those in exiting labor (Ciuriak, 2022; Lam et al., 2015).

To support the existence of a long-run equilibrium relationship between variables, this study employs three additional types of panel co-integration tests developed by Kao (1999), Pedroni (1999; 2004) and Westerlund and Edgerton (2007) tests, as illustrated from Tables 6-8. Accordingly, the results demonstrate that the null hypothesis of no co-integration is rejected at the 1% significance level, indicating a long-run relationship between economic growth and its determinants, namely, physical capital, labor, human capital and R&D.

Considering the above analysis, we can draw the following conclusions. First, the panel ARDL model in the PMG estimator confirms that a long-run relationship exists between economic growth and physical capital, human capital and R&D, except for labor. The findings also reveal that physical capital and human capital have a significant positive influence on economic performance in the short-run. The speed of adjustment is negative and significant in all three estimators, suggesting that there is no omitted variable bias. Second, by examining the panel co-

Table 6: Kao panel co-integration test results

Estimates	Statistical	P-value
Modified Dickey-Fuller *t*	−10.4578***	0.0000
Dickey-Fuller *t*	−8.2060***	0.0000
Augmented Dickey-Fuller *t*	−3.5327***	0.0002
Unadjusted modified Dickey	−14.0652***	0.0000
Unadjusted Dickey-Fuller *t*	−8.6391***	0.0000

***, **, and * denote 1%, 5% and 10% levels of significance, respectively

Table 7: Pedroni panel co-integration test results

Estimates	Statistical	P-value	Weighted statistical	P-value
Alternative hypothesis: common AR coefficient (within-dimension)				
Panel v-Stat.	1.8568**	0.0317	1.9344**	0.0265
Panel rho-Stat.	−2.4504***	0.0071	−2.4004***	0.0082
Panel PP-Stat.	−5.1312***	0.0000	−5.0622***	0.0000
Panel ADF-Stat.	−4.7166***	0.0000	−4.6768***	0.0000
Estimates	**Stat.**		**P-value**	
Alternative hypothesis: individual AR coefficient (between-dimension)				
Group rho-Stat.	−1.7882**		0.0369	
Group PP-Stat.	−6.0232***		0.0000	
Group ADF-Stat.	−5.5958***		0.0000	

***, **, and * denote 1%, 5% and 10% levels of significance, respectively

Table 8: Westerlund and Edgerton panel co-integration test results

Variable	Value	*z* value	P-value	Robust P-value
G_t	−3.743***	−4.201***	0.000	0.000
G_a	−17.278***	−2.548***	0.005	0.000
P_t	−9.117***	−4.070***	0.000	0.000
P_a	−17.767***	−3.904***	0.000	0.000

***, **, and * denote 1%, 5% and 10% levels of significance, respectively. Bootstrap replication is 100

integration process, the panel co-integration tests developed by Kao (1999), Pedroni (1999; 2004) and Westerlund and Edgerton (2007) also suggest that a long-run relationship exists between variables.

In terms of policy implications, the empirical findings of this study offer policymakers a more comprehensive understanding of the relationship between economic growth and factor inputs essential for policy formulation in China, particularly the policy in China's top six economic powerhouses. The important policy implications of this study suggest that policymakers should not ignore the explanatory power of factor inputs, namely physical capital, labor, human capital, and R&D, on growth in navigating economic evolution, e.g., shifts in China's economy during the pre- and post-new normal eras from relying on increasing quantities of inputs to focusing on improving the quality and efficiency of those inputs. In doing so, through their accumulation and utilization in production processes, these factor inputs may collectively enhance an economy's production capabilities and growth potential. The government is required to devise investment policies aimed at boosting the country's GDP and, as a result, improving the welfare of its citizens and devise a population policy for population dividends that will stimulate GDP growth to achieve and maintain high economic expansion. Additionally, policymakers are urged to exert effort to stimulate the factors that drive economic growth, i.e., human capital and R&D. The government must optimally allocate national resources to human capital, thereby increasing the stock of human capital, which includes education, health, intelligence, skills, and training with the intention of increasing the marginal productivity of labor and, in turn, stimulating economic growth, or enhancing the trend of the positive association between capital formation and economic growth by increasing knowledge investment and innovation.

6. CONCLUSION

This study examines the dynamic relationship between economic growth and factor inputs (namely, physical capital, labor, human capital, and R&D) by employing the Pesaran et al. (1999) panel ARDL method for long-run and short-run relationships in China's top six economic powerhouses, i.e., Guangdong, Jiangsu, Shandong, Zhejiang, Henan and Sichuan Province over the period 1996-2022. The results obtained from the modified Romer (1990) model, which uses the panel ARDL method, support the hypothesis that economic growth has a dynamic relationship with its determinants, namely, physical capital, labor, human capital, and R&D. Moreover, the estimated response function of the modified Romer (1990) model suggests that factor inputs, namely physical capital, labor, human capital and R&D, are useful indicators of a government's decision making, and the factor inputs support the prediction of economic growth.

However, the current study has several limitations. First, the sample in this study includes only six provinces and four variables, namely, physical capital, labor, human capital and R&D. A potential field for future study is thereby the inclusion of other variables (e.g., institutional quality) in the modified Romer (1990) model to broaden the scope of the research (Note that this tool is unavoidably complicated when too many variables are included in the growth model). Additionally, it is also possible to replicate procedures such as those used in this study in other countries or regions. Second, considering the time dimensions and the data collection needed, it is also subject to the limitations posed by secondary sources in terms of availability. The findings will yield more meaningful results if more data is available in future research. Moreover, the findings may not be applicable across all regions in China, as the local industrial structure or government policy sometimes drives factor inputs. Finally, this study does not identify the role of technical change, i.e., the limited focus on whether the traditional reliance on factor inputs has been undermined by technical change.

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