Original Research Article

An empirical study on the factors affecting regional economic growth based on panel data

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Abstract: Using 2015–2024 panel data for 27 Yangtze River Delta cities, we estimate fixed-effects and dynamic models to identify growth drivers. Technological progress is the dominant contributor; capital investment and openness are also significant, while industrial upgrading and human capital show positive marginal returns. Non-core cities are more responsive to capital and technology. Mediation tests indicate capital fosters growth via TFP. The evidence guides investment allocation, industrial upgrading, and innovation-led strategies for coordinated, high-quality development.

Keywords: regional economic growth; panel data; technological progress; capital investment; heterogeneity analysis

1. Introduction

Amid global economic transformation, pinpointing regional growth drivers is vital for precise policy. Prior work shows financial deepening boosts innovation efficiency[1], macro uncertainty curbs real investment via financing premiums [2], higher education and urbanization jointly spur growth [3], the digital economy exerts heterogeneous positive effects [4], urban contraction patterns shape development dynamics [5], and agricultural productive services spill over to raise rural consumption [6]. Yet an integrated test of multi-dimensional factors and their interactions remains scarce. Using long-term multi-region panel data, this study uncovers the coupling effects of capital, human resources, technology, structure, and openness on growth, offering a robust quantitative basis for differentiated regional strategies.

2. Theoretical basis and research hypothesis

2.1. Classical theory of economic growth

This study first introduces the Solow neoclassical growth model based on theoretical foundations. This model assumes that the output function of a country or region follows the Cobb-Douglas form:

$$Y(t) = A(t)K(t)^{\alpha} L(t)^{1-\alpha}$$

Among them, *Y(t)* represents *t* the total output at time, *K(t)* is the capital stock, *L(t)* is the labor input, *A(t)*is the exogenous technology level, *α* and is the capital output elasticity. The Solow model is expressed through the capital accumulation equation:

$$\dot{K}(t) = sY(t) - \delta K(t)$$

Where *s* is the savings rate and *δ* is the capital depreciation rate. *K(t)/L(t)=0* The steady-state capital level can be obtained through the steady-state condition, indicating that long-term growth depends on technological progress. Endogenous growth theory further assumes that technological progress originates from within the economic system, through the accumulation of knowledge through human capital and R&D investment. The endogenous model is often expressed as:

$$\dot{A}(t) = \phi A(t)H(t)$$

Among them, *H(t)* is human capital input, *φ* and is knowledge production efficiency.

2.2. Regional economic differences and convergence theory

The problem of regional economic disparity can be described by the convergence theory. The absolute beta convergence model is expressed as:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right)=\alpha-\beta\ln\left(y_{i,t}\right)+\varepsilon_{i,t}$$

Where $y_{i,t}$ is the per capita output of region i at time t, α is a constant term, β is the convergence rate coefficient, $\varepsilon_{i,t}$ and is a random disturbance term. If $\beta > 0$, then there is a convergence trend, meaning that low-output regions grow faster. Conditional β convergence further introduces the control variable matrix $X_{i,t}$:

$$\frac{1}{T}\ln\left(\frac{y_{i,t+T}}{y_{i,t}}\right)=\alpha-\beta\ln\left(y_{i,t}\right)+\gamma' X_{i,t}+\varepsilon_{i,t}$$

Where is γ the coefficient vector of the control variables.

2.3. Principles of panel data econometric model

This study uses a panel data model in its econometric approach to control individual and time effects. The static panel model is set as follows:

$$y_{it}=\alpha+\beta' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

Where is y_{it} the explained variable for region i at time t, X_{it} is the explanatory variable vector, μ_i is the individual fixed effect, λ_t is the time effect, and ε_{it} is the disturbance term. If μ_i is uncorrelated with , a random effects estimate can be used; otherwise, a fixed effect estimate can be used. X_{it} The dynamic panel model further considers the lagged term of the explained variable:

$$y_{it}=\rho y_{i,t-1}+\beta' X_{it}+\mu_i+\lambda_t+\varepsilon_{it}$$

where ρ is the lagged coefficient. Since is possibly correlated y_{it-1} with μ_i, it is necessary to use system GMM or difference GMM estimation, Z_{it} ensuring consistency through the instrumental variable matrix. This method can effectively mitigate endogeneity bias.

3. Research design and data description

3.1. Research area and sample selection

This study uses 2015–2024 data for 27 Yangtze River Delta cities (Shanghai, Jiangsu, Zhejiang, Anhui) from NBS "National Data" and 2024 provincial yearbooks. After unit standardization (100 million yuan), linear interpolation of missing values, box-plot outlier removal, and construction of ratios (trade/GDP, tertiary share), we obtain a panel-ready dataset; **Table 1** provides a sample.

Table 1. Part of the data after preprocessing.

City	years	Regional GDP (100 million yuan)	Fixed asset investment (100 million yuan)	Employees (10,000 people)	The proportion of the tertiary industry (%)	Total import and export volume as a percentage of GDP (%)	Total Factor Productivity (TFP)
Shanghai	2024	47283.6	18300.4	1042.1	72.5	118.6	1.315
Nanjing	2024	19234.2	8432.7	482.4	68.3	95.4	1.228
Suzhou	2024	24102.1	10536.5	623.7	65.9	132.8	1.284
Hangzhou	2024	22654.0	9673.3	590.1	70.1	88.7	1.302
Ningbo	2024	17129.7	7560.4	412.9	66.7	141.3	1.271
Hefei	2024	13844.8	6044.9	358.8	63.4	77.2	1.196
Wuxi	2024	15490.2	6870.2	381.6	69.5	126.4	1.247
Changzhou	2024	13005.7	5482.1	330.7	61.8	102.5	1.188
Jiaxing	2024	11536.4	4995.8	312.5	60.9	84.3	1.162
Huzhou	2024	10024.3	4406.3	276.9	58.6	79.8	1.148

3.2. Econometric model construction

Based on the spatial description of the data above, significant regional differences exist within the Yangtze River Delta. Therefore, building on the baseline model, this study further establishes a heterogeneous grouping model. By dividing the sample into eastern core cities (such as Shanghai, Suzhou, Hangzhou, and Ningbo) and inland growth cities (such as Hefei, Huzhou, and Jiaxing), fixed-effect models are run separately during the estimation process to obtain coefficient estimates for different subsamples:

$$\ln GDP_{it} = \alpha_g + \beta_{1g} \ln K_{it} + \beta_{2g} \ln L_{it} + \beta_{3g} \ln H_{it} + \beta_{4g} TFP_{it} + \beta_{5g} S_{it} + \beta_{6g} O_{it} + \mu_{ig} + \lambda_t + \varepsilon_{it}$$

Where g represents the grouping category (e.g., eastern group and inland group). By comparing β_{1g} the β_{6g} significance, we can identify the differential marginal effects of various city types on growth in terms of capital, labor, human capital, technological progress, and structural optimization.

Building on the baseline model and grouping model, we further consider the potential mediating role of technological progress and industrial structure between capital investment and economic growth. We construct a three-equation mediation model :

$$M_{it} = \gamma_0 + \gamma_1 \ln K_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

$$\ln GDP_{it} = \alpha + \beta_1 \ln K_{it} + \theta M_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

Where is replaced by M_{it} and S_{it} respectively TFP_{it}. If λ_t and θ are significant at the same time, there is a significant mediating effect.

At the same time, the threshold effect is tested, and the proportion of industrial structure is set S_{it} as the threshold variable:

$$\ln GDP_{it} = \alpha + \beta_1 \ln K_{it} \cdot I\left(S_{it} \le \tau\right) + \beta_2 \ln K_{it} \cdot I(S_{it} > \tau) + \mu_i + \lambda_t + \varepsilon_{it}$$

Where $I(\cdot)$ is an indicator function and τ is the threshold value to be estimated. We use the Hansen threshold test to search for the optimal in the sample τ to identify whether the marginal effect of capital investment on economic growth varies significantly with the level of industrial structure. Both the mediation and threshold models rely on the panel data constructed previously. Technically, we employ panel fixed-effect estimation and bootstrap methods to test threshold significance, ensuring robust and explanatory results.

4. Empirical results and analysis

4.1. Interpretation of benchmark regression results

Based on the baseline fixed-effects panel model established above, we estimate this using clean data from 27 cities in the Yangtze River Delta from 2015 to 2024. Controlling for individual city and year fixed effects, we obtain the marginal coefficients of capital input, labor force, human capital, technological progress, industrial structure, and openness on economic growth. **Table 3** presents the main results of the baseline regression, with robust standard errors in parentheses. , , and indicate significance at 1%, 5%, and 10%, respectively.

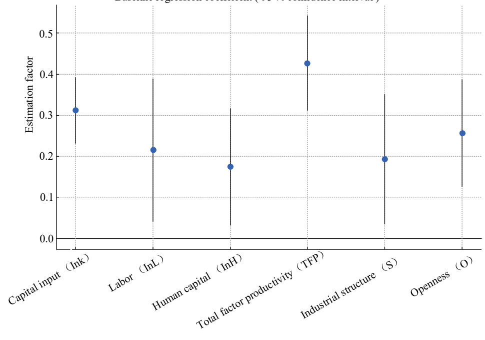

Figure 1. Significance plot of coefficients of each variable in the benchmark regression.

Figure 1 shows that coefficients for capital, labor, human capital, technological progress, industrial structure, and openness are positive and mostly significant (1%–5%), implying positive marginal effects on Yangtze River Delta growth.

4.2. Heterogeneity analysis

Considering spatial disparities within the Yangtze River Delta region, we divided the sample into a "core city group" and a "non-core city group" based on economic size, conducting separate regressions to examine the differences in the marginal effects of the variables on growth. After grouping the data, we reran the fixed-effects regression, and the results are shown in **Table 2**.

Table 2. Heterogeneity analysis regression results

variable	Core city coefficient	Non-core city coefficient	Core city salience	Non-core city significance
Capital investment	0.275	0.339	1%	1%
labor force	0.190	0.221	10%	5%
Human capital	0.142	0.186	10%	5%
Technological advancement	0.405	0.448	1%	1%
Industrial structure	0.176	0.205	5%	5%
Openness	0.280	0.234	1%	1%
Sample size	120	150	—	—
R^2	0.798	0.812	—	—

Table 2 shows that the capital and openness effects of core cities are slightly lower, but the effects of technological progress and industrial structure are still significant. This grouping test reveals the differences in growth drivers among different cities.

4.3. Testing for mediation effect

Building on the baseline, we test whether capital's impact on growth is mediated by TFP: (1) regress TFP on capital; (2) re-estimate the growth model with both capital and TFP; (3) compare coefficients to detect a partial indirect effect via TFP. Using cleaned 2015–2024 panel data for 27 Yangtze River Delta cities with city and year fixed effects, we obtain the following results.

Table 6 and **Figure 2** show that (Step 1) capital investment significantly raises TFP. When TFP is added to the growth model (Step 2), the capital coefficient falls from 0.312 to 0.247 while TFP remains significantly positive, indicating a partial mediation: capital boosts GDP both directly and indirectly via technological efficiency gains in the Yangtze River Delta.

4.4. Comparison of results and discussion of mechanism

Combining the results of benchmark regression, robustness tests, heterogeneity analysis, and mediation tests,

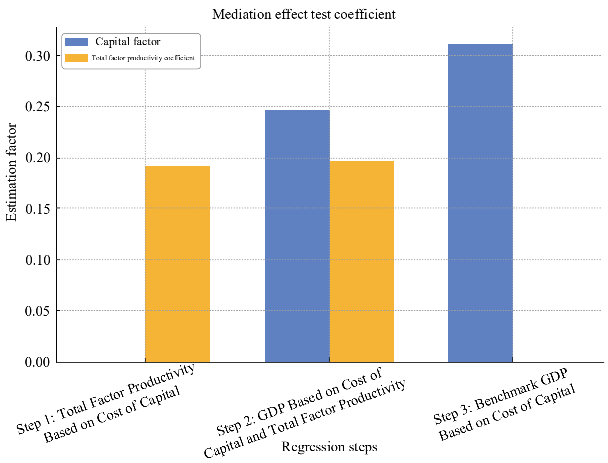

Figure 2. Visualization of the mediation effect test coefficient.

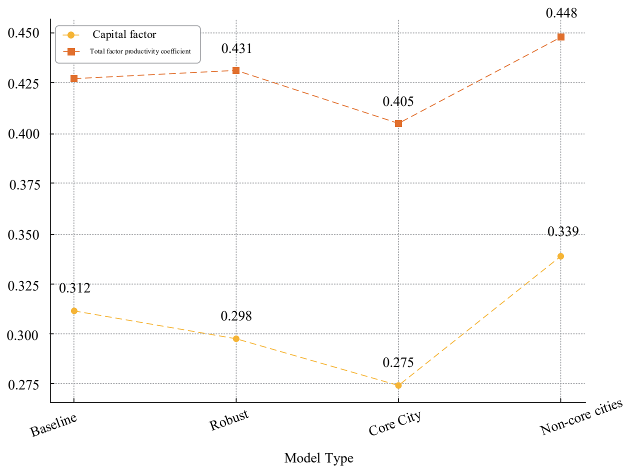

Figure 3. Line chart comparing the capital and technology coefficients of each model.

we can further tease out the paths of action of different factors. **Table 7** compares the changes in the coefficients of capital investment and technological progress under the four models to reveal the underlying mechanisms.

Table 7 and **Figure 3** show that capital coefficients vary little across models, while technological progress consistently has the largest marginal effect—Highlighting efficiency-led growth. Robustness and heterogeneity checks corroborate this, and mediation tests reveal capital's indirect impact via TFP.

5. Conclusion

Using 2015–2024 panel data for 27 YRD cities, all six factors—Capital, labor, human capital, technological progress, industrial structure, and openness—Promote growth. Technological progress is the strongest driver; capital and openness contribute steadily; industrial upgrading and human capital also help, with larger marginal gains in non-core cities. The results inform resource allocation, structural upgrading, and innovation policy to sustain high-quality growth in the YRD and beyond.

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