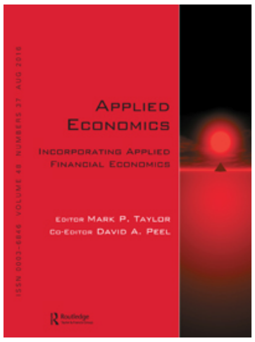


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# Detecting multiple factors in panel data: an application on the growth of local regions in China

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**ABSTRACT**

Due to unbalanced growth in China's local regions, we construct a panel data model with multiple common factors to examine the differences among the growth factors in these areas. This article shows the various impacts from the supply and demand sides on economic growth. Different from the demand side, the supply-side impacts have permanent influences. This article focuses on these deep and profound impacts to explain the reasons behind China's fast economic growing. By using data on 27 regions from 1958 to 2013, we summarize the main permanent influences along three lines. The first comes from the coastal regions, which have learned modern technology and systems from foreign companies, such as in Guangdong, Zhejiang, Fujian and Liaoning. The second comes from big cities, such as Beijing and Shanghai, in which a huge migration has given the companies opportunities to recruit excellent workers, making the resource allocation specialized and more efficient. The third is from the government's major public works, which have improved areas' infrastructure and assisted long-run economic growth, such as for Sichuan, Guangxi and Yunnan.

**KEYWORDS**
Panel data model; common factors; unit root test; whittle method; canonical correlation; temporary and permanent effects

**JEL CLASSIFICATION**
C23; C52



## I. Introduction

Economic impacts that come from the supply side, such as technological advances or physical capital and human capital progress, have profound and permanent influences on economic growth. As these impacts possess permanent effects, implying a capacity for achievement in future economic growth, it is necessary to figure out the share in economic growth from the supply side, especially for developing countries, thus indicating potential strength for development. As is well known, China's territory is vast and its economic growth is unbalanced with large gaps of wealth among different regions. Some places in the interior are poor, while some coastal provinces are prosperous. What causes such a dispersion? This article investigates the hidden strength that causes economic growth and recognizes the impacts coming from the supply side and demand side. We develop a panel data model with multiple factors to decompose economic growth, in which the factors can be either stationary or non-stationary.

A shock with a mean reversion characteristic indicates a temporary effect in an economic series, thus expressing stationary fluctuations. In the long run, these effects will gradually diminish; thus, how to recognize the long-run effects in an economic series has become an important issue in the literature. Different from a temporary effect, a non-stationary process possesses a persistent characteristic, whereby a shock with a non-stationary process has permanent effects. In the long run, these effects always exist. Many economists in the literature have viewed movements in aggregate output as either temporary or permanent shocks when discussing the properties of economic growth. Nelson and Plosser (1982) proposed a test to detect whether macroeconomic time series are better characterized as stationary fluctuations around a trend or non-stationary process. Long and Plosser (1983) and De Long and Summers (1988) regarded that if real GDP is highly persistent, then the shocks must be principally attributed to technology, whereas if there is little persistence, then the shocks must be principally attributed to aggregate demand, such as innovations to monetary and fiscal policies. Campbell and Mankiw (1987a, 1987b) provided a different perspective, claiming that an economic model employs a unit root associated with agents'

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Supplemental data for this article can be accessed here.

environments. Campbell and Mankiw (1987b) and Quah (1988) suggested that the variable can be decomposed into permanent and temporary components. Christiano (1987) and Christiano and Eichebaum (1989) used a parametric approach to estimate the long-run response of real GNP. Cheung and Chinn (1996) noted that the GDP of 126 countries is better described as trend stationary or non-stationary and found that most countries are likely non-stationary. Why should we recognize these different effects? Only through the identification of the different type factors can we understand what are the real causes that influence economic growth in the long run.

The availability of abundant data enables researchers today to analyse issues more precisely, not just for a few macroeconomic series. Many studies have moved on to a large sample with a panel data model. When considering a large dataset, heterogeneity becomes an important issue. Factor models thus provide an effective way for synthesizing information contained in different subjects. Several important studies shed light on the common stochastic components in panel data. Stock and Watson (2002a, 2002b) regarded the factors as unobservable economic indices to capture the co-movement of different variables and then used these factors to improve forecasting accuracy. Bai (2004) discussed non-stationary dynamic factors in a large-dimension factor model, in which co-integration among the factors is permitted. Bai and Ng (2004) developed a useful method for describing the factor structure of large dimensional panels, which they named 'panel analysis of non-stationarity in idiosyncratic and common components' (PANIC). Moon and Perron (2004) assumed data are generated by unobservable common factors and provided a testing method for a large dimension of cross-sectional and time length panel data.

As a method of gathering information from large-dimensional data, these analyses offer fruitful thoughts and illuminate new perspectives on the application of factor models. In addition, how to examine the existence of unit roots in a large number of individuals has become an important issue, which can be seen in Choi and Chue (2007), Baltagi, Bresson, and Pirotte (2007), Pesaran (2007) and Gengenbach, Palm, and Urbain (2009). These studies present an insight into a large-dimensional datasets, developing an asymptotic estimator to test for a non-stationary property, by employing cross-sectional and serial correlation. Tiwari, Chaudhari, and Suresh (2012) examined stationary characteristics of per capita GDP for the sub-panels of 17 Asian countries, developing second-generation tests to reveal stationarity.

This article emphasizes on extracting the factors according to their particular characteristics. By the distinguishing characteristics, we attempt to explain those sources that affect China's economic growth, through the linkage between the factors and the different regions. As each factor has a different degree of persistence and size of fluctuation, we suggest a panel data model with multiple factors, in which we can recognize each factor being either a stationary or non-stationary process. Canonical correlations are used to develop a trace of the likelihood ratio test, in which we examine the property of each factor. This article recognizes those influential sources on China's strong economic growth.

The remainder of this article is arranged as follows. Section II suggests an economic model and discusses why the effects coming from the supply side possess a permanent effect, expressing a non-stationary property that is different from the demand side demonstrating temporary effects with a stationary process. Section III presents a panel data model with multiple factors and the disturbances employ serial correlations, in which we use the trace statistics to detect stationarity and non-stationarity. Section IV estimates the factors for the panel GDP per capita of 27 regions in China (province level) and rebuilds the time series according to the stationary and non-stationary factors. To examine our model with efficiency and accuracy in its application, we use Monte Carlo experiments to determine the sizes of statistics based on the estimates of the empirical results. We illustrate each factor with a decaying rate and a fluctuating size. Section V gives concluding remarks, highlighting this article's contribution.

## II. Economic model

This section investigates the factors that constitute economic growth, as we extend a contract model from a general form. Following Fischer (1977) and Blanchard and Quah (1989), the model shows that the characteristics of impacts from aggregate demand and supply are different. The major permanent effects come from the supply side, while the transitory effects are from the demand side, which are associated with non-stationary and stationary processes, respectively.

According to Lucas (1976), we assume an aggregate supply function, $y_t^s = p_t - w_t + u_t$, where $y_t$ is the logarithm of the output level, $p_t$ is the logarithm of the price level, $w_t$ is the logarithm of the wage and $u_t$ is the disturbance. Using the one-period contract model, we set the wage at the end of period $t$–1 for period $t$ to maintain constancy of the real wage, $w_{t|t-1} = p_{t|t-1}$. Following Fischer (1977), we now have the following aggregate demand and supply functions:

$$y_t^d = m_t - p_t + v_t,$$
$$y_t^s = p_t - p_{t|t-1} + u_t,$$

where $m_t$ is the logarithm of the money stock in period $t$; $v_t$ denotes the shock in the aggregate demand side, which could come from fiscal policy, investment, exports, imports, etc.; and $u_t$ could be productivity or technological improvement from the aggregate supply side.

According to Blanchard and Quah (1989), we assume non-stationary processes, $m_t = m_{t-1} + \xi_t$, $v_t = v_{t-1} + \epsilon_t$ and $u_t = u_{t-1} + \boldsymbol{\eta}_t$, implying they are essentially unstable. By setting $y_t^d = y_t^s = y_t$, we solve for the aggregate demand and supply equilibria:

$$y_t = \frac{1}{2}\left(m_t - p_{t|t-1}\right) + \frac{1}{2}(u_t + v_t).$$

As $y_t^d = y_t^s$, we have $2p_t - p_{t|t-1} = m_t + v_t - u_t$. Taking the expectation at the end of period $t$–1, we have $p_{t|t-1} = m_{t|t-1} + v_{t|t-1} - u_{t|t-1}$. With a random walk assumption, we have $m_{t|t-1} = m_{t-1}$, $v_{t|t-1} = v_{t-1}$ and $u_{t|t-1} = u_{t-1}$.

Putting this into the equation, we get

$$y_t = \frac{1}{2}(m_t - m_{t-1}) + \frac{1}{2}(v_t - v_{t-1}) + \frac{1}{2}(u_t + u_{t-1}).$$

Expanding the above equation, we have

$$y_t = \frac{1}{2}\xi_t + \frac{1}{2}\epsilon_t - \frac{1}{2}\boldsymbol{\eta}_t + \sum_{j=-\infty}^{t}\boldsymbol{\eta}_j,$$

where output includes two parts: one is transitory that mainly comes from aggregate demand, including the first three terms; and the other is permanent, where we see the last term has cumulated shocks, which encompass a non-stationary process from aggregate supply. In the same way, we extend the model to a two-period contract, and the aggregate supply becomes $y_t^s = p_t - \frac{1}{2}\left(p_{t|t-1} + p_{t|t-2}\right) + u_t$. We have

$$y_t = \frac{1}{2}\left(\xi_t + \epsilon_t - \boldsymbol{\eta}_t\right) + \frac{1}{3}\left(\xi_{t-1} + \epsilon_{t-1} - \boldsymbol{\eta}_{t-1}\right) + \sum_{j=-\infty}^{t}\boldsymbol{\eta}_j.$$

In a general model, we set $y_t^s = p_t - \sum_{j=1}^{q}\varpi_j p_{t|t-j} + u_t$, where $\varpi_j$ is a weight of the wage decision and $\sum_{j=1}^{q}\varpi_j = 1$. We have

$$y_t = \underbrace{\sum_{j=0}^{q}\gamma_j\left(\xi_{t-j} + \epsilon_{t-j} - \boldsymbol{\eta}_{t-j}\right)}_{\text{stationary}} + \underbrace{\sum_{j=0}^{\infty}\boldsymbol{\eta}_{t-j}}_{\text{non-stationary}},$$

where $\gamma_j = \frac{1}{2}\left(1 - \sum_{s=1}^{j}\tau_j\right)$, $\tau_j = \left(2 - \sum_{l=1}^{j}\varpi_l\right)^{-1}\sum_{s=1}^{j}\tau_{s-1}\varpi_s$, and $\tau_0 = 1$. We realize that the first term is a MA($q$) process, which is a stationary process indicating transitory effects. In contrast, the impacts ($\boldsymbol{\eta}_j$, for $j = 0, \ldots, t$) in the second term from the supply side will not decay, having permanent effects on output. We can then use the characteristics of the components to recognize the impacts coming from the supply side or demand side.

## III. Estimating the components with different duration time

Following the previous section, this section develops an approach to capture the common factors according to their different degrees of persistence. Thus, we can separate the effects coming from the supply side or demand side. As noted in the previous discussion, the effects from the supply side are permanent and those from the demand side are temporary. We begin with a one-period lagged model:

$$\Delta\boldsymbol{y}_t = \boldsymbol{\alpha} + \zeta_0\boldsymbol{y}_{t-1} + \boldsymbol{u}_t, \quad \text{for } t = 1, \ldots, T,$$

where $\Delta\boldsymbol{y}'_t = \left[\Delta y_{1,t}, \Delta y_{2,t}, \ldots, \Delta y_{N,t}\right]$, $\boldsymbol{y}'_{t-1} = \left[y_{1,t-1}, y_{2,t-1}, \ldots, y_{N,t-1}\right]$, $\boldsymbol{u}'_t = \left[u_{1,t}, u_{2,t}, \ldots, u_{N,t}\right]$, $\boldsymbol{\alpha}$ is an $N \times 1$ intercept, $\zeta_0$ is an $N \times N$ matrix, $N$ is the cross-section dimension and $T$ is the time dimension. Note that $y_{k,t}$ represents the $k$th individual at time $t$, and $\Delta y_{k,t}$ is its corresponding difference.

We note here that if $\boldsymbol{y}_t$ is an I(1) non-stationary process, then its variance–covariance matrix will diverge. In other words, if we let $\Omega_{11} \equiv \frac{1}{T}\sum_{t=1}^{T}$

$(\Delta \boldsymbol{y}_t - \Delta \bar{\boldsymbol{y}})(\Delta \boldsymbol{y}_t - \Delta \bar{\boldsymbol{y}})'$, $\Omega_{22} \equiv \frac{1}{T}\sum_{t=1}^{T}(\boldsymbol{y}_{t-1} - \bar{\boldsymbol{y}})(\boldsymbol{y}_{t-1} - \bar{\boldsymbol{y}})'$ and $\Omega_{12} \equiv \frac{1}{T}\sum_{t=1}^{T}(\Delta \boldsymbol{y}_t - \Delta \bar{\boldsymbol{y}})(\boldsymbol{y}_{t-1} - \bar{\boldsymbol{y}})'$, then the growth rate of $\Omega_{22}$ is $O_p(T)$, which will not have convergent values. According to Johansen (1991), we can get the co-integration vector to obtain the stationary components. We have the eigenvalues and eigenvectors of the canonical correlation matrices by the following relationships:

$$\Omega_{22}^{-1}\,\Omega_{21}\,\Omega_{11}^{-1}\,\Omega_{12}\,A_j = \lambda_j A_j$$
$$\text{and} \quad \Omega_{11}^{-1}\,\Omega_{12}\,\Omega_{22}^{-1}\,\Omega_{21}\,k_j = \lambda_j\,k_j,$$

where eigenvalues $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_N$ and the corresponding eigenvectors are $(A_1, A_2, \ldots, A_N)$ and $(k_1, k_2, \ldots, k_N)$. The above equation can be expressed in an alternative form, $A_j'\,\Omega_{21}\,\Omega_{11}^{-1}\,\Omega_{12}\,A_j = \lambda_j\,A_j'\,\Omega_{22}\,A_j$. If the combination $\boldsymbol{y}'_t A_j$ is stationary, then the left- and right-hand sides will both converge as $O_p(1)$ and $0 < \lambda_j < 1$; otherwise, the combination is non-stationary and the right-hand side will be $O_p(T)$, and $\lambda_j$ will approach zero.

To normalize the common factors, we can adjust the eigenvectors associated with $\tilde{A}_j'\Omega_{22}\tilde{A}_j = 1$ and $\tilde{k}_j'\Omega_{11}\tilde{k}_j = 1$, where $\tilde{A}_j = A_j \div \sqrt{A'_j\Omega_{22}A_j}$, $\tilde{k}_j = k_j \div \sqrt{k'_j\Omega_{11}k_j}$, $\tilde{A} = [\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_N]$ and $\tilde{K} = [\tilde{k}_1, \tilde{k}_2, \ldots, \tilde{k}_N]$. The transformed factors can then be obtained:

$$\boldsymbol{f}_t = \tilde{A}'\tilde{\boldsymbol{y}}_{t-1} \quad \text{and} \quad \boldsymbol{\eta}_t = \tilde{K}'\Delta\tilde{\boldsymbol{y}}_t,$$

where $\boldsymbol{f}'_t = [f_{1,t}, t_{2,t}, \ldots, f_{N,t}]$, $\boldsymbol{\eta}'_t = [\eta_{1,t}, \eta_{2,t}, \ldots, \eta_{N,t}]$ and $\tilde{\boldsymbol{y}}_{t-1}$ and $\Delta\tilde{\boldsymbol{y}}_t$ are the deviation forms of $\boldsymbol{y}_{t-1}$ and $\Delta\boldsymbol{y}_t$, respectively.

Minimizing the determinant of the mean squares of the residuals of the panel model, we have:

$$\left|\frac{1}{T}\sum_{t=1}^{T}(\Delta\tilde{\boldsymbol{y}}_t - \zeta_0\tilde{\boldsymbol{y}}_{t-1})(\Delta\tilde{\boldsymbol{y}}_t - \zeta_0\tilde{\boldsymbol{y}}_{t-1})'\right|.$$

The coefficients of $\Delta\tilde{\boldsymbol{y}}_t$ on regressor $\tilde{\boldsymbol{y}}_{t-1}$ in the above function can be measured by $\Omega_{12}\Omega_{22}^{-1}$. As $\tilde{A}'\Omega_{22}\tilde{A} = I$, the inverse matrix of $\tilde{A}'$ equals $\Omega_{22}\tilde{A}$. When we pre- and post-multiply a matrix by its inverse equal to the identity matrix, we have $\Omega_{22}\tilde{A}\tilde{A}' = I$. Replacing $\Omega_{22}^{-1}$ by $\tilde{A}\tilde{A}'$, we have $\zeta_0 = \Omega_{12}\tilde{A}\tilde{A}'$. In the same way, we have $\Omega_{11}^{-1}$ by $\tilde{K}\tilde{K}'$. Using $\tilde{K}'^{-1}\boldsymbol{\eta}_t = \Delta\tilde{\boldsymbol{y}}_t$ and $\tilde{A}'^{-1}\boldsymbol{f}_t = \tilde{\boldsymbol{y}}_{t-1}$ and putting them into the above equation, we have

$$|\tilde{K}|^{-2}\left|\frac{1}{T}\sum_{t=1}^{T}(\boldsymbol{\eta}_t - \Pi\boldsymbol{f}_t)(\boldsymbol{\eta}_t - \Pi\boldsymbol{f}_t)'\right|,$$

where $\Pi = \tilde{K}\Omega_{12}\tilde{A}$ is the coefficients of $\boldsymbol{\eta}_t$ on $\boldsymbol{f}_t$, and $|\tilde{K}|^{-2} = |\Omega_{11}|$.

As $f_{j,t}$ and $\boldsymbol{\eta}_{j*,t}$ are mutually orthogonal for $j \neq j*$, we get the correlations $\text{corr}(f_{j,t}, \boldsymbol{\eta}_{j,t}) = r_j$ and $\text{corr}(f_{j,t}, \eta_{j*,t}) = 0$ for $j \neq j*$. Each component will be like a simple regression with a deviation form, and thus the coefficient of determination for $f_{j,t}$ on $\eta_{j,t}$ is equal to $r_j^2$. The value of the mean squares of the residuals of the panel data model equals $|\Omega_{11}|\prod_{j=1}^{N}(1 - r_j^2)$, and we can express it alternatively as $|\Omega_{11}|\prod_{j=1}^{N}(1 - \lambda_j)$. If we have $N - h$ elements of $\boldsymbol{f}_t$ that are non-stationary, implying these factors have no explanation capability, then their corresponding canonical correlations, $r_{h+1}, r_{h+2}, \ldots, r_N$, are equal to zero. Using the eigenvalue, we can detect whether each factor is stationary or not; in other words, if $\lambda_j > 0$, then $f_{j,t-1}$ is a stationary process; otherwise, $\lambda_j = 0$ indicates non-stationarity.

Let $\boldsymbol{f}_t^s$ and $\boldsymbol{f}_t^n$ represent the corresponding stationary and non-stationary components[1] of $\boldsymbol{f}_t$. We can then rebuild the stationary $\tilde{\boldsymbol{z}}_t^s$ and non-stationary $\tilde{\boldsymbol{z}}_t^n$ according to these common factors:

$$\tilde{\boldsymbol{z}}_t^s = \Omega_{22}\tilde{A}\boldsymbol{f}_t^s \quad \text{and} \quad \tilde{\boldsymbol{z}}_t^n = \Omega_{22}\tilde{A}\boldsymbol{f}_t^n,$$

where $\tilde{\boldsymbol{y}}_t = \tilde{z}_t^s + \tilde{z}_t^n$. Furthermore, we can measure the impacts from the stationary and non-stationary components, which help us to understand the structure of the panel data. As $\tilde{z}_t^s$ and $\tilde{z}_t^n$ are mutually orthogonal, we can measure their mean squared error to display their shares in an unexpected shock. For an individual, we have two series, $\tilde{y}_{k,t} = \tilde{z}_{k,t}^s + \tilde{z}_{k,t}^n$, where one is non-stationary and the other is stationary.

**Consider serial correlation** Disturbance $u_{k,t}$ is associated with an ARMA$(p, q)$ model:

$$\phi(B)u_{k,t} = \theta(B)a_{k,t},$$

[1] If we take the stationary part, we can leave the stationary elements and replace the non-stationary series by zero. We can do the same thing for the non-stationary part.

where $a_{k,t}$ follows a distribution, $\mathrm{NID}(0, \sigma_k^2)$, and $\sigma_k^2$ varies heteroscedastically as $k$ changes. Term $B$ is a lag operator. The roots of the autoregressive (AR) and moving average (MA) polynomial operator functions, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p = 0$ and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \ldots + \theta_q B^q = 0$, are located outside the closed unit circle.

According to Chen (2006), the cross variance and covariance can then be expressed as the following:

$$\Omega_{11}(\Theta) = 4\pi \sum_{j=1}^{T*} Re\left(\frac{F_{\Delta y}(\omega_j)\bar{F}'_{\Delta y}(\omega_j)}{g(\omega_j;\Theta)}\right),$$

$$\Omega_{22}(\Theta) = \frac{4\pi}{T} \sum_{j=1}^{T*} Re\left(\frac{F_{y-1}(\omega_j)\bar{F}'_{y-1}(\omega_j)}{g(\omega_j;\Theta)}\right) \quad \text{and}$$

$$\Omega_{12}(\Theta) = \frac{4\pi}{\sqrt{T}} \sum_{j=1}^{T*} Re\left(\frac{F_{\Delta y}(\omega_j)\bar{F}'_{y-1}(\omega_j)}{g(\omega_j;\Theta)}\right),$$

where $F_{\Delta y}(\omega_j)$ and $F_{y-1}(\omega_j)$ are the Fourier transforms of $\Delta y$ and $y_{-1}$ at frequency $\omega_j$, respectively; $g(\omega_j;\Theta) = |\theta(e^{-i\omega_j})/\phi(e^{-i\omega_j})|^2$; and $T^*$ is the floor integer of $T/2$, for $\omega_j = \frac{2\pi j}{T}$ and $j = 1, \ldots, T^*$. We can estimate $\hat{\Theta}$ through a likelihood function and achieve the largest value given by

$$L(\Theta) = -\frac{TN}{2} log2\pi - \frac{T}{2} log|\Omega_{11}(\Theta)| - \frac{T}{2}\sum_{j=1}^{N} log(1 - \lambda_j(\Theta)),$$

where $\lambda_j(\Theta)$ are the eigenvalues of $\Omega_{22}^{-1}(\Theta)\, \Omega_{21}(\Theta)\, \Omega_{11}^{-1}(\Theta)\Omega_{12}(\Theta)$ for $j = 1$ to $N$, and $\lambda_j(\Theta)$ can be used to test whether $z_{j,t}$ is stationary or not.

According to Sims, Stock, and Watson (1990), if we set a null hypothesis with $H_0 : r_{h+1} = r_{h+2} = \ldots = r_N = 0$, then it implies $z_{j,t}$ is non-stationary for $j = h + 1, \ldots, N$. We would expect a trace of twice the log likelihood ratio, $2(L_A - L_0) = -T\sum_{h+1}^{N} log\left(1 - \hat{\lambda}_j\right)$, to be an asymptotic distribution with the trace of the following matrix:

$$Q \equiv \left[\int_0^1 \mathbf{W}(s)d\mathbf{W}(s)'\right]' \left[\int_0^1 \mathbf{W}(s)\mathbf{W}(s)'dr\right]^{-1} \left[\int_0^1 \mathbf{W}(s)d\mathbf{W}(s)'\right],$$

where $\mathbf{W}(s)$ is $N - h$ dimensional standard Brownian motions with variance $s$. Based on the characteristics of the factors, we can rebuild the series associated with stationarity and non-stationarity, in which we can observe their changes over different subjects.

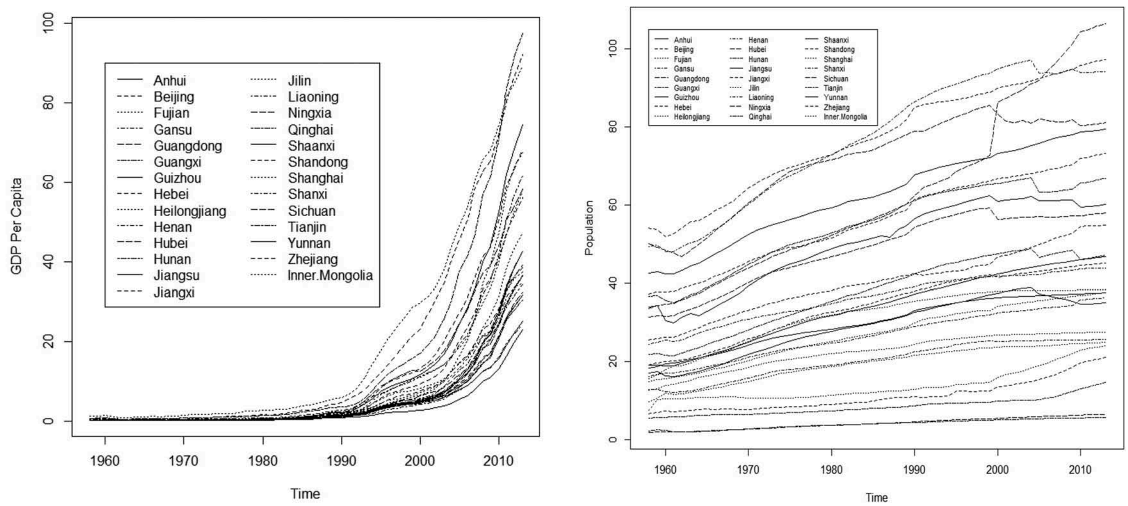
## IV. Empirical study and Monte Carlo experiment

In the empirical study, we examine the GDP of 27 major administrative regions (provincial level) in China,[2] using annual data from 1958 to 2013, which come from the National Bureau of Statistics of China (see Figure 1). Referring to the figure, the annual GDP per capita rose exponentially while the population grew linearly. As is well known, China has huge land areas at disparate stages of economic development. Some regions in China have grown fast, while some have fallen behind, and the discrepancies in modernization and globalization are significant.

The top three regions by GDP per capita are Tianjin, Beijing and Shanghai, and their GDP per capita values hit 97,610, 92,210 and 89,442 RMB annually in 2013, each of which is more than four times the poorest province Quizhou, whose GDP per capita is only 22,862 RMB (see Table 1).

What is the reason that causes such a large gap? We think the main cause is from persistent growth, that is chiefly from the supply side. High persistent growth indicates firms have strong incentives to create and sustain new products. The economic environment provides fertile soil, which usually comes from several aspects, such as technological advances, physical or human capital progress and well-developed systems. With the disparity of GDP per capita in Table 1, we find that most highly developed regions belong to coastal areas; among the top 10 richest 9 are located in coastal regions, which are open to the outside world and have high degrees of globalization with many multinational enterprises located there (see Supplemental data). If a region (or city) is open to the outside world, it will have more opportunities to learn advanced technology or systems, which help firms to make progress. Thus, an important work is to figure out how much of the impact in local economic growth comes from the permanent supply-side effects.

[2]The regions include Anhui, Beijing, Fujian, Gansu, Guangdong, Guangxi, Guizhou, Hebei, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Jiangxi, Jilin, Liaoning, Ningxia, Qinghai, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Yunnan, Zhejiang and Inner Mongolia.




(a) Unit: thousand RMB. (b) Unit: million people.

**Figure 1.** The annual GDP per capita and population for 27 major regions in China from 1958 to 2013. The GDP per capita grew exponentially while the population grew linearly.

**Table 1.** GDP per capita for the 27 major regions (province level) of China in 2013, unit: one RMB.

| | GDP per capita | Growth rate (%) |
|---|---|---|
| Tianjin | 97,610 | 6.53 |
| Beijing | 92,210 | 6.30 |
| Shanghai | 89,442 | 5.21 |
| Jiangsu | 74,516 | 8.40 |
| Zhejiang | 68,331 | 7.37 |
| Inner Mongolia | 67,394 | 5.36 |
| Liaoning | 61,680 | 8.22 |
| Guangdong | 58,403 | 7.76 |
| Fujian | 57,657 | 8.83 |
| Shandong | 56,182 | 8.08 |
| Jilin | 47,183 | 8.00 |
| Shaanxi | 42,628 | 9.66 |
| Hubei | 42,539 | 9.49 |
| Ningxia | 39,209 | 7.74 |
| Hebei | 38,597 | 5.52 |
| Heilongjiang | 37,504 | 4.78 |
| Hunan | 36,621 | 8.88 |
| Qinghai | 36,363 | 9.15 |
| Shanxi | 34,719 | 3.38 |
| Henan | 34,160 | 7.88 |
| Sichuan | 32,393 | 8.75 |
| Jiangxi | 31,707 | 9.32 |
| Anhui | 31,575 | 8.96 |
| Guangxi | 30,468 | 8.62 |
| Yunnan | 25,009 | 11.52 |
| Gansu | 24,274 | 9.70 |
| Guizhou | 22,862 | 13.98 |

*Notes*: The wealth gap between the rich and the poor is large. The highest GDP region is Guangdong and its value is 6216.4 billion RMB, which is about 30 times the lowest province Qinghai with its GDP value of 210.1 billion RMB in 2013.

There also exists another important issue: due to the large wealth gap, a huge migration moved from rural to urban areas, especially for big cities such as Beijing, Shanghai and Tianjin. More and more people entered the big cities, giving entrepreneurs more opportunities to recruit excellent employees and increase specialization and division of labour. This has improved allocation efficiency. With the cities dense population this has spilled over easily, also helping push economic growth.

The following context measures the common factors from the 27 regions (province level), in which we test whether the factors are stationary or not. To reduce the influence of extreme value, we take a logarithm of each subject. After removing the trends and means, we get the common factors. The eigenvalues $\lambda_j$ are 1.000*, 0.9993*, 0.9988*, 0.9976*, 0.9933*, 0.9886*, 0.9766*, 0.9627*, 0.9553*, 0.9302*, 0.923*, 0.8824*, 0.8787*, 0.8261*, 0.7943*, 0.76*, 0.7011*, 0.6776*, 0.5975*, 0.5245, 0.4715, 0.4686, 0.3491, 0.2722, 0.169, 0.1619 and 0.129, respectively; the corresponding trace statistics are 3942.07, 3379.37, 2974.41, 2597.84, 2261.10, 1980.77, 1730.13, 1519.93, 1335.78, 1161.70, 1012.61, 869.01, 749.12, 630.98, 533.03, 444.48, 364.56, 296.93, 233.54, 182.58, 140.95, 105.23, 69.82, 45.78, 27.99, 17.63 and 7.74. Asterisks denote rejection at the significance level of 5%.[3]

Regarding $\lambda_j$ as the determination coefficient, we can calculate the autoregressive coefficients for each implicit factor. As the non-stationary factor's coefficient equals unity, we only need to calculate the stationary factors. Denote $\rho_j$ as the coefficient for the hidden stationary

[3]According to Osterwald-Lenum (1992), the last 10 critical values for the trace statistics of likelihood ratio tests are 12.25, 25.32, 42.44, 62.99, 87.31, 114.90, 146.76, 182.82, 222.21, and 263.42.

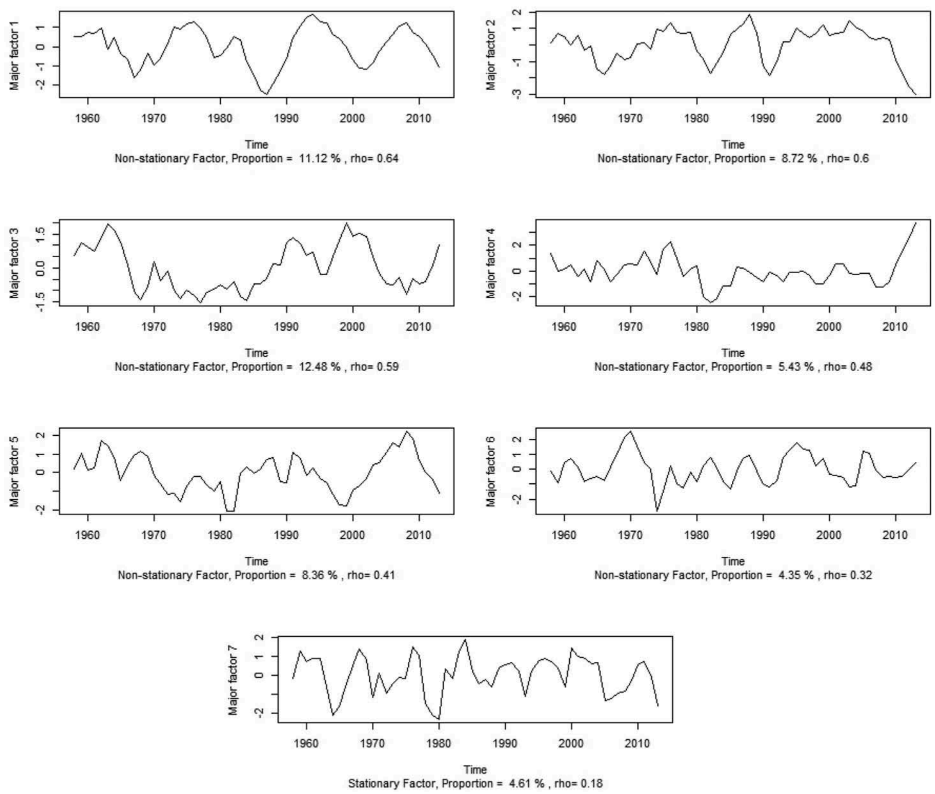



**Figure 2.** The common major factors whose proportions are above 4%.

factor, $f_{j,t} = \rho_j f_{j,t-1} + \hat{u}_{j,t}$, where $\left(1-\rho_j\right)^2 = \lambda_j$ and $\rho_j < 1$. The values of $\rho_j$ are then 0.00, 0.0004, 0.0006, 0.0012, 0.0034, 0.0057, 0.0118, 0.0188, 0.0226, 0.0355, 0.0393, 0.0606, 0.0626, 0.0911, 0.1088, 0.1282, 0.1627, 0.1769, 0.2270, 0.2758, 0.3133, 0.3154, 0.4092, 0.4783, 0.5890, 0.5976 and 0.6408. Their shares associated with the sum of squares are 2.41%, 3.44%, 2.93%, 1.39%, 3.54%, 1.51%, 2.58%, 1.80%, 2.81%, 2.50%, 1.62%, 2.18%, 1.63%, 1.46%, 1.49%, 1.66%, 1.75%, 4.61%, 2.99%, 2.32%, 2.92%, 4.35%, 8.36%, 5.43%, 12.48%, 8.72% and 11.12%, respectively. The last eight factors are non-stationary, and the sum of proportions is 55.7%. Among these components, there are seven factors exceeding 4%, two are stationary and five are non-stationary, which can be seen in Figure 2.

To examine our model with efficiency and accuracy in the application, we use Monte Carlo simulations with 3000 replications to examine the sizes of the statistics. Based on the estimates of the empirical results, we simulate 27 common factors. Here, we generate the disturbances associated with the MA(1) model, where the coefficient spans from –0.5 to 0.9. Table 2 shows the sizes of our test and finds that our method is reliable.

Beginning with our discussion, we use the capital city Beijing as an example. The initial series can be constructed by the common factors:

$$\tilde{y}_{Bj,t} = \underbrace{\begin{array}{l} 3.33f_{1,t} + 0.47f_{2,t} + 2.74f_{3,t} + 0.09f_{4,t} + 4.84f_{5,t} + 4.21f_{6,t} \\ +1.85f_{7,t} + 1.33f_{8,t} + 5.57f_{9,t} + 1.37f_{10,t} + 4.20f_{11,t} \\ +0.57f_{12,t} + 0.97f_{13,t} + 0.72f_{14,t} + 2.57f_{15,t} + 1.36f_{16,t} \\ +1.88f_{17,t} + 1.05f_{18,t} + 2.06f_{19,t} \end{array}}_{\text{stationary}}$$
$$\underbrace{\begin{array}{l} +2.21f_{20,t} + 0.78f_{21,t} + 0.91f_{22,t} + 2.73f_{23,t} + 2.68f_{24,t} \\ +3.27f_{25,t} + 1.14f_{26,t} + 2.28f_{27,t}, \end{array}}_{\text{non-stationary}}$$

**Table 2.** We measure the sizes of our test by 3000 replications. Referring to the empirical study, we choose $N = 27$, $T = 150$. The observations are combined by the implicit factors[a] $f_{j,t}$ and $y_{k,t} = \sum_{j=1}^{N} w_{k,j} f_{j,t}$, where $w_{k,j}$ is randomly generated. Twenty-one of the common factors are stationary and the others are non-stationary. Using the trace log likelihood ratio test, the null hypothesis is $H_0 : \lambda_{22} = \lambda_{23} = \ldots = \lambda_{27} = 0$, where $\lambda_1 \geq \lambda_2 \geq \ldots \geq \lambda_{27}$.

| | $H_0 : \lambda_{22} = \lambda_{23} = \ldots = \lambda_{27} = 0$ | | | |
|---|---|---|---|---|
| Disturbance model | 1%[b] | 2.5% | 5% | 10% |
| $\theta = 0.9$ | 0.0153 | 0.0280 | 0.0477 | 0.0813 |
| $\theta = 0.8$ | 0.0187 | 0.0387 | 0.0593 | 0.0953 |
| $\theta = 0.7$ | 0.0183 | 0.0343 | 0.0567 | 0.0890 |
| $\theta = 0.6$ | 0.0227 | 0.0333 | 0.0550 | 0.0903 |
| $\theta = 0.5$ | 0.0147 | 0.0310 | 0.0520 | 0.0833 |
| $\theta = 0.4$ | 0.0173 | 0.0333 | 0.0593 | 0.0913 |
| $\theta = 0.3$ | 0.0233 | 0.0393 | 0.0610 | 0.0900 |
| $\theta = 0.2$ | 0.0147 | 0.0270 | 0.0450 | 0.0830 |
| $\theta = 0.1$ | 0.0170 | 0.0313 | 0.0560 | 0.0897 |
| $\theta = 0.0$ | 0.0167 | 0.0333 | 0.0580 | 0.0883 |
| $\theta = -0.1$ | 0.0150 | 0.0293 | 0.0507 | 0.0907 |
| $\theta = -0.2$ | 0.0200 | 0.0323 | 0.0580 | 0.0967 |
| $\theta = -0.3$ | 0.0210 | 0.0403 | 0.0633 | 0.0980 |
| $\theta = -0.4$ | 0.0170 | 0.0333 | 0.0570 | 0.0863 |
| $\theta = -0.5$ | 0.0163 | 0.0303 | 0.0507 | 0.0790 |

[a]Constructing the stationary components by using $f_{j,t} = \phi_j f_{j,t} + u_{j,t}$ and $\phi_j < 0.6$. The non-stationary factors are set by $f_{j,t} = f_{j,t} + u_{j,t}$. The disturbance has serial correlation by $u_{j,t} = a_{j,t} + \theta a_{j,t-1}$ and is $\theta$ simulated in different values.
[b]The critical values we use refer to Osterwald-Lenum (1992).



where $\tilde{y}_{Bj,t}$ is the GDP per capita of Beijing, taking away the trend and mean. The first 19 factors are stationary, and the last 8 factors are non-stationary. If we measure the GDP of Tiajing according to the stationary and non-stationary components, we can then divide the growth as follows:

$$\tilde{y}_{Bj,t} = \tilde{z}_t^s + \tilde{z}_t^n,$$

where $\tilde{z}_t^s$ and $\tilde{z}_t^n$ represent the bundles of stationary and non-stationary factors, respectively. We know $\tilde{z}_t^n$ is the permanent effect from the supply side, which could come from technological advances, or physical or human capital growth. If the area is widely connected to the outside world, then firms will easily get advanced technology or learn better management systems. This probably causes high profile growth from the supply side. However, this does not indicate the area already has high GDP, but it does imply the area has potential to push economic growth in the long run.

After reconstruction, two processes for the stationarity and non-stationarity of Beijing can be shown as the following. We use the ADF test[4] to verify the properties and get MSE:

$$\Delta\tilde{z}_t^s = -\underset{(0.0844)}{0.3619}\,\tilde{z}_{t-1}^s + \underset{(0.1119)}{0.2967}\,\Delta\tilde{z}_{t-1}^s - \underset{(0.1175)}{0.2513}\,\Delta\tilde{z}_{t-2}^n + e_{2t}, \text{ and}$$

$$\Delta\tilde{z}_t^n = -\underset{(0.0844)}{0.2344}\,\tilde{z}_{t-1}^n + \underset{(0.1366)}{0.0941}\,\Delta\tilde{z}_{t-1}^n + e_{1t}.$$

The statistics for the ADF test are –4.291 and –2.776,[5] respectively, which indicate that the first one is stationary and the second is non-stationary. Furthermore, we measure that the proportion of the RMS of the non-stationary part is 0.4637 (the stationary part is 0.5363).

In the same way, we calculate every region and summarize the results in Tables 3 and 4. We can verify the reconstruction series for each region and show consistency in the properties. We find that the top five provinces associated with the rate of non-stationary root RMS are Sichuan (0.6245), Guangdong (0.6140), Yunnan (0.5923), Zhejiang (0.5586) and Fujian (0.5556). As is well known, Guangdong, Zhejiang and Fujian are coastal provinces, which conduct a lot of international trading with the outside world, and are southeastern business centres connecting with Hong Kong and having sea routes to Taiwan, Southeast Asia, Europe and the United States. Sichuan is a relay station of China to Central Asia, Mediterranean Sea and Europe. Its capital, Chongqing, is a business centre and the beginning station for a railway across Central Asia to the Europe. Similarly, Yunnan is a pivot region to Indochina Peninsula and Southeast Asia. These five

[4]Here, the lag length used is according to the BIC criterion.
[5]The critical value according to the Dickey–Fuller test based on the estimated OLS $t$-statistics is –3.43 at the significance level of 5%.

**Table 3.** Using the common factors, we reconstruct China's GDP per capita for the 27 provinces according to the non-stationary components. We use the ADF[a] test to verify the property. The proportions are measured by the sum of squares, and the best BIC is used for the optimal lag length $p$. We arrange the proportion values from large to small.

| | Coefficients | | ADF value[b] | Proportion of MSE |
|---|---|---|---|---|
| Province | $\hat{\rho}-1$ | $\hat{\sigma}_p$ | $\frac{\hat{\rho}-1}{\hat{\sigma}_p}$ | Non-stationary innovation |
| Sichuan | −0.2351 | 0.0921 | −2.5528 | 0.6245 |
| Guangdong | −0.2095 | 0.0826 | −2.5365 | 0.6140 |
| Yunnan | −0.2163 | 0.086 | −2.5154 | 0.5923 |
| Zhejiang | −0.2139 | 0.0837 | −2.5536 | 0.5586 |
| Fujian | −0.2084 | 0.0828 | −2.5155 | 0.5556 |
| Guangxi | −0.2335 | 0.09 | −2.5936 | 0.5452 |
| Shandong | −0.2406 | 0.0906 | −2.6554 | 0.5211 |
| Jiangsu | −0.2341 | 0.0887 | −2.64 | 0.5008 |
| Qinghai | −0.2486 | 0.0959 | −2.5934 | 0.5000 |
| Jilin | −0.239 | 0.0923 | −2.5906 | 0.4939 |
| Guizhou | −0.2295 | 0.0924 | −2.4843 | 0.4905 |
| Inner Mongolia | −0.2434 | 0.0947 | −2.5709 | 0.4794 |
| Liaoning | −0.2415 | 0.0893 | −2.7031 | 0.4740 |
| Heilongjiang | −0.2425 | 0.0924 | −2.6256 | 0.4732 |
| Jiangxi | −0.2437 | 0.0956 | −2.549 | 0.4693 |
| Ningxia | −0.2494 | 0.0958 | −2.6031 | 0.4652 |
| Shaanxi | −0.2567 | 0.0972 | −2.6404 | 0.4646 |
| Hubei | −0.2375 | 0.0934 | −2.5424 | 0.4629 |
| Hunan | −0.2492 | 0.0956 | −2.6063 | 0.4580 |
| Hebei | −0.2476 | 0.0914 | −2.708 | 0.4530 |
| Anhui | −0.2508 | 0.0948 | −2.6448 | 0.4374 |
| Shanxi | −0.246 | 0.0924 | −2.6616 | 0.4286 |
| Gansu | −0.2818 | 0.1011 | −2.7865 | 0.4256 |
| Henan | −0.2616 | 0.0958 | −2.7319 | 0.4107 |
| Municipal cities | | | | |
| Beijing | −0.2344 | 0.0844 | −2.7764 | 0.4637 |
| Shanghai | −0.2338 | 0.0841 | −2.7794 | 0.4075 |
| Tianjin | −0.2706 | 0.0956 | −2.8307 | 0.3633 |

[a]The ADF model is $\Delta\tilde{z}_t = \alpha + (\rho-1)\tilde{z}_{t-1} + \delta_1\Delta\tilde{z}_{t-1} + \cdots + \delta_p\Delta\tilde{z}_{t-p} + a_t$.
[b]The critical value at the significance level of 5% is −3.45.

**Table 4.** Using the common factors, we reconstruct China's GDP per capita for the 27 provinces according to the stationary components. We use the ADF test[a] to verify the property. The proportions are measured by the sum of squares, and the best BIC is used for the optimal lag length $p$. We arrange the values of portions from small to large.

| | Coefficients | | | |
|---|---|---|---|---|
| Province | $\hat{\rho}-1$ | $\hat{\sigma}_p$ | ADF value[b] $\left(\frac{\hat{\rho}-1}{\hat{\sigma}_p}\right)$ | Proportion of MSE (stationary innovation) |
| Sichuan | −0.3672** | 0.1057 | −3.4726 | 0.3755 |
| Guangdong | −0.4294** | 0.1086 | −3.9523 | 0.3860 |
| Yunnan | −0.4103** | 0.1073 | −3.8229 | 0.4077 |
| Zhejiang | −0.3772** | 0.1008 | −3.7425 | 0.4414 |
| Fujian | −0.3944** | 0.0998 | −3.9509 | 0.4444 |
| Guangxi | −0.3845** | 0.1015 | −3.7864 | 0.4548 |
| Shandong | −0.356** | 0.0949 | −3.7519 | 0.4789 |
| Jiangsu | −0.367** | 0.0982 | −3.7387 | 0.4992 |
| Qinghai | −0.3302 | 0.1097 | −3.0093 | 0.5000 |
| Jilin | −0.3643* | 0.1074 | −3.3905 | 0.5061 |
| Guizhou | −0.3748** | 0.1079 | −3.4745 | 0.5095 |
| Inner Mongolia | −0.3365** | 0.0949 | −3.5439 | 0.5206 |
| Liaoning | −0.523** | 0.1025 | −5.1048 | 0.5260 |
| Heilongjiang | −0.3594** | 0.0941 | −3.8209 | 0.5268 |
| Jiangxi | −0.3283* | 0.0955 | −3.438 | 0.5307 |
| Ningxia | −0.348* | 0.1023 | −3.4017 | 0.5348 |
| Shaanxi | −0.3623** | 0.1003 | −3.6125 | 0.5354 |
| Hubei | −0.3459** | 0.096 | −3.6033 | 0.5371 |
| Hunan | −0.3291** | 0.0933 | −3.5274 | 0.5420 |
| Hebei | −0.3822** | 0.0934 | −4.0922 | 0.5470 |
| Anhui | −0.3796** | 0.1042 | −3.6449 | 0.5626 |
| Shanxi | −0.3529** | 0.0996 | −3.543 | 0.5714 |
| Gansu | −0.378** | 0.0906 | −4.1708 | 0.5744 |
| Henan | −0.3493** | 0.0921 | −3.7933 | 0.5893 |
| Municipal cities | | | | |
| Beijing | −0.3619** | 0.0844 | −4.2908 | 0.5363 |
| Shanghai | −0.253 | 0.0908 | −2.7869 | 0.5925 |
| Tianjin | −0.29* | 0.0877 | −3.3073 | 0.6367 |

[a]The ADF model is $\Delta\tilde{z}_t = \alpha + (\rho-1)\tilde{z}_{t-1} + \delta_1\Delta\tilde{z}_{t-1} + \ldots + \delta_p\Delta\tilde{z}_{t-p} + a_t$.
[b]The critical value at the significance level of 5% is −3.45.
**denotes rejection at the significance level of 5%.
*denotes rejection at the significance level of 10%.

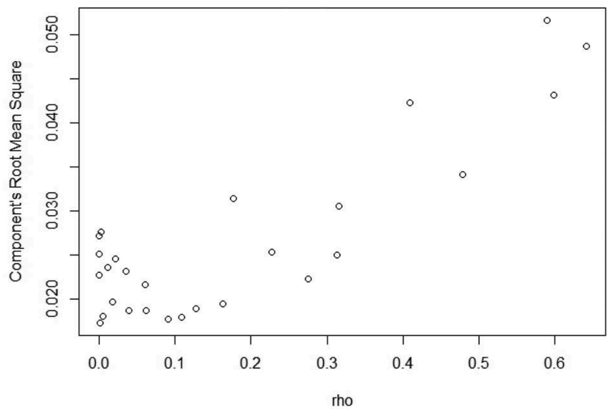



**Figure 3.** The relationship between the components' RMS and $\hat{\rho}$. If the value of $\hat{\rho}$ is great indicating the influence of the component in economic growth is profound and large.

provinces are all important gates for China to the outside world.

We are interested in what are these factors that drove the provinces to have such fast growth. Figure 3 provides insight into the economic growth by using the different decaying rate factors. Along the $x$-axis, when we move rightward, $\hat{\rho}$ increases, indicating the factor is more persistent or has a longer duration. Along the $y$-axis, RMS indicates the size of the shock; if RMS becomes larger, then the shock is important and has a large influence on economic growth.

Figure 3 also illustrates that the degree of the persistence is significantly positively correlated with RMS; when $\hat{\rho}$ becomes large, the size of RMS also increases. With a simple measurement, we calculate the correlations between the top factors and each province. For the first component with the longest persisting factor, we see that the highest correlated five provinces[6] are Guangxi, Shanghai, Beijing, Liaoning and Yunnan, respectively. Similarly, for the second component, the top five provinces are Shanghai, Beijing, Guangdong, Zhejiang and Fujian. For the third, the top five provinces are Yunnan, Fujian, Guangdong, Zhejiang and Sichuan.

According to Figure 3, we know that the factors with high persistent characteristics dominate and push economic growth. From these regions, we mainly split the strength into three lines. The first is from the coastal regions, such as Guangdong, Zhejiang, Fujian and Liaoning, which have gotten technology knowledge from foreign countries, such as Taiwan, Hong Kong, the United States, Japan, South Korea and those from Europe. This development is similar to the United States beginning from coastal regions. The second is from big cities, such as Shanghai and Beijing. These cities have attracted a huge migration from various places and caused technology to spill over fast. These cities have developed their own entrepreneurship platforms. Here, companies have become more and more specialized, and resource allocation has become more efficient. This has benefited domestic firms in their competition with other countries. The third group is from places with the government's important infrastructure, such as Sichuan, which possesses the main train station leading across Central Asia to Europe and Guangxi and Yunnan, which have important investments in the Nananning–Kunming High-Speed Railway. These public construction projects have improved infrastructure, helping long-run economic growth.

## V. Concluding remarks

This article develops a multiple factor panel data model to detect the implicit factors that are pushing China's fast economic growth. Applying our model, we identify the components that come from the supply and demand sides. As the supply-side impacts have permanent effects, we focus on the persisting components.

The strength influencing China's fast growth can be mainly split into three aspects. The first comes from the coastal regions, which have learned modern technology and systems through foreign countries, such as Taiwan, Hong Kong, the United States, Japan and South Korea. The second comes from big cities, which have attracted a huge migration, developed their own entrepreneurial system, which then quickly spill over, such as in Shanghai and Beijing. The third is from the government's important public construction works, which have improved the infrastructure and help long-run regional growth, such as Sichuan, Yunnan and Guangxi. This study provides a useful approach to capture these implicit factors, in which we have identified the components coming from the supply and demand sides, allowing us to clarify the sources of China's strong economic development.

[6]The correlations between the first component and the top five cities are 0.3396, 0.3365, 0.2877, 0.2551 and 0.2463, respectively.

## Disclosure statement

No potential conflict of interest was reported by the author.

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