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WHAT DRIVES CHINA'S LONG-TERM ECONOMIC GROWTH TREND? A RE-MEASUREMENT BASED ON A TIME-VARYING MIXED-FREQUENCY DYNAMIC FACTOR MODEL

Dayu LIU[1], Bin XU[1], Yang SONG[2*], Qiaoru WANG[3]

[1]*Quantitative Economics Center, Jilin University, 2699 Qianjin Street, Changchun, Jilin 130012, China PR*
[2]*School of Public Finance and Taxation, Southwestern University of Finance and Economics, 555 Liutai Avenue, Chengdu, Sichuan 611130, China PR*
[3]*School of Economics and Management, Nanchang University, 999 Xuefu Avenue, Nanchang, Jiangxi 330031, China PR*

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Abstract. The unprecedented downward pressure of China's economic growth trend raises several questions, including what the current level of China's long-term economic growth trend is, and what drives and how to inhibit the downward trend. Therefore, we develop a time-varying mixed-frequency dynamic factor model using data with different start dates to measure the trend, and perform a real-time decomposition of changes in the trend. We find that the trend has entered a downward stage since 2007, left a high-speed phase since 2012, and stepped in an accelerated downward stage since 2018. The current level of the trend is about 4%. However, the lower limit of the 90% confidence interval is below 2%, which is lower than natural rate level. Additionally, decelerated capital deepening, diminishing demographic dividend and technological recession all drive the downward trend. Compared to the relatively weak push-down effects of capital deepening and demographic dividend that are less than two percentage points, the downward trend is mainly driven by technological recession. Given that technological progress is unlikely to improve significantly in the short run, mitigating the mismatch between technological progress and obsolete capital, revitalizing existing capital stock, and increasing the efficiency of technology utilization become more feasible means.

Keywords: economic growth, long-term trend, time-varying mixed-frequency dynamic factor model using data with different start dates, factor decomposition.

JEL Classification: C32, C53, E27.

*Corresponding author. E-mail: *davidsong26@gmail.com*

Introduction

Since the outbreak of COVID-19, China's medium-to-high speed economic growth rate has been fundamentally disrupted, and then the economic growth rate has entered a phase of irregular operation. In the quarter of the epidemic, the economic growth rate has plunged from 5.8% to –6.9%, which forms the first negative growth since China's reform and opening up. As the pandemic becomes gradually under control, the economy rebounds steadily, so that the 2nd–4th quarterly economic growth rates in 2020 reach 3.1%, 4.8% and 6.4%, respectively. In addition, the 1st quarterly economic growth rate in 2021 has sharply rebounded to 18.3% thanks to the base effect earlier, and the 2nd quarterly counterpart is as high as 7.9% still. However, as the public expectation of China's economic growth rate returning to medium-to-high and even high levels, the economy shows sign of losing momentum again. For example, the 3rd quarterly economic growth rate in 2021 has plummeted to 4.9%, and then has declined continually, until 0.4% near zero in the 2nd quarter of 2022. Based on the above facts, China's economic growth rate has neither returned to the medium-to-high level nor even avoided the risk of recession. Therefore, it is pivotal to project the future direction of China's economic growth, which essentially depends on the accuracy of measuring China's long-term economic growth trend as our first core question to answer in this paper.

In fact, besides accurately measuring China's long-term economic growth trend, we need project its future direction in terms of factor contribution in order to principally clarify the mechanism of fluctuations in China's long-term economic growth trend. Previous studies on the causes of China's deceleration from high to medium-to-high growth rate can be classified into three perspectives. Firstly, the theory of investment decline (e.g., Dinlersoz & Fu, 2022) fundamentally attributes China's long-term rapid economic growth over the subsequent three decades since the reform and opening up to investment expansion caused by lack of infrastructure. Given that infrastructure usually lasts for a relatively long time, it is unlikely to reinvest massively in the short run. As a result, the scale and efficiency of investment both decline so significantly that economic growth rate decelerates from the high level to the medium-to-high level. Secondly, the theory of diminishing demographic dividend (e.g., Autor et al., 2013; Hsieh & Ossa, 2016) claims that China has benefited from sizeable demographic dividend considering its overall and per-capita gross domestic product (GDP) since the reform and opening up. Hence, China's relatively low cost of labor is key to account for its long-term rapid economic growth. Nevertheless, as China's real income per capita surpasses the middle-income threshold, its demographic dividend has considerably diminished relative to other emerging economies such as Vietnam, Burma and India, which essentially determines a systematic downward trend of economic growth rate. Thirdly, the theory of technological recession (e.g., Liu & Xia, 2018; Shi et al., 2022) studies the downward trend of China's economic growth with respect to its decelerating technological progress. Although China's rapid economic growth has once been heavily reliant on technology acquisition, the present low-hanging fruit of technology has been plucked as technology advances. Thus, China has to enter a new innovation stage of independent research and development (R&D). However, given the slow technological progress of independent R&D as well as the mismatch between new technology and obsolete capital, decelerating output growth is mainly triggered by the declining rates of technological progress and total factor productivity (TFP). While these plausible theories can account for China's deceleration from high to medium-to-high economic growth rate in a way, they fail to put investment, demographic dividend as well as technological progress into a unified framework, not to mention which of the three factors makes the greatest contribution to fluctuations in China's long-term economic growth trend. In the context of the current strong economic volatility, we are increasingly concerned about whether China's long-term economic growth trend tends to change again, and whether the trend of medium-to-high growth rate tends to end? If so, what are the main drivers of these changes, and to what extent are they contributing? This is our second core question to answer in this paper, which is also a question that has not been discussed in previous studies.

Nevertheless, this paper finds it very challenging to answer the two core questions above, which puts forward higher requirements for empirical research technique improvements. Firstly, in the case of trend measurement, time-varying characteristics must be incorporated into models in order to capture changes in the long-term economic growth trend. For example, Jiang et al. (2017), Antolin-Diaz et al. (2017) and Chernis et al. (2020) find that certain low-frequency information (e.g., consumption and investment) and real-time macroeconomic data both can significantly improve the measurement accuracy of forecasting the long-term economic growth trend. Considering that real-time macroeconomic data is usually characterized by late start date and high frequency, we must add mixed-frequency data with different start dates into forecasting models. Secondly, in the case of investigating the causes of changes in economic growth trend, it is necessary to consider other drivers besides traditional factors of production such as capital, labor and technology. For example, Liu and Xia (2018) and Shi et al. (2022) find that China faces mismatch in capital deepening, that is, the decline in capital utilization driven by technological progress. Hence, we should take this into full consideration during production function decomposition. It requires us to further improve the accuracy of production function decomposition, empirical data match and econometric model estimation, which is also one of our novel contributions in this paper.

Overall, the innovation and contributions of this paper can be summarized as follows. Firstly, in order to measure China's long-term economic growth trend, we develop a time-varying mixed-frequency dynamic factor model with different start dates that meets the requirements of data at mixed frequencies, data with different start dates as well as time-varying estimation. Secondly, we validate that China's medium-to-high economic growth rate trend since 2020 shows signs of unsustainability. More specifically, the trend's lower limit is 4% based on estimation using the 68% confidence interval, while approaching the natural rate of 2% based on estimation using the 90% confidence interval. Thirdly, we decompose the Cobb–Douglas (C–D) production function by decomposing labor productivity into the sum of capital deepening and technological progress, which reveals the essential causes of decreased labor productivity in China more comprehensively. We find that declines in TFP due to technological changes is the fundamental reason for China's current plummeting economic growth rate that has been further exacerbated by widespread R&D stagnation and massive idle capital.

The rest of this paper is organized as follows. We review the literature in Section 1. Section 2 specifies model setting, data selection and methodology introduction. Followed by Section 4 focusing on the contribution decomposition and cause analysis of fluctuations in China's long-term economic growth trend, Section 5 performs a real-time estimation of the trend. The last Section concludes.

1. Literature review

The measurement of the long-term economic growth trend and its mechanism analysis have always been critical in the field of macroeconomics. This section will review the literature in accordance with these two principle lines.

1.1. Measurement of the long-term economic growth trend

There are several common methods of measuring the long-term economic growth trend: the Hodrick–Prescott (H–P) filter (Hodrick & Prescott, 1997), Baxter–King (B–K) filter (Baxter & King, 1999), Christiano–Fitzgerald (C–F) filter (Christiano & Fitzgerald, 2003), Beveridge–Nelson (B–N) decomposition (Beveridge & Nelson, 1981) and universally composable (UC) model (Clark, 1987). Although they can directly separate the trend and cycle components from economic growth, estimation results are highly dependent on parameter setting, data attribute and subjective selection. For example, most studies claim that smoothing weight factor λ should be 100 by using the H–P filter and annual data, while Ravn and Uhlig (2002) considers 6.25 to be to more appropriate. Wang et al. (2019) finds that different values of λ will exert a considerable impact on measuring the long-term economic growth trend whose deviation may exceed two percentage points. Given that the deviation continues to expand as data frequency increases, parameter setting will determine estimation results in consequence. Relatively speaking, the B–K and C–F filters separate the trend and cycle components from the frequency perspective, which greatly overcomes the H–P filter's problem of processing high-frequency data. However, they also have two inherent flaws: first, an ideal band-pass filter requires an infinite sample size, while actual data usually cannot meet this requirement. Thus, an approximate treatment is needed for actual estimation. The symmetry of the filters makes it impossible to keep censoring data, which implies that they are lacking of real-time analysis ability. Secondly, categorizing components at which frequency into trend calls for subjective selection, which may seriously compromise the consistency of estimation results (Zheng & Wang, 2013).

Considering the poor prediction ability of traditional filters as well as their inability to correct estimation results on a real-time basis, Harvey (1989) and Morley et al. (2003) propose a time-domain analysis method represented by the UC–Kalman model based on the B–N decomposition. Using state space to characterize the UC model, this method measures the long-term economic growth trend via the Kalman filter and maximum likelihood estimation. The Kalman filter is superior to traditional filters in terms of estimation accuracy because it makes full use of historical information to update estimation results. However, the UC–Kalman model has a drawback: estimation results are highly dependent on the setting of initial values, which is also involved with subjective selection. In general, the filtering methods have been widely used for the sake of convenience and few restriction (Baxter, 1991; King & Rebelo, 1993; Harvey & Jaeger, 1993; Cogley & Nason, 1995; Hodrick & Prescott, 1997; Canova, 1998; Orphanides & van Norden, 2002). Nevertheless, subject to parameter setting, sample choice and initial value deviation, there are sizeable differences between estimation results of measuring the long-term economic growth trend. In addition, the long-term economic growth trend estimated by using the filtering methods is not often consistent with economic substance, which leads to a lack of economic implication. This is another unneglectable flaw of filtering models (Claus, 2003).

Another popular method of measuring the long-term economic growth trend is the dynamic factor model (DFM) whose pre-filtering is primarily used to remove the low-frequency component of growth rate, and then to measure changes in business cycles in early studies (Stock & Watson, 2012). In contrast, Antolin-Diaz et al. (2017) finds information at low frequency to play an important role in measuring the trend component of the long-term economic growth alternatively. The DFM makes three improvements relative to the above two approaches: first, it contains more variable information that makes the estimation results more complete (Zheng & Wang, 2013). Secondly, it consists of variables at different frequencies that enhances the real-time correction ability towards estimation results (Jiang et al., 2017; Chernis et al., 2020). Thirdly, it significantly improves the corresponding prediction accuracy (Jarocinski & Lenza, 2018). Using different DFMs, Zheng and Wang (2013) and Ye (2015) measure China's long-term trend of GDP growth rate, respectively. Their prediction deviation (not exceed 5% at all times) is extremely low, which explains why the DFM has been increasingly widely used. However, previous studies usually assume that a growth rate series has a constant mean for simplicity, and simplify the setting of innovation shocks using the DFM (Zheng & Wang, 2013; Marcellino et al., 2016). In fact, Cogley (2005) and Stock and Watson (2012) state that it is difficult to maintain the long-term economic growth trend for nations whose economic growth rates are not close to the natural rate. In order to accurately characterize structural changes in the long-term economic growth trend, we should either assign greater weights to recent data or allow the mean to change over time, which deserves to optimize and improve for existing DFM.

1.2. Mechanism analysis of the long-term economic growth trend

As one of the most noteworthy macroeconomic topics, discussions about why China experiences a downward trend of long-term economic growth start from 2012. There are three main theories generalized from existing studies: investment decline, diminishing demographic dividend as well as technological recession.

The theory of investment decline argues that: due to the low level of capital stock at the early stage of the reform and opening-up, China needs massive infrastructure construction urgently, which drives rapid economic growth in consequence. However, since the use of infrastructure usually lasts for a relatively long time, it is unlikely to reinvest massively in the short run. Hence, China's economic growth will decelerate after completing its first round of infrastructure construction (Backhouse & Boianovsky, 2016). Numerous empirical studies have provided support for this theory. For example, Faber (2014) finds that reducing the scale of infrastructure investment causes China's real GDP growth rate to decrease by 2–3 percentage points, which is a critical reason for China's decelerated economic growth falling down to the medium-to-high-speed growth interval. Ju et al. (2015) re-examine the above relationship from a regional perspective. Besides drawing similar conclusions, they find that the scale of infrastructure investment differs across regions significantly, which further leads to regional divergence in China. Dinlersoz and Fu (2022) develops a multi-sector DSGE model to measure the growth effects of infrastructure investment in China. It shows that the contribution of infrastructure investment to economic growth is in a volatility contraction pattern, which suggests that capital as a driver of China's economic growth has a diminishing effect.

The theory of diminishing demographic dividend argues that: since China has been a medium-to-high income nation since 2010, persistent increases in labor costs rapidly weaken its comparative advantage of low-cost labor, which further leads to decelerated economic growth (Autor et al., 2013). Hsieh and Ossa (2016) finds that demographic dividend contributes to China's economic growth up to two percentage points during the decade after joining the World Trade Organization (WTO), which is a key reason for China to maintain a long-term high-speed growth. Leukhina and Turnovsky (2016) finds that decreases in labor supply and increases in labor costs both exert strong inhibiting effects on China's economic growth, in which that of the former is greater than that of the latter.

The theory of technological recession argues that: China's technological progress has transformed from the pattern of imported technology to that of independent innovation since 2010. This transformation, which is usually slow and challenging, may cause a downward trend of the long-term economic growth through two ways. The direct way implies that, as independent innovation has great uncertainty and high trial and error costs, the rate of technological progress for independent innovation is obviously lower than that for imported technology (Minetti & Peng, 2018; Liu & Xia, 2018). The indirect way implies that, since new technology and obsolete capital may mismatch along with technology progress, capital utilization rate and TFP may both decline, which leads to decelerated economic growth eventually (Li & Lin, 2018). Using several time-series approaches, Li et al. (2022) finds that technological progress and economic growth are always positively correlated no matter for the short-run shocks or long-term equilibrium. Given that technological cycle is relatively long and changes slowly, the current decelerated economic growth is more likely to be a long-term trend. Di Giovanni et al. (2014), Zhang (2021) and Shi et al. (2022) all examine the above mismatch problem, and find that the declined rate of capital utilization due to technological progress is another trigger of China's decelerated economic growth.

Overall, it is complicated to analyze the mechanism of changes in China's long-term economic growth trend. Most existing studies account for changes in the trend from a single (e.g., investment, population or technology) perspective, which makes mechanism analysis unsystematic and difficult to specify the main driver of China's long-term economic growth downward trend. Therefore, this paper develops a new time-varying mixed-frequency dynamic factor model, which enables a real-time measurement of changes in the trend and its mechanism analysis. More specifically, this paper makes the following four improvements in our model: first, we combine the DFM and mixed-frequency data in order to comprehensively consider the impact of information at different frequencies on the trend. Secondly, we allow the means of the trend and other series to change over time, which is highly consistent with the fact of China's change of pace in economic growth during recent years. Thirdly, we apply stochastic volatility (SV) to characterize the innovations of factor and heterogeneous component, which helps capture the correction effects of eventful random shocks (e.g., stock market crisis, trade friction, the BR-exit, COVID-19 pandemic, etc.). Fourthly, we accurately decompose the components of capital deepening, population dividend and "technology-capital" mismatch, which helps profoundly interpret how they affect the trend. In addition to resolving disputes over changes in the trend, this paper provides a more accurate quantitative analysis of their mechanism.

2. Model, data and methodology

In order to identify China's long-term economic growth trend accurately, this paper develops a new time-varying mixed-frequency dynamic factor model using data with different start dates to track changes in the trend. In this section, we first introduce the estimation process, data selection and data processing of this model. Then, we compare the estimation results of our model to that of classical estimation methods of the trend (e.g., the H–P filter and UC–Kalman model). By examining the accuracy, stability and economic applicability of the estimation results of the trend, our model is proved to possess comparative advantage for subsequent empirical analysis.

2.1. Model

2.1.1. Basic settings

Let $Y_{\mathbf{t}}$ denote a $n \times 1$ – dimensional observable variable at time t, and $\mathbf{f_t}$ denote a $k \times 1$ – dimensional latent common factor (the number of observable variables is much greater than that of latent common factors, or $n >> k$). The model is:

$$Y_{\mathbf{t}} = \mathbf{c_t} + \mathbf{\Lambda f_t} + \mathbf{u_t}, \tag{1}$$

where $\mathbf{\Lambda}$ is a common factor loading, $\mathbf{u_t}$ is a heterogeneous component, and $\mathbf{c_t}$ is the long-term mean of $Y_{\mathbf{t}}$. In order to reveal time-varying characteristics of different variables' long-term trend, $\mathbf{c_t}$ can be expressed as:

$$\mathbf{c_t} = \begin{bmatrix} \mathbf{B} & \mathbf{0} \\ \mathbf{0} & \mathbf{c} \end{bmatrix} \begin{bmatrix} \mathbf{a_t} \\ 1 \end{bmatrix}, \tag{2}$$

where $\mathbf{a_t}$ is a $r \times 1$ – dimensional time-varying mean vector, $\mathbf{B}$ is a $m \times r$ – dimensional matrix determining the influence of time on $\mathbf{c_t}$, $\mathbf{c}$ is a $(n - m) \times 1$ – dimensional constant (which implies that some variables' means will not change over time). Since we aim to observe changes in the long-term trend of real GDP growth rate, the number of latent common factor is set to be 1 ($\mathbf{f_t} = f_t$). Thus, the latent common factor and heterogeneous component can be expressed as:

$$\left(1-\phi(L)\right) f_t = \sigma_{\varepsilon_t} \varepsilon_t; \tag{3}$$

$$\left(1-\rho_i(L)\right) u_{t,t} = \sigma_{\eta_{i,t}} \eta_{i,t}, i = 1,\ldots,n, \tag{4}$$

where $\phi(L)$ and $\rho_i(L)$ is the p – order and q – order lag operator polynomial, respectively. Following Stock and Watson (1988) and Antolin-Diaz et al. (2017), we set $p - q = 2$. The heterogeneous component is assumed to be cross-section orthogonal and not correlated with the latent common factor, $\varepsilon_t \overset{iid}{\sim} N(0,1)$, and $\eta_{i,t} \overset{iid}{\sim} N(0,1)$. Following Primiceri (2005), the dynamic processes of time-varying parameters are subject to random walks without drift:

$$a_{j,t} = a_{j,t-1} + v_{a_{j,t}}, \quad v_{a_{j,t}} \overset{iid}{\sim} N\left(0, \omega_{a,j}^2\right), j = 1, \ldots, r; \tag{5}$$

$$\log \sigma_{\varepsilon_t} = \log \sigma_{\varepsilon_{t-1}} + v_{\varepsilon,t}, \quad v_{\varepsilon,t} \overset{iid}{\sim} N\left(0, \omega_\varepsilon^2\right); \tag{6}$$

$$\log \sigma_{\eta_{i,t}} = \log \sigma_{\eta_{i,t-1}} + v_{\eta_{i,t}}, \quad v_{\eta_{i,t}} \overset{iid}{\sim} N\left(0, \omega_{\eta,i}^2\right), i = 1, \ldots, n, \tag{7}$$

where $a_{j,t}$ is r time-varying elements of $\mathbf{a_t}$, σ_{ε_t} and $\sigma_{\eta_{i,t}}$ are used to reflect the SV of innovations of latent common factor and heterogeneous component, respectively. The introduction of innovation shocks better characterizes the correction effects of random events over the past few years on the long-term economic growth trend, which is more consistent with China's actual condition. It is noted that traditional dynamic factor models usually have two assumptions: first, latent common factor and heterogeneous component are both stationary time series; secondly, innovations of latent common factor and heterogeneous component are both independent identically distributed. It suggests that such models are not applicable to characterize trend changes. A novelty of this paper is to relax these two assumptions in Eqs (1)–(7), and to let the means and volatility terms of series have random trends. Besides enabling our model to capture changes in the long-term trends of variables, it reflects the correction effects of emergencies and random shocks on the trends. Moreover, by removing time-varying settings of the intercept terms of observable variables in our model, we obtain a DFM with SV as in Marcellino et al. (2016) (let $r = m = 0$, $\mathbf{c_t} = \mathbf{c}$). We can also obtain a DFM as in Banbura and Modugno (2014) by further removing SV (let $\omega_{a,j}^2 = \omega_\epsilon^2 = \omega_{\eta,i}^2 = 0$).

2.1.2. Processing of mixed-frequency data

Our model processes quarterly and monthly data since we aim to track the long-term trend of real GDP growth rate. Assume that there are n observable variables, including n_Q variables on a quarterly basis (values are collected every three months). In other words, they have two missing values every three periods compared to monthly data. Assume that any quarterly variable X_t^Q has a latent monthly series X_t^M that satisfies the condition

$$X_t^Q = X_t^M + X_{t-1}^M + X_{t-2}^M = 3 \times \frac{1}{3}\left(X_t^M + X_{t-1}^M + X_{t-2}^M\right). \tag{8}$$

However, Camacho and Perez-Quiros (2010) and Zheng and Wang (2013) state that conducting a direct estimation of Eq. (8) involves non-linear state space models, which makes the estimation extremely complicated and poorly accurate. Following Mariano and Murasawa (2003), we solve this problem by using geometric mean instead of arithmetic mean. Eq. (8) can be rewritten as:

$$X_t^Q = 3\left(X_t^M \bullet X_{t-1}^M \bullet X_{t-2}^M\right)^{1/3}. \tag{9}$$

Taking the logarithm of both sides of Eq. (9), we have

$$\ln X_t^Q = \ln 3 + \frac{1}{3}\left(\ln X_t^M + \ln X_{t-1}^M + \ln X_{t-2}^M\right). \tag{10}$$

In order to obtain quarter-on-quarter data, we difference Eq. (10) by three periods:

$$\ln X_t^Q - \ln X_{t-3}^Q = \frac{1}{3}\left(\ln X_t^M - \ln X_{t-3}^M\right) + \frac{1}{3}\left(\ln X_{t-1}^M - \ln X_{t-4}^M\right) + \frac{1}{3}\left(\ln X_{t-2}^M - \ln X_{t-5}^M\right). \tag{11}$$

Let $x_t^Q = \Delta_3 \ln X_t^Q$ and $x_t^M = \Delta \ln X_t^M$. As we can substitute log difference for growth rate, x_t^Q is the (observable) quarter-on-quarter growth rate of X_t^Q. Accordingly, x_t^M is the (unobservable) month-on-month growth rate of X_t^M. Eq. (11) can thus be rewritten as:

$$x_t^Q = \frac{1}{3}x_t^M + \frac{2}{3}x_{t-1}^M + x_{t-2}^M + \frac{2}{3}x_{t-3}^M + \frac{1}{3}x_{t\text{-}4}^M. \tag{12}$$

By plugging the corresponding columns from Eq. (1) into Eq. (12), we find that quarterly data depends on latent common factors and their lags. Processing mixed-frequency (quarterly and monthly) data turns to processing monthly data with missing values. Following Antolin-Diaz et al. (2017), we apply the Kalman filter to deal with missing values.

2.1.3. Settings of state-space form

Since this paper aims to estimate time-varying characteristics of the long-term economic growth trend, we take "$\mathbf{B} = 1$ and $\mathbf{a_t} = a_t$ ($m = r = 1$)" for example to illustrate state-space form. Let $\tilde{\mathbf{y}}_\mathbf{t}$ denote the vector of the de-meaning observable vector $Y_\mathbf{t}$, including n_Q de-meaning quarterly data and n_M de-meaning monthly data ($n = n_Q + n_M$). Thus, $\tilde{\mathbf{y}}_\mathbf{t}$ can be expressed as:

$$\tilde{\mathbf{y}}_\mathbf{t} = \begin{bmatrix} y_{1,t}^Q \\ \vdots \\ y_{n_Q,t}^Q \\ y_{1,t}^M - \rho_{1,1}^M y_{1,t-1}^M - \rho_{1,2}^M y_{1,t-2}^M \\ \vdots \\ y_{n_M,t}^M - \rho_{n_M,1}^M y_{n_M,t-1}^M - \rho_{n_M,2}^M y_{n_M,t-2}^M \end{bmatrix}. \tag{13}$$

We can transform Eqs (1) and (13) to the following state-space forms:

$$\tilde{\mathbf{y}}_\mathbf{t} = \mathbf{H}\mathbf{X_t} + \tilde{\boldsymbol{\eta}}_\mathbf{t},\ \ \tilde{\boldsymbol{\eta}}_\mathbf{t} \sim N\left(0, \tilde{\mathbf{R}}_\mathbf{t}\right); \tag{14}$$

$$\mathbf{X_t} = \mathbf{F}\mathbf{X_{t\text{-}1}} + \mathbf{e_t},\ \ \mathbf{e_t} \sim N\left(0, \mathbf{Q_t}\right), \tag{15}$$

where state vector $\mathbf{X}'_\mathbf{t} = \left[a_t, \ldots, a_{t-4}, f_t, \ldots, f_{t-4}, \mathbf{u}_t^{Q\prime}, \ldots, \mathbf{u}_{t-4}^{Q}{}'\right]$. Parameter matrix $\mathbf{H}$ can be expressed as:

$$\mathbf{H} = \left[\mathbf{H}_a \ \ \begin{vmatrix}\mathbf{H}_{\lambda_Q} \\ \mathbf{H}_{\lambda_M}\end{vmatrix} \ \ \mathbf{H}_u\right]. \tag{16}$$

Then we can estimate parameters using Monte-Carlo simulation and Gibbs sampling. The explicit expressions, Gibbs sampling processes and initial parameter value settings of matrices $\mathbf{H}$ and $\mathbf{F}$, $\tilde{\boldsymbol{\eta}}_\mathbf{t}$, $\mathbf{e_t}$, $\tilde{\mathbf{R}}_t$ and $\mathbf{Q}_t$ are given in Appendices A–C.

2.2. Data

Previous studies have shown that coincident indicators can reveal changes in the long-term economic growth trend (Zheng & Wang, 2013; Jarocinski & Lenza, 2018). According to the coincidence rule, we select 8 indicators (i.e., 1) the month-on-month growth rate of total investment in fixed assets, 2) quarter-on-quarter growth rate of per capita disposable income of urban residents, 3) month-on-month growth rate of value-added of the industrial enterprises above designated size, 4) month-on-month growth rate of total retail sales of consumer goods, 5) month-on-month growth rate of electric energy production[1], 6) month-on-month growth rate of exports, 7) month-on-month growth rate of imports, and 8) month-on-month growth rate of gross tax revenue) classified into 4 categories (i.e., revenue and expenditure, production and sales, trade, and public finance).

Based on the Chinese economy's unique characteristics and indicator selection criteria in recent studies, we make two supplements to the set of fundamental indicators. On one hand, considering the strong support provided by real estate industry to China's economic growth during the sampling period, we add the indicator of "real estate climate index" that reflects changes in the real estate market trend comprehensively (Jiang et al., 2017). On the other hand, we also add two types of survey indicator that reflects consumer confidence and business confidence as in Antolin-Diaz et al. (2017), including 1) consumer confidence index, 2) entrepreneur confidence index, 3) business climate index, 4) China manufacturing purchasing managers index (PMI), 5) China non-manufacturing PMI (economic activities) and 6) Caixin services PMI. These timely, reliable and universal survey indicators make significant contributions to correct statistical errors and reflect actual conditions. On the whole, we select 17 indicators classified into 7 categories (i.e., revenue and expenditure, production and sales, trade, real estate market, public finance, consumer confidence, and business confidence). Table 1 provides a summary of fundamental indicators.

It is important to address the following three points regarding fundamental indicators. First, since the quarter-on-quarter statistics of some fundamental indicators are missing, we must process data first in order to obtain the corresponding chain-based growth rate. Taking growth rate of real GDP for example, we first set 1992 as the base year, then calculate real GDP by quarter during the sampling period by using GDP and year-on-year growth rate of real GDP in the current period. After using the X–13 method for seasonal adjustment, we finally calculate the corresponding quarter-on-quarter annualized rate according to seasonally adjusted series[2].

Secondly, we obtain the values of some survey indicators through comparison with the last-period counterpart, which suggests that series itself cannot reflect the corresponding chain-based characteristic. Since the difference between two periods is close to the corresponding chain-based growth rate, we take the first-order difference on these fundamental indicators (i.e., China manufacturing PMI, China non-manufacturing PMI (economic activities) and Caixin services PMI) as in Banbura and Modugno (2014).

[1] Most studies will add the indicator of "electric energy production" during data selection, which is not included in coincident indicators though. This is because its data, which is similar to nighttime light data, can reflect actual changes in GDP growth and exert desirable correction effects on GDP data (Ye, 2015).

[2] All fundamental indicators, except for real GDP, per capita disposable income of urban residents, and value-added of the industrial enterprises above designated size, apply nominal data to obtain the corresponding chain-based growth rate. Additionally, all data are seasonally adjusted before calculating the corresponding quarter-on-quarter annualized rate, which is consistent with most existing studies.

Table 1. Summary of fundamental indicators

Category	Fundamental indicator	Frequency	Sampling interval	Processing method	Data source
Revenue and expenditure	Growth rate of real GDP	Quarterly	1992Q2–2022Q2	%QoQ Ann	CEInet Statistics Database[3]
	Consumer price index	Quarterly[4]	1992Q2–2022Q2	%QoQ Ann	CEInet Statistics Database
	Growth rate of total investment in fixed assets	Monthly	2011M2–2022M6	%MoM	National Bureau of Statistics
	Growth rate of per capita disposable income of urban residents	Quarterly	1994Q2–2022Q2	%QoQ Ann	National Bureau of Statistics
Production and sales	Growth rate of value-added of the industrial enterprises above designated size	Monthly	2011M2–2022M6	%MoM	National Bureau of Statistics
	Growth rate of total retail sales of consumer goods	Monthly	2011M2–2022M6	%MoM	National Bureau of Statistics
	Growth rate of electric energy production	Monthly	1992M1–2022M6	%MoM	National Bureau of Statistics
Trade	Growth rate of exports	Monthly	1994M2–2022M6	%MoM	National Bureau of Statistics
	Growth rate of imports	Monthly	1994M2–2022M6	%MoM	National Bureau of Statistics
Real estate market	Real estate climate index	Monthly	1992M1–2022M6	%MoM	National Bureau of Statistics
Public finance	Growth rate of gross tax revenue	Monthly	1992M2–2022M6	%MoM	Ministry of Finance
Consumer confidence	Consumer confidence index	Monthly	1999M2–2022M6	%MoM	National Bureau of Statistics

[3] Data can be accessed via CEInet Statistics Database (https://db.cei.cn/), National Bureau of Statistics (http://www.stats.gov.cn/), Ministry of Finance (http://www.mof.gov.cn/), and Caixin (https://www.caixin.com/).

[4] The original frequency of consumer price index (CPI) is on an annual basis. In order to facilitate calculation, we first use the function of "frequency converter" in EViews 10 to convert annual data to quarterly data, then calculate its quarter-on-quarter annualized rate.

End of Table 1

Category	Fundamental indicator	Frequency	Sampling interval	Processing method	Data source
Business confidence	Entrepreneur confidence index	Quarterly	2001Q2–2022Q2	%QoQ Ann	National Bureau of Statistics
	Business climate index	Quarterly	2001Q2–2022Q2	%QoQ Ann	National Bureau of Statistics
	China manufacturing PMI	Monthly	2005M2–2022M6	%MdM	National Bureau of Statistics
	China non–manufacturing PMI (economic activities)	Monthly	2007M2–2022M6	%MdM	National Bureau of Statistics
	Caixin services PMI	Monthly	2008M11–2022M6	%MdM	www.Caixin.com

Note: %QoQ Ann denotes quarter-on-quarter annualized rate; %MoM denotes month-on-month growth rate; %MdM denotes first-order difference on a monthly basis (see Appendix D for details).

Thirdly, given the relatively large set of fundamental indicators and late start date of most survey indicator statistics, we actually use data with different start dates. Besides missing values on a quarterly or monthly basis, our sample has missing values due to statistics starting on different dates. Following Stock and Watson (1988) and Antolin-Diaz et al. (2017), we use the Kalman filter to process missing values[5]. The entire sampling interval is set to be 1992M1(Q1)–2022M6(Q2).

Figure 1 depicts China's long-term economic growth trend and its 90% and 68% confidence intervals. Both confidence intervals become obviously narrower over time, which enables more precise recent estimates. There are two main reasons for this: first, the quarter-on-quarter annualized growth rate of real GDP in the latter sampling period shows an obvious downward trend of volatility, which suggests sharp declines in the short-run volatility and noise components of fundamental indicators. Secondly, as we actually use data with different start dates, information covered in the latter sampling period is richer than that covered in the former sampling period. The data of all indicators are available since 2012, in spite of the growth rate of value-added of the industrial enterprises above designated size, growth rate of total retail sales of consumer goods, and Caixin services PMI have missing values before then. It is clear to observe that both confidence intervals have narrowed rapidly since 2012 when the statistics of all indicators are complete. This means that value-added of the industrial enterprises above designated size, total retail sales of consumer goods and Caixin services PMI are indispensable variables for macroeconomic prediction, as their changes can effectively reflect changes in the long-term economic growth trend.

[5] In order to verify the applicability of estimation with different start dates, we also use data starting from 1992 and the benchmark model to measure the long-term economic growth trend. At the sampling interval with missing values, estimation results using data starting from the same period and with different start dates are almost identical. However, at the sampling interval without missing values, new information introduced by data with different start dates can significantly narrow our model's confidence interval and improve estimation accuracy. Therefore, using data with different start dates will not reduce the robustness of estimation, but increase the accuracy of real-time estimation, which is a productive attempt of this paper.

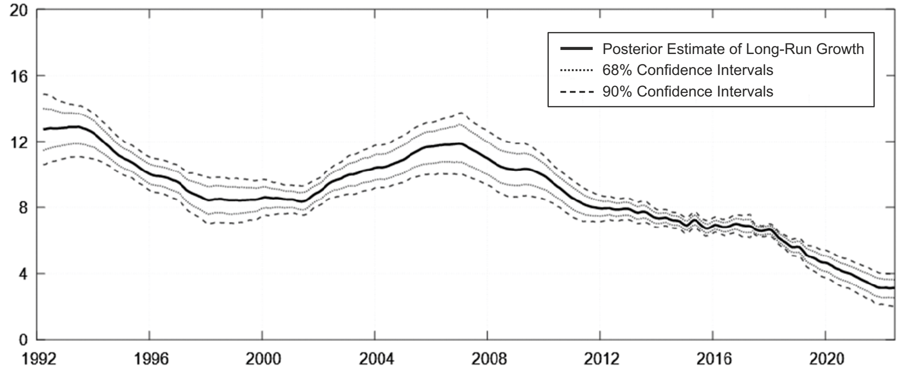


Figure 1. Long-term economic growth trend measured by a TVP–MF–DFM

2.3. Assessment of trend estimation

Before characterizing and decomposing China's long-term economic growth trend, we should examine the applicability of the trend estimation by our model. Therefore, we also estimate the trend by using the classical H–P filter and UC–Kalman model in comparison with estimation results of our model. The estimation results of these models are depicted in Figure 2. There are two obvious differences in the trends estimation: first, the trend estimated by the H–P filter is quite smooth, while the trends estimated by our model and the UC–Kalman model are uneven. This is because our model and the UC–Kalman model are based on real-time data, and thus more likely to capture trend changes in time. Secondly, take the trends estimation after the outbreak of the COVID-19 pandemic for example, estimation results of our model are clearly lower than that of the other two. Since the trends estimated by the H–P filter and UC–Kalman model are significantly different from China's actual growth rate of real GDP, there may exist a problem of pseudo-smoothness. In order to verify the trend estimated by our model has superior statistical and economic applicability, we need rely on objective econometric evaluation.

The econometric evaluation of this paper consists of three parts. The first one is the event feedback test, which examines whether the trends estimated by different models will form

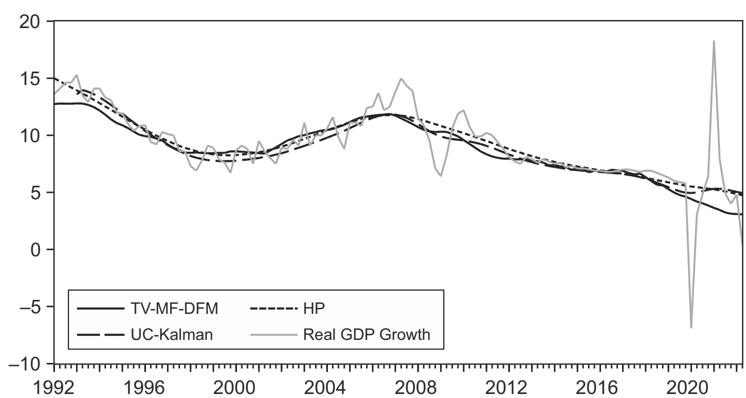


Figure 2. Characteristics of the trend estimated by three models

effective feedbacks to typical event shocks, is a basic prerequisite for indicator availability. The second one is the evaluation of prediction ability. The long-term economic growth trend describes the long-term trend changes in economic growth rate, which suggests that economic growth rate will return to the trend after the short-term volatility. Hence, the evaluation of prediction ability is used to verify the desirability of the estimated trends through examining whether they will predict changes in future economic growth rate effectively. The third one is the evaluation of stability focusing on examining whether the trends estimated by different models will remain stable using data with different start dates, which is related to the accuracy and stability of estimation results.

2.3.1. Evaluation of event feedback

Using the event analysis framework as in Ball and Brown (1968) and Fama et al. (1969), the evaluation of event feedback compares the feedbacks of the trends estimated by different models to typical event shocks. More specifically, it examines whether the trend will change accordingly when typical event shocks occur. We first select three landmark events (see Table 2), and set the window length to be one year (four quarters) to ensure adequate identification. Then, we use the trends estimated by the above three models and the autoregressive integrated moving average (ARIMA) model to predict the trend during the window period assuming that the event does not take place[6]. Lastly, we use differences between the trends estimated by the three models and their expected values to develop the counterfactual T test. Let C_h denote the sum of trend deviation, $C_{ht} = C_t - \hat{C}_t$ denote trend deviation at time t during the landmark event's window, C_t and $\hat{C}_t$ denotes the trend and its expected value, respectively, and $\bar{C}_h = \left(\sum_{i=t}^{t+2} C_{hi}\right) / 4$ is the average abnormal trend volatility during the window. Now we can conduct the counterfactual T test for the abnormal trend gap during the window. The null hypothesis H_0 is: the abnormal trend gap is 0. The T – statistic can be expressed as:

$$T = \bar{C}_h / (s_C / \sqrt{4}), \tag{16}$$

where s_C is the standard error of trend deviation C_{ht}.

Table 2. Three landmark events

Window	Description
2001Q4–2002Q3	China formally joined the World Trade Organization (WTO), accompanying by an accelerated economic growth
2008Q3–2009Q2	The global financial crisis broke out, followed by a downward economic growth trend
2020Q1–2020Q4	The COVID-19 pandemic broke out, along with a recession

[6] We use the H–P filter and event in 2001 to illustrate here. Assuming that the event's window period is 2001Q4–2002Q3, we first use the H–P filter to estimate the trend during 1992Q1–2001Q3. If the event does not occur, then it is reasonable to use estimated results during 1992Q1–2001Q3 and the ARIMA model to estimate the trend during 2001Q4–2002Q3. If this trend is significantly different from the actual trend, then the H–P filter can effectively capture external shocks that change the trend.

Table 3 presents estimation results of the counterfactual *T* test. The trend estimated by our model, which captures all typical event shocks, has strong event sensitivity and economic implication. The trend estimated by the UC–Kalman model capturing two event shocks has weaker event sensitivity. The trend estimated by the H–P filter cannot capture any typical event shocks, which is consistent with empirical evidence in Figure 2. It shows that the H–P filter has a disadvantage of excessive pseudo smoothing, which causes the estimated trend to be lack of economic implication and difficult to reflect the actual trend.

Table 3. Estimation results of the counterfactual *T* test

Model	2001Q4–2002Q3	2008Q3–2009Q2	2020Q1–2020Q4
H–P filter	0.397	–0.132	–0.061
UC–Kalman	–0.180	**–0.487*****	**–0.404*****
TV–MF–DFM	**0.664***	**–0.424*****	**–0.415*****

Notes: Each value is the mean of differences between the trend and its expected value. *, ** and *** means each value is significant at the significance levels of 10%, 5%, and 1%, respectively.

2.3.2. Evaluation of prediction ability

As a test for restoring conception, the essence of evaluating prediction ability is to examine whether the fitted trend can predict future economic growth rate effectively. We use a time-varying Granger causality test as in Asali (2020) to realize the evaluation. This is because traditional Granger causality tests are based on a linear hypothesis, while the trend and economic growth rate vary considerably. A simple linear inference is very likely to lead to a mechanism misjudgment. Following the Hong-approach, the time-varying Granger causality test uses lagged sample cross-correlation coefficient instead of static correlation coefficient to construct the test statistic. Table 4 presents the time-varying Granger causality test results of the trends and growth rates estimated by the three models. In order to improve the evaluation's robustness, the order of lag period is set to be 1, 2 and 3, respectively. The trend estimated by our model is the Granger causality of economic growth rate in all cases. However, the trends estimated by the H–P filter and UC–Kalman model cannot predict economic growth rate in all cases. It shows that the trend estimated by our model has stronger economic implication and is able to restore the basic concept of economic growth trend.

Table 4. Estimation results of time-varying Granger causality test

Order of lag period	H–P filter	UC–Kalman model	TV–MF–DFM
1	1.842	2.785	4.019**
2	1.835	4.964*	12.018***
3	3.821	7.250*	17.211***

Notes: *, ** and *** means each value is significant at the significance levels of 10%, 5%, and 1%, respectively.

2.3.3. Evaluation of stability

The evaluation of stability focuses on examining whether the trends estimated by different models will remain stable using data with different start dates, which is a fundamental prerequisite for estimation. More specifically, we first estimate the trend in three sample intervals: the full sample (1992Q1–2022Q2), 2002–2022 (2002Q1–2022Q2) and 2012–2022 (2012Q1–2022Q2), and obtain three trend series estimated by each model. Then, we make a horizontal comparison in the sample interval (2012Q1–2022Q6). Lastly, we repeat the above two steps for the trend estimated by different models, and compare the stability of all models based on graphic results and the sum of deviation squares. Figure 3a–c depict estimation differences in the trend using sample with different start dates. Table 5 depicts the cumulative sum of squared deviations and maximum estimation differences of each trend component in the sample interval (2012Q1–2022Q2). It shows that the stability of the H–P filter and our model is relatively stronger than that of the UC–Kalman model. The trends estimated by the H–P filter in all sample intervals (the full sample, 2002–2022 and 2012–2022) are very consistent with the sum of squared deviations not greater than 2.

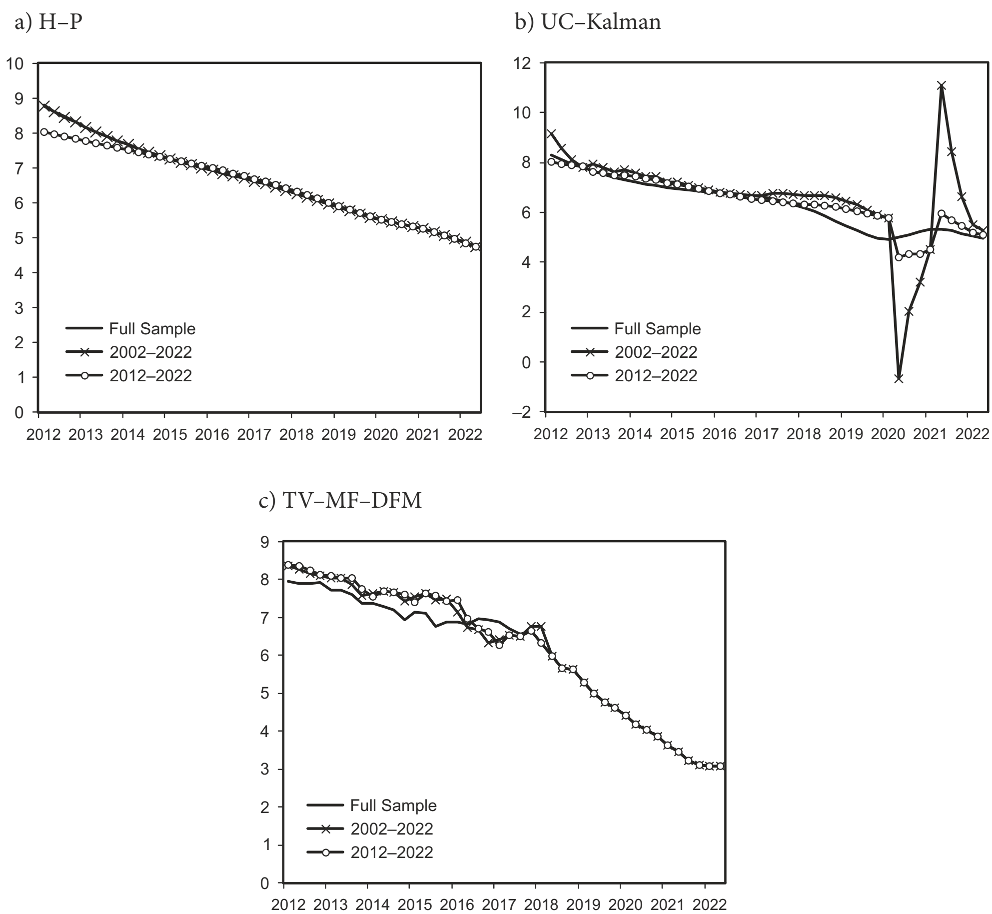


Figure 3. Estimated trends in different sample intervals

The deviations of our model in the sets of "full sample and 2002–2022" as well as "full sample and 2012–2022" are slightly larger than that of the H–P filter. This is because the full sample period lacks historical information at early stage. In addition, most data are supplemented by the UC–Kalman model, which results in measurement errors. However, in the set of "2002–2022 and 2012–2022", the deviation of our model is smaller than that of the H–P filter. It shows that the stability of our model will be much stronger when real-time data is supplemented. In terms of "time point deviation", our model has the smallest measurement errors (only 0.582 as given in Figure 3), while the H–P filter's measurement has a relatively large initial deviation. All in all, our model has a stability advantage over the other two models.

Table 5. Deviations of different models in different sample interval sets

Sample interval set	H–P filter	UC–Kalman model	TV–MF–DFM
Full sample and 2002–2022	<0.001	101.395	3.652
Full sample and 2012–2022	2.030	69.136	4.252
2002–2022 and 2012–2022	2.000	7.704	0.591
Maximum time point deviation	0.777	5.795	0.582

3. Characteristic description and real-time decomposition of the long-term trend

This section consists of two parts: first, we describe several typical morphologic changes in the trend, and intuitively judge the law of trend changes based on data and graphs. Secondly, according to the classical theory of production function, we make a real-time variance decomposition of the trend in terms of factor contribution. Then, we discuss the internal mechanism of China's downward trend of economic growth.

3.1. Characteristic description of the trend

Figure 4 characterizes several typical morphologic changes in the trend. Figure 5 characterizes its amplitude of fluctuations between two adjacent periods. There are several stylized facts depicted in Figures 4 and 5. First, the trend has obvious three stages during the sampling period. In the first stage (1992–2012), with a mean of 9.78% that is mostly above 8%, the trend is characterized by high-speed growth and high volatility. In the second stage (2012–2018), the trend is characterized by medium-to-high-speed growth and low volatility. China's economy has experienced changes in economic growth rate during the six years, which is also the main stage of the "New Normal". In the third stage (2018–present), it has an accelerated downward trend whose posterior mean has dropped to 4%, which is close to the lower limit of medium-to-high-speed growth rate. In terms of the lower limit of the 90% confidence interval, the trend's risk of downward pressure has escalated. There is an obvious expansion of the 90% confidence interval compared to early stages, and the lower limit of the 90% confidence interval is even below 2%. An economic implication is that the trend faces a considerable risk of downward pressure at present. That is, China's economic growth rate may drop below the natural level of 2%, and maintain at a low level for a long time. Another economic implication is that the accelerated downward trend has existed for a while before the outbreak of the COVID-19 pandemic. In fact, the pandemic shock merely enables the trend to proceed, and by no means a cause of it. The real cause of the trend emerges as early as 2018. Therefore, it is pivotal to profoundly analyze the internal mechanism of trend changes. In addition, the driving mechanism of the downward trend may have been principally different from that during the "New Normal", which will be addressed in the subsequent subsection of factor decomposition.

As the trend and year-on-year growth rate is more comparable, we transform the annualized rate of real GDP growth to a year-on-year basis. As depicted in the dark grey areas of Figure 6, year-on-year real GDP growth rate is higher than the trend during 1992Q1–1997Q2, 2005Q1–2008Q2 and 2009Q3–2011Q4, which suggests that the Chinese economy has a typical overheated trend. During 1997Q3–2004Q4 and 2008Q3–2009Q2, the white areas of Figure 6 show that year-on-year real GDP growth rate is significantly lower than the trend, which reflects a continually low-efficient economic operation. In retrospect, dur-

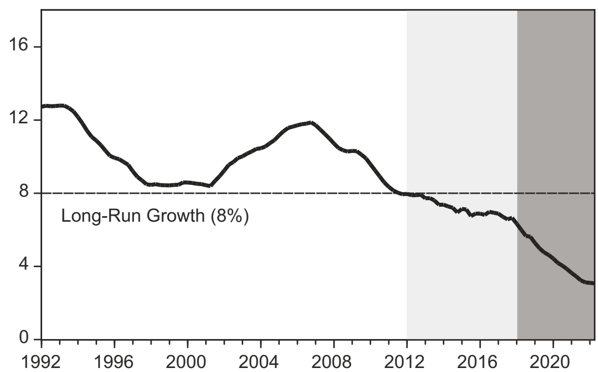


Figure 4. Posterior estimation of the trend measured by quarter-on-quarter annualized rate

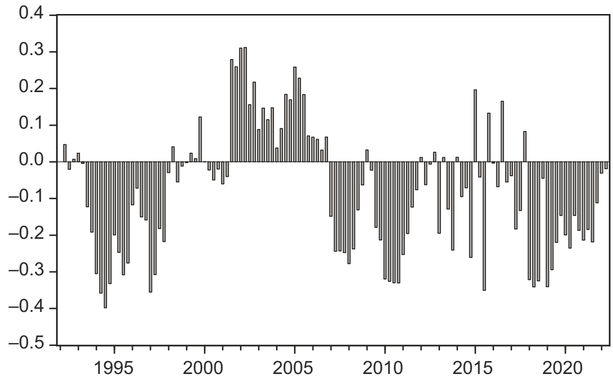


Figure 5. Amplitude of fluctuations in the long-run potential growth rate between two adjacent periods

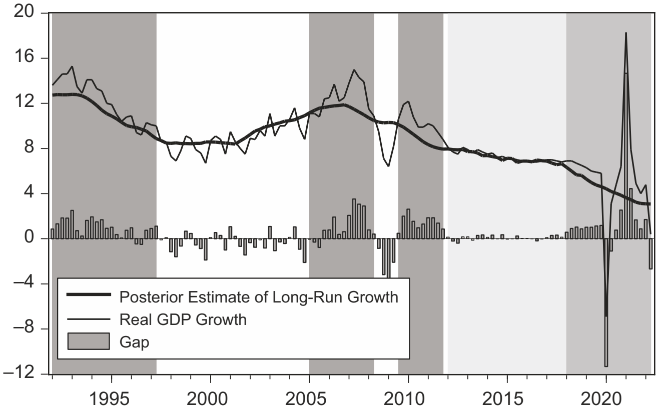


Figure 6. Comparison between the trend and year-on-year real GDP growth rate

ing the early period of China's market system revolution from 1993 to 1997, the Chinese economy has been overheated due to latent demand release, expansionary policy stimulus, and high inflation rate, which leads to a hyper-growth illusion beyond trend. As the most typical investment-led growth period during this century, 2002–2008 is also the case. The expansionary fiscal and monetary policies accelerate growth of total investment in fixed assets, which causes continuous position gap between the year-on-year real GDP growth rate and the trend. Although the formation mechanisms of beyond-trend hyper growth during the two periods are different, they both end up with continually weak growth (i.e., the soft landing that lasts for 5 years after 1997 and post-crisis adjustment period during 2008–2011) in a similar manner. One of the most noticeable characteristics is that year-on-year real GDP growth rate is continually lower than the trend. It implies that economic growth suffers from systematic contraction as well as factor restriction and inefficiency. Therefore, the beyond-trend hyper growth usually has a double-edged-sword effect, and will lead to persistent weak growth and high economic costs.

Since 2012 (the shallow grey and dark grey areas of Figure 6), the trend and year-on-year real GDP growth rate show two periodical characteristics. During 2012–2017, the trend and year-on-year real GDP growth rate almost overlap with low volatility, which is distinct from previous sampling periods. In this main formation phase of China's medium-to-high-speed growth, the government addresses the importance of complying with the law of economic development to make year-on-year real GDP growth rate converge to the trend. Since 2018, affected by a series of random events such as the Sino–US trade frictions and outbreak of the COVID-19 pandemic, year-on-year real GDP growth rate begins to fluctuate so sharply and unregularly that the trend rapidly deviates from the medium-to-high-speed track accompanying an accelerated downward. At present, the trend has dropped to the lower limit of medium-to-high speed near 4%, while year-on-year real GDP growth rate still falls. Thus, we should not exclude the possibility of a persistent downward trend as well as declining year-on-year real GDP growth rate.

3.2. Real-time decomposition of the long-term trend

Now we can investigate the internal mechanism of changes in the trend, after forming a general idea of the trend path. Following Antolin-Diaz et al. (2017) and Liu and Fan (2019), we carry out a real-time decomposition of the trend in terms of factor contribution. First, we develop a C–D production function with technology:

$$Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}, \tag{17}$$

where Y_t, K_t and H_t denotes output, capital stock and labor, respectively, and A_t denotes TFP. Taking total differential on Eq. (17) enables us to obtain the corresponding output growth function:

$$d\ln Y_t = d\ln A_t + \alpha d\ln K_t + \left(1-\alpha\right) d\ln H_t. \tag{18}$$

Eq. (18) can be further written as:

$$d\ln Y_t = d\ln H_t + d\ln A_t + \alpha\left(d\ln K_t - d\ln H_t\right). \tag{19}$$

As shown in Eq. (19), real output growth can be expressed as the sum of labor input growth, technological progress and capital deepening (the ratio of capital to labor). The first term on the RHS of Eq. (19) measures the contribution of labor input growth to output growth, the second and third term collectively measures the contribution of non-labor growth to output growth, that is, the contribution of labor productivity growth to output growth. The quadratic decomposition of Eq. (19) is critical because TFP measures the degree of match between technology and capital. According to the theory of technological recession as in Liu and Xia (2018) and Shi et al. (2022), the mismatch between capital and labor is likely to be a key factor affecting China's labor productivity growth. Decomposing this indicator helps to compare the impact of theories of investment decline, diminishing demographic dividend and technological recession on the trend. Next, we will use the benchmark model to accomplish this theoretical decomposition. The greatest improvement in this paper compared to Liu and Fan (2019) is: we do not assume factor contribution to be constant, so that we can accomplish the real-time decomposition of the trend. It significantly improves the estimation accuracy of our model as well as accounting for the downward trend from the perspective of internal mechanism.

3.2.1. Dual decomposition of the long-term trend

The trend can be decomposed into the sum of labor productivity and labor input contribution as indicated above. Hence, we need to add labor input into the benchmark model, and decompose the trend into two orthogonal components by changing the setting of $\mathbf{c_t}$ in Eq. (2) as follows:

$$\mathbf{a_t} = \begin{bmatrix} z_t \\ h_t \end{bmatrix}, \mathbf{B} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 0 & 1 \end{bmatrix}, \tag{20}$$

where z_t and h_t denotes labor productivity growth and labor input growth, respectively. Their sum is the time-varying intercept of the benchmark model ($g_t = z_t + h_t$[7]). The first three terms

[7] z_t and h_t both follow the random walk process with diagonal covariance matrix defined by Eq. (7). Restricting the form of covariance matrix is not necessary for estimation, which enables us to interpret the trend's innovation as an exogenous shock to the long-term growth rates of variables.

of Y_t are the seasonally adjusted annual rate of real GDP, period-on-period growth rate of consumption and period-on-period growth rate of labor input. The real-time changes in z_t and h_t collectively determine changes in the trends of output and consumption. Moreover, we select annual total employment as the proxy variable for labor input; the sampling period is 1992–2021; data source is the National Bureau of Statistics.

Figure 7 depicts decomposition results of the trend using annual total employment as the proxy variable for labor input, in which Figure 7(a) depicts the posterior mean of three trends, and Figure 7(b) further presents filter estimation of the two factors. First, in terms of the relative contribution of the trend, the trends of labor productivity and output are highly consistent in terms of value and path, which shows that labor productivity has always been a key driver of China's long-term economic growth. Secondly, in terms of the time points of trend changes, the trend has obviously shifted downward since 2007, which suggests that economic growth rate falling below 8% and the appearance of "New Normal" are only periodical phenomena of the current downward trend. In fact, the logical starting point is supposed to be 2007.

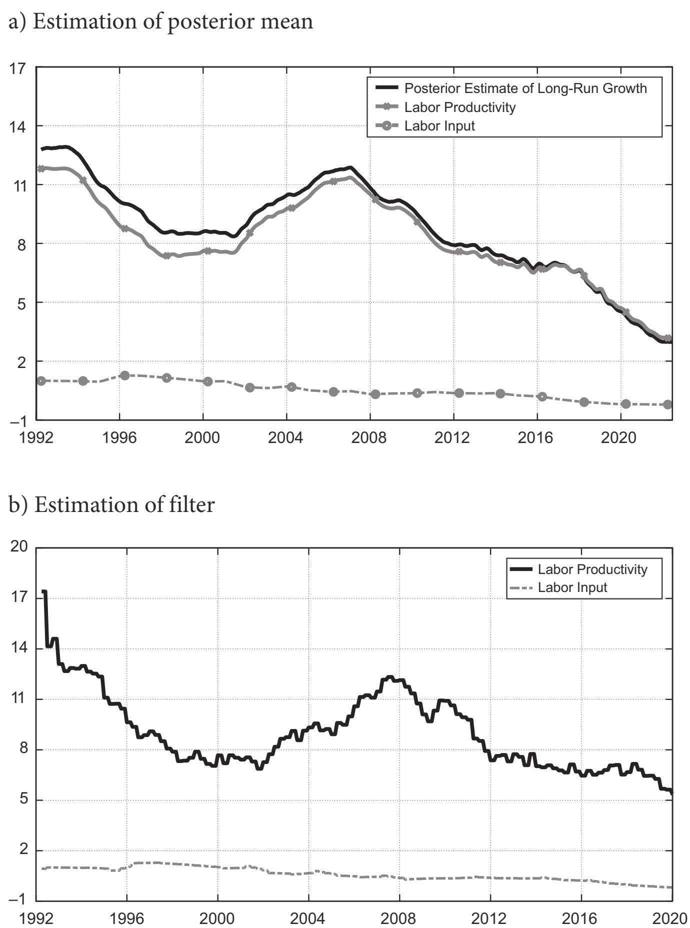


Figure 7. Two-factor decomposition of the trend using annual total employment as the proxy variable for labor force

Thirdly, in terms of the cause of the downward trend, the downward trends of labor productivity and labor input both systematically account for it. Hence, the current downward trend is by no means driven by a single factor. On the contrary, it is a comprehensive outcome caused by common changes in multiple trends. Considering the inevitability of decelerated capital deepening and diminishing demographic dividend, the current downward trend is destined to be sophisticated, long-term and irreversible. Last but not least, in terms of the two factors' relative changes and future trend's path, the posterior mean of the trend of labor productivity is nearly 8%, and has fallen below 5% at present. Meanwhile, the posterior mean of the trend of labor input is nearly 2%, and has fallen to zero at present. It shows that demographic dividend has been depleted, which is also why we find it difficult for China to return to high- or medium-to-high-speed growth.

3.2.2. Further decomposition of the long-term trend

The two-factor decomposition results of the trend show that labor productivity is a key driver of China's long-term economic growth, which becomes increasingly prominent in future. In order to investigate the mechanism of labor productivity changes, we further decompose labor productivity into the technology term and non-technology term according to Eq. (18). The seasonally adjusted annual rate of real GDP can be expressed as the sum of labor input growth $\tilde{h}_t$, technological progress $\tilde{z}_t$ and non-technological progress $\tilde{x}_t$[8]. The corresponding time-varying intercept is thus $g_t = \tilde{h}_t + \tilde{z}_t + \tilde{x}_t$. $\mathbf{c_t}$ can be expressed as follows:

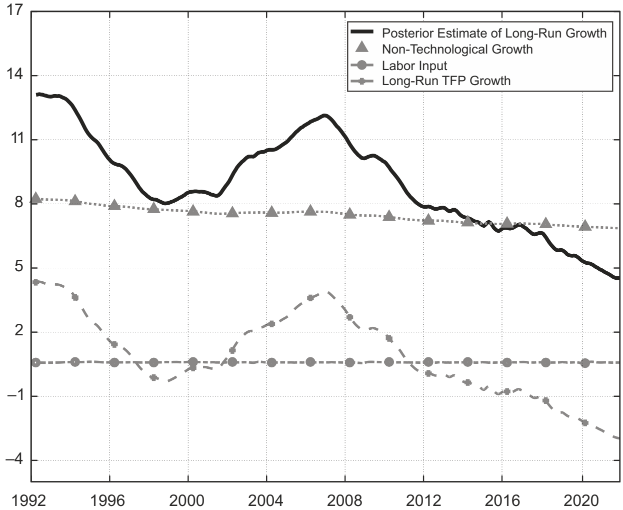
$$\mathbf{a_t} = \begin{bmatrix} \tilde{x}_t \\ \tilde{z}_t \\ \tilde{h}_t \end{bmatrix}, \ \mathbf{B} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}. \tag{21}$$

The first four terms of Y_t are the seasonally adjusted annual rate of real GDP, period-on-period growth rate of consumption, TFP and growth rate of annual total employment. It shows that the long-term trends of real GDP and consumption depend on the sum of changes in labor input $\tilde{h}_t$, technological progress $\tilde{z}_t$ and non-technological progress $\tilde{x}_t$ (i.e., capital deepening) after this decomposition. Changes in TFP only depend on the long-term changes in the technology term $\tilde{z}_t$, and $\tilde{h}_t$ is used to capture the low-frequency trend changes in labor input. In order to avoid estimation bias caused by data difference, we use "TFP at constant national prices" documented by Penn World Table version 10.0 (PWT 10.0) to calculate the growth rate series of TFP between 1992 and 2019. The corresponding decomposition results are depicted in Figure 8. First, the long-term trends of economic growth and labor growth are generally consistent with their counterparts in the benchmark model after introducing TFP, which supports the robustness of two-factor decomposition. Secondly, the long-term trends of technological progress and economic growth are very close, while the non-technology term shows a slow downward trend.

The downward trend of technological progress starting from 2007 can be divided into two phases. The growth rate of TFP keeps plunging until 2016–2017 in the first phase

[8] As $\tilde{x}_t$ is mainly used to measure the time–varying trend of $d\ln K_t - d\ln H_t$, that is, the trend changes in capital stock per capital, it reflects trend changes in capital deepening.

a) Posterior mean estimation



b) Filter estimation

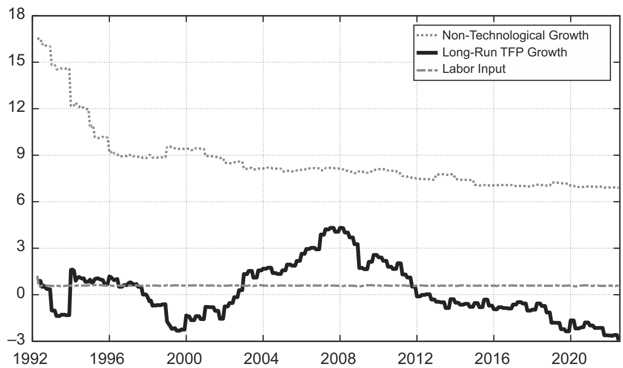


Figure 8. Labor-productivity decomposition of the trend

(2007–2017), which is also the main phase for China's low-hanging fruit of technology to be plucked. In the second phase (2018–present), the growth rate of TFP continues to decline with an obvious trend of negative growth, which suggests that the Chinese economy has entered a typical period of technological recession. This noteworthy phenomenon further confirms the hypothesis brought by Liu and Xia (2018) and Shi et al. (2022) that fail to verify: comprehensive technological regression caused by the capital-technology mismatch is another key reason for the downward trend of China's economic growth. The complex causes of technological regression can be summarized in two aspects. For one thing, the excessive expansion of investment at the early stage leads to sizeable obsolete capital stock entered in the capital account, which becomes increasingly incompatible to newer and higher technology. As a result, it causes not only the capital-technology mismatch but also serious inefficiency of production, or even negative economic growth. For another thing, the COVID-19 pandemic has seriously impaired production efficiency. Additionally, production suspension, quarantine and lockdown have exacerbated capital idle, which further reducing the degree of match between labor and capital, thereby accelerating TFP recession. The negative contribution of the current technological recession to the trend is about three percentage points in general. Considering that the long-term potential economic growth rate is around 4%, the Chinese economy is still likely to return to the medium-to-high-speed growth interval if the problem of technological recession can be properly solved.

In order to further measure the dynamic impact of the three factors on the long-term trend, we calculate the time-varying contributions of the three factors to the trend. First, as depicted in Figure 9, the contribution of capital deepening that accounts for the largest proportion to the trend is constantly greater than 50%. The dominant role means that it is always a key factor of driving the trend, which is consistent with the experience-based judgement. Given that capital deepening still accounts for seven percentage points of annual economic growth, it principally determines that China still maintains a trend of returning to medium-to-high-speed growth.

However, although capital deepening seems to be a key driver of the current trend in terms of numerical evidence, it is an accidental phenomenon caused by two factors in fact. On one hand, the slowly declining absolute contribution of capital deepening to the trend is relatively large, thus it will play a dominant role in the short run. On the other hand, the typical technological recession existed in China during the past five years further strengthens the pillar effects of capital deepening. Given the considerable amount of capital stock at present, future growth rate of capital deepening is very likely to decelerate slowly. Overall, capital deepening simply provides a basis for maintaining economic growth rate, but is not a key driver of the trend of returning to medium-to-high-speed growth.

Secondly, the contribution of labor that accounts for the smallest proportion to the trend is extremely low, which is only 10% at the largest and trivial at present. This means that demographic dividend is not a key driver of the long-term trend despite its influence on the

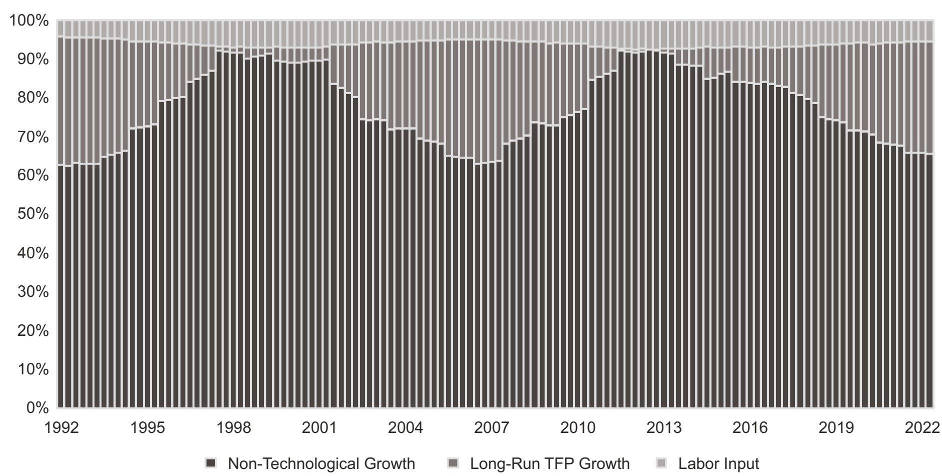


Figure 9. Changes in the time-varying contributions of labor input, technological progress and capital deepening to the trend

downward trend. The contribution of labor input changes to the trend has been almost zero since 2012. Besides the poor impact of demographic dividend on the trend, it suggests that China's future trend will not simply be driven by low-end production pattern. As the Chinese economy gradually quitted from the development phase driven by demographic dividend, it begins to shift to the world's frontier development pattern.

Lastly, technological progress is the most active factor, especially when China becomes a member of the WTO and benefits from the low-hanging fruit of technology during 2001–2012. Meanwhile, the contribution of technology factor to the trend is significant and characterized with a typical inverse U–shaped curve. It shows that technology has once played an important role of determining trend changes in some certain phases. Nowadays, China's first-round Kondratieff cycle of technological absorption has basically ended. The growth rate of TFP has entered the interval of negative growth since 2012, which implies that the Chinese economy has entered the stage of a typical technological recession. Along with the escalating Sino–US trade frictions and COVID-19 pandemic, China has encountered certain technology blockade before fully forming technological progress based on autonomous innovation. As a result, the growth rate of TFP has an accelerated downward trend, whose contribution to the long-term trend is about –3%, thereby becoming a main cause of the downward trend and lack of economic growth momentum. It is worth noting that such a downward trend of technology is caused by two reasons. For one thing, changes in the pattern of technological progress will inevitably decelerate its rate. Since its real income per capita has reached the world's upper middle-income level, China must realize technological progress based on autonomous innovation for sustainable development before converging to the high-income club. In other words, this technical deceleration is inevitable from the long-term strategic perspective. For another thing, the technology-capital mismatch caused by accidental events such as technological progress and the COVID-19 pandemic has accelerated the downward trend of TFP to a great extent. Its push-down effects on technological progress rate should not be ignored after 2018. Technological progress rate has decreased by three percentage points (see Figure 8b) since then, although it can be amended in the short- and medium-run. Therefore, improvements in the downward trend calls for key means including activating the potential of technology factor and improving the inefficiency caused by the technology-capital mismatch. As long as this inefficiency can be properly tackled, it is still highly possible for the Chinese economy to return to medium-to-high-speed growth.

Conclusions

Faced by the triple pressures of demand decline, supply shock and weakening expectation, China's economic growth faces an unprecedented downward pressure, which makes discussions on its long-term trend increasingly vital. An innovation of this paper is to develop a time-varying mixed-frequency dynamic factor model using data with different start dates to measure the trend in a real-time manner. In addition, this paper conducts a real-time decomposition of various factors' contributions to the trend based on the classical C–D production function. The main conclusions are summarized below.

First, in terms of model estimation, our model can identify the characteristics of changes in the trend. Relative to the classical H–P filter and UC–Kalman model, the trend measured by our model shows obvious advantages in terms of event feedback ability, economic forecasting ability and econometric stability.

Secondly, in terms of data usage, the inclusion of some survey data with different start dates (e.g., consumer confidence index, entrepreneur confidence index, business climate index, etc.) can greatly improve the estimation accuracy of our model, which confirms the importance of real-time macroeconomic survey data in predicting changes in the trend.

Thirdly, in terms of the characteristics of changes in the trend, the trend has entered a downward interval as early as 2007, although real GDP growth rate has decelerated since 2010 and fallen below 8% in 2012. The downward trend after 2012 can be divided into two stages: the first stage (2012–2017) is the main stage of China's "New Normal" when the trend's core characteristic is its shift from high- to medium-to-high-speed growth. The trend's core characteristic in the second stage (2018–present) is to accelerate downward. Its average level has fallen to around 4% at present, which is also the bottom line of medium-to-high speed growth. In terms of the lower limit of the 90% confidence interval, it is even lower than the natural rate of 2%, which suggests that the downward trend is not completely caused by random events such as the COVID-19 pandemic. The Chinese economy is experiencing an unprecedented risk of the downward trend.

Fourthly, in terms of the driving mechanism of the trend, decelerated capital deepening, diminishing demographic dividend and technological recession drive the downward trend collectively. Since demographic dividend has been almost depleted since 2014, the unfavorable labor force factor will no longer drive the long-term economic growth. The technological factor trapped by negative growth is jointly caused by the upgrade of technological progress and mismatch between technology and capital. As a main cause of decelerated economic growth, its push-down impact on the trend is up to three percentage points at present. The capital factor makes the greatest contribution to the trend. Given the considerable capital stock in China, it is hardly possible to massively replace capital in the short run. Hence, heavily relying on capital deepening will not mitigate risks of the downward trend.

All in all, we can draw the following basic conclusions. First, our model provides a precise and reliable measurement of the trend, which enables us to identify changes in the trend accurately. Secondly, through systematic comparisons between influences of capital deepening, demographic dividend and technological progress on the trend, we find that the impact of demographic dividend on the trend is the smallest, and capital deepening makes the steadiest contribution to the trend. Technological regression is the main trigger of the downward trend. Therefore, increasing growth rate and improving efficiency of technological progress come first in order to promote the Chinese economy to rebound. Thirdly, it is not realistic to achieve the goals of fundamental technological innovation and large-scale technological upgrade in the short run. Mitigating the mismatch between technological progress and obsolete capital, revitalizing existing capital stock, and increasing the efficiency of technology utilization thus become more feasible means. Last but not least, if it can keep prudent in reducing excessive capacity and inventory and properly balance between economic growth and technological progress, the Chinese economy is still expected to return to the medium-to-high-speed growth interval.

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APPENDIX

Appendix A. Explicit expressions of parameter matrices **H** and **F**, error terms $\tilde{\boldsymbol{\eta}}_{\mathbf{t}}$ and $\mathbf{e_t}$, and covariance matrices of error terms $\tilde{\mathbf{R}}_t$ and $\mathbf{Q}_t$

According to the following two state space models:

$$\tilde{\mathbf{y}}_{\mathbf{t}} = \mathbf{H}\mathbf{X}_{\mathbf{t}} + \tilde{\boldsymbol{\eta}}_{\mathbf{t}},\ \tilde{\boldsymbol{\eta}}_{\mathbf{t}} \sim N\left(0, \tilde{\mathbf{R}}_{\mathbf{t}}\right); \tag{A.1}$$

$$\mathbf{X}_{\mathbf{t}} = \mathbf{F}\mathbf{X}_{\mathbf{t-1}} + \mathbf{e}_{\mathbf{t}},\ \mathbf{e}_{\mathbf{t}} \sim N\left(0, \mathbf{Q}_{\mathbf{t}}\right), \tag{A.2}$$

where state vector $\mathbf{X}'_{\mathbf{t}} = \left[a_t, \ldots, a_{t-4}, f_t, \ldots, f_{t-4}, \mathbf{u}_t^{Q\prime}, \ldots, \mathbf{u}_{t-4}^{Q\prime}\right]$, the parameter matrix **H** can be expressed as:

$$\mathbf{H} = \left[\mathbf{H}_a \quad \begin{vmatrix} \mathbf{H}_{\lambda_Q} \\ \mathbf{H}_{\lambda_M} \end{vmatrix} \quad \mathbf{H}_u \right], \tag{A.3}$$

where $\mathbf{H}_a = \left[\begin{array}{ccccc} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \\ \hline \multicolumn{5}{c}{\mathbf{0}_{(n-1)\times 5}} \end{array} \right]$, $\mathbf{H}_{\lambda_Q} = \begin{bmatrix} 1 & \lambda_2 & \dots & \lambda_{n_Q} \end{bmatrix}' \times \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & 1 & \frac{2}{3} & \frac{1}{3} \end{bmatrix}$,

$\mathbf{H}_{\lambda_M} = \left[\begin{array}{c|c} \lambda_{n_Q+1} - \lambda_{n_Q+1}\rho_{1,1}^M - \lambda_{n_Q+1}\rho_{1,2}^M & \mathbf{0}_{1\times 4} \\ \vdots & \vdots \\ \lambda_n - \lambda_n \rho_{n_M,1}^M - \lambda_n \rho_{n_M,2}^M & \mathbf{0}_{1\times 4} \end{array} \right]$, $\mathbf{H}_u = \begin{bmatrix} \bar{\mathbf{H}}_u \\ \mathbf{0}_{n_M \times 5} \end{bmatrix}$ and

$\bar{\mathbf{H}}_u = \mathbf{1}_{n_Q \times 1} \times \left(1/3 \;\; 2/3 \;\; 1 \;\; 2/3 \;\; 1/3 \right)$.

The parameter matrix **F** can be expressed as:

$$\mathbf{F} = \begin{bmatrix} \mathbf{F}_1 & \mathbf{0} & & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{F}_2 & & & \\ \vdots & & \mathbf{F}_{2+1} & & \vdots \\ \vdots & & & \ddots & \mathbf{0} \\ 0 & \dots & \cdots & \mathbf{0} & \mathbf{F}_{2+n_Q} \end{bmatrix}, \tag{A.4}$$

where $\mathbf{F}_1 = \left[\begin{array}{cc} 1 & 0_{1\times 4} \\ \hline \mathbf{I}_4 & \mathbf{0}_{4\times 1} \end{array} \right]$, $\mathbf{F}_2 = \left[\begin{array}{ccc} \phi_1 & \phi_2 & \mathbf{0}_{1\times 3} \\ \hline \multicolumn{3}{c}{\mathbf{I}_4 \quad \mathbf{0}_{4\times 1}} \end{array} \right]$ and $\mathbf{F}_{2+j} = \left[\begin{array}{ccc} \rho_{j,1}^Q & \rho_{j,2}^Q & \mathbf{0}_{1\times 3} \\ \hline \multicolumn{3}{c}{\mathbf{I}_4 \quad \mathbf{0}_{4\times 1}} \end{array} \right], \left(j = 1, \dots n_Q \right)$.

The error terms $\tilde{\boldsymbol{\eta}}_{\mathbf{t}}$ and $\mathbf{e}_{\mathbf{t}}$ can be expressed as:

$$\tilde{\boldsymbol{\eta}}_{\mathbf{t}} = \left[0_{1\times n_Q}, \tilde{\boldsymbol{\eta}}_t^{M\prime} \right]'; \tag{A.5}$$

$$\mathbf{e}_{\mathbf{t}} = \left[\nu_{a_t} \quad \mathbf{0}_{4\times 1} \quad \epsilon_t \quad \mathbf{0}_{4\times 1} \quad \eta_{1,t} \quad \mathbf{0}_{4\times 1} \quad \cdots \quad \eta_{n_Q,t} \quad \eta_{1,t} \right]'. \tag{A.6}$$

The covariance matrices of error terms $\tilde{\mathbf{R}}_t$ and $\mathbf{Q}_t$ can be expressed as:

$$\tilde{\mathbf{R}}_t = \begin{bmatrix} \mathbf{0}_{n_Q \times n_Q} & \mathbf{0}_{n_Q \times n_M} \\ \mathbf{0}_{n_Q \times n_M} & \mathbf{R}_t \end{bmatrix}, \qquad \mathbf{R}_t = \mathrm{diag}\left(\sigma^2_{\eta_{1,t}^M}, \dots, \sigma^2_{\eta_{n_M,t}^M} \right)$$
$$\mathbf{Q}_t = \mathrm{diag}\left(\omega_a^2, \mathbf{0}_{1\times 4}, \sigma_{\epsilon,t}^2, \mathbf{0}_{1\times 4}, \sigma^2_{\eta_{1,t}^Q}, \mathbf{0}_{1\times 4}, \dots, \sigma^2_{\eta_{n_Q,t}^Q}, \mathbf{0}_{1\times 4} \right). \tag{A.7}$$

Appendix B. Gibbs sampling

Let $\boldsymbol{\theta} \equiv \left\{ \boldsymbol{\lambda}, \boldsymbol{\Phi}, \boldsymbol{\rho}, \omega_a, \omega_\varepsilon, \omega_{\eta_1}, \dots, \omega_{\eta_n} \right\}$ denote a basic parameter matrix, in which $\boldsymbol{\Phi}$ and $\boldsymbol{\rho}$ is a parameter relevant to the factor and heterogeneous component in Eqs (3) and (4), respectively. We use the Gibbs sampling as a Markov chain Monte Carlo (MCMC) algorithm to estimate our model by taking the following nine steps:

1) Making an arbitrary assignment for model parameter $\boldsymbol{\theta}^0$ and stochastic variation series $\{\sigma_{\varepsilon,t}^0, \sigma_{\eta_i,t}^0\}_{t=1}^T$, and setting $j = 1$;
2) Based on model parameter $\boldsymbol{\theta}^{j-1}$ and stochastic variation series $\{\sigma_{\varepsilon,t}^{j-1}, \sigma_{\eta_i,t}^{j-1}\}_{t=1}^T$, sampling latent variable $\{a_t^j, f_t^j, u_t^q\}_{t=1}^T$;

3) Based on latent variable $\{a_t^j\}_{t=1}^T$, sampling the variance of time-varying economic growth component $\omega_a^{2,j}$;
4) Based on common factor $\left\{f_t^{j-1}\right\}_{t=1}^T$ and its stochastic variation series $\{\sigma_{\varepsilon,t}^{j-1}\}_{t=1}^T$, sampling the autoregressive parameter of factor vector autoregressive $\mathbf{\Phi}^j$;
5) Based on common factor $\left\{f_t^{j-1}\right\}_{t=1}^T$, heterogeneous component parameter ρ^{j-1} and its stochastic variation series $\left\{\sigma_{\eta_i,t}^{j-1}\right\}_{t=1}^T$, sampling factor loading $\boldsymbol{\lambda}^j$;
6) Based on common factor $\left\{f_t^{j-1}\right\}_{t=1}^T$, stochastic variation series $\left\{\sigma_{\eta_i,t}^{j-1}\right\}_{t=1}^T$ and factor loading $\boldsymbol{\lambda}^{j-1}$, computing the autocorrelation coefficient of heterogeneous component $\boldsymbol{\rho}^j$;
7) Based on autoregressive parameter $\mathbf{\Phi}^{j-1}$ and common factor $\left\{f_t^{j-1}\right\}_{t=1}^T$, computing the sampling of common factor's stochastic variation series $\{\sigma_{\varepsilon,t}^j\}_{t=1}^T$;
8) Based on factor loading $\boldsymbol{\lambda}^{j-1}$, autocorrelation coefficient of heterogeneous component $\boldsymbol{\rho}^{j-1}$ and common factor $\left\{f_t^{j-1}\right\}_{t=1}^T$, computing the sampling of heterogeneous component's stochastic variation series $\left\{\sigma_{\eta_i,t}^j\right\}_{t=1}^T$;
9) Increasing j by 1, repeating steps 2)–7), until forming a convergent Markov chain.

Appendix C. Time-varying parameter and priori estimate

We aim to measure the trend's time-varying characteristics. Eqs (1) and (2) allow the means of all or partial observable variables in $\mathbf{y_t}$ to have stochastic trends, and a new question comes up: which parameters shall be allowed to have time-varying characteristics. The simplest way is to let $\mathbf{c_t}$ have one time-varying parameter only (i.e., growth rate of real GDP), its intercept follow time-varying process, and $\mathbf{B}$ = 1. As stated in previous studies (e.g., Cogley, 2005), consumption contains important information for predicting the trend. For example, the permanent income hypothesis states that consumers will attempt to smooth consumption over their lifetime, thus consumption is highly correlated with permanent income, and weakly correlated with temporary components. It shows that linking real GDP with consumption helps to separate the trend from cyclical fluctuations. Therefore, the benchmark model assumes real GDP and consumption to grow at the same rate g_t in the long run[9] (r = 1 and m = 2):

$$\mathbf{a_t} = g_t, \mathbf{B} = \left[1,1\right]'. \tag{C.1}$$

More specifically, we put growth rate of real GDP and consumer price index on the top of $Y_\mathbf{t}$, and set the loading of real GDP to be 1. In particular, we only set the intercepts of growth rate of real GDP and of consumer price index to be time-varying parameters, while that of other variables are constant. For variables that may change over time but are not categorized into $\mathbf{a_t}$, we measure time-varying characteristics by using their heterogeneous components[10].

[9] We do not assume investment to grow at g_t because China has experienced typical capital-embodied technological progress during the entire sampling period, which implies that growth rate of investment with a low-frequency trend is different from that of real GDP (Greenwood et al., 1997).

[10] This practice is reasonable because the risk of including wrong variables is much greater than that of excluding wrong variables in the process of setting common trend.

In order to reveal the variation rule of data more objectively, we attempt to use as few priori information as possible by not imposing any priori constraints on factor loading, and correlation coefficients of factor and heterogeneous components. For the innovation variances of time-varying parameters (ω_{α}^2, ω_{ε}^2 and $\omega_{\eta,i}^2$), since they cannot be computed by likelihood estimation only, we let their variances converge to 0 (i.e., standard dynamic factor model without time-varying trends and stochastic variation series) in the priori setting. Following Cogley and Sargent (2005) and Primiceri (2005), we assume the priori setting of ω_{α}^2 to be an inverse gamma distribution with variance and degree of freedom to be 0.001 and 1, respectively.

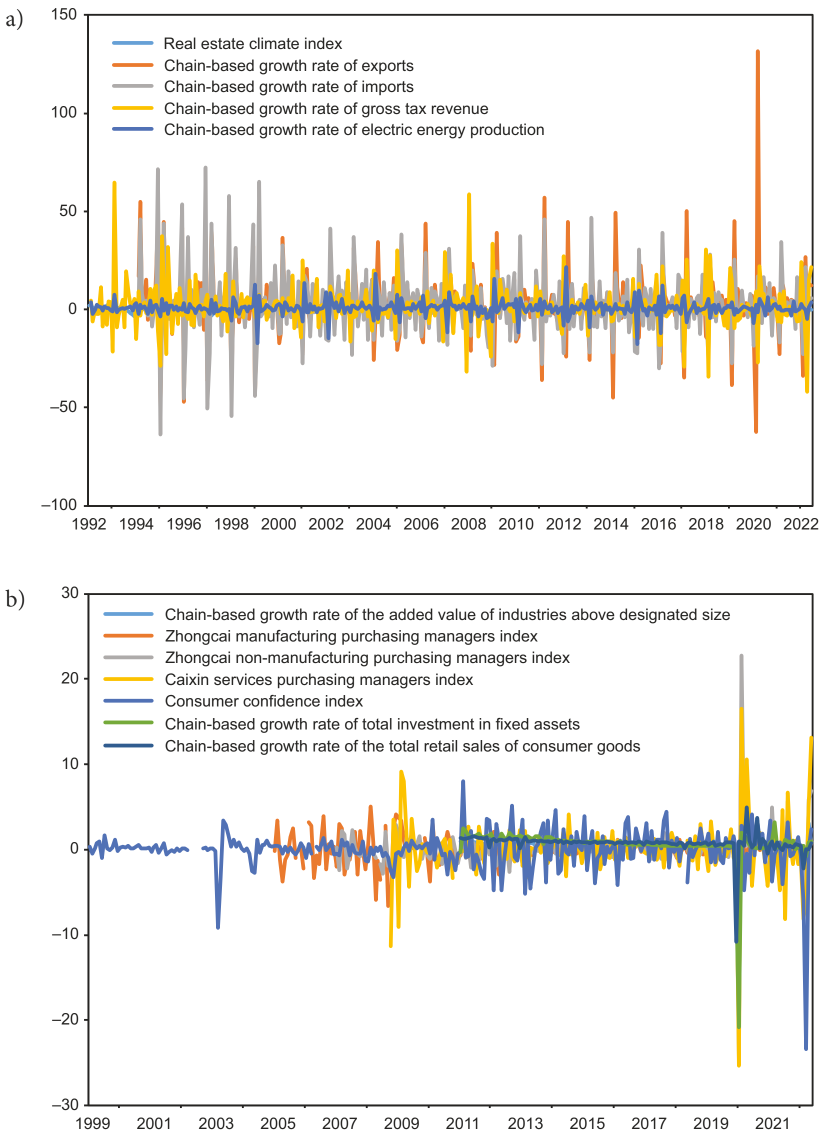

Figure D1. Trend graphs of fundamental factors on a monthly basis

As to ω_ε^2 and $\omega_{\eta,i}^2$, we assume the priori setting to be an inverse gamma distribution with variance and degree of freedom to be 0.0001 and 1, respectively. Then, we conduct Gibbs sampling for 10000 times, and consider the first 2000 times as a burn-in sample before parameter estimation.

Appendix D. Trend graphs and descriptive statistics of fundamental factors

We plot trends of all fundamental factors given in Table D1 in terms of data frequency, followed by a descriptive statistics analysis.

Table D1. Descriptive statistics of fundamental factors

	Mean		Standard deviation		Min		Max	
	Before 2012	After 2012	Before 2012	After 2012	Before 2012	After 2012	Before 2012	After 2012
Growth rate of real GDP	10.461	6.462	3.559	10.311	0.471	–32.800	22.134	55.800
Consumer price index	8.303	7.784	2.883	1.462	0.993	5.025	18.614	11.242
Growth rate of total investment in fixed assets	1.551	0.591	0.678	2.073	–0.230	–20.860	2.450	3.160
Growth rate of per capita disposable income of urban residents	10.660	7.729	12.617	9.108	–16.854	–16.206	69.840	41.530
Growth rate of value-added of the industrial enterprises above designated size	0.935	0.653	0.210	3.825	0.680	–22.100	1.320	36.560
Growth rate of total retail sales of consumer goods	1.384	0.703	0.101	1.192	1.260	–10.770	1.570	4.980
Growth rate of electric energy production	0.860	0.556	3.659	4.144	–16.983	–17.781	18.490	21.703
Growth rate of exports	2.727	2.293	15.482	19.363	–50.399	–62.500	56.856	131.700
Growth rate of imports	3.148	1.206	18.652	13.206	–63.817	–30.200	72.363	46.852
Real estate climate index	0.002	–0.090	0.958	0.577	–3.469	–3.440	3.347	1.216
Growth rate of gross tax revenue	2.020	1.076	11.043	10.706	–33.263	–41.853	59.802	30.568
Consumer confidence index	–0.023	–0.044	1.467	3.144	–9.131	–23.410	8.032	5.177
Entrepreneur confidence index	2.907	6.834	23.195	45.966	–65.906	–84.824	59.386	258.937
Business climate index	2.636	1.942	19.795	28.407	–52.074	–73.364	69.028	134.072
China manufacturing PMI	–0.056	–0.001	2.303	2.116	–6.600	–14.300	5.000	16.300
China non–manufacturing PMI (economic activities)	–0.073	–0.013	1.323	3.395	–2.800	–24.500	2.900	22.700
Caixin services PMI	–0.111	0.016	3.588	3.767	–11.300	–25.300	9.100	16.500

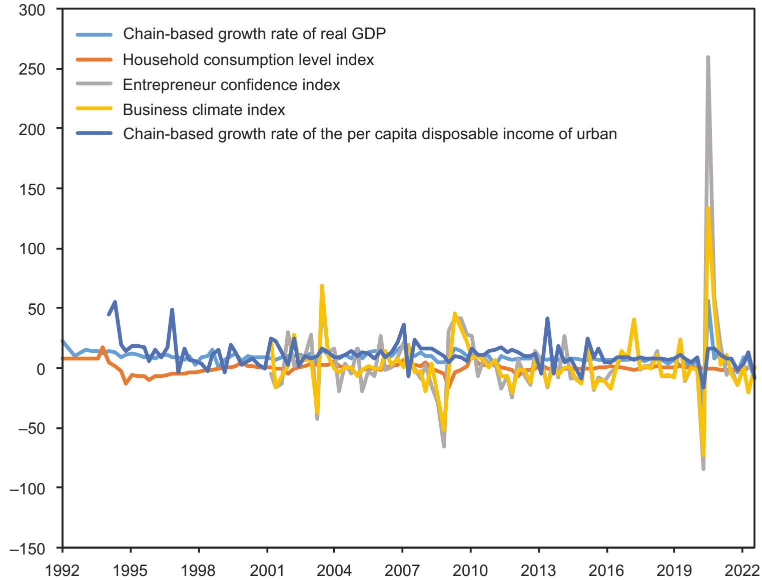

Figure D2. Trend graphs of fundamental factors on a quarterly basis