



# Sustainable development in China? A nonparametric decomposition of economic growth

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## ABSTRACT

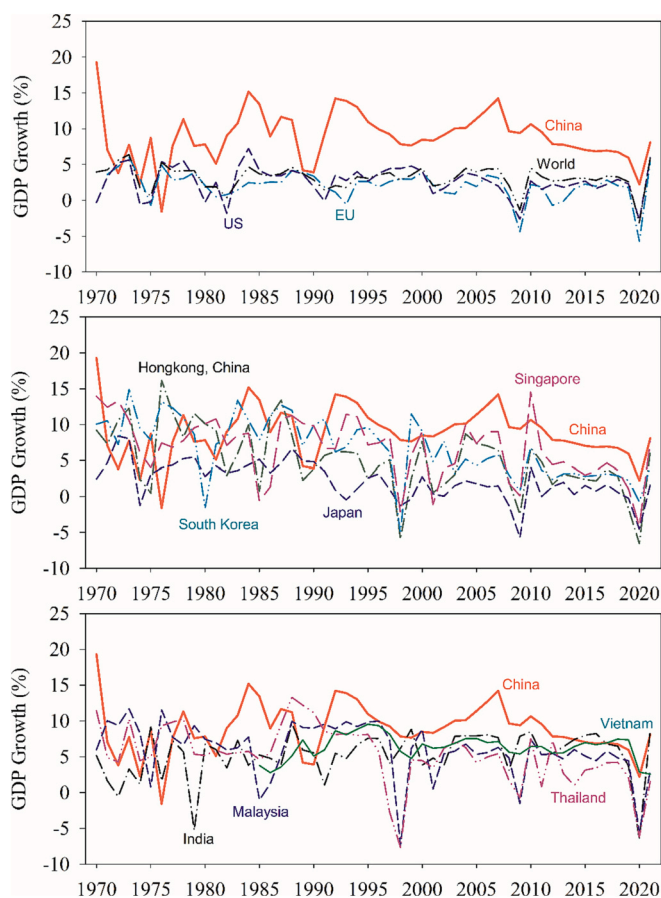
China has undergone significant deviations from the command economy established in 1949, achieving unprecedented success in sustaining high growth. Consequently, numerous scholars have devoted their attention to studying China's economic development. In this study, we contribute to this literature using a new technique to examine China's economic development. This technique utilizes nonparametric directional distance function in the framework of neo-classical growth theory. It avoids the assumptions imposed on parametric production functions that are often short of practical justifications. Our analysis shows that capital and energy inputs account for 75.7% and 20.8% of China's GDP growth during 1985–2020. These figures characterize a capital-driven growth model that is unlikely to be sustainable by conventional wisdom. However, our empirical evidence, obtained through an interactive-fixed effects model, indicates that it is not unreasonable to say that growth in China is government-led rather than capital-driven; the former could be sustained by desirable reforms under strong national leadership while the latter is not.

## 1. Background

The real GDP growth in China averaged at an annual rate of 10.1% during 1985–2020, this has been described as a growth miracle by many scholars (Ang & Madsen, 2011; Chen, 2021; Krugman, 1994; Prasad, 2009). As Fig. 1 shows, China's GDP growth aligned with the world average prior to 1978, but soon following the economic reform, China's growth accelerated at an exceptionally high rate. Places such as Japan, Hong Kong, Singapore, South Korea, Taiwan, and Brazil experienced similar growth miracles (Choi, Kim, & Ma, 2021; Lucas, 1993; Yao, 2014). More recently, India, Vietnam, and parts of Africa start to enjoy this kind of high growth (Ghosh & Parab, 2021; McMillan & Harttgen, 2014; Tompsett, 2020). Nonetheless, China's economic development has certain distinctive features that deserve to be studied on its own. Taking the recent COVID-19 pandemic for instance, the decline of GDP growth in China during 2020 was less critical than other countries, and it recovered immediately to 8.1% in 2021.

Krugman (1994) acknowledged that the task of detangling China's boom is not an easy one. China was once the largest developing country operating under the *socialist planned* economy, a political system originally established by the former Soviet Union. China

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**Fig. 1.** GDP growth rate of China compared with the rest of the world (1970–2021).

*Notes:* The data used in this analysis are sourced from the World Bank. The annual percentage growth rates of GDP are calculated using constant local currency values.

underwent a transition during 1979–1992, right before embarking on the full journey to the *socialist market economy*. One of the characteristics of this economy is the pro-growth bureaucratic incentive system embedded in China's monumental National Five-year Plans (Li & Zhou, 2005; Naughton, 2017). These national plans are the blueprints for China's stage-by-stage economic development. In the last few decades, China established a spectacular growth record and demonstrated strong resilience during several global crises (Chen, 2021). Especially in the past decade or two, the progress of digital technology in China has been nothing short of remarkable. In 2021, the percentage of the population using the internet in China reached an impressive 73%, marking a staggering 41-fold increase from a mere 1.8% in 2000. This growth is particularly astonishing when compared to the global average, which rose from 6.7% to 63% over the same period. Moreover, when considering the number of secure internet servers per 1 million people, data from the World Bank indicates a remarkable 791-fold surge, climbing from 1.2 in 2010 to 948 in 2020. In contrast, the global average experienced a 61-fold increase throughout this decade.

The ride on this remarkable journey is, however, not without bumps. For instance, to combat the 2008 global financial crisis, the Chinese government introduced an RMB¥4 trillion stimulus package, coupled with a revitalization plan of 10 major industries. This robustly pursued capital-driven growth was directly challenged by a decline in global demand. The economy as a result was severely over-capacitated (Ni, Lu, & Xie, 2021), especially for sectors such as steel, cement, flat glass, electrolytic aluminum, refining, etc. As presented in Fig. 2, capacity utilization rates fell significantly below the international warning line of 80%.

Meanwhile, China is holding the world's largest foreign exchange reserve because of the surpluses accumulated in its current account, capital account, and financial account. Investing abroad therefore becomes increasingly acute to preserve the value of this reserve.<sup>1</sup> The Belt and Road Initiative (BRI) was introduced in 2013 under this background. Countries that are experiencing difficulties in global integration due to the lack of infrastructure and technology (Du & Zhang, 2018), are being invested with China's surplus capital to facilitate development in these regions (Ni et al., 2021).

Could China's growth be replicated by other less developed economies? Is this kind of growth sustainable and therefore should be

<sup>1</sup> By November 2019, China's foreign exchange reserve has reached US \$3.1 trillion.

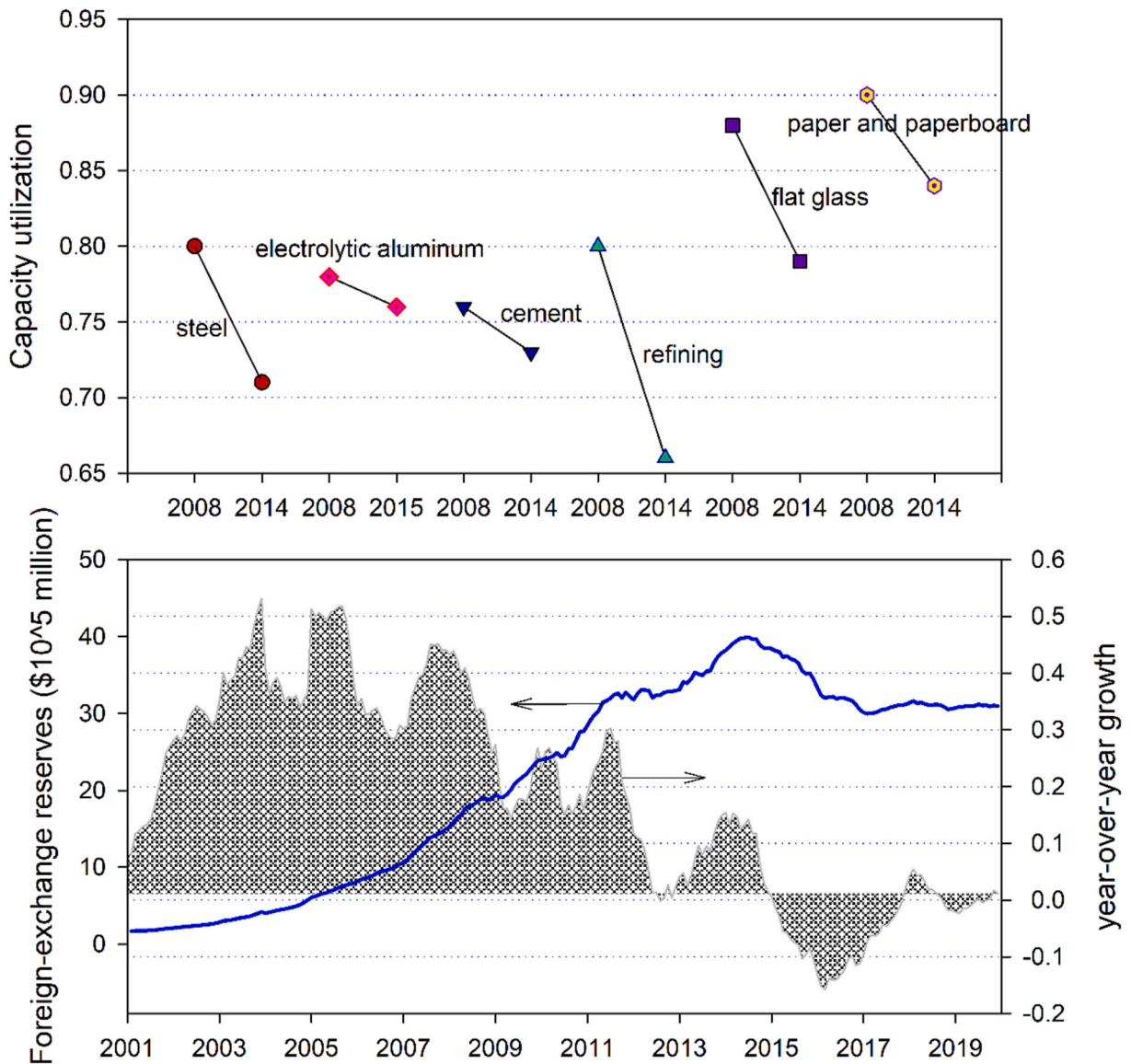


Fig. 2. Capacity utilization and foreign-exchange reserves of China.

Note: The data of capacity utilization come from “Overcapacity in China: An Impediment to the Party’s Reform Agenda” released by the European Chamber of Commerce in 2016; the data of foreign-exchange reserves come from State Administration of Foreign Exchange (<http://www.safe.gov.cn/>).

promoted globally? This line of questioning is not unwarranted given rapid changes in China’s economic landscape, as reflected in its income, labor force composition, factor costs, and external markets (Naughton, 2017; Zhu, 2012).

China has been facing increased environmental challenges and income inequality because of rapid economic growth and urbanization. Using data from the World bank, the ratio of China to World GDP per capita (in constant 2015 \$US) has a 0.98 correlation with China to World CO<sub>2</sub> emissions per capita over 1990–2019.<sup>2</sup> The Gini coefficient in China peaked at 0.44 in 2010, from about 0.30 in 1978 (Ravallion & Chen, 2007), then backed down to around 0.38 in 2019 (the World Bank).

Although the economic growth in China presented in Fig. 1 closely resembles the high-growth period of its Asian neighbours, the trajectory of environmental pollution and inequality in China are more in line with the global counterparts of similar geographical size, such as the Western Europe and America. Similar issues emerged in these countries centuries ago since the Industrial Revolution. A pairwise correlation analysis between China’s share of world GDP and a range of other development indicators is provided in Fig. 3, as

<sup>2</sup> CO<sub>2</sub> emissions before 1990 are not available. And the correlation is about the same when GDP per capita is replaced with the percentage of urban population.

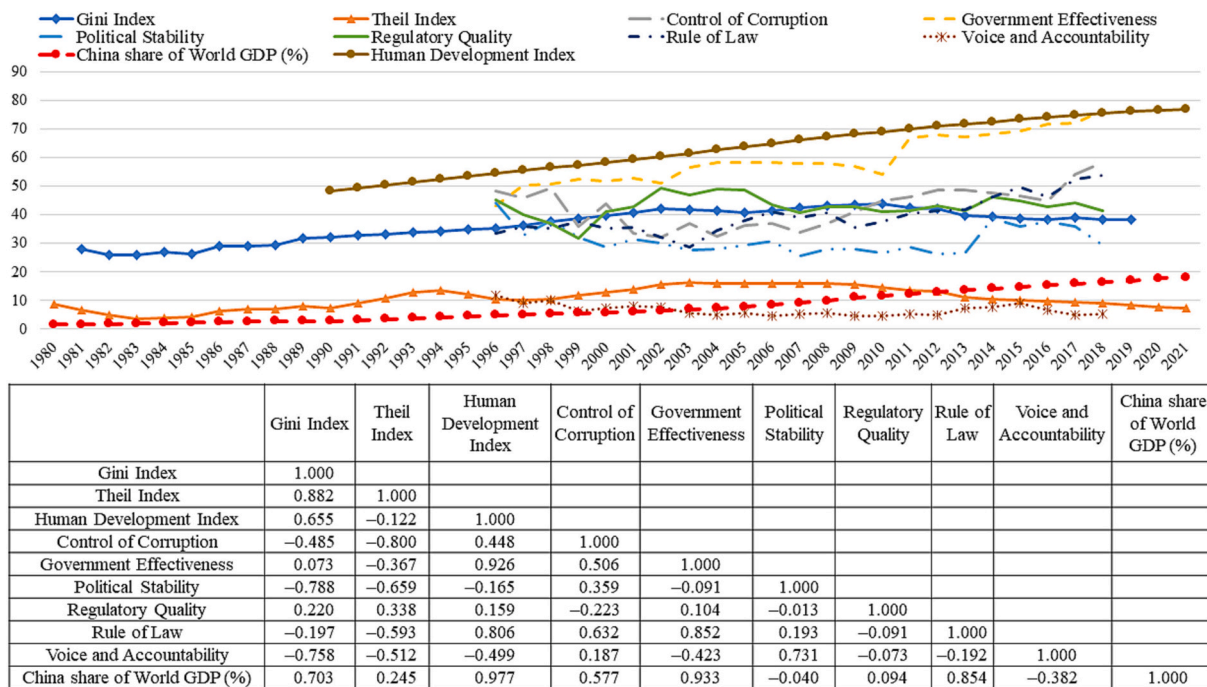


Fig. 3. A Comparison of difference development indicators in China (1980–2021).

Source: The Theil index is compiled by the authors and the Human Development index is compiled by the United Nations Development Program. Gini Index from 1981 to 1989 is from Ravallion and Chen (2007). The rest of the data is from the World Bank.

well as a time trend illustration.

All the indicators shown in Fig. 3 have a range from 0 to 100, except for the Theil Index, which is another measure of income inequality with a maximum value of infinity. A Gini index or Theil Index of zero indicates a perfectly equal distribution of income, while a higher index value signifies greater inequality. These two indexes exhibit a strong correlation with each other, as evidenced by a correlation coefficient of 0.88. However, only the Gini index demonstrates a high correlation of 0.7 with China’s share of world GDP. This difference may be attributed to the nonlinear nature of the Theil index.

The human development index is compiled by the United Nations, it captures improvements in life expectancy and education together with economic development. As can be seen, it has a very high correlation of 0.98 with China’s share of world GDP. The Kuznets hypothesis seems to account for not only the experience of the United States up to the 1970s but also that of China in the past four decades, which makes China more of an alliance in sustaining the global economic development and simultaneously combating the issues of climate change and inequality. As many had experienced similar stages of development in the past and China should be able to lean on their understanding and knowledge to conquer future challenges. A comprehensive survey of the impacts of China’s economic development on income inequality has been provided by Zhang (2021), and the impacts on the environment has been recently analysed by Yang, Gao, and Li (2022).

China is also going through a transformation of social and political landscape. Besides the above-mentioned human development index, this can be reflected through the Worldwide Governance Indicators (WGI). These indicators are reported by the World Bank for over 200 countries and territories over the period 1996–2021 and we use China’s percentile ranks across six dimensions of governance.

China’s share of world GDP, measured in constant 2015 US\$, has a correlation of 0.93 with its percentile rank in government effectiveness and 0.85 with its rank in rule of law. China will need to improve its rank in voice and accountability, which correlates positively with improvements made in income inequality and political stability. These dimensions are likely to be trading off with a country’s government effectiveness and human development measure, as demonstrated by their negative correlations in Fig. 3. This implies that the Chinese government has chosen a development path that first takes care the survival needs of its citizens, which constitutes 22% of the world population. Increased living standards will cumulate human and social capital over time, which lead to a more advanced civilization. This is also evidenced in the development of Western Europe and America, although the paths through which they arrived at their modern civilizations are slightly different, the milestones are nonetheless more or less the same.

In fact, growth in China has already begun to slow down since 2010 and surpassed by India in 2015. Moreover, the Chinese government implemented extremely tight measures of prevention and control to combat the recent COVID-19 pandemic, at a substantial cost of curbing economic vitality. Some scholars suspect that China might slip into a ‘middle-income trap’ (e.g., Eichengreen, Park, & Shin, 2011), others (e.g., Wei, Xie, & Zhang, 2017) indicate that China has been struggling in raising total factor productivity (TFP) that requires the transformation from ‘made in China’ to ‘innovated in China’.

To tackle these concerns, China launched a new set of measures in 2015, they are instruments for the structural reform targeting the

supply-side of the market. Over time, these new indicators are supposed to replace the pro-growth bureaucratic incentive system. The targets include capacity reduction, destocking, deleveraging, and developing the underdeveloped fields.

This new structural reform, together with the BRI, constitute the China's so-called soft-landing policies. This study provides some empirical evidence on the impacts of these policy measures using an interactive fixed effects model derived from the endogenous growth theory. This is to segregate the contribution of national intervention to China's economic growth.

In short, the contributions of this study to the growth literature are two-fold: Methodologically, we developed a new technique to examine China's historical economic growth. This technique utilizes nonparametric directional distance function in the framework of neoclassical growth theory. It avoids the assumptions imposed on parametric production functions that are often short of practical justifications. Empirically, we enriched the endogenous growth theory by demonstrating that the second-generation semi-endogenous model explains better the economic success driven by central governance in China.

The remainder of this paper is structured as follows: [Section 2](#) reviews the related literature. [Section 3](#) explains how we develop the new technique for decomposing economic growth. This nonparametric technique is called the slacks-based measure of directional distance function (i.e., SBM-DDF). It has the advantage of identifying the contributions from different production factors to output growth in the absence of neoclassical assumptions. Then this technique is applied in [section 4](#) to evaluate China's economic development in the last four decades. [Section 5](#) tries to measure the additional contribution of central governance to endogenous growth. [Section 6](#) concludes and outlines some policy implications.

## 2. Literature summary

In general, the techniques of output growth decomposition can be classified into four categories. The first category is a direct result of the neoclassical theory. It involves the identification of an aggregate production function, and the segregation of total factor productivity (TFP) growth from the contributions of input-factor growth. The literature started with the Solow residual model (Solow, 1957), then evolved into the latent variable model (Fuentes & Morales, 2011) and stochastic frontier analysis (Kumbhakar, Wang, & Horncastle, 2015). However, the issues involved in the specification of production functions have been constantly under debate (Blackwood, Foster, Grim, Haltiwanger, & Wolf, 2021; Foster, Grim, Haltiwanger, & Wolf, 2016; Foster, Haltiwanger, & Syverson, 2008). The function is usually constructed under restrictive assumptions such as Hicks neutral technical change and constant returns to scale (CRS) (Deng, Qin, & Song, 2020). Especially when parametric techniques are employed, the resulting output elasticities are often inflexible (De Loecker, Goldberg, Khandelwal, & Pavcnik, 2016; Deng & Chen, 2015). These constraints on the production functions are increasingly difficult to justify given the current big data technology evolution, coupled with exponential world population growth.

The second category of decomposition technique is based on a straightforward GDP accounting exercise; it is originally used to compute the shares of growth from household consumption, government expenditure, investment, and net exports. This approach simply compartmentalizes GDP growth into different segments according to an accounting identity, without necessarily diving into the underlying causes for growth. For example, Wang (2000) performed this analysis across different types of sectors and found that the state sector constituted 35% of China's economic growth during 1979–1998, meanwhile, Bosworth and Collins (2008) showed that nearly half of the China's GDP growth since 1978 was from the industrial sector, and the service sector accounted for most of the growth in employment. Whalley and Xin (2010) reported that foreign invested enterprises in China added up to over 40% of the output growth in 2004. Yao (2014) indicated that about 30% of China's GDP growth in the period between 2002 and 2008 came from exports. Zheng and Walsh (2019) demonstrated that urbanization contributed an additional economic growth by 0.267% to 1.091% during 2002–2013.

The third category draws on the theory of endogenous growth. This approach focuses mainly on the contribution of TFP and the drivers of TFP growth. For instance, the R&D-based endogenous growth theories have been widely used to explain the economic development in OECD (Coe & Helpman, 1995; Ha & Howitt, 2007; Madsen, 2007; Zachariadis, 2004) and Asia (Ang & Madsen, 2011; Ghosh & Parab, 2021; Lucas, 1993; Madsen, Saxena, & Ang, 2010). The first-generation of endogenous growth models, represented by Romer (1990) and Aghion and Howitt (1992), are no longer considered to be an empirical regularity because of the assumptions of constant returns to knowledge and the counterfactual implication (Cozzi, 2017). The second-generation, such as the Schumpeterian growth models (He, 2018; Parello, 2022) and the semi-endogenous growth models, have gradually become the main paradigm and are providing better explanations for output growth (Ang & Madsen, 2011; Jones, 2022; Madsen, 2007).

The fourth category of growth decomposition is primarily based on nonparametric data envelopment analysis (DEA). Under the conventional assumption of Hicks neutral technical change, the elasticity of TFP is unity and thus, the contribution degree of TFP equals to the growth rate of TFP.<sup>3</sup> This kind of nonparametric analysis is conceptually similar to the Solow growth model (Dong & Liang, 2013; Li, Qu, Wei, Ai, & Jia, 2020; Tian & Yu, 2012), but the growth rate of TFP, so does the contribution degree of TFP to economic growth, can be easily computed with Divisa or Malmquist index (Feng, Wang, Liu, & Huang, 2017), there is no need to specify a parametric production function. However, the results may be unreliable when the underlying technical change is not neutral. In addition, this method can compute the contribution from TFP growth, but not the contributions from other input factors. Dong and Liang (2013) tried to resolve this issue through an algebraic decomposition of the production frontier, using the slacks obtained from DEA. Nonetheless, the resulting input-factor contributions captured only the shifts in the production frontier, not growth in output. More recently, Deng and Chen (2015) utilized shadow prices to measure output elasticities, which was substituted back into the Solow

<sup>3</sup> TFP is characterized by variable  $A$  in the aggregate production function from the Solow growth model (i.e.,  $Q = Af(K, L)$ ), in which the contribution of TFP to output growth is shown to be  $\Delta \ln A$ .

**Table 1**  
Decompositions of Chinese growth in literature.

Literature	Physical capital		Labor		Human capital		TFP		Other	
<i>Wang (2000)</i>	<i>1979–1991</i>	<i>1991–1999</i>	<i>1979–1991</i>	<i>1991–1999</i>	<i>1979–1991</i>	<i>1991–1999</i>	<i>1979–1991</i>	<i>1991–1999</i>		
	0.571	0.673	0.116	0.059	0.155	0.049	0.158	0.219		
<i>Chow and Lin (2002)</i>	<i>1952–1978</i>	<i>1978–1998</i>	<i>1952–1978</i>	<i>1978–1998</i>			<i>1952–1978</i>	<i>1978–1998</i>	<i>1952–1978</i>	<i>1978–1998</i>
	0.793	0.629	0.154	0.106			0.053	–0.024	0.000	0.289
<i>Guo and Jia (2005)</i>	<i>1979–2014</i>									
	0.905						0.095			
<i>Bosworth and Collins (2008)</i>	<i>1978–1993</i>	<i>1993–2004</i>	<i>1978–1993</i>	<i>1993–2004</i>	<i>1978–93</i>	<i>1993–2004</i>	<i>1978–1993</i>	<i>1993–2004</i>		
	0.27	0.433	0.281	0.124	0.045	0.031	0.393	0.402		
<i>Zhu (2012)</i>	<i>1952–1978</i>	<i>1978–2007</i>	<i>1952–1978</i>	<i>1978–2007</i>	<i>1952–78</i>	<i>1978–2007</i>	<i>1952–1978</i>	<i>1978–2007</i>		
	1.162	0.005	0.036	0.071	0.523	0.146	–0.72	0.779		
<i>OECD (2013)</i>	<i>2001–2006</i>	<i>2006–2011</i>	<i>2001–2006</i>	<i>2006–2011</i>			<i>2001–2006</i>	<i>2006–2011</i>		
	0.591	0.65	0.153	0.131			0.255	0.218		
<i>Dong and Liang (2013)</i>	<i>1978–2010</i>									
	0.854		0.037				0.109			
<i>Deng and Chen (2015)</i>	<i>1986–2000</i>	<i>2000–2012</i>	<i>1986–2000</i>	<i>2000–2012</i>			<i>1980–2008</i>	<i>2000–2012</i>	<i>1980–2008</i>	<i>2000–2012</i>
	0.638	0.742	0.033	0.032			0.146	–0.052	0.183	0.278
<i>Wei et al. (2017)</i>	<i>1979–2008</i>	<i>2008–2015</i>			<i>1979–2008</i>	<i>2008–2015</i>	<i>1979–2008</i>	<i>2008–2015</i>		
	0.588	1.070			0.191	0.162	0.221	–0.232		

Note: The figures in italics indicate time periods. The other factor studied in [Chow and Lin \(2002\)](#) is the reform that China launched in 1978, while in [Deng and Chen \(2015\)](#), it is energy consumption.

model to decompose output growth. This approach is also not without issues because instantaneous elasticities cannot be used to decompose discrete statistical data.

In addition to these four abovementioned mainstream techniques, some political studies discussed various influences on China's economic development (Chan, Xu, & Gao, 2015; Kwan, Zhang, & Zhuo, 2018; Li & Zhou, 2005; Naughton, 2017; Yao, 2014; Zhu, 2012). These factors include national institutions, demographic structure, economic reforms, official incentives, and industrial policies etc. To illustrate, China's economy suffered critical damage during the late 1980s, which was more damning compared to the global crises as seen in Fig. 1. This was caused by the political movement at the time and demonstrated the importance of considering social turmoil when investigating economic growth (Yao, 2014).

A summary of the main findings from previous literature has been provided in Table 1. Most empirical studies, except two (Bosworth & Collins, 2008; Zhu, 2012), reported that capital-input contributed over 50% to GDP growth. In comparison, the contribution from TFP was consistently small and could even be negative in some cases. This capital-driven growth path was not sustainable according to the conventional wisdom as demonstrated by the Solow model and the Kuznets' curve; even Keynes, a supporter for investment, urged that capital under-utilization is not helpful. Nonetheless, China's economy had maintained four decades of high growth, this record was unprecedented compared to the length sustained by others when they were in the same stage of development. This study is therefore motivated to explore the secrets behind this success.

### 3. The slacks-based measure of directional distance function

A conventional production function with energy as one of the inputs is depicted in Eq. (1). This is to recognize the energy-intensive nature of China's development (Feng et al., 2017; Pang, Deng, & Hu, 2015; Zheng & Walsh, 2019).

$$Y_t = F(K_t, L_t, E_t, t) \quad (1)$$

where  $Y$  denotes gross domestic (or regional) product;  $K$ ,  $L$ , and  $E$  denote capital, labor, and energy inputs, respectively. The trend variable  $t$  can be used to accommodate the time variant nature of the production function. A commonly recognized specification has a time variant total factor productivity (TFP), denoted by  $A_t$  in Eq. (2):

$$Y_t = F(K_t, L_t, E_t, A_t) \quad (2)$$

Parametric techniques are often employed to estimate Eq. (2) under the assumptions of Hicks-neutral technical change and constant returns to scale (CRS).<sup>4</sup> However, the first issue under this analytical framework is that technical change is unlikely to be neutral, the marginal rates of technical substitution across inputs are rapidly changing under the evolution of information technology over the last half century. Simultaneously, the validity of the CRS assumption has been theoretically and empirically challenged (Banker, Cooper, Seiford, Thrall, & Zhu, 2004; Deng et al., 2020), whereas the variable returns to scale (VRS) assumption is gathering more supports due to the Dixit-Stiglitz-Krugman model. The third concern is that China's geographical development is highly unbalanced, the production functions and output elasticities may vary substantially across different regions. The following technique is therefore being developed to address these issues.

#### 3.1. The Solow decomposition

Let's start with the Solow decomposition and take the partial derivative of Eq. (2) with respect to time  $t$ , this would give us Eq. (3):

$$\frac{\partial Y_t}{\partial t} = \frac{\partial F}{\partial K_t} \frac{\partial K_t}{\partial t} + \frac{\partial F}{\partial L_t} \frac{\partial L_t}{\partial t} + \frac{\partial F}{\partial E_t} \frac{\partial E_t}{\partial t} + \frac{\partial F}{\partial A_t} \frac{\partial A_t}{\partial t} \quad (3)$$

Divide both sides of Eq. (3) by  $Y_t$  would lead us to the output growth decomposition in Eq. (4):

$$\frac{\dot{Y}_t}{Y_t} = \frac{\partial \ln Y_t}{\partial \ln K_t} \frac{\dot{K}_t}{K_t} + \frac{\partial \ln Y_t}{\partial \ln L_t} \frac{\dot{L}_t}{L_t} + \frac{\partial \ln Y_t}{\partial \ln E_t} \frac{\dot{E}_t}{E_t} + \frac{\partial \ln Y_t}{\partial \ln A_t} \frac{\dot{A}_t}{A_t} \quad (4)$$

where the last term on the right-hand side, denoted by  $r_t \equiv \frac{\partial \ln Y_t}{\partial \ln A_t} \frac{\dot{A}_t}{A_t}$ , is the well-known Solow residual (Solow, 1957). This  $r_t$  represents the contribution *degree* of TFP growth to output growth.

Under the assumption of Hicks neutral technological change, we would have  $\frac{\partial \ln Y_t}{\partial \ln A_t} = 1$ , therefore  $r_t = \frac{\dot{A}_t}{A_t}$ . This is to say that the contribution *degree* of TFP growth to output growth is equivalent to the TFP growth itself, if and only if today's big data technological evolution can be justified as Hicks neutral (Dong & Liang, 2013; Li et al., 2020). Fortunately, our technique doesn't rely on this assumption as we will demonstrate soon.

The decomposition in Eq. (4) requires the computation of output elasticities for all input factors, i.e.,  $\frac{\partial \ln Y_t}{\partial \ln K_t}$ ,  $\frac{\partial \ln Y_t}{\partial \ln L_t}$ , and  $\frac{\partial \ln Y_t}{\partial \ln E_t}$ . A large body of literature before the 1990s followed Solow (1956, 1957) and Chenery, Robinson, and Syrquin (1986), they approximated these output elasticities using input expenditure shares, which would be problematic in the presence of factor price distortions. Moreover, if

<sup>4</sup> Technical discussions of the common functional forms for approximating  $F(\bullet)$  can be found in Barnett and Lee (1985) and Chambers, Färe, Grosskopf, and Vardanyan (2013) etc.

parametric techniques are used to estimate these output elasticities from a presumed production function, the findings were often impractical with limited use.<sup>5</sup>

Before proceeding further, it could be useful to review the differences between TFP, TFP index, and TFP contribution. TFP measures the ability of producer using multiple inputs to generate output(s), and this is embedded in the concept of production efficiency. TFP index, such as the widely used Divisa, Malmquist, and Luenberger indexes, measures the *variation* of TFP across time and/or producers. TFP contribution, also referred to as the contribution *degree* of TFP growth to output growth (or decline), is denoted by the Solow residual  $r_t$  in Eq. (4). The corresponding contribution *rate* of TFP growth measures the *proportion* of the contribution made by TFP growth to output growth (or decline), and it is denoted by  $C_{A,t}$  in Eq. (5):

$$1 = \underbrace{\frac{\partial Y_t}{\partial K_t} \frac{\dot{K}_t}{Y_t}}_{C_{K,t}} + \underbrace{\frac{\partial Y_t}{\partial L_t} \frac{\dot{L}_t}{Y_t}}_{C_{L,t}} + \underbrace{\frac{\partial Y_t}{\partial E_t} \frac{\dot{E}_t}{Y_t}}_{C_{E,t}} + \underbrace{\frac{\partial Y_t}{\partial A_t} \frac{\dot{A}_t}{Y_t}}_{C_{A,t}} \tag{5}$$

where  $C_{K,t}$ ,  $C_{L,t}$ , and  $C_{E,t}$  represent the contribution rates of capital, labor, and energy inputs, respectively.

### 3.2. The conventional parametric techniques

To further demonstrate how conventional parametric techniques are used to decompose output growth, let's consider the Cobb-Douglas production function with CRS:

$$Y_t = A_t K_t^\alpha E_t^\beta L_t^{1-\alpha-\beta} \tag{6}$$

Take the natural logarithm of Eq. (6) would give us:

$$\ln \frac{Y_t}{L_t} = \ln A + \alpha \ln \frac{K_t}{L_t} + \beta \ln \frac{E_t}{L_t} + \varepsilon_t \tag{7}$$

The Solow residual  $r_t$  is provided by  $\Delta \ln A_t$ , where  $\ln A_t \equiv \ln A + \varepsilon_t$  in Eq. (7).

The *latent variable* (LV) approach utilizes the state-space model in control engineering. The term,  $\ln A_t \equiv \ln A + \varepsilon_t$ , is specified as a state variable satisfying a first-order autoregressive process as depicted in Eq. (8):

$$\ln A_t = \rho \ln A_{t-1} + v_t \tag{8}$$

where  $v_t$  is the conventional white noise component. The state-space model can estimate  $\alpha$ ,  $\beta$  and  $\rho$  simultaneously, then compute the logged TFP (i.e.,  $\ln A_t = \ln \frac{Y_t}{L_t} - \alpha \ln \frac{K_t}{L_t} - \beta \ln \frac{E_t}{L_t}$ ) and the corresponding contribution *degree* of TFP growth (i.e.,  $\Delta \ln A_t = \ln A_t - \ln A_{t-1}$ ).

In comparison, the *stochastic frontier analysis* (SFA) estimates Eq. (7) through the imposition of an exogenous distributional assumption on  $\ln A_t$ . The specification is described as:

$$\ln \frac{Y_t}{L_t} = c + \alpha \ln \frac{K_t}{L_t} + \beta \ln \frac{E_t}{L_t} - u_t + \varepsilon_t \tag{9}$$

$$u_t = c - \ln A_t \sim N^+(\mu, \sigma_u^2), \text{ and } \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \tag{10}$$

As can be seen, there are two error terms in this model, one is the error term  $u_t$  that represents inefficiency, and it is assumed to follow a normal distribution truncated from above at 0. The other is the conventional random error term  $\varepsilon_t$  that is assumed to be independently and identically distributed normal with zero mean. The model is usually estimated with maximum likelihood.

Another less recognized approach is the *potential output* (PO) method extended from the LV model, the purpose of which is to address production capacity utilization. The Solow residual  $\Delta \ln A_t$  in Eq. (8), only captures long-term technical change according to Guo and Jia (2005), and they re-specify the production function as the following:

$$Y_t = U_t A_t K_t^\alpha E_t^\beta L_t^{1-\alpha-\beta} \tag{11}$$

where  $U_t$  denotes capacity utilization. We now have  $\Delta \ln TFP_t = \Delta \ln A_t + \Delta \ln U_t$ , in which  $\Delta \ln A_t$  can be estimated using the LV model as discussed before. Meanwhile, the long-term trend in  $\ln Y_t$  (namely,  $\ln Y_t^*$ ), and thus the log of capacity utilization, i.e.,  $\ln U_t = \ln Y_t - \ln Y_t^*$ , can be obtained with the Hodrick–Prescott filter.

The exogenous constraints under which these parametric production functions are constructed can be easily challenged, such as CRS and Hicks-neutral technical change, as well as the independence assumption between input factors and TFP. Some tried to relax this assumption by introducing endogenous growth into the parametric specification (Ang & Madsen, 2011), nonetheless this approach doesn't allow a clear distinction of factor contributions to productivity growth from productivity growth itself.

The alternative is the non-parametric directional distance function that are free from the common assumptions imposed on

<sup>5</sup> Even for translog or other more flexible function forms, the variation of output elasticities across time and/or Decision-Making Units (DMUs) were very limited. Common issues with flexible functions include: (1) estimated output elasticities could be negative for some DMUs in certain periods; and (2) the estimates were often not significantly different from zero due to multicollinearity.

parametric functions (Deng & Chen, 2015; Feng et al., 2017; Guo & Jia, 2005), but it has several limitations of its own. First, the opportunity to gain insights into the associated economic properties through parametric analysis is sacrificed; second, the constructed production frontier is sensitive to data outliers; moreover, the issue of selecting an appropriate direction to project the DMUs onto the production frontier is complex but crucial to the results obtained. A comprehensive review on direction selection is provided by Wang, Xian, Lee, et al. (2019). In addition to the above, this non-parametric technique doesn't provide insights on the factors that influence productivity. The methodology we will introduce in the next section is trying to deal with this limitation.

### 3.3. Measuring TFP with the SBM\_DDF

First, we start with the measurement of TFP, data on inputs and outputs can be utilized to construct the inverted Eq. (2):

$$A_t = D(K_t, L_t, E_t, Y_t) \tag{12}$$

Then we propose to use the SBM\_DDF to estimate Eq. (12). The production possibility set in an SBM\_DDF can be defined by:

$$\mathbb{T}^{\text{SBM}} = \{(K, L, E, Y) : \text{such that } K, L, \text{ and } E \text{ can produce } Y\} \tag{13}$$

One can refer to Tone (2001) and Fukuyama and Weber (2009) for the standard assumptions made on the technology. Considering  $N$  decision making units (DMUs) and  $T$  periods, the production possibility set can be formalized using the following Data Envelopment Analysis:

$$\mathbb{T}^{\text{SBM}} = \left\{ (K_t, L_t, E_t, Y_t) \mid \begin{cases} \sum_{\tau=1}^T \sum_{i=1}^N \lambda_{\tau}^i K_{\tau}^i \leq K_t \\ \sum_{\tau=1}^T \sum_{i=1}^N \lambda_{\tau}^i L_{\tau}^i \leq L_t \\ \sum_{\tau=1}^T \sum_{i=1}^N \lambda_{\tau}^i E_{\tau}^i \leq E_t \\ \sum_{\tau=1}^T \sum_{i=1}^N \lambda_{\tau}^i Y_{\tau}^i \geq Y_t \\ \sum_{\tau=1}^T \sum_{i=1}^N \lambda_{\tau}^i = 1; \lambda_{\tau}^i \geq 0 \end{cases} \right\} \tag{14}$$

where  $\lambda_{\tau}^i$  ( $i = 1, \dots, N; \tau = 1, \dots, T$ ) represents the weight that each DMU contributes to the construction of the technology frontier(s). When  $\tau = 1, \dots, T$ ,  $\mathbb{T}^{\text{SBM}}$  represents a global benchmark technology (Pang et al., 2015); if  $\tau = t$  and  $t + 1$ , then  $\mathbb{T}^{\text{SBM}}$  is a biennial benchmark technology (Pastor, Asmild, & Lovell, 2011; Pastor, Lovell, & Aparicio, 2020); and when  $\tau = 1, \dots, t$ , then  $\mathbb{T}^{\text{SBM}}$  is a sequential benchmark technology (Shestalova, 2003). It is very common to set  $\tau = t$ , therefore the technology frontier is constructed with only contemporaneous data (Deng, Jiang, & Pang, 2021; Färe, Grosskopf, & Whittaker, 2013).

Given that we want to evaluate China's output growth over the last four decades, the global benchmark technology is chosen. That means we utilize data from all provinces in China during 1985–2020. Furthermore, because there is only one global benchmark technology, we don't need to take the geometric mean of adjacent TFP indexes as the conventional Malmquist index does. But our analysis must be constantly updated whenever new data becomes available.

For the  $\mathbb{T}^{\text{SBM}}$  specified in Eq. (14), a slacks-based measure of efficiency is the weighted sum of input excesses and good output shortfalls, which is described as:

$$\overline{\text{SBM}}(z; v) = \max\{vs : (z + s)' \in \mathbb{T}^{\text{SBM}}\} \tag{15}$$

Here,  $z = (K, L, E, Y)' \in \mathfrak{R}_+ \times \mathfrak{R}_+ \times \mathfrak{R}_+ \times \mathfrak{R}_+$  is our collective vector of inputs and output;  $v = (v_K, v_L, v_E, v_Y) \in \mathfrak{R}_- \times \mathfrak{R}_- \times \mathfrak{R}_- \times \mathfrak{R}_+$  is the vector of exogenous weights assigned to various dimensional slacks that are provided by the vector  $s = (s_K, s_L, s_E, s_Y)' \in \mathfrak{R}_- \times \mathfrak{R}_- \times \mathfrak{R}_- \times \mathfrak{R}_+$ . As comprehended in previous studies (Atkinson & Tsionas, 2016; Deng et al., 2021; Färe, Grosskopf, Noh, & Weber, 2005), properties of the SBM\_DDF include:

- P1: Translation:  $\overline{\text{SBM}}(z + \psi v; v) = \overline{\text{SBM}}(z; v) - \psi(\|v\|_2)^2$ .
  - P2: Homogeneity of degree one in  $v$ :  $\overline{\text{SBM}}(z; \psi v) = \psi \overline{\text{SBM}}(z; v)$ .
  - P3: Input monotonicity:  $\overline{\text{SBM}}[(\bar{K}, L, E, Y)'; v] \geq \overline{\text{SBM}}[(K, L, E, Y)'; v]$  for  $\bar{K} \geq K$ ;  $\overline{\text{SBM}}[(K, \bar{L}, E, Y)'; v] \geq \overline{\text{SBM}}[(K, L, E, Y)'; v]$  for  $\bar{L} \geq L$ ; and  $\overline{\text{SBM}}[(K, L, \bar{E}, Y)'; v] \geq \overline{\text{SBM}}[(K, L, E, Y)'; v]$  for  $\bar{E} \geq E$ .
  - P4: Good output monotonicity:  $\overline{\text{SBM}}[(K, L, E, \bar{Y})'; v] \leq \overline{\text{SBM}}[(K, L, E, Y)'; v]$  for  $\bar{Y} \geq Y$ .
  - P5: Concavity:  $\overline{\text{SBM}}(z; v)$  is concave in  $(z + s)' \in \mathbb{T}^{\text{SBM}}$ .
  - P6: Non-negativity:  $\overline{\text{SBM}}(z; v) \geq 0$  if  $(z + s)' \in \mathbb{T}^{\text{SBM}}$ .
- Property P1 states that if inputs are contracted by  $\psi(|v_K|, |v_L|, |v_E|)$  and good outputs are expanded by  $\psi v_Y$ , then the value of the

resulting slacks-based measure will be more efficient by the amount  $\psi(\|v\|_2)^2$ . Property P2 implies that a change in the unit of the weight vector does not affect the relative size of inefficiency. Property P3 represents disposability of inputs, inefficiency will not decrease for a firm that produces the same level of outputs with more inputs. Likewise, Property P4 is a monotonicity property with respect to desirable output(s), this property is crucial to ensure convergence of the iteration process that we will discuss next. Property P5 says the production possibility set,  $\mathbb{T}^{SBM}$ , is convex. Finally, Property P6 indicates inefficiency cannot be negative, this is soon to be relaxed in the next section.

The vector of exogenous weights ( $v$ ) is equivalent to the direction in the conventional DDF analysis (Deng et al., 2021). A large body of literature provides guidance on direction selection (Atkinson & Tsionas, 2016; Chambers, Chung, & Färe, 1996; Deng et al., 2021; Färe et al., 2013; Feng & Serletis, 2014; Krüger, 2017; Lee, 2014; Zofio, Pastor, & Aparicio, 2013). This study follows Fukuyama and Weber (2009), i.e.  $v = (-\frac{1}{6K}, -\frac{1}{6L}, -\frac{1}{6E}, \frac{1}{2Y})$ , which implies equal weights and has been adopted by studies such as Tone and Tsutsui (2009) and Pang et al. (2015).

The SBM\_DDF that we provide has several advantages over other alternatives: (1) all the conventional DEA and DDF approaches, are radial models and therefore, cannot measure non-radial slacks, this often leads to an over-estimation of TFP (Tone & Tsutsui, 2009). Our SBM\_DDF model is conceptually equivalent to the conventional DDF models but with endogenous directions; it alleviates the errors from pre-setting a direction (Deng et al., 2021; Färe et al., 2013; Pastor et al., 2020); (2) the global benchmark technology allows TFP across different time periods to be comparable; and (3) it is not constrained by the conventional neoclassical assumptions imposed on parametric functions.

Because the values computed from the SBM\_DDF are measures of inefficiency, the resulting TFP can be obtained from  $1 - \overrightarrow{SBM}$  (Adler & Volta, 2016; Pang et al., 2015; Pastor, Lovell, & Aparicio, 2012). We can substitute this into Eq. (12):

$$A_t = D(K_t, L_t, E_t, Y_t) = 1 - \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) \tag{16}$$

Given that TFP can be denoted as  $\bar{A}$ , we can write  $\bar{A} - 1 + \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) = 0$ . Taking the derivatives of this implicit function would give us the following:

$$\frac{\partial Y_t}{\partial K_t} = - \frac{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial K_t}{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial Y_t} \tag{17}$$

$$\frac{\partial Y_t}{\partial L_t} = - \frac{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial L_t}{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial Y_t} \tag{18}$$

$$\frac{\partial Y_t}{\partial E_t} = - \frac{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial E_t}{\partial \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v) / \partial Y_t} \tag{19}$$

Assuming  $\overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v)$  is continuously differentiable, and the growth of input-output variables ( $\dot{K}_t, \dot{L}_t, \dot{E}_t$ , and  $\dot{Y}_t$ ) are observed, Eqs. (17)–(19) can be estimated and the resulting factor contribution rates ( $C_{K,t}$ ,  $C_{L,t}$ , and  $C_{E,t}$ ) in Eq. (5) can be obtained, as well as the contribution rate of TFP growth:

$$C_{A,t} = 1 - C_{K,t} - C_{L,t} - C_{E,t} \tag{20}$$

However, theory from operational research says that Eqs. (17)–(19) are just shadow prices at a specific data point and the assumption of continuously differentiable  $\overrightarrow{SBM}(K_t, L_t, E_t, Y_t; v)$  is routinely challenged. This implies the marginal outputs will be over-estimated given Property P5. We therefore propose an iteration method next to deal with this issue.

### 3.4. Contribution degrees and contribution rates

By converting Eqs. (4) and (5) into a discrete case, one would obtain the following:

$$\frac{Y_{t+1} - Y_t}{Y_t} = \frac{\Delta Y_{K,t \rightarrow t+1}}{Y_t} + \frac{\Delta Y_{L,t \rightarrow t+1}}{Y_t} + \frac{\Delta Y_{E,t \rightarrow t+1}}{Y_t} + \frac{\Delta Y_{A,t \rightarrow t+1}}{Y_t} \tag{21}$$

$$1 = \underbrace{\frac{\Delta Y_{K,t \rightarrow t+1}}{Y_{t+1} - Y_t}}_{C_{K,t \rightarrow t+1}} + \underbrace{\frac{\Delta Y_{L,t \rightarrow t+1}}{Y_{t+1} - Y_t}}_{C_{L,t \rightarrow t+1}} + \underbrace{\frac{\Delta Y_{E,t \rightarrow t+1}}{Y_{t+1} - Y_t}}_{C_{E,t \rightarrow t+1}} + \underbrace{\frac{\Delta Y_{A,t \rightarrow t+1}}{Y_{t+1} - Y_t}}_{C_{A,t \rightarrow t+1}} \tag{22}$$

where the components on the right-hand side of Eq. (21) are the contribution degrees of different factors to output growth from period  $t$  to  $t + 1$ ; their corresponding contribution rates are provided in Eq. (22), and the following holds:

$$\begin{cases} \Delta Y_{K,t \rightarrow t+1} = F(K_{t+1}, L_t, E_t, A_t) - F(K_t, L_t, E_t, A_t) \\ \Delta Y_{L,t \rightarrow t+1} = F(K_t, L_{t+1}, E_t, A_t) - F(K_t, L_t, E_t, A_t) \\ \Delta Y_{E,t \rightarrow t+1} = F(K_t, L_t, E_{t+1}, A_t) - F(K_t, L_t, E_t, A_t) \\ \Delta Y_{A,t \rightarrow t+1} = F(K_t, L_t, E_t, A_{t+1}) - F(K_t, L_t, E_t, A_t) \end{cases} \quad (23)$$

This shows that we can estimate Eq. (23) to compute the output growth decomposition depicted in Eqs. (21)–(22). And given the output,  $F(K_t, L_t, E_t, A_t) = Y_t$ , that can be observed, we only need to estimate  $F(K_{t+1}, L_t, E_t, A_t)$ ,  $F(K_t, L_{t+1}, E_t, A_t)$ , and  $F(K_t, L_t, E_{t+1}, A_t)$ . This would give us  $\Delta Y_{K,t \rightarrow t+1}$ ,  $\Delta Y_{L,t \rightarrow t+1}$ , and  $\Delta Y_{E,t \rightarrow t+1}$ . Therefore,  $\Delta Y_{A,t \rightarrow t+1}$  can be computed as  $\Delta Y_{A,t \rightarrow t+1} = Y_{t+1} - Y_t - \Delta Y_{K,t \rightarrow t+1} - \Delta Y_{L,t \rightarrow t+1} - \Delta Y_{E,t \rightarrow t+1}$ .

Let's illustrate with  $F(K_{t+1}, L_t, E_t, A_t)$ . As explained before, the SBM\_DDF method can be applied on the input-output data to obtain  $A_t$ :

$$A_t = 1 - \overrightarrow{SBM}(K_t, L_t, E_t, Y_t; \nu) \quad (24)$$

It is crucial to recognize that the following holds for  $F(K_{t+1}, L_t, E_t, A_t)$ :

$$1 - \overrightarrow{SBM}(K_{t+1}, L_t, E_t, F(K_{t+1}, L_t, E_t, A_t); \nu) = A_t \quad (25)$$

Therefore,  $F(K_{t+1}, L_t, E_t, A_t)$  can be estimated by the following iteration process:

**Step 1:** Use the SBM\_DDF to compute  $A_t$  according to Eq. (24).

**Step 2:** Set the initial value of iteration as  $\theta_{K,t+1}^0 = Y_{t+1}$ .

**Step 3:** Run the following iteration.

Step 3.1: Use the SBM\_DDF method to compute  $\overrightarrow{SBM}(K_{t+1}, L_t, E_t, \theta_{K,t+1}^0; \nu^0)$  and obtain  $A_t^0$ .

Step 3.2: If  $A_t^0 > A_t$ , then  $\theta_{K,t+1}^0$  is over-estimated; if  $A_t^0 < A_t$ , then  $\theta_{K,t+1}^0$  is under-estimated. Therefore, let  $\theta_{K,t+1}^1 = \theta_{K,t+1}^0 - (A_t^0 - A_t)\theta_{K,t+1}^0\varphi$ , where  $\varphi > 0$  is an adjuster to determine the speed of convergence.

Step 3.3: Use the SBM\_DDF method to compute  $\overrightarrow{SBM}(K_{t+1}, L_t, E_t, \theta_{K,t+1}^1; \nu^1)$  and obtain  $A_t^1$ .

Step 3.4: If  $A_t^1 > A_t$ , then  $\theta_{K,t+1}^1$  is over-estimated; if  $A_t^1 < A_t$ , then  $\theta_{K,t+1}^1$  is under-estimated. Therefore, let  $\theta_{K,t+1}^2 = \theta_{K,t+1}^1 - (A_t^1 - A_t)\theta_{K,t+1}^1\varphi$ .

Step 3.5: Repeat the above process  $\Lambda$  times until  $|A_t^\Lambda - A_t| \leq 0.0001$ . The corresponding  $\theta_{K,t+1}^\Lambda$  is the estimate for  $F(K_{t+1}, L_t, E_t, A_t)$ .

**Step 4:** Using the SBM\_DDF to compute  $\overrightarrow{SBM}(K_{t+1}, L_t, E_t, \theta_{K,t+1}^\Lambda; \nu^\Lambda)$  and test Eq. (25), i.e. to determine whether  $1 - \overrightarrow{SBM}(K_{t+1}, L_t, E_t, \theta_{K,t+1}^\Lambda; \nu^\Lambda)$  is equal to  $A_t$ .

**Step 5:** Let  $F(K_{t+1}, L_t, E_t, A_t) = \theta_{K,t+1}^\Lambda$ , then the contribution *degree* of capital is  $\Delta Y_{K,t \rightarrow t+1} / Y_t = (\theta_{K,t+1}^\Lambda - Y_t) / Y_t$  and the corresponding contribution *rate* of capital is  $C_{K,t \rightarrow t+1} = (\theta_{K,t+1}^\Lambda - Y_t) / (Y_{t+1} - Y_t)$ .

It should be noted that  $A_t^i$  may be negative because the global frontiers are constructed using only the input-output data, instead of data generated during the iteration process. Furthermore, the envelope theorem can be used to prove that we now have *strong* disposability for good output (i.e., Property P4).

This strong disposability of output means that when  $A_t^i > A_t$  ( $1 \leq i < \Lambda$ ),  $A_t^{i+1}$  can be obtained by  $\theta_{K,t+1}^{i+1} = \theta_{K,t+1}^i - (A_t^i - A_t)\theta_{K,t+1}^i\varphi$  and the SBM\_DDF will satisfy  $A_t^{i+1} < A_t^i$ ; conversely, when  $A_t^i < A_t$  ( $1 \leq i < \Lambda$ ), the SBM\_DDF will give us  $A_t^{i+1} > A_t^i$ ; and when  $A_t^i = A_t$ , the SBM\_DDF will satisfy  $A_t^{i+1} = A_t$ . Thereby, if and only if  $\varphi$  is not too large,  $A_t^{i+1}$  will be closer to  $A_t$  instead of  $A_t^i$ . This would ensure that  $A_t^\Lambda \rightarrow A_t$  through repeated iteration.

As for the speed of convergence, the larger the adjuster  $\varphi$ , the faster the convergence, but a large  $\varphi$  may result in non-convergence; on the contrary, the smaller the  $\varphi$ , the slower the convergence but it is guaranteed. To have an accelerated speed, we set  $\varphi = 0.2$ . Meanwhile, the following condition is added to make sure that  $\varphi$  is sufficiently small for a convergence: if  $\theta_{K,t+1}^i - 0.2(A_t^i - A_t)\theta_{K,t+1}^i < 0$  or  $\theta_{K,t+1}^i - 0.2(A_t^i - A_t)\theta_{K,t+1}^i > 1.2Y_t$ , then  $\varphi = 1/\theta_{K,t+1}^i$ .

### 3.5. Aggregate factor contributions

To perform this growth decomposition, we treat each province/municipality in China as a DMU. If one is into the national level factor contribution *degrees* and contribution *rates*, a weighted sum must be computed.

In this study, the weight that we choose is the proportion of real output *variation* for each province in China to the overall GDP *variation*. This is because the contribution *rate* of capital in the whole country can be specified as  $TC_{K,t \rightarrow t+1}$ :

$$TC_{K,t \rightarrow t+1} = \sum_i \left( \frac{\Delta Y_{K,t \rightarrow t+1,i}}{GDP_{t+1} - GDP_t} \frac{Y_{t+1,i} - Y_{t,i}}{Y_{t+1,i} - Y_{t,i}} \right) = \sum_i \left( \frac{Y_{t+1,i} - Y_{t,i}}{GDP_{t+1} - GDP_t} C_{K,t \rightarrow t+1,i} \right) \quad (26)$$

this leaves us  $\frac{Y_{t+1,i} - Y_{t,i}}{GDP_{t+1} - GDP_t}$  ( $i = 1, \dots, N$ ) as the weights.

As for the contribution *degrees*, we use the output *share* in national GDP at the beginning of each year due to the following:

$$\frac{\sum_i (\Delta Y_{K,t \rightarrow t+1,i})}{GDP_t} = \sum_i \left( \frac{Y_{t,i}}{GDP_t} \frac{\Delta Y_{K,t \rightarrow t+1,i}}{Y_{t,i}} \right) \quad (27)$$

where  $\frac{\Delta Y_{K,t \rightarrow t+1,i}}{Y_{t,i}}$  is the contribution *degree* of capital in province  $i$  at time  $t$ . Thus,  $\frac{Y_{t,i}}{GDP_t}$  ( $i = 1, \dots, N$ ) is the corresponding weight.

Overall, compared with the alternative SR, LV, SFA, and PO methods briefed in [section 3.2](#), this decomposition technique is more flexible and potentially more accurate. The only assumption we need is that the production function must be enveloped by the sample data, which is more practical compared to the conventional neoclassical assumptions. The empirical results across different techniques will be computed and compared next.

#### 4. China's growth decomposition

To examine the sources of China's development, production data since 1985 was utilized for the growth decomposition exercise in this section. Technological progress induced economic growth is perceived as intensive growth, relative to extensive growth. We also examined the effect of government intervention in the next section and tested whether the current development trajectory is sustainable.

##### 4.1. Data

The data consists of 30 provinces and municipalities in China, observed each year from 1985 to 2020.<sup>6</sup> The regional real gross product (with 1952 as the base year) is the output, while real capital stock, employee counts, and energy consumption are the inputs. Refer to [Table 2](#) for the construction of this dataset and [Table 3](#) for descriptive statistics of the four economic regions in China.

As shown in [Table 3](#), the annual average output growth in China is 10.1% from 1985 to 2020, this is a marvelous record. The growth rate for capital input is also extraordinarily high, averaged at 13.7% per year over the entire period, whereas labor has an annual average growth of only 1.3%, and energy consumption of 8.4%. The eastern region performs the best in output growth, averaging at 10.8% per year. This is expected as Beijing, Shanghai and Guangdong in the eastern region are under prioritized development because of their strategic positions.

##### 4.2. TFP from the SBM\_DDF

The TFPs for each province and municipality over 1985–2020 are computed using the SBM\_DDF technique described in [Section 3.3](#) and the results are summarized in [Fig. 4](#). The upward trajectory for the aggregated national TFP was obviously starting at 1990 (from 0.0018 in 1991 to 0.4278 in 2020) and it has been sustained for an unexpected period beyond conventional wisdom. Although TFP in the 2000s was flattened out, it started to regain strength after 2015 when the government implemented the supply-side structural reform, and the BRI began to roll out. The government also announced in 2015 that the Chinese economy has entered a “new normal” status and a development path that relies on technology innovation is under cultivation ever since. This is evident in [Fig. 4](#) by the significant boost in TFP growth, especially in the eastern developed region from 2015.

Eastern region's TFP, on average, is 0.17 higher than the national average, and 0.50 higher than the western region. The north-eastern region had relatively high TFP before 2008, but a severe decline was experienced after that and the growth momentum was never regained despite the desires of the State Council.<sup>7</sup> Same for the western region, it experienced a sharp decline from 2007, obviously any impact of the Western Development Strategy (launched in 1999) once had was short-lived.

##### 4.3. Factor contributions

Based on the SBM\_DDF technique and the aforementioned iteration steps in [Section 3.4](#), output growth from 1985 to 2020 is decomposed for each province and municipality in China and the results are aggregated at the national level using the weights introduced in [Section 3.5](#).

As can be seen in [Table 4](#), capital, labor, energy consumption and TFP contributed 7.33%, 0.39%, 2.12% and 0.27% respectively, to the national average output growth rate of 10.10%; or alternatively speaking, capital, labor, energy consumption and TFP, accounted for 75.67%, 2.68%, 20.84% and 0.81% of the output growth in China respectively (according to the contribution rates defined in [Section 3.4](#)). This seems to be a capital driven growth instead of the so-called miracle and it is comparable with the figures from previous studies as listed in [Table 1](#).

High-savings and high-investment lead to rapid capital accumulation and thus, contribute to a great extent to economic growth. This is not a surprising miracle but a common growth strategy being widely adopted in late-developing regions such as India, South Korea, and African countries. And as being pointed out in the Solow model, this kind of growth pattern is unlikely to be sustainable. It

<sup>6</sup> Tibet, Hong Kong, Macao and Taiwan are not included due to incomplete observations.

<sup>7</sup> To deal with this, on 4 March 2012, the China's State Council issued the *Twelfth Five Year Plan for Revitalizing the Northeast*; on 8 August 2014, the State Council formulated several key measures; and on 26 April 2016, the document - *Several Opinions of the CPC Central Committee and the State Council on the Comprehensive Revitalization of the Northeast and Other Old Industrial Bases* was issued.

**Table 2**  
Data sources and treatments.

Variables	Indicators	Symbols	Data sources before 2008	Data sources after 2008	Special treatments
Output	Regional real gross product (¥100 million)	$Y_t$	<i>China Compendium of Statistics 1949–2008</i> .	China Statistical Yearbooks	All the nominal variables have been deflated to constant price in 1952.
Inputs	Real capital stock (¥100 million)	$K_t$	Some provinces (e.g., Yunnan and Jiangsu) adjusted their historical figures in subsequent yearbooks.	China Statistical Yearbooks. Estimated by perpetual inventory method (see <a href="#">Shan, 2008</a> )	Prior to 1997, Chongqing was a part of Sichuan province. In this study, separate capital stocks from these two regions are considered. Subsequently, the method proposed by <a href="#">Hall and Jones (1999)</a> is employed to estimate an aggregated capital stock for the base year.
	Labor (10,000 person)	$L_t$	We used the latter whenever such discrepancy appeared.	Statistical yearbooks of various provinces, municipalities and autonomous regions. Measured by the number of employee counts at the end of each year	
	Energy consumption (10,000 tons of standard coal)	$E_t$		China Energy Statistical Yearbooks	
					Before 1988, Hainan was a part of Guangdong province. In this study, when the price index data for Hainan is missing, data from Guangdong province is utilized as a substitute.

can be seen from [Fig. 1](#) that growth in China starts to decline from 2010; and surpassed by India after 2015.

It is also increasingly challenging to maintain the high-saving rate in China. According to the World Bank data, China's share of savings in gross GDP gradually declined from 51.79% in 2008 to 44.02% in 2020. Meanwhile, high depreciation rate starts to offset a large part of gross investment, macro depreciation rate in China was up to 10.96% according to [Shan \(2008\)](#).

Meanwhile, although investment is favored for output growth, but excess supply is undesirable because the surplus capital cannot be converted into GDP when outputs are not consumed, this has been an on-going concern in China.<sup>8</sup> In addition, the aging population and the strained Sino-US trade relations also take a toll on the growth momentum. Therefore, China has been projected not to be able to maintain this growth record.

[Figs. 5 and 6](#) illustrate the annual average changes in factor contribution degrees and contribution rates during 1985–2020. Capital has consistently made the largest contribution across nearly all years, closely followed by energy. On the other hand, labor contribution has been relatively modest, and the contribution of TFP has shown erratic fluctuations. This pattern is expected since TFP tends to exhibit significant variations, primarily due to the challenges associated with sustaining technological progress. This challenge is also one of the primary reasons why maintaining continuous growth becomes difficult in the neoclassical Solow model. The complexities involved in continuously advancing technology contribute to this difficulty. Several studies, utilizing various indices such as the Malmquist index and Luenberger index, have consistently demonstrated this phenomenon by measuring TFP variations.

Overall, the conclusion that China's high growth in the 1990s and 2000s was primarily driven by capital accumulation is robust, more rigorous tests of which are performed next.

#### 4.4. Results robustness

To examine the robustness of the growth decompositions presented in [Table 4](#), we computed the contributions of TFP using the national aggregate input-output data and alternative techniques (i.e., the SR, LV, SFA, and PO models in [section 3.2](#)). The findings are presented in [Table 5](#) and the comparisons are made in [Fig. 7](#). The contribution degree of TFP from the SBM\_DDF method correlates closely with those obtained from the SR, LV, SFA, and PO models, meaning our nonparametric decomposition technique is reasonably robust.

Nonetheless, [Table 5](#) shows that TFP contribution obtained from the SBM\_DDF seems to be higher than those computed using other techniques, implying that TFP contribution may be conventionally underestimated. This is because for Eqs. (7)–(11) or others alike, technology neutrality is assumed, and they do not account for the potential interactions between TFP and other input factors. Whereas in practice, when part of the variation in TFP is absorbed by factor variations, the contribution of TFP would be underestimated using conventional parametric techniques, this is another drawback on top of the neoclassical constraints.

Our nonparametric decomposition is free from these issues and could serve as a valuable addition to the toolbox. Moreover, the contributions of TFP obtained from the SR, LV, SFA, and PO models are negative across many years, which is unlikely to be justified by the current state of technological development in China. Although no one can argue that the growth record depends primarily on capital investment, TFP from the SBM\_DDF, as presented in [Fig. 4](#), still shows a growth trend and therefore, better resembles the situation in China.

<sup>8</sup> Since the beginning of 2003, the State Council of China has indicated excess capacities in sectors including steel, calcium carbide, coke, and automobile etc. During the central economic work conferences from 2007 to 2019, this issue of excess capacity remained as a key task for the Chinese government to address.

**Table 3**  
Descriptive statistics of input-output variables (1985–2020).

Variable	Unit	Northeast region		Eastern region		Central region		Western region		The whole country	
		Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
$Y_t$	¥100 million	2001.49	2259.69	3257.70	3793.37	1480.74	1543.47	893.07	1083.77	1909.66	2687.37
$K_t$	¥100 million	5491.99	8234.85	8707.22	12,057.79	5271.24	7116.10	3237.20	4887.26	5692.83	8900.38
$L_t$	10,000 person	1671.26	399.76	2543.87	1839.73	3148.58	1176.98	1694.19	1170.02	2266.00	1502.07
$E_t$	10,000 tons of standard coal	8979.76	5160.10	10,341.66	9995.37	8999.23	5954.62	5715.60	5084.00	8240.76	7509.41
Number of observations		108		360		216		396		1080	
Growth rate of $Y_t$ (%)		8.96	4.01	10.79	4.40	9.83	3.44	9.94	3.29	10.10	3.83
Growth rate of $K_t$ (%)		14.53	17.68	13.94	7.92	13.34	6.17	13.49	6.12	13.71	8.56
Growth rate of $L_t$ (%)		0.70	3.52	1.79	3.00	0.99	3.34	1.24	3.35	1.32	3.27
Growth rate of $E_t$ (%)		3.29	5.96	13.67	95.00	5.33	6.55	6.69	9.03	8.41	55.31

## 5. An assessment of central governance in China

In Section 4, we concluded that China's growth during 1985–2020 is primarily driven by extensive capital investment rather than intensive TFP growth. This trajectory is conventionally regarded as unsustainable. The puzzle is that China's output growth in 2021 was still up to 8.1%, which is well above the world's average of 5.8%. The government declared its confidence in maintaining this kind of growth rate for an extended future period and attributed this to the strength of national leadership, which can provide China with the desired macro policy stability, in-depth economic reforms, and the transformation of new-old economic drivers.<sup>9</sup> To gain a better understanding of this political claim, we assess government intervention in the context of two stylized facts.

### 5.1. Two stylized facts

The contributions of TFP presented in Figs. 5 and 6 seem to have no obvious regularity, except that a significant increase at the start of each five-year cycle, this could be due to policy intervention and stimulation. The period from 1986 to 1990 is covered by China's 7th Five-Year Plan, 1991–1995 is covered by the 8th Five-Year Plan, and so on so forth.

Achieving the targets set up in the five-year plan is important for the local council performance appraisal. To ensure the future of their political careers, local government officials are motivated to take relatively strong stimulus policy measures at the beginning of each five-year plan. And the pressure to achieve is gradually reduced towards the end of the cycle.

Another observation is that during 1992 and after 2015, the contributions of TFP experienced a relatively obvious upward lift. The former could be closely related to the 1992 market economy reform in China. After that, as personal income increases, low-quality factor supply in China can no longer satisfy new demand and becomes redundant. The government therefore proposed the supply-side structural reform in 2015 and introduced a package of measures to promote TFP. This is evident in Figs. 4–6, TFP (Fig. 4) and its contribution degree to economic growth (Fig. 5), as well as its corresponding contribution rate (Fig. 6), have begun to increase since 2015. Especially in 2019, before the Covid-19 pandemic, the contribution rate of TFP exceeded the contribution of capital input.

This is even more obvious in Fig. 8, the trajectory for TFP contribution was reversed from 2015 - from a downward trend during 2011–2014 to an upward trend, especially the jumps experienced by the eastern and western regions. This reform is therefore considered to be crucial in transforming the economy to a TFP driven growth path. One can argue that China's growth miracle is the combined efforts of capital pulling and policy stimulus, i.e., the wisdom of Keynesianism.

Consider an alternative approach to robustness testing. Based on the regional development and industrial structure in China, if the empirical results are accurate, the impact of the supply-side structural reform on endogenous growth in North China should be more pronounced. Therefore, we have chosen to employ the Difference-in-Differences (DID) methodology to examine the effects of the supply-side structural reform in both the northern and southern regions. Initially, we conducted a parallel trend test on the TFP contribution degree, treating the northern provinces (or municipalities) as the treatment group and the other provinces (or municipalities) as the control group. The treatment point in time was set at 2015. The results of this analysis are presented in Fig. 9. As depicted in Fig. 9, prior to the implementation of the supply-side structural reform, there was no substantial disparity in the TFP contribution degree between the northern and southern regions. However, following the reform, a notable divergence emerged—significantly higher confidence intervals consistently positioned above the “zero value.” This observation indicates that the reform yielded distinct effects in the northern and southern regions, confirming that this reform has a more significant impact on the economy of the north.

### 5.2. The effect of government intervention

To quantify the effect of China's central governance, we employed the following classic model from the endogenous growth theory (Ang & Madsen, 2011; Ha & Howitt, 2007; Madsen et al., 2010 and Venturini, 2012):

$$\Delta \ln A = \lambda + \sigma \left[ \ln RD - \ln Q + \left( \frac{\phi - 1}{\sigma} \right) \ln A \right], Q \propto L^b \quad (28)$$

where  $\lambda$  is a parameter for research productivity;  $RD$  represents innovative activity and is measured by R&D input in this study;  $Q$  denotes product variety that is positively correlated with  $L^b$ , whereas  $L$  is employment or population, and  $b$  is the parameter of product proliferation;  $\sigma$  is a duplication parameter ( $\sigma = 0$  if all innovations are duplications and  $\sigma = 1$  if there are no duplicating innovations); and  $\phi$  is the returns to scale in knowledge.

According to Ha and Howitt (2007) and Ang and Madsen (2011), we have a *first-generation* endogenous growth model if  $\phi = 1$  and  $b = 0$ ; and a *second-generation* endogenous growth model if  $\phi < 1$  or  $b \neq 0$ . More specifically, if  $\phi < 1$  and  $b = 0$ , we will be looking at a second-generation *semi-endogenous* growth model; and if  $\phi = 1$  and  $b = 1$ , this would be a second-generation *Schumpeterian* model.

<sup>9</sup> According to official government documents, the transformation of new-old driving forces will be achieved through building an economy characterized by the new generation information technology industry. This includes high-end CNC (computer numeric control) machine tools and robots, aerospace equipment, marine engineering equipment and high-tech ships, advanced rail transit equipment, energy-saving and new energy vehicles, electric power equipment, agricultural machinery equipment, new materials, biomedicine and high-performance medical equipment, and the corresponding producer services.

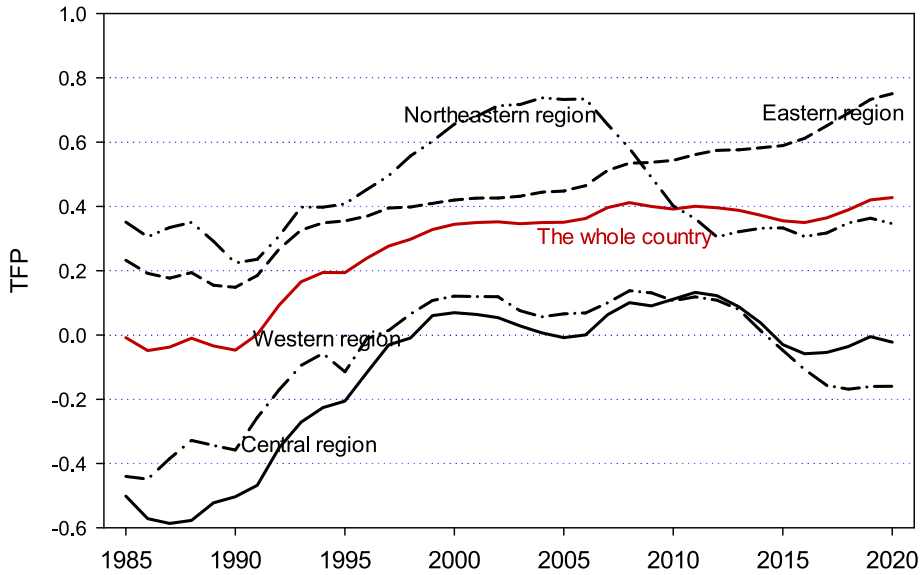


Fig. 4. TFP from the SBM\_DDF method (1985–2020).

Let  $Q = cL^b$ , where  $c$  is a constant. Substituting this into Eq. (28) yields:

$$\Delta \ln A = \beta_0 + \sigma \ln RD + \beta_1 \ln L + (\phi - 1) \ln A \tag{29}$$

where  $\beta_0 \equiv \lambda - \sigma \ln c$  and  $\beta_1 \equiv -\sigma b$ .

As mentioned before in Section 3, for a conventional production function with Hicks neutral technological change,  $\Delta \ln A$  is the contribution degree of TFP to economic growth. Therefore, Eq. (29) can also be used to explain the growth pattern under neoclassical assumptions. But without Hicks neutral technological change, one can obtain the contribution degrees of TFP and input factors using the SBM-DDF iteration method introduced in Section 3.4.

There are a range of other factors that could drive growth in addition to R&D input, such as industrial structure, urbanization, marketization, and government intervention. This is especially true for a developing China so that we add several new components as in Eq. (30):

$$y_{it} = \beta_0 + \sigma \ln RD_{it} + \beta_1 \ln L_{it} + (\phi - 1) \ln A_{it} + M_{it} + GI_{it} \tag{30}$$

where  $M_{it} \equiv \beta_2 \ln Ind_{it} + \beta_3 \ln Urb_{it} + \beta_4 \ln Mrk_{it}$ ;  $Ind_{it}$ ,  $Urb_{it}$ , and  $Mrk_{it}$  denote industrial structure, urbanization rate, and the degree of marketization, respectively.  $GI_{it}$  represents the total unobservable effects including government intervention. The dependent variable  $y_{it}$  is either TFP growth (i.e.  $\Delta \ln A_{it}$ ), or the contribution degree of TFP obtained from the abovementioned iteration technique.

To estimate Eq. (30), one first needs to deal with the unobservable  $GI_{it}$  that is likely to vary across different years and states, especially for government intervention. Local councils in China are often assigned with varying targets and policy measures under the same national initiative. To handle this, we use an interactive fixed effects model that sets  $GI_{it} = \omega_i' F_t + \varepsilon_{it}$ . Generally speaking,  $F_t$  is a vector of common factors (including central governance); and  $\omega_i$  is the vector of factor loadings for province  $i$  (Bai, 2009), a measure for differentiated treatment under the same intervention or initiative.<sup>10</sup>

Now substituting the interactive-fixed-effect term  $\omega_i' F_t$  into Eq. (30):

$$y_{it} - \omega_i' F_t = \beta_0 + \sigma \ln RD_{it} + \beta_1 \ln L_{it} + (\phi - 1) \ln A_{it} + M_{it} + \varepsilon_{it} \tag{31}$$

the coefficients can be estimated by conventional panel-data models, which in turn can be substituted into Eq. (30) to give us the following:

$$y_{it} - \beta_0 - \sigma \ln RD_{it} - \beta_1 \ln L_{it} - (\phi - 1) \ln A_{it} - M_{it} = \omega_i' F_t + \varepsilon_{it} \tag{32}$$

where  $F_t$  and  $\omega_i$  can be obtained using factor-analysis. Bai (2009) estimated all the parameters and unobservable common factors simultaneously through iterating Eqs. (31) and (32).

However, given that one cannot take logarithm of the TFP contribution obtained from the SBM\_DDF as some have negative values,

<sup>10</sup> Note that we try to assess the effect of government intervention, not the strength of government intervention. The objective is not to examine the relationship between intervention power and economic outcome.

**Table 4**  
China growth decomposition (1985–2020).

Provinces	Economic growth rates	Contribution degrees of factors				Contribution rates of factors			
		Capital	Labor	Energy	TFP	Capital	Labor	Energy	TFP
Beijing	0.0947 (0.0291)	0.0635 (0.0406)	0.0028 (0.0047)	0.0064 (0.0089)	0.0220 (0.0399)	0.6745 (0.4795)	0.0278 (0.0586)	0.0274 (0.2917)	0.2703 (0.6528)
Tianjin	0.1076 (0.0461)	0.0818 (0.0659)	0.0046 (0.0070)	0.0106 (0.0138)	0.0106 (0.0460)	0.7178 (0.3749)	0.0444 (0.1004)	0.0858 (0.2372)	0.1519 (0.3996)
Hebei	0.1024 (0.0333)	0.0651 (0.0416)	0.0006 (0.0014)	0.0185 (0.0240)	0.0182 (0.0414)	0.6548 (0.4270)	0.0048 (0.0140)	0.1678 (0.2183)	0.1726 (0.4560)
Shanxi	0.0912 (0.0361)	0.0579 (0.0425)	0.0034 (0.0091)	0.0123 (0.0370)	0.0177 (0.0572)	0.8063 (0.9294)	0.0265 (0.0727)	0.0876 (0.3845)	0.0795 (0.9476)
Inner Mongolia	0.1109 (0.0531)	0.0785 (0.0497)	0.0018 (0.0096)	0.0234 (0.0345)	0.0071 (0.0465)	0.7953 (0.5252)	-0.3016 (1.8702)	0.3102 (0.5321)	0.1960 (1.4910)
Liaoning	0.0886 (0.0438)	0.1069 (0.1127)	0.0107 (0.0268)	0.0172 (0.0355)	-0.0463 (0.1150)	1.1915 (1.5102)	0.1033 (0.2746)	0.1890 (0.3494)	-0.4837 (1.6645)
Jilin	0.0968 (0.0458)	0.0784 (0.0471)	0.0007 (0.0043)	0.0112 (0.0249)	0.0065 (0.0483)	0.7451 (0.6492)	-0.0023 (0.0432)	0.0990 (0.2636)	0.1582 (0.7075)
Heilongjiang	0.0834 (0.0284)	0.0562 (0.0340)	0.0000 (0.0037)	0.0138 (0.0313)	0.0135 (0.0447)	0.9611 (1.4995)	-0.0186 (0.0856)	0.1192 (0.3615)	-0.0617 (1.4140)
Shanghai	0.0947 (0.0357)	0.0709 (0.0501)	0.0033 (0.0096)	0.0095 (0.0089)	0.0109 (0.0450)	0.8174 (0.6114)	0.0360 (0.1171)	0.1113 (0.1953)	0.0353 (0.6751)
Jiangsu	0.1154 (0.0465)	0.0676 (0.0374)	0.0005 (0.0010)	0.0190 (0.0236)	0.0284 (0.0347)	0.5905 (0.3285)	0.0060 (0.0204)	0.1408 (0.1674)	0.2626 (0.3996)
Zhejiang	0.1107 (0.0469)	0.0747 (0.0315)	0.0011 (0.0009)	0.0318 (0.0279)	0.0030 (0.0342)	0.5147 (1.2056)	0.0098 (0.0155)	0.2188 (0.4608)	0.2568 (1.5767)

Provinces	Economic growth rates	Contribution degrees of factors				Contribution rates of factors			
		Capital	Labor	Energy	TFP	Capital	Labor	Energy	TFP
Anhui	0.1009 (0.0407)	0.0881 (0.0501)	0.0002 (0.0020)	0.0200 (0.0186)	-0.0075 (0.0532)	0.9400 (0.7346)	-0.0042 (0.0510)	0.1557 (0.2268)	-0.0915 (0.8059)
Fujian	0.1173 (0.0403)	0.0848 (0.0523)	0.0016 (0.0015)	0.0336 (0.0272)	-0.0027 (0.0552)	0.7695 (0.5088)	0.0142 (0.0182)	0.2792 (0.2197)	-0.0629 (0.4658)
Jiangxi	0.1002 (0.0283)	0.0805 (0.0364)	0.0002 (0.0005)	0.0169 (0.0201)	0.0027 (0.0475)	0.8619 (0.4126)	0.0022 (0.0061)	0.1749 (0.2506)	-0.0390 (0.4971)
Shandong	0.1105 (0.0387)	0.0607 (0.0360)	0.0005 (0.0013)	0.0187 (0.0255)	0.0307 (0.0389)	0.5291 (0.2530)	0.0031 (0.0110)	0.1769 (0.2486)	0.2909 (0.3882)
Henan	0.1024 (0.0343)	0.0606 (0.0364)	0.0001 (0.0013)	0.0186 (0.0244)	0.0230 (0.0403)	0.6113 (0.3600)	0.0008 (0.0130)	0.1710 (0.2146)	0.2169 (0.3970)
Hubei	0.0973 (0.0385)	0.0725 (0.0365)	0.0003 (0.0017)	0.0191 (0.0236)	0.0054 (0.0353)	0.7502 (0.4296)	0.0079 (0.0278)	0.1784 (0.2032)	0.0636 (0.3907)
Hunan	0.0976 (0.0276)	0.0642 (0.0399)	0.0001 (0.0011)	0.0246 (0.0464)	0.0087 (0.0510)	0.6681 (0.4565)	-0.0017 (0.0244)	0.2150 (0.4602)	0.1186 (0.5851)
Guangdong	0.1202 (0.0465)	0.0674 (0.0298)	0.0013 (0.0010)	0.0265 (0.0273)	0.0249 (0.0338)	0.5926 (0.2481)	0.0112 (0.0082)	0.1922 (0.1955)	0.2040 (0.3049)
Guangxi	0.1011 (0.0373)	0.0784 (0.0456)	0.0003 (0.0013)	0.0356 (0.0313)	-0.0132 (0.0414)	0.8570 (0.6261)	0.0011 (0.0264)	0.3261 (0.2456)	-0.1842 (0.5176)
Hainan	0.1052 (0.0642)	0.1023 (0.1135)	0.0122 (0.0527)	0.0438 (0.0690)	-0.0531 (0.1943)	1.0032 (1.5483)	0.1872 (0.9287)	0.5041 (1.0628)	-0.6945 (3.3264)
Chongqing	0.1075 (0.0348)	0.0853 (0.0601)	0.0002 (0.0012)	0.0224 (0.0168)	-0.0005 (0.0484)	0.7474 (0.4154)	0.0021 (0.0116)	0.2179 (0.2045)	0.0327 (0.4454)

Provinces	Economic growth rates	Contribution degrees of factors				Contribution rates of factors			
		Capital	Labor	Energy	TFP	Capital	Labor	Energy	TFP
Sichuan	0.1000 (0.0295)	0.0612 (0.0401)	0.0001 (0.0003)	0.0219 (0.0683)	0.0167 (0.0631)	0.6357 (0.4340)	0.0019 (0.0034)	0.1997 (0.6771)	0.1627 (0.6433)
Guizhou	0.0966 (0.0252)	0.0555 (0.0294)	0.0002 (0.0011)	0.0326 (0.0380)	0.0082 (0.0379)	0.5916 (0.3248)	0.0038 (0.0111)	0.3594 (0.4148)	0.0452 (0.3901)
Yunnan	0.0978 (0.0266)	0.0700 (0.0372)	0.0007 (0.0006)	0.0343 (0.0350)	-0.0071 (0.0394)	0.7666 (0.4814)	0.0070 (0.0073)	0.3449 (0.3495)	-0.1184 (0.4798)
Shaanxi	0.1042 (0.0371)	0.0780 (0.0386)	0.0005 (0.0006)	0.0210 (0.0230)	0.0046 (0.0438)	0.7800 (0.3912)	0.0056 (0.0082)	0.2113 (0.2313)	0.0030 (0.4234)
Gansu	0.0962 (0.0243)	0.0669 (0.0438)	0.0001 (0.0016)	0.0181 (0.0175)	0.0111 (0.0410)	0.7106 (0.4710)	0.0015 (0.0158)	0.1801 (0.1824)	0.1078 (0.4401)
Qinghai	0.0903	0.0806	0.0210	0.0224	-0.0337	0.9454	0.0434	0.5209	-0.5097

(continued on next page)

Table 4 (continued)

Provinces	Economic growth rates	Contribution degrees of factors				Contribution rates of factors			
		Capital	Labor	Energy	TFP	Capital	Labor	Energy	TFP
Ningxia	(0.0326)	(0.0483)	(0.0897)	(0.0360)	(0.1103)	(0.5826)	(4.0188)	(1.9215)	(4.9727)
	0.0939	0.0805	0.0382	0.0110	-0.0358	0.8148	0.5016	0.0712	-0.3875
	(0.0251)	(0.0586)	(0.0502)	(0.0381)	(0.0732)	(0.5694)	(0.7828)	(0.5664)	(0.9232)
Xinjiang	0.0955	0.0595	0.0081	0.0208	0.0071	0.6563	0.0802	0.2154	0.0481
	(0.0238)	(0.0284)	(0.0236)	(0.0223)	(0.0372)	(0.3369)	(0.2223)	(0.2499)	(0.3894)
The whole country	0.1010	0.0733	0.0039	0.0212	0.0027	0.7567	0.0268	0.2084	0.0081
	(0.0383)	(0.0519)	(0.0234)	(0.0330)	(0.0658)	(0.7091)	(0.8384)	(0.5193)	(1.3295)

Note: The figures displayed here are annual averages, while their standard deviations are in parentheses.

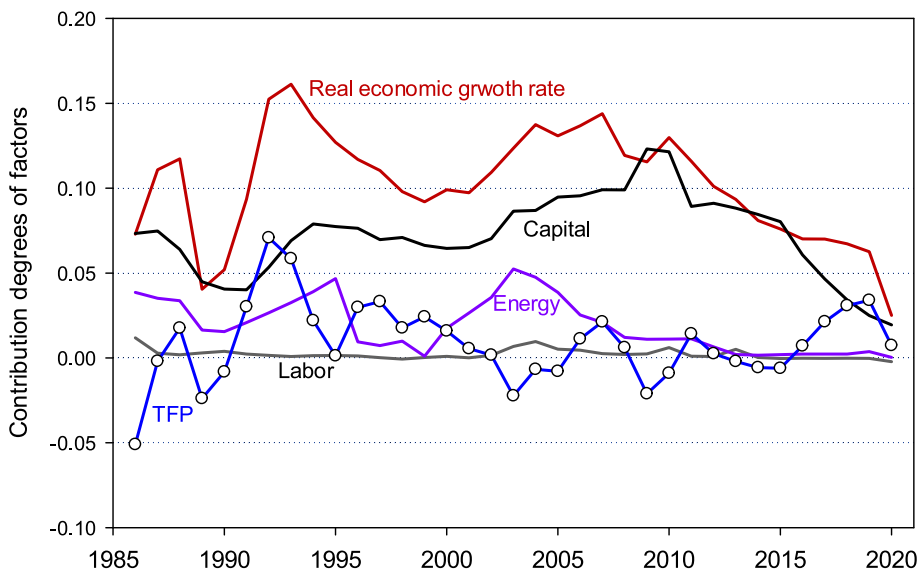


Fig. 5. Contribution degrees of different factors (1986–2020).

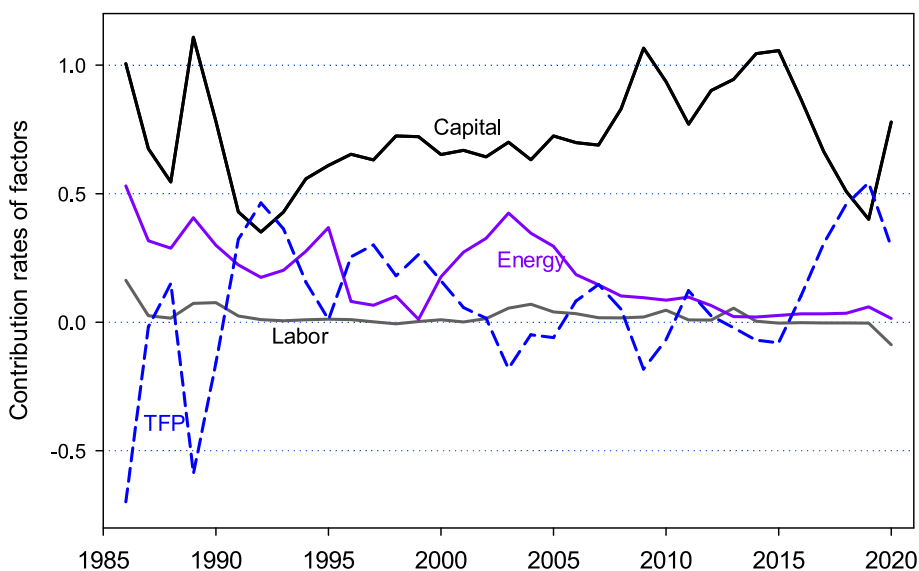


Fig. 6. Contribution rates of different factors (1986–2020).

**Table 5**  
TFP contribution degrees and rates from alternative methods.

Year	SR		LV		SFA		PO		SBM	
	Deg.	Rate	Deg.	Rate	Deg.	Rate	Deg.	Rate	Deg.	Rate
1986	-4.49	-61.60	-3.82	-52.31	-4.38	-60.01	-7.28	-99.79	-5.10	-69.87
1987	-0.69	-6.19	-0.33	-2.99	-0.89	-8.03	-0.33	-2.94	-0.19	-1.72
1988	0.62	5.30	0.78	6.62	0.37	3.14	1.35	11.50	1.77	15.07
1989	-2.87	-70.83	-2.56	-63.27	-2.92	-72.13	-9.13	-225.54	-2.38	-58.88
1990	-1.79	-34.49	-1.62	-31.11	-1.86	-35.76	-7.12	-136.82	-0.82	-15.68
1991	2.76	29.51	2.69	28.79	2.33	24.91	1.03	10.96	3.02	32.32
1992	5.55	36.38	5.17	33.87	4.70	30.81	8.71	57.09	7.08	46.44
1993	3.52	21.85	3.39	21.02	2.84	17.63	7.64	47.41	5.86	36.33
1994	0.60	4.20	0.88	6.23	0.27	1.92	3.39	23.95	2.21	15.61
1995	-1.73	-13.65	-1.26	-9.92	-1.62	-12.79	-0.06	-0.46	0.13	1.03
1996	1.25	10.66	1.56	13.34	0.73	6.23	1.85	15.80	2.98	25.50
1997	1.27	11.47	1.52	13.73	0.79	7.14	1.20	10.88	3.32	30.08
1998	-0.06	-0.57	0.31	3.21	-0.39	-4.02	-1.14	-11.58	1.77	18.05
1999	0.79	8.55	1.09	11.86	0.35	3.80	-0.92	-9.99	2.43	26.40
2000	0.39	3.94	0.58	5.84	0.15	1.52	-0.79	-7.94	1.59	16.09
2001	-0.07	-0.73	0.15	1.59	-0.20	-2.03	-1.36	-13.99	0.56	5.72
2002	-0.08	-0.70	0.15	1.36	-0.14	-1.32	-0.28	-2.52	0.18	1.62
2003	-1.07	-8.67	-0.70	-5.70	-0.89	-7.20	0.16	1.32	-2.23	-18.02
2004	-0.43	-3.11	-0.14	-1.01	-0.29	-2.13	1.99	14.47	-0.67	-4.84
2005	-1.67	-12.73	-1.19	-9.06	-1.45	-11.08	0.40	3.09	-0.78	-5.99
2006	-0.03	-0.25	0.27	1.94	-0.18	-1.29	2.45	17.88	1.13	8.29
2007	2.75	19.09	2.66	18.47	2.35	16.31	5.54	38.52	2.13	14.77
2008	1.16	9.69	1.31	11.01	0.80	6.74	2.13	17.81	0.62	5.15
2009	-1.61	-13.93	-1.04	-9.02	-1.74	-15.06	-0.46	-4.02	-2.10	-18.20
2010	-0.39	-3.04	0.01	0.11	-0.63	-4.87	1.99	15.31	-0.89	-6.85
2011	-0.35	-3.00	-0.03	-0.25	-0.46	-3.97	0.83	7.15	1.43	12.30
2012	-1.55	-15.28	-1.03	-10.14	-1.68	-16.59	-1.37	-13.55	0.26	2.54
2013	-1.92	-20.52	-1.30	-13.88	-2.11	-22.61	-2.22	-23.77	-0.20	-2.15
2014	-2.88	-35.58	-2.19	-27.09	-3.00	-37.00	-4.15	-51.23	-0.56	-6.92
2015	-2.56	-33.69	-1.94	-25.56	-2.71	-35.60	-4.26	-56.05	-0.60	-7.93
2016	-1.89	-26.96	-1.42	-20.30	-2.07	-29.47	-4.21	-59.98	0.72	10.25
2017	-0.78	-11.17	-0.48	-6.78	-0.99	-14.06	-3.20	-45.61	2.14	30.56
2018	-0.17	-2.57	0.05	0.81	-0.39	-5.74	-2.89	-42.87	3.09	45.86
2019	-0.34	-5.43	-0.13	-2.00	-0.51	-8.16	-3.48	-55.62	3.40	54.32
2020	-3.00	-119.60	-2.66	-105.91	-3.07	-122.39	-9.60	-382.63	0.74	29.41
alpha	0.6625***		0.6451***		0.7060***					
beta	0.2872***		0.2870***		0.2413***					
gamma	0.0503***		0.0679***		0.0527***					
rho			0.9334***							

Note: \*\*\* indicates significant at 1%.

we set  $TFP = 1/(1 + inefficiency)$  following the Divisia TFP growth index and Shephard output distance function (Deng et al., 2021; Li et al., 2020), where the values of inefficiency have been computed by the SBM<sub>DDF</sub>.

The degree of marketization is measured by the well-known marketization index constructed by Wang, Hu, and Fan (2021). Industrial structure is measured by the proportion of value added by the service-industry to the total industrial value added. Urbanization rate is the proportion of resident population who have lived in cities and towns for six months or longer. Consistent records for R&D expenditure start only from 2006.<sup>11</sup>

The results are presented in Table 6. Model 1 is the benchmark, in which  $\phi$  is estimated to be  $0.904 < 1$  and  $b$  is not significantly different from 0. Therefore, the second-generation semi-endogenous model seems to better represent the growth in China. Although it is not our objective to test the endogeneity theory, these results confirm the important role that technology has for sustained economic growth in China. Across models 2–6, R&D input has significant positive associations with the contribution degree of TFP, but the contrary was true for capital and energy, implying sustained productivity growth in China hinges on technological development and the corresponding economic transformation. This is especially demonstrated during China's recent combat with the Covid-19 global pandemic. A white paper recently released by the China Academy of Information and Communications Technology indicated the number of published papers in the field of big data in China accounted for 31% of the world in 2021, and the total number of accepted patents related to big data accounted for over 50% of the world, ranking first. Meanwhile, China incurred \$46.8 billion worth of imported intellectual property (IP) charges in 2021, while charging about \$11.7 billion for exported IP. Exported IP is now 25% of its imports, compared to 17% in 2017.

<sup>11</sup> The China National Bureau of Statistics published data on R&D funds raised before 2006, while only the data on funds expended (including internal and external expenditures) is available for the subsequent period.

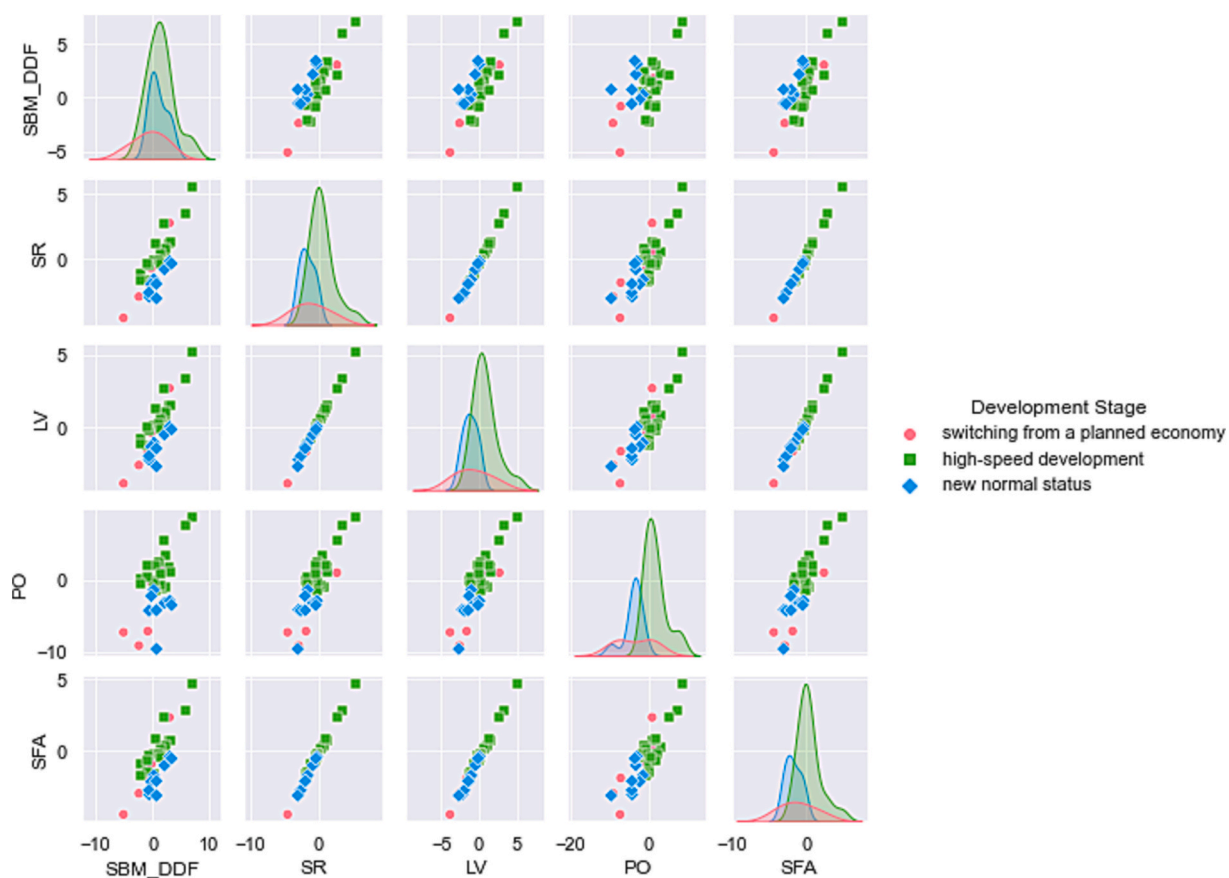


Fig. 7. Contribution degrees of TFP from different techniques (1986–2020).

Upgrading the industrial structure is also shown to promote the contribution degree of TFP and refrain the contribution of capital. Industrial structure upgrade will lift up the technological frontier, create more employment opportunities and demand. It is already on the government's economic development agenda. The estimated effect of urbanization on TFP contribution is insignificant, which is consistent with previous findings in [Koen, Herd, Wang, and Chalaux \(2013\)](#). The urbanization experienced in China is extensive and neglects connotative development ([Guan, Wei, Lu, Dai, & Su, 2018](#)). As for marketization, the positive effect on TFP contribution is only significant in Model 6. One possible explanation is that other unobservable factors such as central governance might interfere with the effect of marketization.

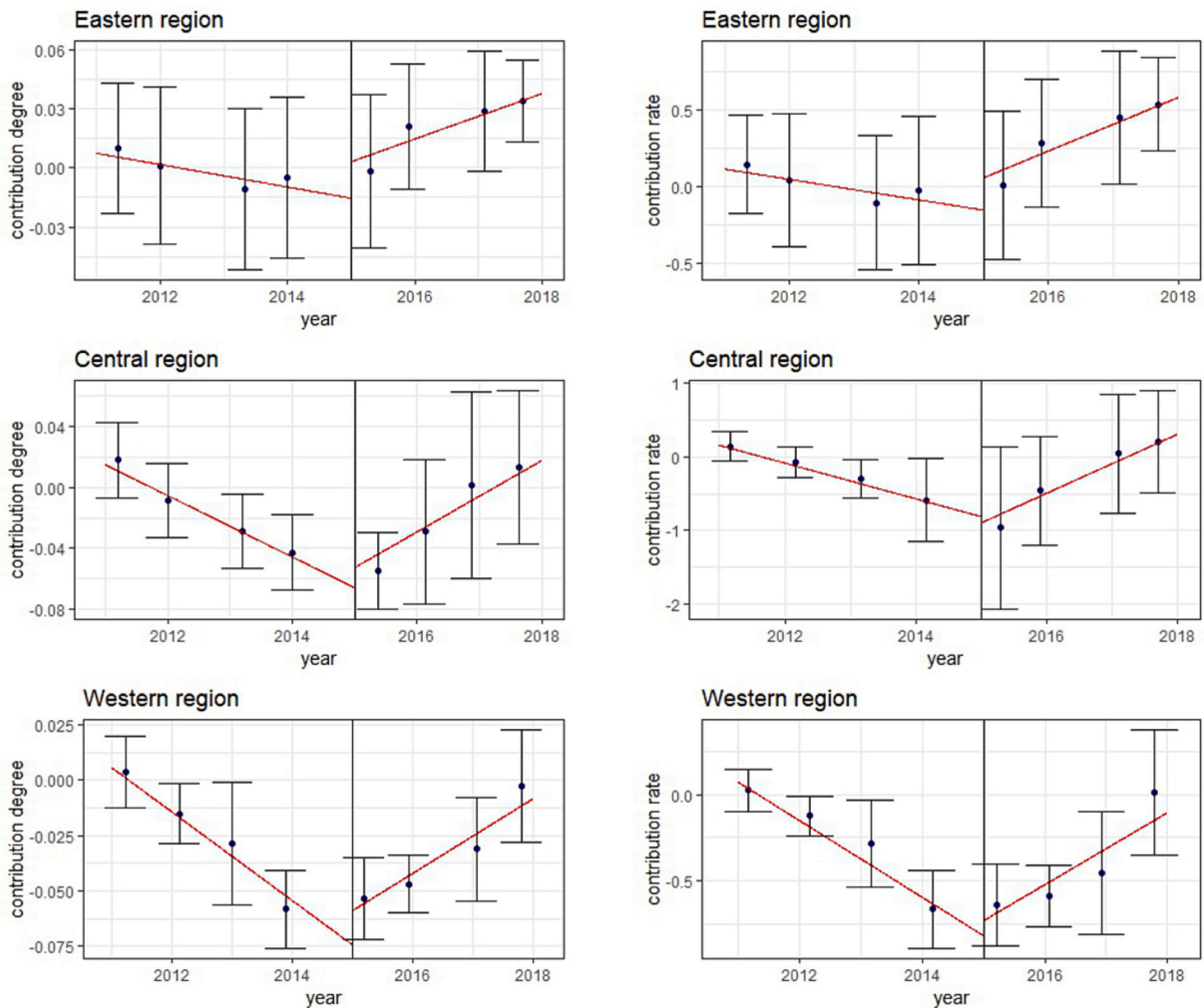
Model 6 is estimated by the interactive-fixed-effect model.<sup>12</sup> This gives us the total unobservable effect ( $GI_{it}$ ) and common factors ( $F_t$ ) presented in [Fig. 10](#). The right panel identifies four common factors, and we need to infer which one resembles government intervention.

This could be inferred from the following facts: (1) A few years after 2007, in response to the global financial crisis, the government implemented a large-scale stimulus package, including the RMB¥4 trillion plan. This intervention is likely to have a negative impact on TFP contribution within the endogenous growth model. (2) In 2015, the government initiated the supply-side structural reform, which is expected to have a positive association with TFP contribution. (3) The COVID-19 pandemic emerged in 2019, leading to increased investment in infrastructure and the big data technology market by the government in 2020. However, this stimulus may potentially undermine the effectiveness of the supply-side structural reform.

As a result, common factor 1 in [Fig. 10](#) seems to be the best candidate to represent government intervention. In contrast, factor 2 has no obvious signs in 2015 and 2019, while factors 3 and 4 have fluctuations in 2018, all of which are not consistent with the facts being considered.

To compare the potential effect of government intervention (i.e., factor 1) among other common factors, we computed the relative size of the eigenvalues for these common factors using factor analysis. The explanatory powers are 44.11%, 36.21%, 13.47% and 6.21%, respectively, for factors 1–4. This is to say that, government intervention is perhaps one of the most important factors in China's

<sup>12</sup> In the first step, we examine the presence of common factors. In the second step, we investigated the number of common factors, considering both fixed effects and non-fixed effects scenarios. Using nine different criteria, we consistently reached the conclusion that there are four common factors.



**Fig. 8.** Cutoff points for TFP contribution (2011–2018).  
 Note: The northeastern region is not displayed because it has only three provinces.

endogenous growth model, in addition to R&D, product variety, technology accumulation, industrial structure, urbanization and marketization,

### 6. Conclusion and policy implications

After about four decades of high-speed growth, China becomes an increasingly powerful player on the global stage. China’s contribution to the global GDP has surged to 18% in 2021, a significant leap from its mere 1.5% share in 1978. Furthermore, within the East Asia & Pacific region, China’s GDP share has expanded to 57%, up from a modest 10% in 1978. The tangible effects of China’s economic progress on its global and regional influence are clearly evident when examining its share of imports and exports, as illustrated in Fig. 11.

China has emerged as the world’s largest exporter and the second-largest importer. Approximately 10% of global imports are directed towards China, as evidenced by China’s significant share of world exports. Moreover, China contributes to 15.6% of global imports. It has become the primary source of demand and supplier for numerous countries. Specifically, within the East Asia & Pacific region, China accounted for 19% of imports in 2020, while in South Asia, it provided 17% of the imports during the same period. The launch of the Belt and Road Initiative in 2013 has significantly contributed to the noticeable increase in China’s outbound flow of goods and services. As a result, all three curves representing China’s partner share of imports have shown an upward trend. Scholars like Ding and Li (2017) and Gong (2019) have elaborated on China’s increasingly vital role in regional economic development through trade.

The changing relationship between China and the world has been subjected to a comprehensive analysis by the McKinsey Global Institute (Woetzel, Seong, Leung, et al., 2019). The report highlights that from 2000 to 2017, the world’s level of exposure to China has

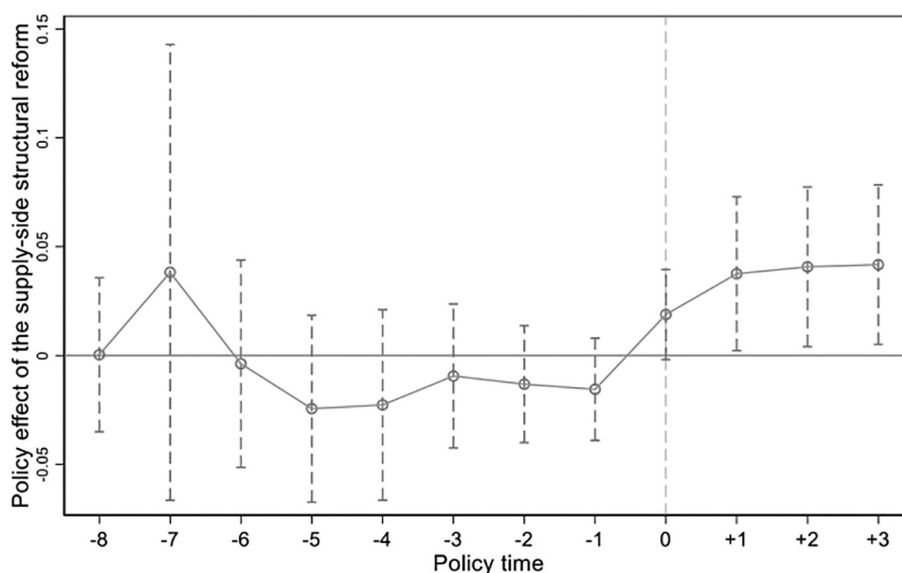


Fig. 9. The parallel trend test of the TFP contribution degree.

increased, while China's exposure to the rest of the world has declined. This assessment takes into account not only trade but also technology and capital.

Inward Foreign Direct Investment (IFDI) has played a significant role in accelerating technological progress and economic development in China. Traditionally, technology spillover from developed countries to developing ones through FDI has been the predominant form of capital flow. However, in recent times, there has been a notable increase in outward FDI (OFDI) originating from developing countries, particularly China. According to [Dong, Miao, and Zhang \(2021\)](#), China's OFDI towards developed countries effectively promotes innovation activities through direct technology acquisitions, access to high-tech inputs, and international mobility of personnel. This outward investment from China helps counterbalance the impact on domestic employment caused by industrial structure upgrading, as highlighted by [Liao, Yang, Dai, and Van Assche \(2021\)](#). Furthermore, as per [Fang, Collins, and Yao \(2021\)](#), China's reliance on FDI in relation to GDP decreases over time as per capita GDP increases, indicating a declining dependence on foreign investment as the economy matures.

These figures exemplify the accomplishments of the Chinese government in successfully rebalancing economic growth towards domestic consumption and further enhancing its integration into the regional production and technology value chain ([He, Huo, & Yu, 2023](#); [Sun, Luo, & Zhou, 2022](#)).

To find out what makes the economic growth in China more sustainable and more resilient than other East Asian countries, such as Japan and South Korea. This study utilizes a new nonparametric technique that is derived from neoclassical growth theory and directional distance function. We decompose the economic growth in China during 1985–2020 and compares it with the results with those obtained from existing parametric growth decomposition techniques (including SR, LV, SFA and PO methods). Our new decomposition technique does not require an exogenously imposed functional form and is free from the CRS assumption and Hicks-neutral technological change. The results indicate that capital, labor, energy consumption and TFP contributed 7.33%, 0.39%, 2.12% and 0.27% respectively, to the national average growth rate 10.10%; or alternatively speaking, capital, labor, energy consumption and TFP accounted for 75.67%, 2.68%, 20.84% and 0.81% of the output growth in China during this period. Therefore, the growth trajectory in China resembles an unsustainable capital-driven growth model. And this finding is robust compared with those obtained using different techniques.

To investigate how could an unsustainable capital-driven growth model be sustained for so long in China, the first observation is that the central governance, characterized by the national five-years-plan, has a significant association with TFP contribution; and the second observation is that the supply-side structural reform, launched in 2015, is crucial to the transformation of the driving forces behind economic growth. More rigorously, building upon endogenous growth theory, we used an interactive fixed effects model to empirically examine potential factors influencing TFP contribution to growth. The results provided several insights including: the second-generation semi-endogenous model is the best representation for growth in China; R&D expenditure, industrial structure upgrade, and further marketization all promote TFP contribution; and government intervention is indeed a crucial factor with an explanatory power of 44.11% among all unobservable common factors. Thereby, it is not unreasonable to say that growth in China is government-led rather than capital-driven; the former could be sustained by desirable reforms under strong national leadership while the latter is not.

This implies that in a highly diversified country like China, a cohesive national leadership is essential in driving and safeguarding growth instead of impeding it. This is expected to become even more crucial for China to sustain its future economic growth.

China is currently undergoing a crucial phase of growth transformation, shifting its focus from quantity to quality. However, this

**Table 6**  
Factors influencing China's TFP growth (2006–2020).

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Growth of TFP	Contribution degree of				
		Capital	Labor	Energy	TFP	TFP
$\ln RD_{it}$	0.0201*** (0.0054)	-0.0181** (0.0091)	-0.0001 (0.0023)	-0.0038* (0.0019)	0.0209** (0.0092)	0.0186*** (0.0068)
$\ln L_{it}$	-0.0123 (0.0084)	0.0074 (0.0135)	0.0001 (0.0033)	0.0081*** (0.0029)	-0.0130 (0.0137)	-0.0156 (0.0110)
$\ln A_{it}$	-0.0964*** (0.0200)	0.0752*** (0.0207)	0.0122* (0.0064)	-0.0212*** (0.0042)	-0.1085*** (0.0205)	-0.0598** (0.0301)
$\ln Ind_{it}$		-0.0554*** (0.0119)	-0.0006 (0.0029)	0.0122*** (0.0026)	0.0355*** (0.0121)	0.0100 (0.0105)
$\ln Urb_{it}$		0.0568 (0.0391)	-0.0005 (0.0108)	-0.0157* (0.0081)	-0.0301 (0.0391)	-0.0481 (0.0330)
$\ln Mrk_{it}$		-0.0188 (0.0223)	-0.0029 (0.0063)	-0.0079* (0.0046)	0.0186 (0.0223)	0.0448** (0.0195)
Constant	-0.0333 (0.0501)	0.2209*** (0.0615)	0.0164 (0.0148)	0.0003 (0.0134)	-0.0918 (0.0629)	-0.1290*** (0.0030)
Year fixed effects	control	control	control	control	control	control
Interactive fixed effects	uncontrol	uncontrol	uncontrol	uncontrol	uncontrol	control

Note: \*, \*\* and \*\*\* indicate significant at 10%, 5% and 1%, respectively. Standard errors are in parentheses.

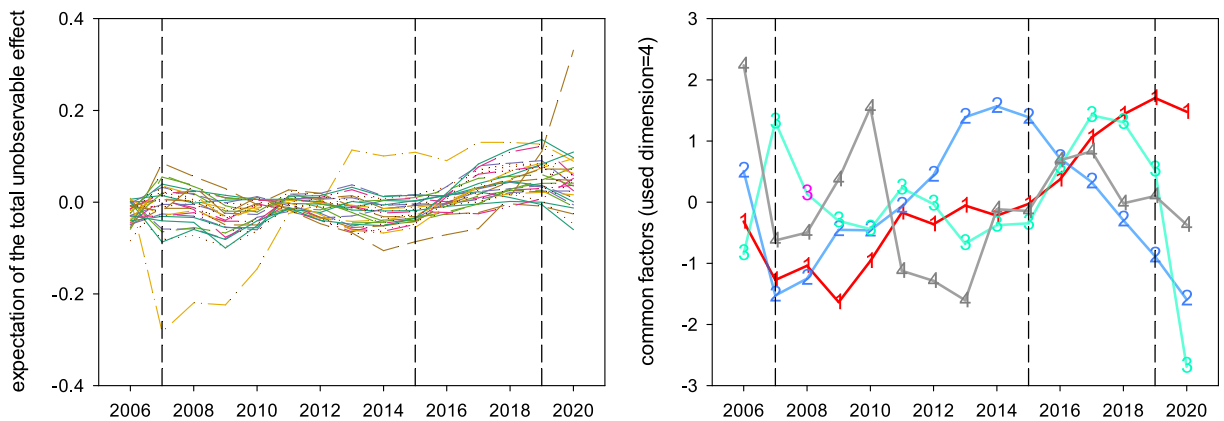


Fig. 10. Estimated interactive fixed effects (2006–2020).

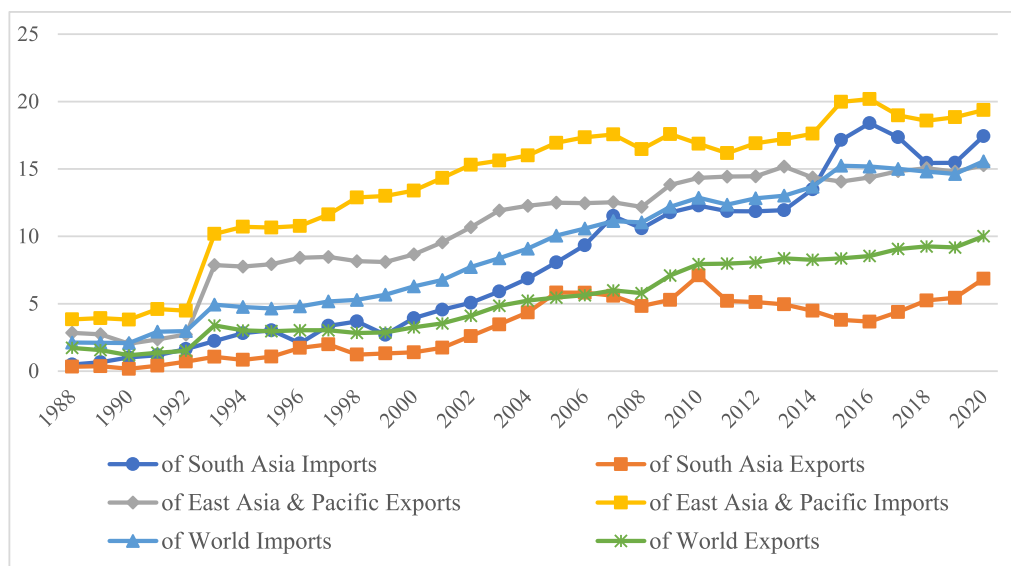


Fig. 11. China's partner share of imports and exports (1988–2020).  
(Source: World Integrated Trade Solution (the World Bank))

transition will not be effortless, as China continues to attract significant global investment due to its vast domestic market, rising per capita wealth, and well-established industrial supply chain. It is important for China to be cautious of falling into the “middle-income trap” and to have a strong and unified government that can guide its development trajectory and prevent such a setback. Fortunately, China is now shaping a new dual development circulation pattern, with a primary emphasis on domestic economic circulation as the foundation. This approach aims to buffer and complement the external circulation of trade and capital. This strategic shift, as described by Fang et al. (2021), is instrumental in navigating the challenges and maximizing the potential of China’s growth trajectory.

However, this can only be viewed as an initial step towards a growth path driven by technology and innovation. To fully capitalize on the advancements China has achieved, the government must address concerns regarding uneven geographic development and income inequality. By doing so, the country can foster upward socioeconomic progress and enhance its capacity to learn and absorb high technologies (Dong et al., 2021).

By drawing insights from China’s experience, several valuable recommendations can be provided to later-developing countries in regions such as India and Africa. At the initial stage of development, leveraging a capital-driven growth model can prove advantageous for low-income countries, enabling them to kickstart their economic progress rather than being seen as a drawback. Emphasizing partnerships with neighboring countries and active participation in the regional production and technology value chain should be given priority. This approach offers mutual benefits by sharing in the prosperity of the region and capitalizing on the synergies and opportunities that arise.

When a country reaches a specific stage of economic development, undergoing an economic transition becomes essential for sustaining growth. To achieve this transition successfully, strong central governance is necessary. A robust national leadership can support long-term economic development by creating a conducive macroeconomic environment and implementing stable macroeconomic policies. This is evident in the extensive and beneficial economic reforms undertaken in China, leading to the successful transformation of new and old growth engines.

## Data availability

Data will be made available on request.

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