Technological Innovation and Structural Change for Economic Development in China as an Emerging Market

Xiaoxiao Zhou[a], Ziming Cai[b], Kim Hua Tan[c], Linling Zhang[d*], Juntao Du[e], Malin Song[f]

[a] School of Finance, Anhui University of Finance and Economics, Bengbu 233030, P. R. China

[b] Nottingham University Business School, Nottingham, England, UK

[c] University of Nottingham, Nottingham, England, UK

[d] School of Public Finance and Taxation, Nanjing University of Finance and Economics, Nanjing 210023, P. R. China

[e] School of Statistics, Dongbei University of Finance and Economics, Dalian 116025, P.R. China

[f] School of Statistics and Applied Mathematics, Anhui University of Finance and Economics, Bengbu 233030, P. R. China

Abstract: As an emerging and transforming market, China has emphasized the key role of technological innovation and industrial structural change in economic growth. Using a nonlinear econometric model and provincial data from 2000 to 2014, this study investigates the direction of technological innovation and structural change for driving China's economic growth. From a national perspective, an inverted U-shaped relationship exists between technological progress and economic growth, revealing a need to shift the technological progress approach from imitation to innovation. Once the turning point is reached, structural upgrading stimulates China's economic growth. Regional heterogeneity is apparent in regional regression. Both energy-saving and environmental conservation technologies positively contribute to the eastern and central regions' economies, while only environmental conservation technology accelerates the western region's economic development. On structural adjustment, central areas should utilize industrialization and achieve sustainable development, whereas the eastern and western regions do not benefit from industrial structural change. The study's findings can be applied to design policies and strategies that could promote sustainable economic growth through technological innovation and structural change.

[*] Corresponding author. E-mail address: zll3474@nufe.edu.cn (L. Zhang) Tel: +8618051028632.

Keywords: Economic growth; Technological innovation; Structural change; Emerging market; Regional heterogeneity

1. Introduction

Energy scarcity and environmental pollution are common challenges faced by humanity. Emerging economies face greater energy and environmental pressures during the process of rapid industrialization and economic catch-up. On one hand, emerging markets need abundant energy resources to support poverty eradication, industrialization, and urbanization; therefore, energy shortage is an unavoidable problem for them (Proskuryakova, 2017). On the other hand, sustainable development agendas highlight environmental concerns (Asongu et al., 2017). The conflicting relationship between economic growth and carbon emission has seriously hindered the sustainable development of emerging countries. Further, it is not conducive to the realization of global emission reduction targets (Wang and Jiang, 2020; Liu et al., 2020). As the largest energy consumer and carbon emitter (BP Statistical Review of World Energy, 2019), China bears a major responsibility toward global energy conservation and emission reduction.

Energy and environmental dilemmas have constrained China’s economic development and restructuring (Wang and Jiang, 2020; Liu et al., 2020; Wang and Feng, 2020). In the last few decades, the nation’s rapid economic growth has contributed to environmental degradation, energy shortage, disequilibrium, and so on. As shown in Fig. 1, China has a clear downward economic growth trend, however, it has an upward energy consumption and CO_2 emission trend in the "new normal" period. As a major emerging country, China is urgently seeking optimal methods to contribute to a "triple win" between energy saving, emission reduction, and economic development.

In accordance with Schniederjans (2017), Amankwah-Amoah et al. (2018), and You et al. (2019), technological innovation plays a central role in driving productivity and economic development, especially in emerging countries. It is also a great equalizer for whittling down inequality across regions once a long-term “technological catch-up” effect persists in developing countries (Amankwah-Amoah and Hinson, 2019; You et al., 2019; You et al., 2020). However, not all technological progress results in the reduction of resource needs (Tsuboi, 2019). For example, You et al. (2020) pointed out that despite the progress in internet and power technologies, around 41% of the world's population in 2016 were still not cooking with energy-efficient and environmentally friendly sources of power. Energy and/or environment-related technological progress are widely accepted as solutions to reducing the energy-environment-economy conflict (Acemoglu et al., 2012; Acemoglu et al., 2018; Song and Wang, 2018). Energy- and environment-saving technologies present opportunities for emerging economies to catch up or even leapfrog developed countries, ultimately achieving sustainable development (Zhang et al., 2020; Wang and Wei, 2020).

[Insert Fig. 1 here]

While innovation is technological, it can also be non-technological (organizational innovation or structural innovation) (Geldes et al., 2016). Structural change is inseparable from the economic growth process. As an emerging and transitioning market, China has relied on multi-dimensional industrial structural adjustments and optimization as effective methods to achieve national economic development and transformation (Brondino, 2019; Zhou et al., 2020). It should be noted that the interactions between different forms of technological progress have played leading roles in structural change (Samaniego and Sun, 2016; Święcki, 2017). Thus, this study focuses on the impact of innovation on economic growth from the perspective of technological progress and structural change.

Historically, economists have struggled for centuries to understand the relationship between technological progress, industrial structural change, and economic growth (Arrow, 1962; Romer, 1994; Grossman and Helpman, 1994; Lucas, 1998; Freire, 2019). However, in recent years, due to the new environment characterized by Industry 4.0 (e.g., big data, digital economy, Internet of Things, etc.), technology is more complex and takes on new characteristics (Sheng et al., 2019). The technological progress and upgrade paths also present new characteristics in emerging economies (Lacasa et al., 2019; Radosevic et al., 2019; Wang and Wei, 2020). Likewise, the trend of structural change in the context of transformation is uncertain.

If the Great Recession made industrialization popular again (Alcácer and Cruz-Machado, 2019), then structural ecologicalization is essential for green development in emerging countries. Having the proper level of optimal technology and booming industries is vital for emerging countries to survive the aftermath of the Great Recession and win in global competition (Wang and Wei, 2020). As such, a better understanding of the relationship between diversified innovation and economic development could guide the design and implementation of policies for high-quality growth. It could also allow emerging countries to catch up with developed economies.

Our framework, based on empirical regressions of provincial data from China, highlights the central roles played by energy- and environment-biased technological progress and structural change to promote economic development. The findings of this study provide evidence on the importance of existing technological innovation and structural adjustment theories. We built a mediation effects model with directed technological change and probed into its distinguishing effects at the national and regional levels. In addition, we comparatively examined the contributions of industrialization and servitization to economic growth. Finally, we indicated the direction of structural adjustment for emerging and transforming markets. These results could provide basic recommendations for China's central and local governments to formulate corresponding technological strategies and industrial policies for high-quality development and could be of great interest to policymakers in emerging countries.

The remainder of the paper is organized as follows. Section 2 comprehensively reviews the literature related to this topic, outlines the conceptual framework, and presents the hypotheses. Section 3 constructs the econometric model, and Section 4 presents the results and discussions. The conclusions and corresponding policy suggestions are provided in Section 5.

2. Theoretical background

Economic development must result comprehensively from the cooperation of labor, capital, techniques, energy, and environment (Guo et al., 2012). To build a sustainable, steady, and effective economic entity from a strategic perspective, governments should enhance the level of resource utilization by improving technological progress. Additionally, to reinforce allocation efficiency, they must adjust the proportion of various input factors in the economy. In the following discussion, we consider the relationships between technological innovation, structural optimization, and economic growth. Considering China's conditions, research hypotheses are presented to lay a theoretical foundation for the following empirical study.

2.1. Technological innovation, diversification, and economic development

Originating from growth theory, Schumpeter's classic endogenous growth theory elaborates on how economic growth is promoted by a mechanism formed through innovation activities, known as "creative destruction." This goes beyond the economic growth mechanism depicted by Solow's theory of exogenous technological progress (Robert, 1957) and objectively captures the essence of economic growth. Endogenous growth theories further indicate that a strong causal relationship exists between technological progress and economic growth (Romer, 1994; Grossman and Helpman, 1994; Lucas, 1998). Since the development of these theories, combined with well-established econometrics, empirical studies have sprung up in abundance to explore the specific effects of technological innovation on economic development.

Acikgoz and Mert (2014) focused on the source of economic growth and analyzed results from Hong-Kong, the Republic of Korea, Singapore, and Taiwan to prove that technological progress is a fundamental source of rapid growth. Silva and Styles (2017) revealed that tech-innovation has a positive impact on the economic performance of firms in international business. Shin et al. (2019) affirm that appropriate technology and grassroots innovation contribute to the economy. The survey by Chege and Wang (2020) on 204 small businesses in Kenya showed that technological innovation positively affects environment-friendly companies.

While studies have proven that technological progress has a significant role in promoting economic growth, the different effects of directed technological change on China's economy, due to unbalanced growth across its regions, must still be distinguished. Along with the segmentation and diversification of technological progress and the booming on the theory of directed technological change, it is apparent that different regions with varied resource endowments should have comparative advantages in their benefits from various types of technological progress. Furthermore, given the looming constraints of energy and environmental resources, much attention is focused on detecting whether technological progress in energy and environmental conservation has stimulating effects on economic growth. Schipper et al. (2000), Alisa and Martin (2016), and Battelle and Melton (2017) took different economic entities as examples and proved that improvement in energy efficiency contributes to economic growth. Guo et al. (2016) also showed that energy technology innovations could promote the transition from a coal-based economy in China. Furthermore, there is extensive research on clean-tech innovation. Marcon et al. (2017) confirmed that the "environmentally sustainable innovation-oriented learning" variable is most often addressed by Brazil multinationals during their organizational innovation activities to balance business interests with environmentally sustainable growth. Song et al. (2017) examined the evidence to confirm that promoting environmental efficiency can sustainably boost economic development. Both research studies by Sohag et al. (2019) on Turkey and Khan and Ulucak (2019) on Brazil, Russia, India, and China (BRIC) confirmed that environment-related technologies positively contribute to green growth.

However, using panel data from China, Shen et al. (2012) proved that there is a threshold effect on economic growth from energy efficiency; the flexibility of energy efficiency on economic growth decreases with the improvement of energy efficiency. Wang et al. (2013) empirically analyzed the relationship between energy economic efficiency and economic growth in China and showed that they have an inverted U-shaped curvilinear relationship. Thus, it is necessary to further investigate the specific impact of directed technological progress on regional economic growth. Therefore, this study introduces mediation variables to explore the role of technological progress on economic growth, as specified in the theoretical model (Fig. 2). Considering that differences in environment and resource endowments across regions may lead to different propensities for innovation, we suggest the following hypothesis:

Hypothesis 1: Different types of technological progress have different effects on promoting economic growth, and there is regional heterogeneity in these effects.

2.2. Structural change and economic growth

As the mainstream growth theory focuses on the result and not the process, capital accumulation, increased labor supply, and technological innovation are believed to be the drivers of economic growth. The input-output of different production factors is the same in different industries, and the flow of resources among different departments is thought to be relatively unimportant. Hirschman (1958) pointed out that industrial structure has no substantive impact on the element output ratio in developed countries. Therefore, studies based on the theory of economic growth often overlook the effect of structural change. For a specific economic development period (the industrialization stage), however, industrial structure optimization can also promote the development of the economy and should be introduced as an important factor into an economic growth model.

Peneder (2002) stated that different industrial sectors vary in productivity and productivity growth rates and revealed the core reason industrial structure promotes economic growth. When factors flow from a sector with low productivity to one with high productivity, a “structure dividend” is produced that promotes high-speed economic growth. Maddison (1987) conducted empirical studies to prove that industrial structure is one of the important factors for promoting economic growth. Several years later, the economic growth theory model still emphasizes the importance of structural change in productivity growth (Grossman and Helpman, 1994). Recently, several new growth models are becoming increasingly popular; they represent effective methods for analyzing the process of structural change. More encouragingly, some find harmony between structural change and the extensive modes of aggregate balanced growth (Gabardo et al., 2017).

Numerous empirical studies have testified the vital effect of structural change on propelling economic growth (Dieteich, 2012). Fan et al. (2003) explored the reasons behind China’s high-speed economic growth and concluded that the redistribution of resources from low-productivity to high-productivity sectors is the main contribution of structural change. Vu (2017) introduced a new index of “effective structural change” and found that it had a robust and positive effect on gross domestic product (GDP) growth in Asian economies.

Even though technological progress could lead to industrial structure optimization to some degree, its systematic promotion could cause technological imbalance among various sectors, considering China’s national conditions. Eliminating this imbalance heavily relies on the corresponding structural change. However, the time lag in the flow of elements often causes hysteresis in structural change (there is especially a lock-in effect in the typical path of labor force transformation) and, to a certain extent, will damage technological innovation efficiency. Essentially, adjusting the industrial structure can be considered as a reallocation to ensure that production factors flow among various industries. Therefore, it can be regarded as an innovation in management, which has already become a vital policy for promoting the efficiency of resource allocation.

In the economic development process, China gave subsidies to some industries with lower development prospects in an attempt to balance social development and reduce the gap between the rich and the poor. As a result, research and development (R&D) resources (skilled labor) were tied up in inefficient departments. Subsidies were paid to incumbents, and to some extent, they supported the existence and extension of enterprises at the cost of potentially superior entrants (Acemoglu et al., 2018). Therefore, as an economy facing these historic problems, structural optimization and technological innovation policies must be coordinated to achieve innovation efficiency for sustainable development. Moreover, emerging economies, like China, that are experiencing an R&D input expansion are more likely to experience resource misallocation. Indeed, state-owned enterprises with lower production efficiency and innovation ability in China consume more resources than private enterprises (Li et al., 2017). Innovation capacity and performance across regions in the country could be substantially facilitated once resource allocation inefficiencies are eliminated through management innovations, such as structural adjustment. However, when adopting structure optimization, as a periodic adjustment policy, it is necessary to consider whether the policy is applicable to the different states of structures in various regions in China. In other words, it must be determined whether a unified structural change direction can achieve the same optimizing effect in regions with different development levels and resource endowments.

Zheng et al. (2010) conducted a series of studies that presented persuasive evidence that while structure bonus actually exists, it is weakened by industry upgrading. Prior to that, the empirical studies by Ngai and Pissarides (2007) showed that rigorous model hypotheses could result in the absence of the overall growth effect of structural change. As such, we introduce Hypothesis 2:

Hypothesis 2: Structure optimization has an indeterminate effect on economic growth, and there is regional heterogeneity in its effect.

2.3. Technological progress and structural change

The relationship between technological progress and structural change can be described as follows. Technological progress causes production efficiency differences among departments and impels the flow of production elements into industry divisions with high productivity. This process creates a flow of elements across departments and promotes the transformation and upgrade of the industrial structure.

Acemoglu and Guerrieri (2004) constructed a two-sector non-equilibrium model.

The model proved that relative prices among products in different departments change along with differences in technological progress rates and capital growth in these departments, promoting industrial structure transformation on the supply side. Čadil et al. (2014) suggested that the intermediation of economic structure is necessary for human capital to impact economic growth. Wang et al. (2014) conducted a new structural decomposition analysis (SDA) model and concluded that production technology affects China's structural change. By constructing a dynamic stochastic general equilibrium model, Zhang et al. (2019) proved that improvement in technology helps to develop economic restructuring in China.

Generally, structural change has no direct effect on technological progress; although industrial structure optimization could provide technological progress with adequate resources by promoting economic growth, its direct promoting effect is not clear (Fagerberg, 2000; Ghosh, 2013; Atalla and Bean, 2017). An unreasonable industrial structure, which leads to resource retention in rarely efficient industries without sufficient effects overall, impedes the ability of technological progress to increase efficiency. Therefore, optimizing the structure would promote efficiency in technological progress and improve resource allocation efficiency. Given these reasons, can better sustainable economic development be achieved by only coordinating the two factors with each other?

From a micro perspective, both the diffusion and overflow of technological innovation require the rationalization of industrial structure. The application and flow of technology among commodities inevitably leads to structural optimization; otherwise, an isolated technological innovation in a single department does not contribute towards all-purpose technological progress and economic growth (Andergassen et al., 2017). Therefore, technological innovation can change a factor's marginal productivity so that the factor flows into highly efficient departments. This promotes a change in industrial structure and realizes the goal of economic growth. Meanwhile, the benefits from productivity can be distributed across sectors through the adjustment of relative processes. Thus, the technology spillover effect contributes to the value-added processes of the relatively stagnant sectors (Datta, 2019). In conclusion, technological progress can induce economic structural change and lead to subsequent economic growth, viz. the so-called technological structure effect as shown in Fig. 2. We present Hypothesis 3 below:

Hypothesis 3: Technological progress can promote industrial structural

change, but the economic-promoting effect of industrial structure is uncertain; therefore, the structure effect of technological progress on economic growth is uncertain.

[Insert Fig. 2 here]

3. The model and variable description

3.1. Basic model

The study aims to investigate how technological progress and structural change influence economic growth. To avoid unobserved variables and alleviate multicollinearity, we used an annual panel data comprising 30 Chinese provinces between 2000 and 2014 and defined the baseline model as:

$$GRP_{it} = c + \beta_1 TFP_{it} + \beta_2 IS_{it} + \delta X_{it} + region_i + year_t + \varepsilon_{it} \tag{1}$$

Here, we chose the GDP of the region (GRP_{it}) as the proxy variable for the local economic growth. IS_{it} is the industrial structure, and i and t represent region and year, respectively. TFP_{it} is the total factor productivity (TFP), and it is treated as the measure of the aggregate technological progress. X_{it} represents the control variables, $region_i$ and $year_t$ respectively refer to individual and time effect that are not objectively measurable, and ε_{it} is the random disturbance term.

According to the aforementioned theoretical analysis, there are nonlinear relationships between technological progress and/or structural change and economic growth. Following the environmental Kuznets curve, we established Model 2 by introducing the square of technological progress and industrial structure based on Model 1. In addition, the cross-term of TFP_{it} and IS_{it} in Model 3 was included to clarify the structural effect of technological progress on economic growth.

$$GDP_{it} = c + \beta_1 TFP_{it} + \beta_2 TFP_{it}^2 + \beta_3 IS_{it} + \beta_4 IS_{it}^2 + \delta X_{it} + region_i + year_t + \varepsilon_{it} \tag{2}$$

$$GDP_{it} = c + \beta_1 TFP_{it} + \beta_2 IS_{it} + \gamma TFP_{it} * IS_{it} + \delta X_{it} + region_i + year_t + \varepsilon_{it} \tag{3}$$

Furthermore, to verify the economic effect of two types of directed technological progress (energy-saving and environmental conservation technological progress), we constructed a mediating effect model to show how directed technological progress transitions to total technological progress.

$$TFP_{it} = c + \alpha_1 EST_{it} + \alpha_2 ECT_{it} + \delta X_{it} + region_i + year_t + \varepsilon_{it} \tag{4}$$

where EST_{it} and ECT_{it} represent energy-saving technological progress and environmental conservation technological progress, respectively.

3.2. Variables

(1) Economic growth as the dependent variable

The deflated provincial GDP, using the year 2000 as the base period, is an indicator of economic growth.

(2) Technological progress as the core independent variable

Total factor productivity is generally measured by using the Solow residual method, stochastic frontier analysis (SFA), data envelopment analysis (DEA), and semiparametric method. The most effective method is the DEA, as confirmed by theories and practices. Economic growth is always associated with byproducts or undesirable outputs, such as wastewater, waste gas, and solid waste. Generation of these byproducts is widely considered to prevent maximum economic efficiency. In other words, serious environmental problems are always derived from the excessive pursuit of economic growth when undesirable outputs are disregarded. Extensive research has focused on how to deal with these undesirable outputs, however, most fail to solve the problem.

As an extension of the CCR-DEA model and the BCC-DEA model, proposed by Charnes et al. (1978) and Banker et al. (1984), respectively, a non-radial and non-oriented measure called the slacks-based measure (SBM) emerged from the contributions of Tone (2001) and appeared to be superior to the traditional DEA model. Regarding excessive input or insufficient output, decision-making units (DMUs) face overestimated efficiencies when conducted using the radial-DEA model. Similarly, an oriented-DEA model produces a biased result. While it successfully avoids this dilemma, the SBM model is computationally complicated. Based on the SBM model, Färe et al. (2010) proposed a generalized SBM and a directional distance function measure (DDM).

Based on Wang and Feng (2015), we included the undesirable outputs and defined the DDM as follows:

$$D(x, y, b; g^x, g^y, g^b | CRS) = max \sum_{n=1}^{N} w_n^x \beta_n^x + \sum_{m=1}^{M} w_m^y \beta_m^y + \sum_{i=1}^{I} w_i^b \beta_i^b \quad (5)$$

$$s.t.\ \sum_{k=1}^{K} z_k x_{kn} \le x_{k^*n} - \beta_n^x g_n^x;$$

$$\sum_{k=1}^{K} z_k b_{ki} \le b_{k^*i} - \beta_i^b g_i^b;\ z_k \ge 0; \beta_n^x \ge 0; \beta_m^y \ge 0; \beta_i^b \ge 0; \forall n, m, i, k \ge 0$$

where (x, y, b) and their superscripts respectively represent inputs (labor, capital, and energy), desirable output (GDP), and undesirable output (a comprehensive indicator of carbon dioxide, wastewater, exhaust gas, and solid waste by means of an entropy evaluation method), and *n*, *m*, *i* are the quantities of inputs, desirable output, and undesirable output, respectively. $g = (g^x, g^y, g^b)$ on behalf of the directional vector of (x, y, b) . $w^x, w^y, and\, w^b$ represent the weight vectors, and $\beta_n^x, \beta_m^y, and\ \beta_i^b$ denote inefficiency. Given the assumption of constant returns to scale embraced in the CRS model as well as the precondition that the importance of inputs is equal to that of outputs, we described the weight vector as $w = \left(\frac{1}{2N}, \frac{1}{2(M+1)}, \frac{1}{2(M+I)}\right)$. The calculation of Equation (5) is treated as $IE = D(x, y, b; g^x, g^y, g^b|CRS)$ to indicate productivity inefficiency; thus, the TFP can be represented by the difference between one and IE, such that $TFP = 1 - IE = 1 - D(x, y, b; g^x, g^y, g^b|CRS)$. In addition, the values of energy efficiency and environmental efficiency are separately defined as $EST = 1 - \beta^e$ and $ECT = 1 - \beta^b$, where β^e and β^b represent the inefficiency of energy and environment, respectively.

Directed technological progress represents the different directions of technological progress. This study focuses on how technological progress in energy-saving and environmental conservation influence economic growth. Energy-saving technological progress can contribute to the improvement of energy utilization efficiency and break through the restriction of energy resources in economic growth. Considering this, we took the energy efficiency as its proxy. Correspondingly, technological progress in environmental conservation could promote the efficiency of environmental resource utilization and reduce the damage from environmental pollution to sustainable economic development. Therefore, we took the environmental efficiency as its proxy.

(3) Industrial structural change as the core independent variable

At present, China mostly focuses the direction of economic structure adjustment on industrial structure upgrades. From the macro perspective, we relied on three major sectors (primary, secondary, and tertiary), which comprise a large proportion of GDP, to grasp the features of industrial structure. According to the Petty-Clark Theorem, the increase in non-agricultural industries leads to “industrialization.” However, it is difficult to show how information technology has shocked industrialization. On the path to informatization, the speed of development in the tertiary sector is greater than that in the secondary sector. The boom in the tertiary sector has signaled the servitization of economic development and an upgrade of the industrial structure

(Hladkiewicz and Gawlowicz, 2013). Allowing for the differences in industrial growth, we sought a proportion of the tertiary sector to GDP as the metric of the "post-industrialization" trend of industrial structure (SI). To ensure the robustness and credibility of the regression results, we considered different adjustment directions for the industrial structure and applied the proportion of GDP comprised by the secondary sector as an indicator of the industrial structure's (IS) industrialization.

(4) Control variables

Following existing studies, we chose capital stock (K), energy consumption (EC), level of opening (OPEN), human capital (EDU), urbanization (URB), and foreign direct investment (FDI) as the control variables (Gunby et al., 2016; Tang et al., 2016; Saidi et al., 2017; Tiba and Omri, 2017). Capital stock is always represented by the proportion of social capital stock in GDP. The annual real stock of capital is generally computed using a perpetual inventory method: $K_{i,t} = (1-\delta)K_{i,t-1} + I_t / \omega_{i,t}$. With 2000 as the baseline year, I_t is the corresponding investment in fixed assets, $\omega_{i,t}$ is the capital accumulation price index, and δ is the depreciation rate of 5% (Han and Ke, 2016). EC, OPEN, and FDI are depicted by total energy consumption, total import and export amounts, and proportion of FDI in GDP, respectively. The value (expressed in million-dollar units) is discounted with the corresponding exchange rate. Human capital is expressed by the per capita years of education, and the level of urbanization is defined as the proportion of urban residents in the total population.

The basic data were obtained from the *China Statistical Yearbook* (2001–2015) and the Easy Professional Superior (EPS) database. The variables associated with price were all deflated based on the year 2000. Excluding proportional data, the logarithmic values of all variables were included to eliminate heteroscedasticity. A descriptive analysis identifying the features of the main variables is shown in Table 1.

[Insert Table 1 here]

4. Results and discussion

4.1. The national regression

To avoid the estimation bias resulting from endogenous variables, we regressed the model using the system-generalized method of moments (SYS-GMM), using the lag of the dependent variable as an instrumental variable. AR(1) rejects the null hypothesis, while AR(2) does not, indicating that the model has a first-order but no second-order sequence autocorrelation. Therefore, the lag item of the explained variable was incorporated into the benchmark model. The Hansen test did not reject the null hypothesis, indicating that the model does not trap in over-identification problems. Therefore, the empirical model using GMM estimation is valid. As shown in Table 2, Model 1 presents the linear regression results. Models 2 and 3 are the nonlinear regressions with the square of TFP and industrial structure, respectively, while Model 4 introduces both the square of TFP and industrial structure. Furthermore, the cross-term in Model 5 was included to measure the structural effect of technological innovation on economic growth.

From the comparison of the estimation results of Models 1 to 5 in Table 2, we obtained the following results:

(1) The coefficient of TFP and its square are positive and negative, respectively, which indicates that an inverted U-shaped relationship exists between technological progress and China's economic growth. This suggests that unbiased technological progress did play a driving role in the early stage of the economy, in line with the result by Jung et al. (2017). At one point, China relied too strongly on technological imitation and acquisition as the main driver for economic growth. With the improvement of technology, the economic breakthrough benefiting from China's manufacturing weakened with the gradual decline of the economic catch-up effect based on the post-advantage. Meanwhile, the more advanced technology becomes, the more difficult it is to promote economic growth through technological progress (Zhou et al., 2020). Therefore, technological progress no longer has an ultimately positive effect on economic growth. Synthesizing the regression results of Models 2, 4, and 5, the inflection point of technological progress is approximately higher than 0.7426 (from Model 2). Compared to the mean (0.602) and median (0.584) of TFP, most of the regions are currently in the interval where technological progress can still effectively promote economic growth. Consequently, considering the differentiated effect of diversified technological sources (Yang et al., 2017), it is suggested that emerging countries should not only promote technological progress but also transform technological imitation into innovation for further economic growth.

(2) The coefficients of the SI indicator and its square are significantly negative and positive, respectively. In contrast, after taking the cross-terms of TFP and SI into consideration, the coefficient of SI2 is insignificant. Additionally, the mean and

median of SI are lower than the inflection value (0.2905 from Model 4). In a word, the industrial structures of many regions are still in the negative interval, indicating that considering the interaction effects of technological progress and structural change, structural adjustment does not significantly stimulate economic growth in the early stage (Zhou et al., 2020).

The 2008 Great Recession cut short the rapid growth of emerging countries (Kantis et al., 2020) and made reindustrialization popular again (Alcácer and Cruz-Machado, 2019). In the absence of adequate institutions and environments, some emerging countries are not suitable for deindustrialization. Otherwise, premature deindustrialization reduces economic growth potential and possibilities to catch up with advanced economies in the long term (Du and Xie, 2020). Both "The 13th Five-Year Plan" and "Made in China 2025" support green industrialization as the driving force of China's economic growth. When this turning point occurs, the tertiary sectors in some regions will boom and local economic growth will be vigorously promoted through servitization.

(3) The interaction between technological progress and industrial structure is significant. Technological progress has an indirect effect on economic growth through the optimization of industrial structure. To assess the role of industrial structure in modulating the effect of technological progress on economic growth, the net effect was computed (Brambor et al., 2016; Asongu and Nwachukwu, 2018a, 2018b; Tchamyou and Asongu, 2017; Tchamyou, 2019; Asongu et al., 2017). The net effect coefficient calculated is -0.0975, indicating that a mismatch between technological progress and industrial structure cannot improve China's economic growth. Even with the spillover of international technology for emerging markets, the lack of industrial structures able to properly integrate advanced technologies into the productive system leads countries to disappointing economic returns (Teixeira and Queirós, 2016).

Regarding control variables, some results are drawn as follows. The economic growth of China is still driven by capital and energy investment. It also benefits from opening up in trade and FDI, to some extent. A comparison between Models 1 and 5 reveals that FDI and OPEN have significant positive influences on promoting economic growth after fully considering the nonlinear effect of technological progress. However, the coefficients of URB and EDU are almost insignificant. It shows that Chinese education currently cannot act as an effective impetus for economic growth, and the effect of urbanization is insignificant due to the lagged and lower level of urbanization. As the regression results of the control variables in other models are in line with Table 2, no further discussion of these results is provided in the remainder of this paper.

[Insert Table 2 here]

4.2. The regional regression

Due to regional heterogeneities, the 30 provinces were divided into eastern, central, and western regions, and sub-sample regressions were performed as shown in Table 3. From the coefficients of technological progress, the TFP and economic growth in eastern and central regions have an inverted U-shaped relationship, in line with the national regression. However, the contribution of the TFP to economic growth in the western areas is insignificant. Omri (2020) verified that technological innovation presents a different impact on economic growth during a different stage of development. In China, the eastern region's remarkable human resources and technological advantages are conducive to the use of technology in its economy. With its abundant labor and extensive markets, the central region absorbs technology from the eastern region and forms a “post-advantage” relative to the latter. In contrast, the western region makes little use of technological progress because of its lower economic development level, as well as a relative lack of proper capital, labor, and other infrastructure.

Combined with the coefficients of industrial structure, a U-shaped relationship exists between structural change and economic growth in central areas, and a negative effect of structural change is observed in eastern and western regions. Despite the existing regional heterogeneity, considering the fact that the industrial structure is much lower than the turning point in central areas (1.2619), it can be generally stated that currently, it is not suitable to propel post-industrialization in China, keeping in line with the conclusions of national regressions. With the Great Recession and the resulting reindustrialization (Alcácer and Cruz-Machado, 2019), emerging countries should also redesign their industrialization process. In summary, the implication is that premature deindustrialization is harmful to China’s economic growth (Zhou et al., 2020), and policymakers should adjust the relative policies for gaining the persisting dividend of industrialization.

The cross-terms of technological progress and industrial structure are significant in all regions. The net effects in the eastern, central, and western regions are significantly positive 3.3078, 3.7493, and 0.0964, respectively. This means that technological progress in all the sub-sample regions has promoted economic growth by modulating the industrial structure. Due to the lagged development in the western regions, it notably has a lower result. Not surprisingly, regions with proper industrial systems can absorb more benefits from technological progress (Teixeira and Queirós, 2016). Therefore, to gain higher economic growth, strengthening the coordination of technological progress and industrial structure in all regions is a good choice.

[Insert Table 3 here]

4.3. Structure change: industrialization or deindustrialization

To test the robustness of the model and distinguish the trend of structural adjustment between different regions, we introduced the indicator of industrialization IS, which is depicted by the share of the value-added of the secondary sector in the GDP.

According to the national regression in Table 4, the result illustrates the robustness of the regressions in Table 2 to some degree. According to the coefficients of TFP and TFP2, inverted U-shaped relationships exist between technological progress and economic growth in China. The conclusion is consistent with the corresponding results in Table 2 as well. The coefficients of IS are positive but not significant, excluding central areas, which means that although premature deindustrialization may hinder the long-run growth (Du and Xie, 2020), the dividends of industrialization have gradually disappeared with the development of economy in China. The coefficient of the cross-term is insignificant, and the net effect is also insignificant -0.1047, indicating that technological change fails to accelerate economic growth by compelling industrialization nationwide. However, the net effects of the cross-terms in eastern and middle regions are significantly positive 2.3526 and 1.0410, respectively. This means that the drag effect of structure optimization on economic growth is mainly derived from policies and institutions.

The regional regressions in Table 4 suggest that the results are basically aligned with those in Section 4.2. That is, industrialization positively affected economic growth in central regions, but failed to influence growth in eastern and western regions. The coefficients of technological progress and its quadratic term are significantly positive and negative, respectively, meaning that technological progress has an inverted U-shaped effect on regional economic growth. Thus, for long-run growth, regions should make full use of technological progress and transform technological imitation into innovation to deal with the forthcoming turning points. In summary, the robustness test provides comparable results with those of the aforementioned analysis and proves that the results are robust.

[Insert Table 4 here]

4.4. Directed technological progress

To test the direction of technological progress, a mediation effect model was constructed by taking the TFP as the explained variable and energy efficiency (energy-saving technological progress) and environmental efficiency (environmental conservation technological progress) as the main explanatory variables. The results in Table 5 reveal that the direction of technological progress in the various regions varies.

From the national regression, the coefficient of the lagged term of the TFP is negative but insignificant. This implies that, disregarding the direction of technological innovation, the total factor productivity is not path-dependent in time, which is contradictory to Canh et al.'s (2019) findings. For directed technological change, the coefficient of EST is larger than that of ECT. In summary, the direction of technological innovation should switch to improve the environmental conservation technological progress, as higher environmental efficiency can accelerate growth more quickly than improving energy utilization. Nevertheless, considering the crucial role of resource-intensive industries in the national economy and the symbiotic relationship between energy consumption and environmental pollution, the promotion of energy efficiency is also significant. China's current policies should aim for a valid resource and environmental market system for long-run growth, especially in terms of the distorted energy prices determined by administrative pricing (Shi and Sun, 2017).

The regional regression in Table 5 indicates that, in the central and western regions, improving environmental efficiency is the optimal direction for technological innovation, whereas energy-saving technological progress is the priority direction for technological innovation in the eastern region. As the origin and concentration of China's industry, the eastern region possesses a relative advantage to further develop energy-conservation technology. Before the turning point of the TFP, improvement in energy efficiency will inevitably have a heavy scale effect on economic growth. The reason the contribution of environmental efficiency is higher than that of energy efficiency is that the central region lies in the learning effect of the eastern region. In other words, by learning from the eastern region and improving environmental efficiency, the central region is expected to realize cleaner industrialization without "treatment after pollution." Since China's major rivers originate from the western region, the implementation of a "source protection" policy has played a prominent role in guaranteeing the protection of the ecological environment in the middle and downstream areas. Thus, it is optimal for the western region to redirect technical change towards clean technologies and improve environmental efficiency. With the booming economic growth from the "Belt and Road" policy, the protection of the ecological environment becomes one of the important directions for technological progress and economic development in western China.

[Insert Table 5 here]

5. Conclusion and policy implications

Considering the slowing economic growth brought about by the Great Recession and the increasing pressure for energy-saving and environmental protection, this study identifies the effect of technological innovation and structural change on economic growth in China, as an emerging and transforming market. The results are as follows: (1) Technological progress shows an inverted U-shaped effect on China's economic growth. Premature deindustrialization may reduce an emerging country's growth potential. Simultaneously, the structural effect of technological progress on economic growth is apparent in the national regression. (2) Regional heterogeneity tests indicate that the TFP has a greater impact on economic growth in the eastern and central areas than it does in the western area. An inverted U-shaped relationship exists between the TFP and economic growth in all three regions. (3) The direction of industrial structural change is different among the regions. The central region should make full use of industrialization and develop the tertiary sector for sustainable growth. The eastern and western areas are not suitable for premature deindustrialization. (4) Regarding the direction of technological innovation, the priority of the central and western regions is to develop environmental conservation technology in the process of industrial transformation, whereas the eastern region ought to foster energy-saving innovations because of its tremendous consumption of energy resources.

The aforementioned conclusions explaining technological progress and economic growth could be of great interest to policymakers of China and other emerging countries in designing and implementing policies for high-quality growth to catch up with developed economies. Accordingly, some suggestions are proposed as follows: (1) Sub-regions should hold and implement differentiated technology strategies. Due to different resource endowments, economic infrastructures, and technological foundations, different regions should identify the advantages of technology and advance biased technological progress to catch up with developed regions. Some provinces in China have been endowed to develop local proper and matched technology using multiple strategies and policies, such as the Talent Subsidy Scheme, the project "Building a nest to attract the phoenix,” and collaborations among enterprises, universities, and research institutes. (2) As an emerging and transforming market, China should switch from technological imitation to innovation using related entrepreneurship policies. Although research shows that an underdeveloped economy can catch up with developed countries by imitating international advanced technologies, with the increase of global competition and geopolitical risk, an economy should target independent innovation to master core technology and ultimately achieve long-run growth. An emerging and transforming country should especially pay attention to the cultivation of innovation consciousness and the construction of an innovation environment for further technological progress and sustainable growth. For example, China has tried to transition from "Made in China" to "Created in China" and executed some entrepreneurship policies. (3) During the transformation, China should strive for a concurrent and matched industrial structural change to absorb more spillover of technological progress. With the challenges posed by the Great Recession and changed global environment, emerging countries also have to transform and strive for more sustainable growth. As spillover of advanced technology can be absorbed with a proper industrial system, China has laid out a structural change coupled with corresponding technological progress by related industrial policies, for example, high-tech industry development strategy. A matched technological progress and industrial structural adjustment may be the potential driving force behind further long-term sustainable development in emerging countries.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant Nos. 71934001, 71471001, 41771568, 71533004, 71503001, 71804001), the National Key Research and Development Program of China (Grant No. 2016YFA0602500), and the Planning Project of Philosophy and Social Science Research in Anhui Province (Grant No. AHSKQ2017D03).

Conflicts of interest

The authors declare no conflict of interest.

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Table Captions:

Table 1 Descriptions of the main variables

Variable	Full name	Sample	Mean	Mediate	Minimum	Maximum
GRP	gross regional production	450	8.574	8.654	5.575	10.825
TFP	total factor productivity	450	0.602	0.584	0.201	1.000
EST	energy saving technological progress	450	0.490	0.451	0.162	1.000
ECT	environment conservation technological progress	450	0.372	0.308	0.094	1.000
SI	post-industrialization of industrial structure	450	-0.115	-0.152	-0.699	1.297
IS	industrialization of the industrial structure	450	-0.789	-0.737	-1.622	-0.527
K	capital stock	450	9.423	9.477	6.605	11.644
EC	energy consumption	450	8.9s58	8.994	6.174	10.569
OPEN	the level of opening up	450	-1.703	-2.033	-3.332	0.543
EDU	per capita education in years	450	2.113	2.111	1.798	2.487
FDI	foreign direct investment	450	-4.020	-3.478	-7.290	-0.672
URB	urbanization	450	-0.776	-0.790	-1.461	-0.110

Source: Provincial administrative unit dataset described in the text and authors' calculations.

Table 2 The basic regression results

	Model 1	Model 2	Model 3	Model 4	Model 5
VARIABLES	GRP	GRP	GRP	GRP	GRP
L.GRP	0.8098***	0.4432***	0.5259***	0.4577***	0.3125***
	(54.46)	(4.08)	(10.22)	(5.95)	(3.45)
TFP	0.1697***	2.0807***	0.3280***	2.1219***	3.8830***
	(10.84)	(2.96)	(7.16)	(4.60)	(6.23)
TFP2		-1.1401***		-1.2360***	-2.5920***
		(-2.79)		(-4.70)	(-5.89)
SI	0.0242	0.0687*	-0.0378	-0.1777***	-0.4383**
	(1.40)	(1.81)	(-1.51)	(-4.34)	(-2.59)
SI2			0.1000***	0.3058***	0.0082
			(3.22)	(5.71)	(0.15)
TFP*SI					0.8018***
					(3.10)
K	0.0008	0.2729***	0.2660***	0.2825***	0.3848***
	(0.06)	(3.14)	(8.37)	(5.73)	(5.35)
EC	0.1937***	0.2811***	0.1832***	0.3028***	0.2617***
	(11.50)	(5.50)	(9.92)	(12.10)	(11.39)
OPEN	-0.0051	0.0198	0.0268***	0.0076	0.0165**
	(-1.08)	(1.08)	(3.73)	(1.07)	(2.48)
EDU	-0.0111	0.0123	0.0238	-0.0269	0.0310
	(-0.37)	(0.12)	(0.65)	(-0.93)	(0.84)
FDI	0.0109***	0.0255	0.0688***	0.0478***	0.0199**
	(4.55)	(1.35)	(6.87)	(4.23)	(2.35)
URB	0.1879***	-0.0387	-0.0428	-0.0455	-0.0182
	(4.93)	(-0.38)	(-0.81)	(-0.75)	(-0.27)
Constant	0.0851	-0.9911***	-0.0473	-1.4715***	-1.3714***
	(0.80)	(-2.88)	(-0.26)	(-5.42)	(-6.30)
Observations	420	420	420	420	420
Number of id	30	30	30	30	30
AR(1)	-1.761*	1.704*	2.042**	1.693*	1.717*
P-AR(1)	[0.0783]	[0.0884]	[0.0412]	[0.0904]	[0.0859]
AR(2)	-1.510	0.701	0.844	0.303	0.985
P-AR(2)	[0.131]	[0.484]	[0.398]	[0.762]	[0.325]
Hansen	27.16	10.84	25.81	17.68	20.91
P-Hansen	[0.166]	[0.211]	[0.172]	[0.280]	[0.104]

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Z values in parentheses, P values in brackets. The full definitions of abbreviations can be found in Table 1. AR(1): first-order sequence autocorrelation, AR(2): second-order sequence autocorrelation. HANSEN statistic to test whether our model is overidentified.

Table 3 The sub-regional regression results

	Eastern area	Central area	Western area
VARIABLES	GRP	GRP	GRP
L.GRP	0.6970***	0.7307***	1.1704***
	(8.40)	(10.32)	(23.69)
TFP	3.3129***	3.5357**	-0.1982
	(5.44)	(2.49)	(-0.82)
TFP2	-2.0002***	-3.1795***	-0.2797
	(-5.15)	(-2.72)	(-1.29)
SI	-0.3297***	-0.4013*	-0.3118***
	(-2.61)	(-1.74)	(-2.83)
SI2	0.0034	0.1590**	0.0852
	(0.11)	(2.01)	(0.85)
TFP*SI	0.4098**	-0.8753**	-0.7329***
	(2.35)	(-2.30)	(-3.28)
K	0.1260**	0.1473***	-0.2027***
	(2.40)	(2.73)	(-5.13)
EC	0.1828***	0.1137***	0.0119
	(6.11)	(4.78)	(0.39)
OPEN	0.0205*	0.0487***	-0.0000
	(1.96)	(4.57)	(-0.00)
EDU	-0.1047	-0.0338	-0.0120
	(-1.19)	(-0.61)	(-0.21)
FDI	0.0048	0.0118	0.0001
	(0.52)	(1.20)	(0.02)
URB	0.0037	-0.1150***	0.2482***
	(0.13)	(-4.06)	(5.04)
Constant	-1.1485***	-0.8523**	0.9119***
	(-3.76)	(-2.00)	(4.04)
Observations	154	126	140
Number of id	11	9	10
AR(1)	-2.009	1.752	-2.661
P-AR(1)	[0.0445]	[0.0798]	[0.00780]
AR(2)	-1.274	-0.256	-0.649
P-AR(2)	[0.203]	[0.798]	[0.516]
Hansen	3.97	19.84	18.35
P-Hansen	[0.265]	[0.342]	[0.433]

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Z values in parentheses, P values in brackets. The full definitions of abbreviations can be found in Table 1. AR(1): first-order sequence autocorrelation, AR(2): second-order sequence autocorrelation. HANSEN statistic to test whether our model is overidentified.

Table 4 The robustness test

	Nationwide	Eastern area	Central area	Western area
VARIABLES	GRP	GRP	GRP	GRP
L.GRP	0.4344***	0.8450***	0.7971***	1.1192***
	(4.39)	(14.09)	(19.24)	(39.87)
TFP	1.4439***	2.2346***	3.9184***	0.4519*
	(2.88)	(5.08)	(3.70)	(1.92)
TFP2	-0.6381*	-1.3592***	-3.8386***	-0.7166***
	(-1.80)	(-4.39)	(-5.99)	(-4.22)
IS	0.0376	0.0638	0.6648**	0.1145
	(0.12)	(0.36)	(2.24)	(0.39)
IS2	0.1734	-0.0387	-0.1698	0.0381
	(0.80)	(-0.48)	(-0.84)	(0.26)
TFP*IS	0.1337	-0.1461	-1.4118*	0.2883
	(0.42)	(-0.98)	(-1.90)	(0.78)
K	0.2867***	0.0340	0.1083***	-0.0862***
	(3.76)	(0.86)	(3.99)	(-4.46)
EC	0.2769***	0.1606***	0.0941***	-0.0188
	(4.97)	(6.09)	(5.94)	(-1.27)
OPEN	0.0256	0.0306***	0.0504***	0.0029
	(1.21)	(2.72)	(5.86)	(0.54)
EDU	-0.0371	-0.1981***	-0.1574***	0.0197
	(-0.29)	(-2.63)	(-3.28)	(0.54)
FDI	0.0486**	0.0184***	0.0175***	0.0048
	(2.22)	(2.71)	(3.57)	(1.62)
URB	-0.0462	-0.0168	-0.0759***	-0.0383
	(-0.38)	(-0.58)	(-4.51)	(-1.54)
Constant	-0.6429	-0.6896***	-0.5625	0.2024
	(-1.59)	(-2.78)	(-1.35)	(1.13)
Observations	420	154	126	140
Number of id	30	11	9	10
AR(1)	2.321**	-2.255**	-0.428*	-2.242**
P-AR(1)	[0.0203]	[0.0241]	[0.0668]	[0.0249]
AR(2)	0.903	0.135	0.849	0.253
P-AR(2)	[0.367]	[0.892]	[0.396]	[0.801]
Hansen	5.944	7.36	2.34	10.47
P-Hansen	[0.654]	[0.289]	[0.505]	[0.400]

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Z values in parentheses, P values in brackets. The full definitions of abbreviations can be found in table 1. AR(1): first-order sequence autocorrelation, AR(2): second-order sequence autocorrelation. HANSEN statistic to test whether our model is overidentified.

Table 5 Directed technological progress

	Nationwide	Eastern area	Central area	Western area
VARIABLES	TFP	TFP	TFP	TFP
L.TFP	-0.0049	-0.1036**	0.0605**	0.8629***
	(-0.09)	(-2.41)	(2.00)	(13.04)
EST	0.2198	0.4829***	0.1572***	-0.0921**
	(1.21)	(12.89)	(4.01)	(-2.21)
ECT	0.2901***	0.3851***	0.3359***	0.1103***
	(4.31)	(13.25)	(11.94)	(3.48)
SI	0.0981	-0.0043	-0.0910***	-0.0931***
	(0.76)	(-0.29)	(-4.48)	(-2.62)
K	0.1145	-0.1362***	-0.0684***	0.0307**
	(0.94)	(-8.07)	(-4.76)	(2.03)
EC	-0.1032	0.1701***	0.0919***	-0.0035
	(-0.75)	(8.12)	(3.78)	(-0.21)
OPEN	0.0996**	0.0176***	0.0101**	-0.0048
	(2.20)	(2.98)	(2.09)	(-0.67)
EDU	-0.0639	-0.0351	0.0894***	-0.0918***
	(-0.30)	(-0.75)	(3.29)	(-2.68)
FDI	0.0739***	0.0087*	-0.0026	0.0155***
	(3.00)	(1.80)	(-0.66)	(3.23)
URB	-0.5001**	0.0295	-0.0033	-0.0241
	(-2.18)	(1.50)	(-0.30)	(-0.73)
Constant	0.5351	0.1915*	-0.0598	-0.0171
	(0.99)	(1.94)	(-0.44)	(-0.15)
Observations	420	154	126	140
Number of id	30	11	9	10
AR(1)	2.001**	1.704*	1.682*	-2.473**
P-AR(1)	[0.0454]	[0.0883]	[0.0926]	[0.0134]
AR(2)	-0.151	0.784	0.0519	-0.816
P-AR(2)	[0.880]	[0.433]	[0.959]	[0.414]
Sargan	5.75	5.63	2.84	5.69
P-Sargan	[0.218]	[0.131]	[0.418]	[0.224]

Notes: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. Z values in parentheses, P values in brackets. The full definitions of abbreviations can be found in table 1. AR(1): first-order sequence autocorrelation, AR(2): second-order sequence autocorrelation. HANSEN statistic to test whether our model is overidentified.

Figure Captions:

Fig. 1: China's GDP growth, total energy consumption growth, and CO2 emission growth from 1992 to 2017

Fig. 2: Mechanism of the influence of technological innovation and structural adjustment on economic growth

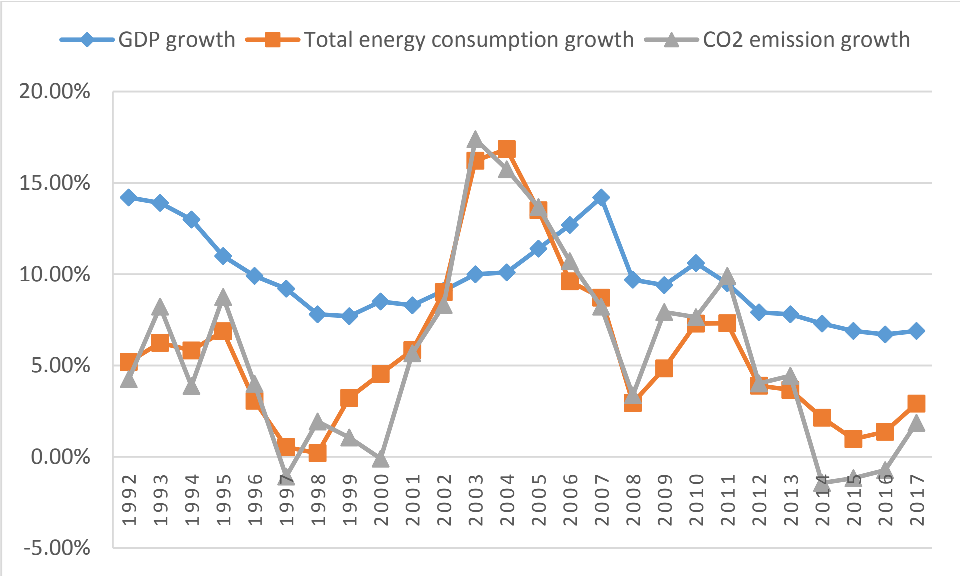

Fig. 1 China's GDP growth, total energy consumption growth, and CO_2 emission growth from 1992 to 2017

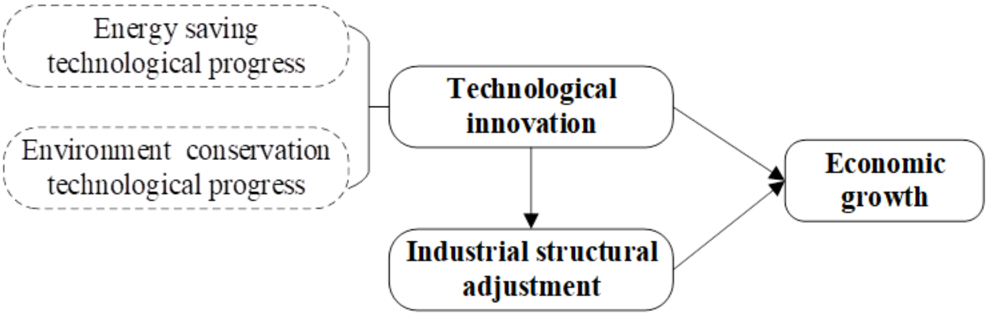

Fig. 2 Mechanism of the influence of technological innovation and structural adjustment on economic growth