



Drivers and trajectories of China's renewable energy consumption

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Abstract

Renewable energy is significant for addressing climate change and energy security. This study focused on the drivers of China's renewable energy consumption (REC) by an extended production-theoretical decomposition analysis and emphasized REC technical efficiency and technological change in 28 provinces during 1997–2017. We then projected China's REC to 2030 based on nine scenarios using a Monte Carlo simulation approach and specifically considering the impacts of the COVID-19 pandemic on the national economy. The decomposition results showed that economic growth and population scale generally contributed to an increase in REC at national and provincial levels over the period while the overall technical efficiency and technological change in REC played limited roles in prompting REC nationally. The projection results indicated that the target that generates 50% of its electricity from renewable energy sources for China, could be achieved by 2030 if enough actions are taken to accelerate renewable energy development. Finally, we provided policy proposals that support our findings.

Keywords Renewable energy consumption · COVID-19 pandemic · Production-theoretical decomposition analysis · Monte Carlo simulation

1 Introduction

Renewable energy has been widely regarded as an efficient tool for mitigating climate change and achieving energy security (Akintande et al., 2020; Anton & Nucu, 2020; Chen & Lin, 2020; Ozcan & Ozturk, 2019; Steffen et al., 2020). Due to the significant decrease in costs of renewable power generation recently (International Renewable Energy Agency, IRENA, 2020), global renewable energy consumption (REC) has been growing rapidly, for

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example, at an annual growth rate of 13.7% over 2008–2018 (British Petroleum Company, BP, 2020).

This is particularly true for China, the largest developing country and energy consumer. The country consumed 22.9% of global renewable energy in 2019, which was approximately the sum of the annual REC in the UK, Italy, Japan, Australia, South Africa, France, Germany, and Canada in 2019 (BP, 2020). Therefore, the research on China's REC is of significance theoretically and practically.

To achieve emission reduction and energy transformation, the Chinese government has issued a series of renewable energy development policies. In 2005, the first *Renewable energy law of the People's Republic of China* was issued; it was amended in 2009. This law is the basis for renewable energy development and utilization in China, including resource investigation and development planning, industrial guidance and technical support, promotion and application, price management and cost sharing, and economic incentives and supervision measures. In 2020, renewable energy was listed as the energy development priority in the first draft of the *Energy law of the People's Republic of China* (National energy administration, NEA, 2020). The country will formulate medium and long-term targets for the total amount of renewable energy development and utilization, as well as the target for the proportion of REC in primary energy consumption, which will be included in the national economic and social development plan as well as annual binding targets; it will also be broken down into provinces for easier implementation.

As early as 2016, the *Thirteenth Five-Year Plan for Renewable Energy Development* set a national target of 1.9 trillion kwh of renewable energy power generation by 2020, accounting for 27% of the total power generation (NEA, 2016). The *National strategy on energy production and consumption revolution (2016–2030)* has set the goal of achieving 50% (as much as possible) of all non-fossil energy power generation by 2030 in the country (NDRC, 2016). However, although China formulated a renewable energy development roadmap, the dominance of thermal power generation has not fundamentally changed in the current stage and the share of renewable energy in the total power generation remains low, affected by factors like the slow diffusion of renewable energy technologies (Chen & Lin, 2020) and growing environmental challenges (Wang et al., 2018). In this respect, it is necessary to study the driving forces behind the changes in China's REC to better facilitate renewable energy development.

The existing literature has mainly focused on the relationship between REC and some socioeconomic variables such as GDP (Ozcan & Ozturk, 2019; Rahman & Velayutham, 2020), CO₂ emissions (Jebli et al., 2020; Karasoy & Akçay, 2019), foreign direct investment (FDI) (Fan & Hao, 2020), urbanization (Bao & Xu, 2019; Chen, 2018), financial development (Anton & Nucu, 2020; Eren et al., 2019), and income inequality (Topcu & Tugcu, 2020; Uzar, 2020). The conclusions vary from studies focusing on REC and variables nexus above. For example, in terms of the relationship between economic growth and REC, Ozcan and Ozturk (2019) showed that there is not any mutual nexus between REC and GDP, in nearly all emerging market economies, whereas, Rahman and Velayutham (2020) found that there is a unidirectional causality running from the economic growth to REC in five South Asian countries. In terms of REC and income inequality nexus, Topcu and Tugcu (2020) found that REC reduces income inequality while Uzar (2020) discovered that a decline in income inequality help to improve REC. As for the REC and urbanization nexus, Bao and Xu (2019) found that there is no causality relationship between REC and urbanization for most provinces in China, while Chen (2018) found that changes in urbanization level affect REC. In terms of FDI and REC nexus, Fan and Hao (2020) concluded that there is long-run equilibrium between REC and FDI for China. However, there

is nearly no debate that REC contributed to decrease in CO₂ emission (Jebli et al., 2020; Karasoy & Akçay, 2019).

On the other hand, some studies analyzed a specific topic on renewable energy. For example, in terms of the renewable energy technologies, Gallagher et al. (2019) showed that the lowest environmental burdens per kilowatt-hour of electricity generation was hydro in comparison with other two renewable energy technologies. Steffen et al. (2020) found that dynamic cost of operation and maintenance of renewable energy technologies need to be considered in energy system modeling. In the field of renewable energy policy, Mamat et al. (2019) found that the barriers of renewable energy policy implementation were social, political and economic pressures in Southeast Asia. The similar studies can also be seen in Gungah et al. (2019) and Fraundorfer and Rabitz (2020). As for the renewable energy supply chain, studies like Fernando et al. (2018) showed that renewable energy supply chain management enables companies to achieve competitiveness in Malaysia. In addition, other studies assessed the determinants of REC (Akintande et al., 2020; Wang et al., 2018). They found that socioeconomic factors such as population growth and human capital are the main determinants of REC in Africa (Akintande et al., 2020) and showed that energy security was the major drivers contributing to REC development in China (Wang et al., 2018).

However, although REC is particularly important for climate change mitigation and energy security, the research on the socioeconomic determinants of REC are far from conclusive, especially for China. Although several studies analyzed the determinants of REC (e.g., Akintande et al., 2020), the roles of REC technical efficiency and technological change which are important for improving REC performance, have been ignored to a large extent. Moreover, although REC has been projected by statistical model or scenario analysis (Wang et al., 2018; Wu et al., 2019), the uncertainties of key variables have received little attention for projecting REC. More importantly, few scenario analyses have been combined with the realizability of national REC targets in China in particular. Achieving these goals would be important for China to achieve leapfrog development of renewable energy and mitigate climate change during its energy transformation.

With the context above, this study first focused on the determinants of China's REC from a production perspective using an extended production-theoretical decomposition analysis (PDA) approach (Zhou & Ang, 2008). In the field of factorial decomposition, index decomposition analysis (IDA) especially for logarithmic Divisa decomposition index analysis (LMDI), structural decomposition analysis (SDA) are widely used in energy and emission related studies (e.g., Chen et al., 2021; Lam et al., 2019; Wang et al., 2018). Compared with LMDI and SDA, PDA is built on the total-factor framework (Xu, 2020). As such, PDA can provide new insights related to technical efficiency and technological change for contributing to changes in an aggregate indicator (e.g., energy consumption and CO₂ emission). PDA has been applied in many energy-related studies (Chen et al., 2021; Liu et al., 2018). As discussed above, the roles related to technical efficiency and technological change were rarely explored for contributing to changes in REC. Therefore, to fill that gap, we used an extended PDA approach to quantify and emphasize the roles related to technical efficiency and technological change in determining REC for China and helping to improve the total-factor performance of REC through improving the production system. Moreover, we fully considered uncertainties of key variables and projected China's REC using a Monte Carlo simulation approach (Zaroni et al., 2019; Zhang et al., 2020) with a focus on the realizability of China's REC targets.

In summary, this study contributes to the existing literature as follows:

First, we decomposed China's REC using an extended PDA approach, where REC was incorporated into production process, and emphasized the factors related to REC

technical efficiency and technological change for contributing to changes in REC. In comparison with previous studies on the determinants of REC (e.g., Akintande et al., 2020; Wang et al., 2018), the REC technical efficiency and technological change, for the first time, were quantified and emphasized under the extended PDA framework, which could introduce more production-based information to China's REC. In addition, unlike many previous studies on economic growth, population, and REC nexus using econometric models (Fan & Hao, 2020; Ozcan & Ozturk, 2019; Rahman & Velayutham, 2020), we analyzed the impacts of economic growth and population scale on the changes in REC using the single decomposition approach (PDA), which can avoid the possible problems that are difficult to observe the trends by year or non-linear trends in the econometric model.

Second, we projected China's REC to 2030 using scenario analysis combined with a Monte Carlo simulation approach and analyzed the realizability of REC targets set by the NDRC (2016). In particular, we considered the impact of the COVID-19 pandemic on the economy and adjusted the scenario setting of economic growth according to actual conditions. Moreover, based on scenario analysis, we emphasized the urgency of accelerating the development of renewable energy to achieve the national target in which 50% of the electricity is derived from renewable energy sources by 2030. Such comprehensive analysis could aid the understanding of the status quo and future trends of REC in China and thus could assist in related policymaking.

2 Methodology and data

2.1 Non-radial directional distance function

Data envelopment analysis (DEA) has been widely used in environmental studies for technical efficiency measurement. Assuming x and y are vectors of inputs and outputs, then the production technology can be expressed as

$$P = \{(x, y) : x \text{ can produce } y\} \quad (1)$$

here, we specified the production technologies by incorporating REC, nonrenewable energy consumption (NEC), capital (K), and labor (L) as inputs and GDP (Y) as output. Notably, although many studies have introduced undesirable outputs (e.g., CO₂ emission and SO₂) into the production theory framework (Wang et al., 2019; Xu, 2020), we focused on the technical efficiency of RE and thus followed Liu et al. (2018) only to incorporate Y as output. The production technology can be rewritten as

$$T = \{(REC, NEC, K, L, Y) : (REC, NEC, K, L) \text{ can produce } Y\} \quad (2)$$

T is often assumed to a closed and bounded set, indicating that a finite number of inputs can only produce a finite number of outputs (Färe & Primont, 1995). Both the Shephard distance function and directional distance function are also widely used in the environmental studies; however, compared with those two distance functions, non-radial directional distance function (NDDF) has the advantages of flexible adjustments of inputs and outputs including desirable and undesirable outputs. Therefore, this study adopted the NDDF for measuring REC efficiency performance.

Referring to Zhou et al. (2012), we defined the NDDF as

$$\vec{D}(REC, NEC, K, L, Y; g) = \sup \{ W^T \alpha : ((REC, NEC, K, L, Y) + g \cdot \text{diag}(\alpha)) \in T \} \tag{3}$$

where α is a vector of scaling factors representing slacks of inputs/output and $\alpha = (\alpha_{REC}, \alpha_{NEC}, \alpha_K, \alpha_L, \alpha_Y)^T \geq 0$, $\text{diag}(\alpha)$ means a diagonal matrix of α , W^T indicates a normalized weight vector assigned to the numbers of inputs/output and $W^T = (w_{REC}, w_{NEC}, w_K, w_L, w_Y)^T$, g is an explicit directional vector determining the directions of scaling inputs/output, and $g = (-g_{REC}, -g_{NEC}, -g_K, -g_L, g_Y)$. The NDDF can be solved by following linear programming:

$$\vec{D}(REC, NEC, K, L, Y; g) = \max w_{REC}\alpha_{REC} + w_{NEC}\alpha_{NEC} + w_K\alpha_K + w_L\alpha_L + w_Y\alpha_Y$$

$$s.t. \begin{cases} \sum_i \lambda_i REC_i \leq REC_o - \alpha_{REC} \cdot g_{REC} \\ \sum_i \lambda_i NEC_i \leq NEC_o - \alpha_{NEC} \cdot g_{NEC} \\ \sum_i \lambda_i K_i \leq K_o - \alpha_K \cdot g_K \\ \sum_i \lambda_i L_i \leq L_o - \alpha_L \cdot g_L \\ \sum_i \lambda_i Y_i \geq Y_o + \alpha_Y \cdot g_Y \\ \lambda_i, \alpha_{REC}, \alpha_{NEC}, \alpha_K, \alpha_L, \alpha_Y \geq 0, i = 1, 2, \dots, N \end{cases} \tag{4}$$

Like Zhang and Choi (2013a) and Chen et al. (2019), we set $W = (1/8, 1/8, 1/8, 1/8, 1/2)$ as there are four inputs (REC, NEC, K, and L) and one output (Y) in the study. For a robust analysis, we also checked the results under the weight vector, $W = (1/4, 1/4, 0, 0, 1/2)$, as this weight vector reflects the REC and NEC performance without changing K and L input (Zhang & Choi, 2013b). The values for REC technical efficiency presented a few different values but were generally consistent. Therefore, although this is an overly simplified setting to some extent, we finally adopted the former weight vector ($W = (1/8, 1/8, 1/8, 1/8, 1/2)$), to avoid different scores due to different choices of W (Lin and Du, 2015).

Similar to Wang et al. (2019), we defined the REC-oriented distance function based on slacks as

$$D_{REC,o} = \frac{1}{1 - \alpha_{REC,o}} = \frac{1}{REUE_o} \tag{5}$$

where $\alpha_{REC,o}$ represents the slack of REC of entity o and the entity o is located on the best practice frontier if $\alpha_{REC,o} = 0$, $REUE_o$ means the REC technical efficiency of entity o with respect to the frontier, and $0 < REUE_o \leq 1$.

2.2 Decomposition model on REC

According to Kaya Identity Theory (Kaya, 1990), we decomposed the changes in REC at the national level as follows:

$$\begin{aligned}
 REC &= \sum_i \frac{REC_i}{Y_i} \times \frac{Y_i}{P_i} \times P_i \\
 &= \sum_i \frac{REC_i}{Y_i} \times PY_i \times POP_i
 \end{aligned}
 \tag{6}$$

where i denotes province i ; and $\frac{REC_i}{Y_i}$ represents the REC intensity, which is similar to the widely accepted concept of energy consumption intensity. The larger $\frac{REC_i}{Y_i}$ is, the larger REC given GDP and better development of RE; PY_i ($\frac{Y_i}{P_i}$) and POP_i (P_i) reflect GDP per capita and population scale.

As discussed above, REC intensity could be reduced by its inefficiency. Therefore, similar to Zhou and Ang (2008), we incorporated the distance functions into Eq. (6) as follows:

$$REC = \sum_i \frac{REC_i / D_{REC,i}}{Y_i} \times \frac{Y_i}{P_i} \times P_i \times D_{REC,i}
 \tag{7}$$

To avoid arbitrary selection of choosing different production technologies due to periods, we followed Zhou and Ang (2008) to use the geometric mean of the production technologies taking year t and $t + 1$ as the reference. Therefore, Eq. (7) can be rewritten at year t at the national level as

$$\begin{aligned}
 REC^t &= \sum_i \frac{REC_i^t / \left[D_{REC,i}^t(t) \cdot D_{REC,i}^{t+1}(t) \right]^{1/2}}{Y_i^t} \times \frac{Y_i^t}{P_i^t} \times P_i^t \times D_{REC,i}^t(t) \times \left[\frac{D_{REC,i}^{t+1}(t)}{D_{REC,i}^t(t)} \right]^{1/2} \\
 &= \sum_i PREI_i^t \times PY_i^t \times POP_i^t \times REUE_i^t \times TCREU_i^t
 \end{aligned}
 \tag{8}$$

where $D_{REC,i}^t(t)$ and $D_{REC,i}^{t+1}(t)$ are the REC-oriented distance functions taking year t and $t + 1$ for constructing production technologies; $PREI_i^t$ ($\frac{REC_i^t / \left[D_{REC,i}^t(t) \cdot D_{REC,i}^{t+1}(t) \right]^{1/2}}{Y_i^t}$) denotes potential REC intensity (PREI) in province i at year t , which is similar to Zhou and Ang (2008) in the case of energy consumption; $REUE_i^t$ ($D_{REC,i}^t(t)$) and $TCREU_i^t$ ($\left[\frac{D_{REC,i}^{t+1}(t)}{D_{REC,i}^t(t)} \right]^{1/2}$) represents the REC technical efficiency and technological change province i at year t [see Zhou and Ang (2008) and Wang et al. (2019) for similar examples]; and PY_i ($\frac{Y_i}{P_i}$) and POP_i (P_i^t) reflect GDP per capita and population scale in province i at year t . A noteworthy point is that although the definition of $REUE_i^t$ is similar to the $\left[D_{REC,i}^t(t) \cdot D_{REC,i}^{t+1}(t) \right]^{1/2}$ in $PREI_i^t$ to some extent, they should be treated differently as the former is derived from Malmquist productivity index for two-period comparison and the latter is produced for avoiding arbitrary selection of choosing different production technologies due to periods (Zhou & Ang, 2008).

Similarly, RE at year $t + 1$ at the national level can be decomposed as

$$\begin{aligned}
 REC^{t+1} &= \sum_i \frac{REC_i^{t+1} / \left[D_{REC,i}^{t+1}(t+1) \cdot D'_{REC,i}(t+1) \right]^{1/2}}{Y_i^{t+1}} \\
 &\times \frac{Y_i^{t+1}}{P_i^{t+1}} \times P_i^{t+1} \times D_{REC,i}^{t+1}(t+1) \times \left[\frac{D_{REC,i}^t(t+1)}{D_{REC,i}^{t+1}(t+1)} \right]^{1/2} \\
 &= \sum_i PREI_i^{t+1} \times PY_i^{t+1} \times POP_i^{t+1} \times REUE_i^{t+1} \times TCREU_i^{t+1}
 \end{aligned} \tag{9}$$

The terms in Eq. (9) can be similarly explained as Eq. (8). As LMDI has many desirable properties such as theoretical foundation, adaptivity, easy operation, and readability (Ang, 2015), we further used LMDI to decompose the changes in national RE as

$$\Delta REC = REC^{t+1} - REC^t = \Delta PREI + \Delta PY + \Delta POP + \Delta REUE + \Delta TCREU \tag{10}$$

where

$$\Delta PREI = L(REC_i^{t+1}, REC_i^t) \times \ln \left(\frac{PREI_i^{t+1}}{PREI_i^t} \right),$$

$$\Delta PY = L(REC_i^{t+1}, REC_i^t) \times \ln \left(\frac{PY_i^{t+1}}{PY_i^t} \right),$$

$$\Delta POP = L(REC_i^{t+1}, REC_i^t) \times \ln \left(\frac{POP_i^{t+1}}{POP_i^t} \right),$$

$$\Delta REUE = L(REC_i^{t+1}, REC_i^t) \times \ln \left(\frac{REUE_i^{t+1}}{REUE_i^t} \right),$$

$$\Delta TCREU = L(REC_i^{t+1}, REC_i^t) \times \ln \left(\frac{TCREU_i^{t+1}}{TCREU_i^t} \right),$$

where $L()$ is the weighted function and $L(REC_i^{t+1}, REC_i^t) = (REC_i^{t+1} - REC_i^t) / (\ln REC_i^{t+1} - \ln REC_i^t)$ for $REC_i^{t+1} \neq REC_i^t$.

2.3 Scenario design and Monte Carlo simulation approach

Scenario analysis is popularly used in energy and emission projections (Grant et al., 2020; Grubler et al. 2018). Given the importance of the share of REC in the total energy consumption (SRT), here, we used the following equation to project REC:

$$REC = \frac{REC}{REC + NEC} \times (REC + NEC) = \frac{REC}{TEC} \times TEC \tag{11}$$

where *TEC* denotes the total energy consumption. It should be noted that although energy intensity is an important driver for REC, we did not incorporate it into Eq. (11) because of research purpose and simplification of scenario analysis. The study established nine different scenarios according to different assumptions of economic growth and SRT ($\frac{REC}{TEC}$) using Eq. (11). Specifically, we calculated the average annual growth rates (AAGRs) of SRT over 1997–2000, 2001–2005, 2006–2010, 2011–2015, 2011–2017, and 1997–2017. The periods were chosen because of different Five-Year Plan (FYP) periods, the overall sample period, and a recent period in China [see Lin and Ouyang (2014) for similar application]. We chose three AAGRs of SRT according to recent periods as the Low, Middle, and High scenarios reflecting the different rates of SRT.

As *TEC* is logarithmically highly correlated with economic growth, according to Fig. 1b, we calculated the AAGRs of economic growth over the different periods above and used GDP-based scenario to represent the *TEC* scenarios. This is because GDP may be a more suitable indicator than REC in terms of scenario analysis in the study. We used the following regression model to recalculate the AGRs of *TEC*:

$$\log(GDP) = \beta_0 + \beta_1 \cdot \log(TEC) \tag{12}$$

We emphasized more on the AAGRs of the two drivers in recent periods, which are more correlated with future. In terms of AAGR of economic growth, we fully considered the recent facts in China. The first is that China’s economy is now experiencing a sudden drop because of the COVID-19 pandemic. According to a recent report by the China Macroeconomy Forum (2020), China’s economic growth rate will be approximately 3% in

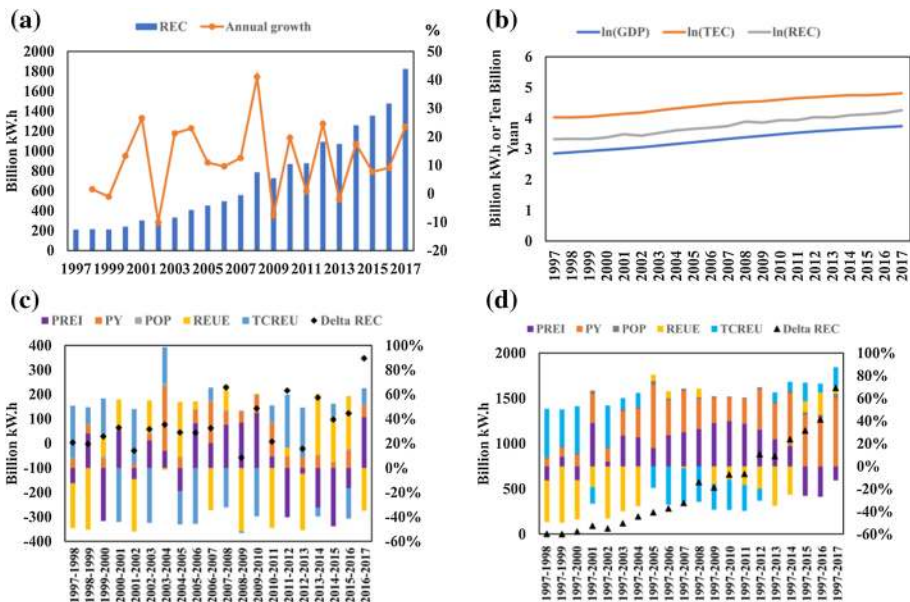


Fig. 1 Renewable energy consumption (REC) trends (a), and its comparison with GDP and total energy consumption (TEC) trends in logarithmic forms (b), as well as its decomposition results for the consecutive periods (c) and the cumulative periods (d) for China

2020. Therefore, we calculated the AAGR of economic growth during 13th FYP period (2016–2020) based on the historical data from 2016 to 2019 and expected data in 2020. However, the negative effect of slow economic growth is likely to be eliminated over time and the economy should return to its normal trajectory. The second is that China has already entered the new normal economy in which economic growth has slowed (Chen et al., 2020). With the context above, we assumed that the AAGR of economic growth over the next ten years (2021–2030) will be similar to that during the 13th FYP period. We followed Lin and Lin (2016) to set three scenarios of GDP: business-as-usual (BAU), Moderate, and Advanced GDP scenarios. The Moderate and Advanced GDP scenarios are based on the BAU GDP scenario with variation ranges at 1.0 percentage increments for AAGRs. As there are historical effects and policy implication uncertainties, we next followed Zhang et al. (2020) to set three different levels of AAGRs of the two drivers, the Best, Middle, and Baseline levels. The Best and Baseline levels are based on the Middle level with the variation range of 0.5 percentage of AAGR. The detailed scenario settings can be seen in Table 1. Because there are many other alternative choices of scenarios, this study is not intended to present accurate estimations of RE based on different economic conditions, but to show how the conditions related to economic growth and SRT would affect the RE in future.

Monte Carlo simulation has been widely used to analyze the problems related to uncertainty (Zaroni et al., 2019; Zhang et al., 2020). In this study, we adopted the Monte Carlo simulation approach to project REC. In general, there are three steps for performing a Monte Carlo simulation. The first is to define prior probabilities for the key input parameters based on a specific equation. The second is to conduct multiple simulations through randomly sampling the parameter space based on the pre-defined probability distributions. The third is to calculate the simulation results by frequency distributions with a full spectrum of possible output values.

Therefore, using Eq. (11) and Monte Carlo simulation, we first defined the future changes in SRT and *TE*. The minimum and maximum of ranges as well as the most expected values for the two drivers above are certain to some extent; therefore, we followed Ramírez et al. (2008) and Zhang et al. (2020) to use the triangular distribution function to randomly select the driver change rates. Then we conducted 100,000 Monte Carlo simulations and calculated the potential RE in the future based on the large number of simulation results. As Monte Carlo simulation generated many simulation results, more accurate results can be acquired and thus the approach can provide stakeholders with helpful information on the frequency and probability distributions for REC.

2.4 Data

This study covered 28 Chinese provinces excluding Tianjin, Shanghai, Tibet, Hongkong, Macao, and Taiwan because of incomplete data during 1997–2017. Renewable energy consumption (REC), nonrenewable energy consumption (NEC), capital (K), labor (L), GDP (Y), and population (P) are considered in the study.

Following Destek and Aslan (2017) and Bao and Xu (2019), REC is represented by electricity generation from renewable sources in billion kW·h. According to the China Energy Statistical Yearbook (CESY), China's electricity can be generated from six sources: thermal power, wind energy, hydro energy, nuclear energy, solar energy, and other energy sources. In this study, we classified wind energy, hydro energy, solar energy, and other energy sources as REC and classified thermal power and nuclear energy as NEC. In

Table 1 Assumptions of the average annual growth rates of the share of renewable energy consumption in the total energy consumption (SRT) and GDP-based SRT over 2018–2030 for China (Unit: %)

Economic growth	SRT growth											
	Low				Medium				High			
	Baseline	Middle	Best	Best	Baseline	Middle	Best	Best	Baseline	Middle	Best	Best
BAU												
Base-line	(4.96, 1.23)	(4.96, 1.73)	(4.96, 2.23)	(4.96, 2.23)	(4.96, 4.03)	(4.96, 4.53)	(6.29, 5.93)	(6.29, 5.93)	(4.96, 5.74)	(4.96, 6.24)	(4.96, 6.74)	(4.96, 6.74)
Mid-dle	(5.46, 1.23)	(5.46, 1.73)	(6.79, 2.23)	(6.79, 2.23)	(5.46, 4.03)	(5.46, 4.53)	(5.46, 5.93)	(5.46, 5.93)	(5.46, 5.74)	(5.46, 6.24)	(5.46, 6.74)	(5.46, 6.74)
Best	(5.96, 1.23)	(5.96, 1.73)	(5.96, 2.23)	(5.96, 2.23)	(5.96, 4.03)	(5.96, 4.53)	(5.96, 5.93)	(5.96, 5.93)	(5.96, 5.74)	(5.96, 6.24)	(5.96, 6.74)	(5.96, 6.74)
Moderate												
Base-line	(5.90, 1.23)	(5.90, 1.73)	(5.90, 2.23)	(5.90, 2.23)	(5.90, 4.03)	(5.90, 4.53)	(5.90, 5.93)	(5.90, 5.93)	(5.90, 5.74)	(5.90, 6.24)	(5.90, 6.74)	(5.90, 6.74)
Mid-dle	(6.40, 1.23)	(6.40, 1.73)	(6.40, 2.23)	(6.40, 2.23)	(6.40, 4.03)	(6.40, 4.53)	(6.40, 5.93)	(6.40, 5.93)	(6.40, 5.74)	(6.40, 6.24)	(6.40, 6.74)	(6.40, 6.74)
Best	(6.90, 1.23)	(6.90, 1.73)	(6.90, 2.23)	(6.90, 2.23)	(6.90, 4.03)	(6.90, 4.53)	(6.90, 5.93)	(6.90, 5.93)	(6.90, 5.74)	(6.90, 6.24)	(6.90, 6.74)	(6.90, 6.74)
Advanced												
Base-line	(6.84, 1.23)	(6.84, 1.73)	(6.84, 2.23)	(6.84, 2.23)	(6.84, 4.03)	(6.84, 4.53)	(6.84, 5.93)	(6.84, 5.93)	(6.84, 5.74)	(6.84, 6.24)	(6.84, 6.74)	(6.84, 6.74)
Mid-dle	(7.34, 1.23)	(7.34, 1.73)	(7.34, 2.23)	(7.34, 2.23)	(7.34, 4.03)	(7.34, 4.53)	(7.34, 5.93)	(7.34, 5.93)	(7.34, 5.74)	(7.34, 6.24)	(7.34, 6.74)	(7.34, 6.74)
Best	(7.84, 1.23)	(7.84, 1.73)	(7.84, 2.23)	(7.84, 2.23)	(7.84, 4.03)	(7.84, 4.53)	(7.84, 5.93)	(7.84, 5.93)	(7.84, 5.74)	(7.84, 6.24)	(7.84, 6.74)	(7.84, 6.74)

addition, as there was statistical modification (Zheng et al., 2018), the total generation data did not be equal to the sum of the six energy categories in CESY for several values. Therefore, we re-balanced the total generation data according to the non-negative principle of electricity generated from other energy sources. As electricity generated from other energy sources accounted for little of the total generation, this re-balance can make the data more accurate and reasonable while having limited impact.

As there are no official provincial K in China, we estimated by the perpetual inventory method (PIM) as described by Li (2010). The key parameter for the depreciation rate was set as 10% and was assumed to be unchanged across provinces in accordance with Chen et al. (2017). Data on Y and the fixed asset investment for estimating K were collected from National Bureau of Statistics China (NBSC) and adjusted at the 1997 constant price index. Data on P were collected from NBSC and data on L were collected from various Statistical Yearbooks at provincial levels.

3 Result and discussion

3.1 Drivers of renewable energy consumption

Figure 1a shows that REC represented by electricity generated from renewable energy in China increased by 8.67 times over the period, from 210.38 billion kW·h in 1997 to 1,824.71 billion kW·h in 2017. Although the annual growth rates presented a fluctuating trend, the average annual growth rate of REC was 11.41% during 1997–2017, indicating a relatively fast renewable energy development pathway in the country. Figure 1b further suggests that GDP in China is highly correlated with TEC and REC in logarithmic forms, which may be because electricity is one of the key powers driving economic growth.

Figure 1c,d depicts the contributions of drivers accounting for the changes in RE during consecutive and cumulative periods. Clearly, REC increased yearly, especially for recent periods at the largest growth rates, reflecting that renewable energy in China has entered a new phase of development. In terms of determinants, GDP per capita and population scale were the positive factors driving the increase in REC while the PREI, the RE usage technical efficiency (REUE), and the REC technological change (TCREU) made unstable impacts on the changes in REC for consecutive periods.

Specifically, GDP per capita effect contributed to the 12.96% increase in REC on average over the period. This may be because economic growth and REC demonstrated bidirectional causality (Lin & Moubarak, 2014; Zafar et al., 2019). As a country in rapid transition, China achieved an economic growth rate of 10.74% on average during the study period, resulting in a strong rising need of energy consumption. China placed more emphasis on developing renewable energy during urbanization and industrialization. For example, the country aimed to increase the share of non-fossil energy in primary energy consumption to 20% by 2030 (Qi et al., 2020). Therefore, China's economic growth and attached importance to renewable energy development contributed to a positive rise in REC over the period.

Second, population scale effect also accounted for the increase in REC during the consecutive periods at the national level; however, its average contribution to POP was 0.75%, indicating a very limited role in affecting the changes in REC. This is not a surprising result and is consistent with Akintande et al. (2020) who studied the five determinants of REC in five countries in Africa. However, compared with Akintande et al. (2020), the impacts of

POP on REC are smaller. On the one hand, the overall population scale increased by 0.59% on average although the country added 153.82 million persons during 1997–2017 according to China’s Statistical Yearbook (2018). However, renewable energy is largely dependent on resource endowments such as the conditions of annual wind, river conditions, and light, rather than population, although the distance and size of population will affect the final cost of REC.

Third, PREI, REUE, and TCREU contributed to the increase in REC over nearly half of the consecutive periods. However, TCREU mainly played a positive role in increasing REC for the recent consecutive periods since 2010, indicating the technological change of REC was effective recently for increasing REC. REUE showed a positive role in increasing REC for the most recent consecutive periods, reflecting the improvement in REUE recently. The roles of PREI mainly were negative in increasing REC for the recent consecutive periods, suggesting that PREI reduced by REUE still needs to be improved for increasing REC in the future. However, in general, the directions of the three drivers above accounting for the increase in REC were mixed for different consecutive periods.

Figure 1d confirmed the findings of the roles of PY and POP in affecting the increase in REC from the cumulative periods. It also depicted that PREI contributed to the increase in REC for most cumulative periods but contributed to the decrease in REC in recent years nationally, which was roughly similar to the analysis above. However, REUE contributed to the increase in REC during the whole period, although the impact was relatively limited. In general, the overall TCREU made a positive impact on increasing REC at the national level over the period. However, given the negative impacts of TCREU over some years and the relatively small overall contributions of TCREU to changes in REC over the period, the overall renewable change technologies diffused slowly (Chen & Lin, 2020).

As there is often heterogeneity across provinces in China for factors like economic condition, resource endowment, and technological levels, a further analysis at the provincial level is necessary. Figure 2 shows that PY and POP were still the positive factors driving the increase in REC at provincial levels on average, confirming the results from Fig. 1c,d nationally. However, Heilongjiang was the exception in terms of the role of POP

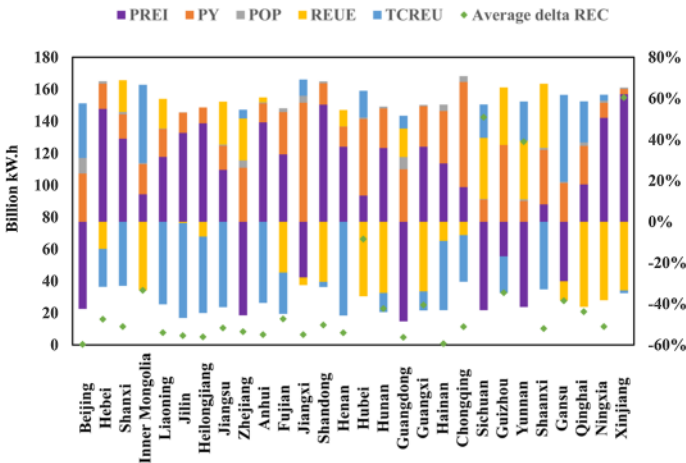


Fig. 2 Average contributions of decomposed components to changes in REC at the provincial level in China (1997–2017)

in affecting the changes in REC. According to NBSC data, the overall population in Heilongjiang decreased over recent years, from 38.35 million people in 2013 to 37.89 million people in 2017, opposite the natural population growth rate. Therefore, the emigration of the population in Heilongjiang had a small but negative impact on REC.

In addition, provincial differences were still relatively significant in terms of the two drivers above. For example, on average, PY contributed to a 51.10% increase in REC in Chongqing while accounting for a 9.80% increase in Henan over the same period. In terms of POP, Beijing contributed to a 7.61% increase in REC while Jilin accounted for a 0.05% increase on average over the period. Those different impacts of PY and POP on REC further confirmed the provincial heterogeneity and implied that sustaining economic growth and reasonable population growth may be important for promoting REC, especially in the long term.

Figure 2 depicts that on average the PREI contributed to a REC increase for most provinces over the study period. For example, PREI contributed to a 13.35% increase in REC in Inner Mongolia and 54.87% increase in Hebei on average. As discussed above, PREI reflects the renewable consumption intensity of GDP after considering the inefficiency of REC during production, which is similar to Zhou and Ang (2008). Therefore, PREI can be regarded as an improved indicator representing better REC adjusted by REC inefficiency. Therefore, the results of the different roles of PREI in determining changes in REC at provincial levels on average may be because of differences in RECs and their technical efficiencies.

Figure 2 indicates that the average contributions of TCREU to the increase in REC varied from provinces. In other words, technological changes in renewable energy usage were mixed among China's provinces, which is consistent with the observations of Lin and Zhu (2019) using patents as the proxy for REC technological innovations. It is worth noting that TCREU reflects the shift in renewable energy usage-side technology, which is similar to Zhou and Ang (2008), and therefore, TCREU may not directly reflect the technological progress in engineering but represent the technological change of REC under the total-factor framework. On average, REUE showed the negative impacts on increasing REC over the period in sixteen provinces including Hebei, Inner Mongolia, Jilin, Heilongjiang, Fujian, Jiangxi, Shandong, Hubei, Hunan, Guangxi, Hainan, Chongqing, Gansu, Qinghai, Ningxia, and Xinjiang. With respect to those economically less developed provinces over the period, an important understanding is that the renewable energy usage efficiency of economically less developed provinces should be more emphasized for further improvement in future.

3.2 REC projections

Based on the Monte Carlo simulation approach, we projected China's REC to 2030 under nine scenarios (see Fig. 3 for illustrations), which are based on national economic growth and SRT growth (the larger the value, the higher level of REC). According to Fig. 4, during 2018–2030, China's REC will increase to 4552.71 billion kW·h (by 249.50%) under the BAU-Low scenario, 6475.75 billion kW·h (by 354.89%) under the BAU-Middle scenario, 8003.43 billion kW·h (by 438.61%) under the BAU-High scenario, 5108.04 billion kW·h (by 279.94%) under the Moderate-Low scenario, 7267.18 billion kW·h (by 398.26%) under the Moderate-Middle scenario, 8981.01 billion kW·h (by 492.19%) under the Moderate-High scenario, 5727.11 billion kW·h (by 313.86%) under the Advanced-Low scenario,

Fig. 3 Scenario definitions based on economic growth and the share of REC in the total energy consumption (SRT) in the study

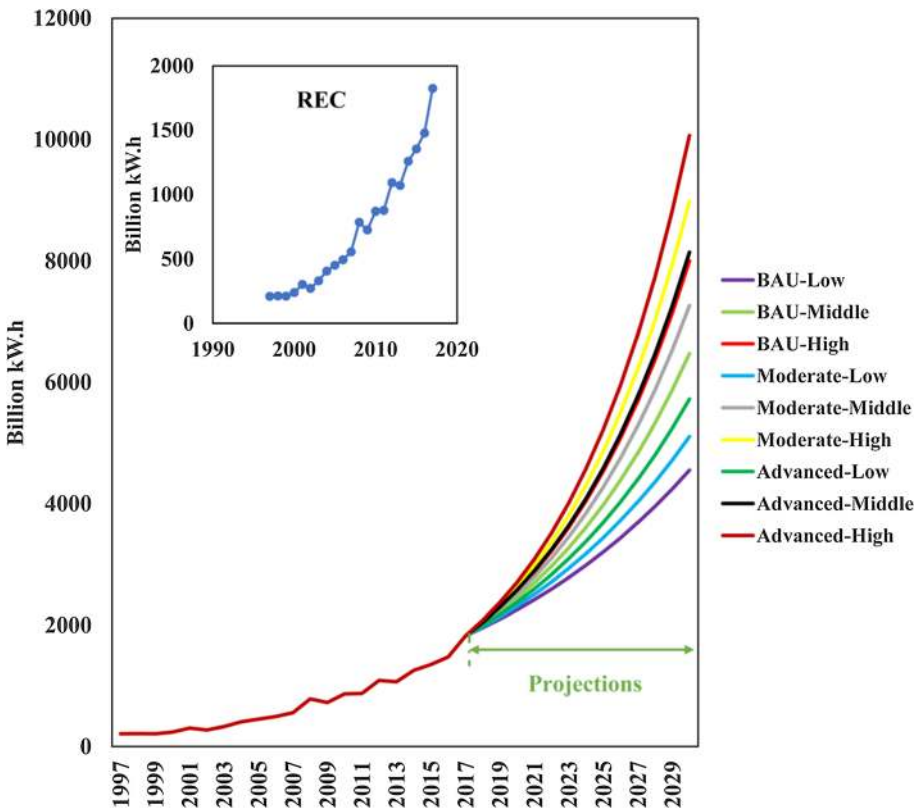
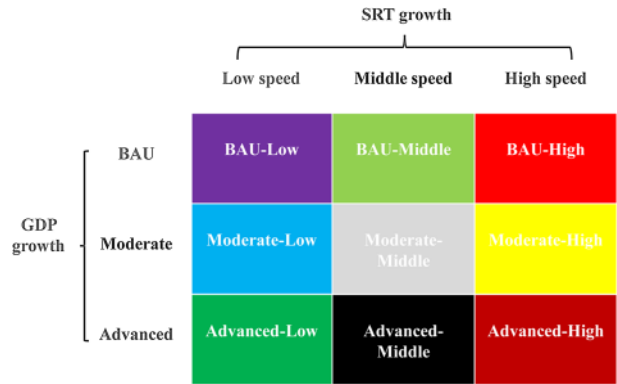


Fig. 4 Historical and projection results of REC in China under different scenarios (1997–2030)

8147.33 billion kW·h (446.50%) under the Advanced-Middle scenario, and 10,065.84 billion kW·h (551.64%) under the Advanced-High scenario.

According to the NEA (2016), a 27% share of electricity in the total power generation should be generated from renewable energy by 2020. Furthermore, based on NDRC (2016), 50% of electricity will be generated from non-fossil energy sources by 2030, implying a

25% share of non-fossil energy in primary energy consumption. This is a strengthened target, higher than the 20% share of non-fossil energy in primary consumption by 2030 in the Paris Agreement for China (Qi et al., 2020). As the scopes of non-fossil energy and renewable energy are largely coincident, the strengthened target also applies to REC in the study. Based on the scenarios above, we calculated the SRTs by 2020 and 2030. We showed that the 2020 target would be achieved in all scenarios. However, we found, in terms of renewable energy development, that the ratio would be 34.61% under the low-speed scenario, 49.23% under the middle speed scenario, and 60.84% under the high-speed scenario. Given that we only considered 28 provinces in China, the projected ratios could be underestimated. Combing the projected REC in 2030 under nine scenarios, we could conclude that if there were not enough actions to accelerate the development of renewable energy, China may fail the strengthened target in 2030. However, we remain optimistic for China achieving the strengthened target under the other scenarios, as the projected ratios (49.23% and 60.84%) would be very close to or would surpass the target by 2030.

The goal of REC is of great significance not only to emission reduction, but also to energy security. Unlike previous studies, which have focused on the influencing RE factors in energy security [see Wang et al. (2018) for an example], this study targets the realizability of REC goals under different scenarios. In addition, the dynamic scenario simulation method based on Monte Carlo simulation is used to show the maximum possible future REC based on probability distribution, which has important practical significance for quantifying the energy security accessibility of renewable energy in the target year (e.g., 2030). Unlike the background in most previous studies, due to the COVID-19 pandemic, the global economy is generally affected by slowed economic growth. In the post-pandemic era, the challenges between reviving economic growth and accelerating renewable energy development will be considerable in addition to improving energy efficiency, which raises the requirements for the realization of energy security.

4 Conclusion and policy implication

4.1 Conclusion

With growing worldwide attention on sustainable development (Dubey et al., 2019; Turturean et al., 2019), renewable energy is becoming increasingly crucial for climate change mitigation and ensuring energy security. This study first focused on the drivers of REC in 28 China's provinces during 1997–2017 and emphasized the roles of technical efficiency and technological change in REC using an extended PDA approach. The study then projected China's REC to 2030 by combining scenario analysis with the Monte Carlo simulation approach and further analyzed the realizability of national REC targets under different scenarios. The main findings are listed as follows:

First, economic growth and population scale nearly always contributed to increased REC at national and provincial levels over the period. The PREI contributed to the increase in REC for most cumulative periods but contributed to the decrease in REC in recent years nationally. Second, the overall technical efficiency and technological change of REC played limited roles in increasing REC at the national level, in which such impacts were mixed across provinces over the period. Third, the expected REC in China ranged from 4552.71 to 10,065.84 billion kW·h under nine scenarios by 2030. The 2020 target would be achieved based on all scenarios. However, the projection results indicated that although the

country target of generating 50% electricity from renewable energy sources by 2030 could be achieved, it may also fail if there are not enough actions accelerating renewable energy development.

4.2 Policy implication

Based on the results above, we provide the following policy proposals.

First, we suggest that the relevant departments should support advanced renewable energy power-generation technologies (such as energy storage technology) by more reasonable funds and policies to further improve the efficiency of renewable energy power generation. At the national level, the analysis shows that although China's renewable energy generation efficiency and technological progress have a positive role in promoting REC during the sample period, the contribution is relatively low overall. Previous studies have shown that energy storage technology is of great significance to the development of renewable energy power (Arani et al., 2017; Gu et al., 2016). Therefore, focusing on the development of advanced technology, especially economically feasible energy storage technology, will help to reduce the cost of REC and promote the benign REC cycle. At the provincial level, the results show that there was notable heterogeneity in REC use efficiency and technology over the period. Given improving energy efficiency is significant for technological development (Lu et al., 2017), the key technology support policies for the development of renewable energy cannot be "one size fits all", but must fully consider the factors like regional resource endowment, technology reserve, and renewable energy development strategy.

Second, we advise that related policymakers should also introduce several policies to pay greater emphasis to the role of socio-economic factors (e.g., the scale of renewable energy users) in promoting the development of renewable energy in addition to the development of renewable energy technology itself. Our results show that economic growth and population size can promote RE development. This means that vigorously developing the economy and developing the user base is still an important focus of cultivating the REC market. For years, the power generation costs of various renewable energy sources in China have been significantly reduced. According to IRENA (2020), the weighted-average levelized cost of electricity (LCOE) of newly commissioned utility-scale solar PV projects in China decreased from 0.3012 USD/kW·h in 2010 to 0.0541 USD/kW·h in 2019, while the weighted-average LCOE of newly commissioned onshore wind projects decreased from 0.1760 USD/kW·h in 1996 to 0.0470 USD/kW·h in 2019. However, it should be noted that at present, China's renewable energy market is still dependent on government subsidies, which may have a potential adverse impact on the establishment of a benign cycle of renewable energy power at competitive prices with no need for national subsidies in the market. The market therefore should play a better role in improving REC in the national economy.

Third, we believe that the relevant departments should further strengthen international cooperation to promote REC. At present, the outbreak of the COVID-19 pandemic is deeply affecting many aspects of human society. By early April 2020, for example, global CO₂ emissions will be reduced by 17% compared with the average in 2019 (Le Quéré et al., 2020). Although this is only a short-term decline, there may still be a rebound in carbon emissions with a relatively high-speed economic recovery in the future. However, this provides people with more opportunities to reflect and examine the feasibility of renewable energy development for emission mitigation except for other factors such as emission trading schemes (Liu et al., 2017). On the other hand, the

pandemic situation inevitably impacts international cooperation on renewable energy, which also has some adverse effects on the domestic renewable energy market. In this context, strengthening international cooperation will become a powerful driving force for the development of renewable energy.

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