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Drivers and strategic options for renewable energy development in China: LMDI-elasticity analysis perspective based on photovoltaic and wind energy

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A B S T R A C T

This study examines the drivers and development strategies of PV and wind energy development in China based on the logarithmic mean Divisia index (LMDI) model and the elasticity analysis model. The study revealed a significant increase in the value added of photovoltaic (PV) and wind power generation in China, with growth rates of 400.54 % and 102.27 %, respectively, from the 12th Five-Year Plan to the 13th Five-Year Plan. The primary driver of PV power generation in each region is the substitution effect between PV power and traditional energy sources. The key drivers of China's wind power generation are the substitution factor and economic considerations between wind power and traditional energy sources, demonstrating that China's wind power generation is influenced by both production and consumption factors. Model predictions indicate an upward trend in PV and wind power generation across all provinces in China. Western China continues to be the primary region for future PV power generation, while wind power generation in certain regions may experience a decline. The strategic analysis results suggest that a capital-led strategy continues to be the preferred approach for the future advancement of PV power generation in Chinese provinces, while the development of wind energy should be tailored to specific circumstances.

Nomenclature

Abbreviations:	
PV	photovoltaic
LMDI	logarithmic mean Divisia index
IEA	international energy agency
PDA	production-theoretical decomposition analysis
R&D	research and development
IDA	index decomposition analysis
IPC	international patent classification
BAU	baseline as usual
Parameters:	
R	renewable energy generation
T	thermal power generation
E	total power generation
G	gross regional product
P	population count in the region
$RT_{i,t}$	substitution factors
$TE_{i,t}$	supporting factors
$EG_{i,t}$	strength factors
$GP_{i,t}$	economic factors
$P_{i,t}$	demographic factors

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(*continued*)

Abbreviations:	
ΔX	change in variable X
α	growth rate of substitution factors
β	growth rate of supporting factors
γ	growth rate of strength factors
δ	growth rate of economic factors
φ	growth rate of demographic factors
K	capital inputs
T	technology inputs
A	generalized technological innovation
a, b, and c	additional exogenous parameters
ϕ, ω, η and ε	parameters of equation
MP_K	marginal output of capital factor
MP_T	marginal output of technology factor
σ_K	output elasticities of capital factor
σ_T	output elasticities of technology factor
TRS_{KT}	marginal technology substitution rate
σ_{KT}	elasticity of substitution

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1. Introduction

Energy security and environmental conservation have emerged as universal challenges faced by every nation across the globe. The rapid economic growth and continual population expansion have heightened the consumption of conventional energy sources, exacerbating environmental pollution and escalating greenhouse gas emissions. Climate change has evolved into a pivotal strategic consideration for nations worldwide in achieving sustainable development goals. Being the world's largest energy consumer and carbon emitter, China's advancements in renewable energy hold profound implications, not only for its domestic economic growth paradigm but also for reshaping the global energy landscape and addressing climate change governance.

Amidst China's rapid economic growth, the escalating energy demand has led to substantial consumption of traditional fossil fuels, resulting in significant environmental pollution and greenhouse gas emissions[1]. In light of this context, the Chinese government places significant emphasis on advancing renewable energy as a pivotal strategy to reshape the energy landscape, curb carbon emissions, and foster sustainable and low-carbon growth. Photovoltaic (PV) and wind power generation, the cornerstones of renewable energy, have witnessed swift progress in China. Fig. 1 illustrates the evolution of PV and wind power generation in China from 2008 to 2023. The data reveals a near-exponential surge in China's PV and wind power generation, with PV generation witnessing a thousandfold increase from 2010 to 2023, paralleled by a similar trajectory in wind power. The swift expansion of PV and wind power generation in China stands out as a remarkable phenomenon, underscoring China's ambition and commitment towards renewable energy development. Additionally, China's rapid progress in PV and wind power will offer invaluable insights and motivation for reshaping the global energy landscape.

Despite the advancements in renewable energy research, the majority of studies are limited to the national level due to data scarcity, with a notable dearth of research at the regional level within the country. Undoubtedly, variations in resource availability, economic development, policy backing, and other factors across regions inevitably lead to inter-regional disparities in renewable energy development. Hence, exploring and analyzing the pivotal factors influencing PV and wind energy development in China is crucial for optimizing energy distribution, enhancing energy efficiency, and fostering harmonized regional development.

Drawing from China's wind and PV sectors as case studies, this research delves into the driving forces behind PV and wind power generation in China. Leveraging data spanning 2011–2022 at the provincial scale, the study employs the logarithmic mean Divisia index

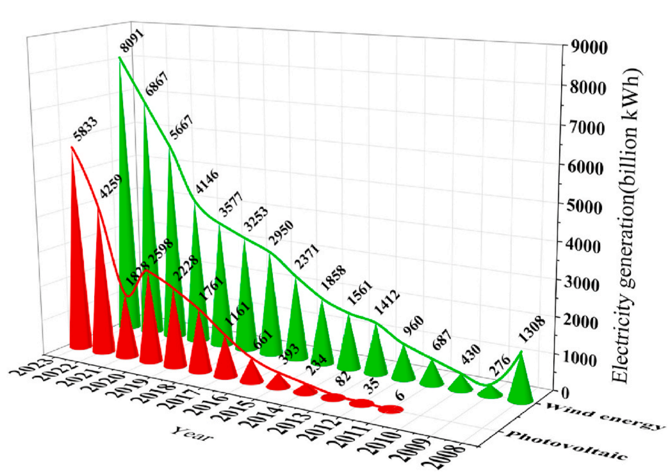


Fig. 1. Growth trend of China's wind power generation and photovoltaic power generation.

(LMDI) decomposition model to forecast future PV and wind power generation capacities. Subsequently, employing a perspective centered on capital investment and innovation, the study conducts factor elasticity analysis to gauge the output and substitution elasticities of capital and technology components across various Chinese provinces. Lastly, leveraging insights from factor elasticity analysis, this study discusses strategic pathways for wind and PV development across Chinese provinces, aiming to offer actionable insights for policy makers and energy planners.

This study introduces several innovations. Firstly, it offers a comprehensive classification of the factors influencing wind and PV power generation in China. Of particular note is the inclusion of forecasts pertaining to wind and PV power generation across different provinces in China, a unique aspect not extensively covered in prior research. Secondly, this study pioneers the integration of factor substitution factors into the analytical framework of renewable energy, thereby examining the repercussions of output efficiency and substitution effects across diverse factors on China's renewable energy development. Lastly, this paper advocates for tailored renewable energy development strategies based on the unique circumstances of individual provinces in China. The objective is to foster a balanced growth of renewable energy and facilitate the optimization and enhancement of the country's energy structure.

The rest of the paper is structured as follows. In Section 2, we review the relevant literature. Section 3 discusses the methodology and data sources. Section 4 presents and discusses the research results. In Section 5, we summarize the main findings and policy recommendations.

2. Literature reviews

2.1. Application of the LMDI decomposition model

Index decomposition boasts a rich historical legacy within the realm of energy and environmental economics research[2]. Through the decomposition of indices, the underlying drivers behind index changes can be analyzed. Besides academia, governmental energy agencies like the International Energy Agency (IEA) and the World Bank have employed index decomposition to scrutinize trends in energy consumption and the development of renewable energy[3]. The LMDI model stands out as the most widely adopted decomposition model due to its remarkable flexibility and capacity to achieve thorough decomposition without residuals, making it particularly suitable for examining influencing factors at both national and regional levels[4].

Jiang et al. [5] employed the Kaya-LMDI framework to conduct a comprehensive analysis of China's non-residential electricity usage, examining both temporal dynamics and geographical variations. Their study revealed that economic expansion is the predominant determinant of the increase in non-residential electricity demand. Chong et al. [6] applied the LMDI decomposition technique to elucidate the determinants of coal consumption in China. The findings underscored the pivotal roles of economic expansion, energy intensity, adjustments in economic structure, the configuration of end-use energy sources, the efficiency of coal-fired power generation, and power supply mechanisms in shaping the trajectory of China's coal consumption patterns. In general, the LMDI decomposition model finds extensive application in researching energy consumption and environmental economics; however, its application in studying energy consumption and renewable energy development remains limited.

Recent studies have seen a shift in focus among researchers toward renewable energy and carbon emissions, with the application of the LMDI decomposition model in the renewable energy research domain. Regarding the nexus between renewable energy consumption and carbon emissions, Moutinho et al. [7] dissected carbon emissions across 23 nations into six influencers using the LMDI decomposition model (carbon trade intensity, the trade of fossil fuels effect, fossil fuels intensity, renewable sources productivity, electricity financial power effect, and the financial development effect). The study revealed that carbon emissions spur the adoption of renewable energy, thus emphasizing that the advancement of renewable energy aids in achieving carbon reduction targets. Yu et al. [8] elucidated shifts in renewable energy generation by breaking down renewable energy generation into peaking capacity of the power system, power system flexibility, generation intensity, energy factor, and electricity consumption using the PDA-LMDI decomposition model, thereby unveiling disparities in driving factors between China and leading renewable energy markets.

Regarding the direct analysis of factors impacting renewable energy consumption, Wang et al. [9] employed an LMDI decomposition model to investigate various factors (Substitution Rate of renewable energy to oil import, Energy security or energy dependence, Energy Intensity, Carbon Productivity -Low carbon economy indicator, and Carbon emission effect) affecting renewable energy consumption and forecasted the trend of these factors on renewable energy consumption under varied scenarios. Sadorsky [10] disentangled the factors driving wind energy consumption across 17 nations using an LMDI decomposition model. Their findings indicate that the share of renewable energy exerts the most significant influence on wind energy consumption, whereas the rise in energy intensity serves as the primary driver for wind energy consumption reduction. Furthermore, Perry projected wind energy development under three distinct scenarios: business-as-usual, high--growth rate, and low-growth rate.

Recent studies have witnessed innovative applications of the LMDI decomposition model in various research domains. Chen and Lin [11] utilized an extended LMDI methodology in technology innovation research to dissect the growth of patents in renewable energy technologies into nine drivers, aligned with China's three five-year planning phases. Their study revealed that distinctions in innovation and advancement of specific renewable energy technologies were prioritized nationally throughout these planning phases. Prioritizing innovation in specific renewable energy technologies, enhancing the efficiency of R&D spending, increasing the allocation of R&D spending and the adoption of renewable energy, promoting the low-carbon economy concept, and expanding carbon scaling will lead to a rise in patents for particular renewable energy technologies. The success of the LMDI decomposition model across diverse research areas fosters its broader application in exponential decomposition modeling.

Although existing studies have focused on the prospects of applying the LMDI model in the field of renewable energy, the research on renewable energy development is still limited. First, existing studies lack the direct application of LMDI model in renewable energy development. This study decomposes the influencing factors of clean energy development into substitution factors, supporting factors, strength factors, economic factors and demographic factors. By comparing the changes in indicators at different time points, the contribution of each factor can be clearly identified and quantified, providing more research references for clean energy transition drivers. Second, the expansion of LMDI model in the field of renewable energy development is limited. This study innovatively predicts the scale of clean energy development based on the LMDI model, which verifies the potential value of the LMDI model in forecasting. And it perfectly combines the LMDI model with the elasticity analysis model to provide a feasible analytical framework for making regional clean energy development decisions by determining the elasticity relationship between capital and technology factors.

2.2. Substitution elasticity of production factors and development strategy of renewable energy

Capital and technology, as pivotal inputs in production, have sparked extensive debates regarding their role in fostering economic development and are undeniably critical for the advancement of renewable energy. The classical Solow-Swann model treats technology as an exogenous variable and emphasizes the significance of capital accumulation in the process of economic growth[12]. Endogenous economic growth theory views technology as an endogenous variable within economic growth models and recognizes it as a central catalyst for economic growth[13]. Energy technology innovation is a prerequisite for the progress of renewable energy development, and technology is widely acknowledged as a production factor in contemporary research on renewable energy production[11,14]. Capital investment can swiftly propel industrial development, whereas technological innovation can facilitate industrial transformation and upgrading, thereby highlighting the substitution relationship between capital and technology as a reflection of the government's policy orientation towards renewable energy development.

The elasticity of substitution between factors is a crucial technical parameter that shapes the production function, illustrating the relative variation between the marginal technical substitution rate and the factor inputs ratio[15]. The elasticity of substitution reflects the market characteristics of industrial development[16]. In scenarios with no elasticity of substitution between factors, industrial growth necessitates upgrading all factors; conversely, in cases with elasticity of substitution between factors, the market exhibits an unbalanced expansion structure. Previous studies have demonstrated a substitution relationship between capital and labor, which is regarded as a pivotal factor in industrial economic growth[17].

In studies on energy substitution elasticity, existing research is bifurcated into two primary themes. Firstly, the majority of scholars consider energy as a production factor itself and investigate its substitution dynamics with other production factors. Ouyang et al. [18] investigated the energy substitution effect in Shanghai's transportation sector by assessing the output elasticity and substitution elasticity of energy and labor, concluding that energy consumption can be curtailed through capital investment. Khalid et al. [19] examined the substitution relationship between energy and non-energy factors in Pakistan, revealing that labor-energy and capital-energy exhibit substitutability, underscoring the importance of focusing on technological advancements and employment opportunities. Secondly, recent studies have begun to concentrate on the factor substitution relationships involving renewable energy. Raza and Lin [20] explored the potential for energy substitution using the Translog production function, affirming the role of renewable power generation in economic progress through an assessment of output elasticity and substitution elasticity across all factors. Agyeman and Lin [21] utilized the Translog production model to estimate factor output and energy substitution involving oil, gas, and renewable energy in North African nations from 1990 to 2017, demonstrating that technological progress can facilitate a transition to low-carbon energy by enabling the substitution of conventional energy sources with cleaner alternatives.

Renewable energy represents a nascent industry, pivotal in achieving national carbon neutrality and transitioning energy sources. Capital and technology stand as pivotal production factors within this sector, guiding diverse governmental strategies in renewable energy development based on their prioritization of these factors[22]. The capital-centric development approach proves highly effective in the initial stages of the renewable energy industry, given the significantly higher technology input costs compared to capital costs, coupled with the capital's substantial impact on industry-scale expansion compared to technology. According to Boadu and Otoo [23], the deployment of a substantial number of renewable energy generators correlates with increased utilization of clean energy, fostering industry growth particularly in its nascent phases and generating a certain scale effect in early-stage industry development. Consequently, numerous governments and organizations are dedicated to enlarging the installed capacity of renewable energy and augmenting the proportion of renewable energy in overall energy consumption[24].

Nevertheless, capital-centric development strategies do not consistently yield desired outcomes, as haphazard capital expansion risks resource wastage[14]. Penghao et al. [25] have raised concerns regarding the installed capacity and power generation efficiency within

China's hydropower sector. Technological advancements serve as a crucial catalyst for industry evolution, particularly in the advanced phases of renewable energy development, where a technology-centric approach facilitates industry-wide transformation and enhancement. Song et al. [26] utilize green innovation data from leading nations to illustrate the positive impact of green technological innovations on energy efficiency enhancement.Chen et al. [27] employ a machine-learning assessment approach to showcase the beneficial influence of R&D investments and patent acquisition on energy transition processes.

A comprehensive review of current research findings highlights several notable research gaps. (1) Numerous studies empirically examine the pivotal role of renewable energy in reducing carbon emissions, yet there is a dearth of research exploring the driving forces behind renewable energy adoption. (2) While numerous studies employ elasticity analysis to investigate substitution relationships between energy and external factors (e.g., capital and labor), there is a scarcity of research examining the elasticity of substitution among energy input factors. (3) In the realm of renewable energy development strategies, most researchers concentrate on the significance of capital inputs, neglecting the strategic interplay between capital and technology crucial for long-term renewable energy development.

This paper addresses the identified research gaps through three key contributions: (1) employing the LMDI decomposition model to decompose renewable energy generation, facilitating an analysis of the driving forces behind renewable energy development. (2) Evaluating capital and technology as input parameters, this study computes the output and substitution elasticities of renewable energy inputs, delving into the factor orientation and developmental attributes of renewable energy markets across diverse regions. (3) Analyzing the output and substitution elasticities of input factors, this paper offers insights into regional renewable energy development strategies, emphasizing the perspectives of capital expansion and technological innovation.

3. Methodology

3.1. Model

3.1.1. LMDI decomposition model

The LMDI decomposition model represents an extension of Kaya Identity research. The model can flexibly decompose the index into various influencing factors based on the characteristics of the core research index. It is the most commonly used decomposition model in Index Decomposition Analysis (IDA). In basic research applications, LMDI avoids generating residual terms that complicate the analysis in the decomposition process, and achieves a precise decomposition of research indexes. Furthermore, the LMDI decomposition model meets Fisher's (1922) factor inversion test, ensuring convergence of results[28, 29]. The LMDI decomposition model offers unique advantages compared to other index decomposition models, leading to its extensive applications in energy and environmental economics.

Building upon the work of Yu et al. [8], this study dissects the generation of renewable energy (solar PV and wind) in province i of China during cycle t into the subsequent driving factors.

$$R_{i,t} = \frac{R_{i,t}}{T_{i,t}} \times \frac{T_{i,t}}{E_{i,t}} \times \frac{E_{i,t}}{G_{i,t}} \times \frac{G_{i,t}}{P_{i,t}} \times P_{i,t} \tag{1}$$

Here, R represents renewable energy generation, with photovoltaic and wind power generation acting as proxies in this study. T represents thermal power generation, while E represents total power generation. G denotes gross regional product (GDP), and P denotes the population count in the region.

Equation (1) provides a precise decomposition without generating residual terms, thereby clearly illustrating the drivers of renewable energy development. It can also be expressed as equation (1):

$$R_{i,t} = RT_{i,t} \times TE_{i,t} \times EG_{i,t} \times GP_{i,t} \times P_{i,t} \tag{2}$$

- $RT_{i,t}$: The substitution factors denote the ratio between renewable energy and traditional thermal power generation. Renewable energy generation exhibits a degree of intermittency, necessitating more flexible adjustments in the power system due to the mutual substitution among various energy sources. This factor indicator mirrors the regional power system's capacity to manage load fluctuations during peak periods.
- $TE_{i,t}$: The supporting factors represent the ratio of thermal power generation to the total regional power generation capacity. Thermal power generation plays a crucial role in maintaining the stable operation of the power system. thus, this indicator reflects the supporting capacity of the regional power system.
- $EG_{i,t}$: The strength factors indicate the power consumption per unit of GDP. Power serves as the primary driving force for the smooth operation of socio-economic activities; thus, this indicator reflects the energy intensity of socio-economic development.
- $GP_{i,t}$: The economic factors refer to GDP per capita, which reflects the overall welfare level of the regional society and serves as a crucial reference indicator for economic activities.
- $P_{i,t}$: Demographic factors refer to changes in renewable energy generation resulting from demographic changes.

As LMDI is a method that thoroughly decomposes index changes into relevant factors without encountering residual factors, following Ang [30] LMDI additive decomposition process, the change in regional renewable energy generation can be expressed as equation (3):

$$\Delta R = \Delta RTef \times \Delta TEef \times \Delta EGef \times \Delta GPef \times \Delta Pef \tag{3}$$

where ΔR denotes the change in renewable energy generation between the target year (T) and the base year (0), the components of the additive decomposition of the LMDI can be expressed as the following equation:

$$\Delta RTef = \frac{R_T - R_0}{\ln R_T - \ln R_T} \cdot \ln\left(\frac{RT_T}{RT_0}\right) \tag{4}$$

$$\Delta TEef = \frac{R_T - R_0}{\ln R_T - \ln R_T} \cdot \ln\left(\frac{TE_T}{TE_0}\right) \tag{5}$$

$$\Delta EGef = \frac{R_T - R_0}{\ln R_T - \ln R_T} \cdot \ln\left(\frac{EG_T}{EG_0}\right) \tag{6}$$

$$\Delta GPef = \frac{R_T - R_0}{\ln R_T - \ln R_T} \cdot \ln\left(\frac{GP_T}{GP_0}\right) \tag{7}$$

$$\Delta Pef = \frac{R_T - R_0}{\ln R_T - \ln R_T} \cdot \ln\left(\frac{P_T}{P_0}\right) \tag{8}$$

3.1.2. Index forecasting based on the LMDI decomposition model

The LMDI decomposition model can also be employed for predicting the future development of the index. Building upon the LMDI additive decomposition process and equations (2)–(8), the LMDI decomposition model can be reformulated as equation (9).

$$R_T = R_0 + \Delta RTef + \Delta TEef + \Delta EGef + \Delta GPef + \Delta Pef \tag{9}$$

Assuming that $\alpha, \beta, \gamma, \delta, \varphi$ are the growth rates of each decomposition factor from the base year (0) to the target year (T), the relationship between the target year (T) and the base year (0) of each decomposition factor can be expressed as follows:

$$\begin{cases} RT_T = (1+\alpha)\cdot RT_0 \\ TE_T = (1+\beta)\cdot TE_0 \\ EG_T = (1+\gamma)\cdot EG_0 \\ GP_T = (1+\delta)\cdot GP_0 \\ P_T = (1+\varphi)\cdot P_0 \end{cases} \tag{10}$$

According to equation (2), the renewable energy generation in the base year and target year is:

$$\begin{cases} R_0 = RT_0 \times TE_0 \times EG_0 \times GP_0 \times P_0 \\ R_T = RT_T \times TE_T \times EG_T \times GP_T \times P_T \end{cases} \tag{11}$$

According to Eqs. (10) and (11), it can be obtained:

$$R_T = R_0 \times (1+\alpha) \times (1+\beta) \times (1+\gamma) \times (1+\delta) \times (1+\varphi) \tag{12}$$

Bringing Eqs. (10) and (12) into Eqs. (4)–(8) gives:

$$\Delta RTef = Z\cdot(1+\alpha) \tag{13}$$

$$\Delta TEef = Z\cdot(1+\beta) \tag{14}$$

$$\Delta EGef = Z\cdot(1+\gamma) \tag{15}$$

$$\Delta GPef = Z\cdot(1+\delta) \tag{16}$$

$$\Delta Pef = Z\cdot(1+\varphi) \tag{17}$$

where $Z = \frac{R_0[(1+\alpha)(1+\beta)(1+\gamma)(1+\delta)(1+\varphi)-1]}{\ln[(1+\alpha)(1+\beta)(1+\gamma)(1+\delta)(1+\varphi)]}$.

This can be obtained by bringing Eqs. (13)–(17) into Eq. (9):

$$R_T = R_0 + Z\cdot(1+\alpha) + Z\cdot(1+\beta) + Z\cdot(1+\gamma) + Z\cdot(1+\delta) + Z\cdot(1+\varphi) \tag{18}$$

Given knowledge of the growth rate of each decomposition factor, we can forecast future renewable energy power generation using equation (18). Taking into account China's unique national economic planning system, we utilize data spanning 2016–2022 as our baseline. We employ the linear trend forecasting method to predict China's renewable energy power generation data in the latter stages of the 14th Five-Year Plan. We utilize regression forecasts to develop the BAU (Business as Usual or baseline scenario). The upper 95 % confidence interval of these forecasts is employed to generate forecasts for the High development (High) scenario, while the lower 95 % confidence interval is utilized to create forecasts for the Low development (Low) scenario.

3.1.3. Factor elasticity analysis model based on capital and innovation

The renewable energy industry is characterized by substantial capital investment and volatile risk-return profiles. Capital and innovation are pivotal factors influencing the renewable energy industry. This study specifically concentrates on providing strategic guidance for capital and technology factors in the later stages of renewable energy development. Consequently, this study develops an analytical model based on factor output elasticity and the substitution elasticity among factors.

Primarily, it is imperative to delineate the suitable form of the production function. The Cobb-Douglas production function posits that the elasticity of substitution between all input factors equals 1, a premise incompatible with our research objectives. Despite the CES production function treating the factor elasticity of substitution as an exogenously unknown parameter σ, it fails to depict the genuine characteristics of substitution elasticity, which fluctuates with relative scarcities among factors and technological advancements. Revankar (1971) derived the Variable Elasticity of Substitution (VES) production function, assuming the elasticity of substitution to be variable[14]. In this study, we employ the Cobb-Douglas production function as the operative production function for the renewable energy sector. In this study, we construct the subsequent VES production function utilizing capital and technology as input factors in the realm of renewable energy:

$$R = AK^{\frac{a}{1+c}}\left[T + \left(\frac{b}{1+c}\right)K\right]^{\frac{ac}{1+c}} \tag{19}$$

Here, R represents the output of renewable energy, K signifies the capital inputs dedicated to renewable energy, T denotes the technology inputs for renewable energy, A embodies the exogenous parameters of generalized technological innovation (excluding capital and technology inputs), while a, b, and c represent additional exogenous parameters.

Taking logarithms on both sides of equation (19) yields:

$$\ln R = \ln A + \frac{a}{1+c}\ln K + \frac{ac}{1+c}\ln\left(T + \frac{b}{1+c}K\right) \tag{20}$$

Taylor series expansion of Eq. (20) yields the following linear expression:

$$\ln R = \ln A + \phi \ln K + \omega \ln T + \eta \frac{K}{T} + \varepsilon \tag{21}$$

where:

$$\begin{cases} \phi = \dfrac{a}{1+c} \\ \omega = \dfrac{ac}{1+c} \\ \eta = \dfrac{abc}{(1+c)^2} \end{cases} \Rightarrow \begin{cases} a = \phi + \omega \\ \omega = \dfrac{\eta(\phi+\omega)}{\phi\omega} \\ \eta = \dfrac{\omega}{\phi} \end{cases}$$

According to equation (19), the marginal output of renewable energy capital factor (K) and technology factor (T) can be derived:

$$MP_K = \frac{a(T+bK)}{(1+c)T+bK}\cdot\frac{R}{K} \tag{22}$$

$$MP_T = \frac{acR}{(1+c)T+bK} \tag{23}$$

According to Eqs. (22) and (23), the output elasticities σ_K and σ_T of the renewable energy capital factor (K) and technology factor (T), as well as the marginal technology substitution rate TRS_{KT} can be introduced:

$$\sigma_K = \frac{\partial \ln R}{\partial \ln K} = \frac{K}{R}\cdot\frac{\partial R}{\partial K} = \frac{K}{R}\cdot MP_K \tag{24}$$

$$\sigma_T = \frac{\partial \ln R}{\partial \ln T} = \frac{T}{R}\cdot\frac{\partial R}{\partial T} = \frac{T}{R}\cdot MP_T \tag{25}$$

$$TRS_{KT} = -\frac{MP_K}{MP_T} = -\frac{\frac{a(bK+T)}{(1+c)T+bK}\cdot\frac{R}{K}}{\frac{acR}{(1+c)T+bK}} = -\frac{b+\frac{T}{K}}{c} \tag{26}$$

Therefore, the elasticity of substitution between the capital factor (K) and the technology factor (T) for renewable energy can be derived as σ_{KT}:

$$\sigma_{KT} = \frac{d\ln\left(\frac{T}{K}\right)}{d\ln(TRS_{KT})} = \frac{\frac{K}{T}\cdot d\left(\frac{T}{K}\right)}{\frac{c}{b+\frac{T}{K}}\cdot\frac{d\left(\frac{T}{K}\right)}{c}} = 1 + b\frac{K}{T} \tag{27}$$

Through the estimation of equation (21), we can derive the exogenous parameters. Subsequently, utilizing equations (24) and (25), we can compute the factor output elasticity for the renewable energy capital factor (K) and technology factor (T). Furthermore, the substitution elasticity between these factors can be determined by equation (27). Finally, we can elucidate the relationship between the capital factor (K) and technology factor (T) and their strategic implications for renewable energy development across Chinese provinces. The classification results are depicted in Fig. 2.

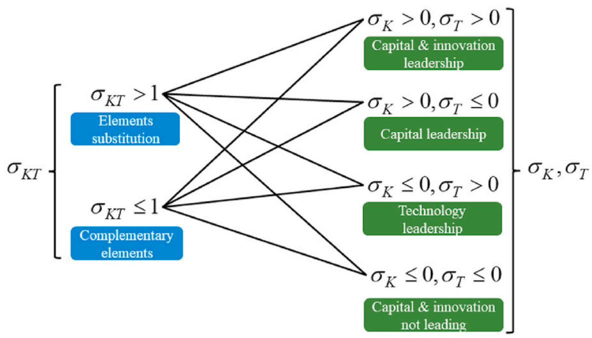


Fig. 2. Factor elasticity and renewable energy development strategies.

- If the factor elasticity of substitution $\sigma_{KT} > 1$ is present, it signifies a mutual substitution relationship between the capital factor (K) and the technology factor (T) in the renewable energy market. Consequently, the market's future trajectory leans towards the group with lower factor prices. If the factor elasticity of substitution $\sigma_{KT} \leq 1$ exists, it indicates a complementary relationship between the capital factor (K) and the technology factor (T) in the renewable energy market. Therefore, enhancing renewable energy power generation necessitates simultaneous improvements in capital and technology.
- The factor output elasticity serves as a measure of the contributions made by the capital factor (K) and the technology factor (T) within the renewable energy market. Considered as an example, when $\sigma_K > 0$, it suggests that the capital factor contributes positively to renewable energy development; conversely, when $\sigma_K \leq 0$, it signifies a diminishing utility of the capital factor in renewable energy development, prompting the consideration of other contributing factors at this juncture.

Drawing from the preceding description, the strategic trajectory of regional renewable energy development can be categorized into eight distinct paths, as depicted in Fig. 2.

3.2. Variable and data

3.2.1. Variables

(1) Renewable Energy Development

Renewable energy stands in contrast to traditional energy sources, and in alignment with the energy ladder theory, the evolution of energy usage towards a more efficient and environmentally friendly renewable energy stage corresponds to economic advancement and social development[31]. Renewable energy encompasses sources that are environmentally benign and renewable, including photovoltaic, wind, geothermal, and biomass energy. Acknowledging the challenges in acquiring regional renewable energy data, this study focuses on PV and wind energy as representative renewable energy sources, utilizing regional PV and wind power generation data as proxies for renewable energy development variables.

(2) Renewable energy capital

In this study, capital refers to physical capital, representing tangible assets in the form of renewable energy machinery, equipment, infrastructure, and other physical assets, resulting from long-term investment and accumulation during the production process. From the input-output perspective, the physical capital of the renewable energy sector is the aggregate of non-service sector outputs utilized by the renewable energy sector in the input-output table, thereby comprising the installed capacity of renewable energy generation. Consequently, Aryani et al. [32] contend that the installed capacity of renewable energy generation serves as the primary investment target in the renewable energy market, representing a tangible manifestation of capital accumulation within the renewable energy sector.

(3) Renewable Energy Technologies

Technological innovation is acknowledged as a distinctive production factor capable of altering production outcomes and restructuring industries[33]. This study consults pertinent literature on measuring innovation in renewable energy technology, evaluating renewable energy technology innovation from a patent-oriented standpoint. PV and wind energy patents across multiple provinces in China were systematically searched using IPC classification codes. A total of 287,561 patents (212,652 for PV and 74,909 for wind energy) were classified, organized, and assessed for patent stock using the Perpetual Inventory Method (Eq. (28)) during the study period. The specific IPC classification code can be seen in appendix A.

$$T_{i,t} = (1 - \pi)T_{i,t-1} + NT_{i,t} \tag{28}$$

Here, $T_{i,t}$ denotes the stock of renewable energy technology innovations in province i during year t, $NT_{i,t}$ represents the count of renewable energy technology patent applications in province i in year t, $T_{i,t-1}$ signifies the stock of renewable energy technology patents in province i in the previous year (t-1), and π denotes the depreciation rate of patents. Furthermore, based on existing literature[34], we establish $\pi = 15\%$. In cases where provinces exhibit 0 patents, we refer to prior research and employ the substitution of 10^{-20}[35].

3.2.2. Data

Due to data availability considerations, this study focuses on 30 mainland Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan) spanning the years 2011–2022. The patent data is sourced from the China Patent Database (http://epub.cnipa.gov.cn/), while data pertaining to renewable energy generation and installed capacity is extracted from the China Electricity Statistical Yearbook (https://cec.org.cn/). Additionally, data utilized in the LMDI decomposition model is obtained from the China Statistical Yearbook (https://data.stats.gov.cn/). The descriptive statistics for each variable are presented in Table 1.

4. Results and discussion

4.1. Driver decomposition results

4.1.1. Driving factors for PV development in two five-year Plan periods

To investigate the factors driving renewable energy development across different regions of China, this study employs the LMDI decomposition model to analyze the drivers of PV development in each province during the Twelfth Five-Year Plan period (2011–2015) and the Thirteenth Five-Year Plan period (2016–2020). This analysis decomposes PV development into five major drivers, with detailed results presented in Table 2.

The findings presented in Table 2 reveal that China experienced a substantial increase in PV power generation, with a rise of 38,704 million kWh during the 12th Five-Year Plan period and a notable surge of 193,730 million kWh during the 13th Five-Year Plan period, equating to a remarkable 400.54 % increase in value added. Throughout the 12th Five-Year Plan period, the provinces exhibiting the most significant cumulative growth in PV power generation were situated in western China, particularly Qinghai (74.10), Gansu (58.50), Inner Mongolia (56.90), Xinjiang (57.40), and Ningxia (34.00). This can be attributed to the relatively abundant solar energy resources in western China and its sparsely populated nature, allowing ample physical space for PV construction in contrast to the densely populated central and eastern regions of China. In the 13th Five-Year Plan period, the scale of PV power generation in China's provinces continued to expand, notably in regions

Table 1
Results of descriptive statistics of variables.

Variable	Observations	Mean	Std. Dev.	Min	Max
Photovoltaic power generation (10^8 kWh)	360	42.3430	64.2420	0.0000	462.0000
Wind energy generation (10^8 kWh)	360	104.7650	141.4500	0.0300	1077.0000
Thermal power generation (10^8 kWh)	360	1587.5280	1276.2000	91.8000	5546.6900
Total generating capacity (10^8 kWh)	360	2188.2100	1442.4260	172.9100	6440.3000
GDP (10^8 CNY)	360	27178.4680	22996.1580	1370.4000	129513.6000
Population (10^4 persons)	360	4614.5560	2858.8250	568.0000	12684.0000
Capital_PV (10^4 kW)	360	449.5030	639.8700	0.0000	4270.0000
Capital_wind (10^4 kW)	360	581.1380	715.3170	2.0000	4548.0000
Stock of technological innovation_PV (dimensionless)	360	1553.3850	2777.8740	10.2500	23440.7160
Stock of technological innovation_Wind (dimensionless)	360	527.5200	686.5570	3.7000	4555.3190

Table 2
Decomposition results of China's PV development over different five-year periods.

Provinces	Twelfth Five-Year Plan period						Thirteenth Five-Year Plan period					
	Δ*RTef*	Δ*TEef*	Δ*EGef*	Δ*GPef*	Δ*Pef*	Δ*R*	Δ*RTef*	Δ*TEef*	Δ*EGef*	Δ*GPef*	Δ*Pef*	Δ*R*
Beijing	0.40	0.00	0.00	0.00	0.00	0.40	4.78	−0.02	−0.68	0.83	−0.01	4.90
Tianjin	0.60	0.00	0.00	0.00	0.00	0.60	14.22	−0.27	0.21	2.09	−0.35	15.90
Hebei	16.29	−0.01	−0.05	0.07	0.01	16.30	152.80	−8.94	2.98	22.92	1.23	171.00
Shanxi	7.68	−0.04	−0.05	0.11	−0.01	7.69	113.42	−5.52	−5.74	30.35	−0.51	132.00
Inner Mongolia	54.56	−0.16	−0.32	2.93	−0.11	56.90	58.66	−3.25	20.77	30.57	−1.75	105.00
Liaoning	1.40	0.00	0.00	0.01	0.00	1.40	45.64	−2.01	−0.40	4.08	−0.31	47.00
Jilin	1.00	0.00	0.00	0.01	0.00	1.00	37.79	−0.91	2.11	3.69	−1.09	41.60
Heilongjiang	0.20	0.00	0.00	0.00	0.00	0.20	40.06	−1.15	1.17	2.68	−1.05	41.70
Shanghai	0.87	0.00	−0.17	0.09	0.02	0.80	8.84	−0.10	−0.78	1.00	0.03	9.00
Jiangsu	29.23	−0.05	−1.91	2.84	0.30	30.40	119.34	−9.05	−17.22	25.85	1.08	120.00
Zhejiang	7.70	−0.02	−0.04	0.04	0.01	7.70	107.26	−4.32	−13.13	15.33	3.86	109.00
Anhui	3.68	0.00	−0.01	0.03	0.00	3.70	98.23	−2.43	−8.89	21.37	0.71	109.00
Fujian	1.00	−0.01	0.00	0.01	0.00	1.00	13.69	1.90	−0.75	2.42	0.24	17.50
Jiangxi	2.39	−0.01	0.00	0.02	0.00	2.40	41.88	0.68	−1.53	9.82	0.15	51.00
Shandong	5.56	−0.04	0.10	0.74	0.05	6.40	175.02	−7.94	−11.87	18.03	1.76	175.00
Henan	3.10	0.00	−0.02	0.02	0.00	3.10	100.69	−4.22	−9.16	12.46	0.73	100.50
Hubei	2.30	0.00	−0.01	0.02	0.00	2.30	48.40	−0.36	−1.77	8.46	−0.73	54.00
Hunan	0.80	0.00	−0.01	0.01	0.00	0.80	26.69	0.48	−1.80	2.90	0.03	28.30
Guangdong	3.51	−0.05	−0.17	0.15	0.05	3.49	60.28	−0.98	−2.27	7.23	1.73	66.00
Guangxi	0.50	0.00	0.00	0.00	0.00	0.50	12.32	1.37	0.37	1.65	0.19	15.90
Hainan	1.66	0.00	0.00	0.17	0.03	1.86	11.53	−0.90	−0.92	1.88	0.42	12.00
Chongqing	0.00	0.00	0.00	0.00	0.00	0.00	3.98	0.00	−0.01	0.03	0.00	4.00
Sichuan	2.21	−0.04	0.00	0.02	0.00	2.20	10.97	0.67	−2.42	6.53	0.26	16.00
Guizhou	0.20	0.00	0.00	0.00	0.00	0.20	41.94	−0.14	−2.59	4.49	0.30	44.00
Yunnan	7.41	−2.30	0.09	0.88	0.02	6.10	7.71	8.48	−3.29	13.77	0.33	27.00
Shannxi	5.57	0.00	−0.01	0.04	0.00	5.60	84.93	−2.74	−0.50	16.16	1.15	99.00
Gansu	58.32	−2.24	−1.52	4.08	−0.15	58.50	52.98	−14.12	10.08	24.75	−0.69	73.00
Qinghai	68.82	1.57	−3.41	6.83	0.29	74.10	123.78	−114.45	31.88	33.45	2.33	77.00
Ningxia	32.71	−1.09	−0.96	2.72	0.63	34.00	38.70	−2.21	12.98	28.24	3.29	81.00
Xinjiang	56.21	0.00	0.79	0.33	0.08	57.40	49.27	−3.24	5.95	31.20	6.83	90.00
Total	375.87	−4.50	−7.69	22.16	1.21	387.04	1705.79	−175.68	2.79	384.23	20.17	1937.30

like Shandong (175.00) and Hebei (171.00), reflecting China's intensified efforts in advancing the deployment of PV and other clean energy sources amidst the context of carbon peaking.

Regarding the drivers, the primary factor influencing PV power generation in each region is the electricity substitution effect between PV and thermal power generation (Δ*RTef*), indicating that the electricity production sector plays a predominant role in driving PV power generation in China. Throughout the transition from the 12th Five-Year Plan period to the 13th Five-Year Plan period, the primary driver of PV power generation in each Chinese region has undergone a notable structural transformation. During the 12th Five-Year Plan period, the primary driver of PV power generation was the electricity substitution effect (Δ*RTef*) between PV and thermal power generation. However, in the 13th Five-Year Plan period, due to the increased contributions from the economic factor (Δ*GPef*) and intensity factor (Δ*EGef*), the significance of the electricity substitution effect (Δ*RTef*) has relatively diminished. This observation indicates a shift in China's PV power generation from production-driven to production-consumption joint-driven during the 13th Five-Year Plan period. Notably, during the 13th Five-Year Plan period, the support factor (Δ*TEef*) of the power system negatively influences PV power generation. This can be attributed to the significant improvements in China's new type of power system engineering, leading to a substantial reduction in the instability of renewable energy sources within the power grid operations. As a result of mutual substitution in the power production mode, China's thermal power generation has witnessed a decline in annual production, resulting in an increase in Δ*RTef* and a decrease in Δ*TEef*. The study findings suggest that the implementation of a new type of power system in China is yielding positive outcomes in addressing carbon peaking and facilitating the energy transition.

4.1.2. *Driving factors for wind energy development in two five-year Plan periods*

Table 3 presents the outcomes of decomposing the drivers of wind power generation using the LMDI decomposition model. The findings presented in Table 3 indicate that China's wind energy development has a solid foundation compared to PV. Wind power generation during the Twelfth Five-Year Plan period witnessed an increase of 111,737 million

Table 3
Decomposition results of China's wind energy development over different five-year periods.

Provinces	Twelfth Five-Year Plan period						Thirteenth Five-Year Plan period					
	Δ*RTef*	Δ*TEef*	Δ*EGef*	Δ*GPef*	Δ*Pef*	Δ*R*	Δ*RTef*	Δ*TEef*	Δ*EGef*	Δ*GPef*	Δ*Pef*	Δ*R*
Beijing	−1.55	0.02	0.32	0.88	0.24	−0.10	0.85	−0.03	−0.81	1.00	−0.01	1.00
Tianjin	4.62	−0.03	−0.92	0.70	0.22	4.60	4.34	−0.27	0.21	2.07	−0.34	6.00
Hebei	74.75	−4.56	−17.38	24.26	1.93	79.00	101.52	−24.80	8.27	63.59	3.42	152.00
Shanxi	86.47	−1.35	−1.66	4.05	−0.52	87.00	82.80	−14.32	−14.89	78.73	−1.32	131.00
Inner Mongolia	100.30	−5.37	−10.91	100.75	−3.77	181.00	50.84	−14.80	94.64	139.30	−7.98	262.00
Liaoning	39.53	−10.51	−1.43	19.23	−0.82	46.00	53.24	−17.31	−3.44	35.20	−2.67	65.00
Jilin	19.58	−1.04	−11.29	14.83	−2.07	20.00	40.53	−5.37	12.48	21.79	−6.43	63.00
Heilongjiang	26.63	−1.23	−6.65	13.19	−3.94	28.00	37.56	−10.89	10.99	25.24	−9.90	53.00
Shanghai	7.20	−0.02	−3.11	1.66	0.28	6.00	4.34	−0.41	−3.27	4.20	0.14	5.00
Jiangsu	30.93	−0.26	−9.87	14.66	1.53	37.00	129.92	−14.75	−28.08	42.15	1.76	131.00
Zhejiang	10.67	−1.07	−2.29	2.38	0.71	10.40	12.17	−2.05	−6.24	7.28	1.83	13.00
Anhui	16.67	−0.18	−1.30	3.25	0.06	18.50	14.98	−1.81	−6.62	15.91	0.53	23.00
Fujian	26.85	−10.71	−6.94	11.17	1.63	22.00	27.35	22.21	−8.80	28.39	2.86	72.00
Jiangxi	7.75	−0.58	−0.40	2.01	0.01	8.80	39.80	0.91	−2.04	13.13	0.20	52.00
Shandong	51.10	−1.28	3.25	24.40	1.54	79.00	112.05	−16.99	−25.41	38.58	3.77	112.00
Henan	10.23	−0.01	−1.73	1.68	0.13	10.30	121.26	−5.66	−12.28	16.70	0.98	121.00
Hubei	18.88	−0.23	−2.25	2.99	0.11	19.50	36.83	−0.65	−3.21	15.36	−1.33	47.00
Hunan	22.70	−1.06	−2.48	2.31	0.03	21.50	49.46	3.13	−11.75	18.97	0.19	60.00
Guangdong	26.76	−2.35	−7.62	7.00	2.22	26.00	38.87	−2.42	−5.61	17.88	4.28	53.00
Guangxi	6.09	−0.52	−0.20	0.47	0.05	5.90	65.65	10.46	2.85	12.58	1.45	93.00
Hainan	−1.59	−0.03	−0.02	2.01	0.34	0.70	−0.28	−0.73	−0.75	1.53	0.34	0.10
Chongqing	1.76	−0.04	−0.55	0.75	0.08	2.00	7.37	0.04	−1.29	2.60	0.27	9.00
Sichuan	10.56	−1.90	0.23	0.88	0.04	9.80	51.98	1.73	−6.27	16.90	0.67	65.00
Guizhou	32.70	−2.52	−2.87	4.69	0.40	32.40	28.78	−0.93	−16.58	28.79	1.94	42.00
Yunnan	108.63	−43.22	1.66	16.58	0.35	84.00	−7.28	47.63	−18.49	77.28	1.87	101.00
Shannxi	15.63	−0.15	−0.58	2.08	0.12	17.10	53.09	−2.70	−0.49	15.96	1.13	67.00
Gansu	54.67	−16.91	−11.46	30.79	−1.10	56.00	69.49	−28.58	20.41	50.09	−1.40	110.00
Qinghai	6.61	0.11	−0.23	0.47	0.02	6.97	84.85	−31.44	8.76	9.19	0.64	72.00
Ningxia	70.61	−3.71	−3.24	9.22	2.12	75.00	−10.32	−3.93	23.12	50.28	5.85	65.00
Xinjiang	47.32	−0.31	50.14	20.77	5.07	123.00	92.61	−9.65	17.72	92.97	20.34	214.00
Total	933.07	−111.04	−51.79	340.12	7.01	1117.37	1394.65	−124.40	23.12	943.64	23.08	2260.10

kWh, while during the Thirteenth Five-Year Plan period, it surged by 226,010 million kWh, resulting in a 102.27 % growth. Notably, during the Twelfth Five-Year Plan period, the growth of wind power generation in China was particularly evident in provinces such as Inner Mongolia (262.00), Xinjiang (214.00), Shanxi (87.00), among others, reflecting the region's abundant wind energy resources and aligning with the Chinese government's strategy of developing renewable energy tailored to local conditions. Conversely, the 13th Five-Year Plan period experienced a notable increase in wind power generation across all provinces in China (with certain regions unsuitable for wind power development due to specific policy attributes, e.g., Beijing, Shanghai, Tianjin, etc.), as a result of China's extensive layout of the renewable energy industry during this period.

According to the decomposition results, the electricity substitution effect (Δ*RTef*) and economic factors (Δ*GPef*) emerge as the primary drivers of wind power generation in China, indicating that China's wind power sector is propelled by both production and consumption dynamics. Conversely, the power system support factor (Δ*TEef*) exerts a negative influence on wind power generation, with its impact gradually intensifying. This corroborates the trend where the scale of wind power generation in China is steadily expanding, leading to a year-on-year decrease in the proportion of thermal power generation in electricity production, thereby indicating the gradual transition from traditional to clean energy production. Furthermore, the intensity factor (Δ*EGef*) transitioned from a negative to a positive value between the 12th and 13th Five-Year Plan periods, signifying that shifts in social energy consumption have emerged as an additional driving force for wind energy development. This trend is particularly evident in provinces abundant in wind energy resources, such as Inner Mongolia, Gansu, and Ningxia, within China.

4.1.3. Analysis of differences in the drivers and causes of PV and wind energy development in different provinces

The preceding analysis adopts a macroscopic lens to examine the impetuses behind the progression of PV and wind energy sectors in China across two consecutive Five-Year Plan periods. It is imperative to recognize that a province-specific analysis, informed by regional disparities, holds enduring significance. Specifically, the acceleration of PV development in Northwest China during the 12th Five-Year Plan is attributed predominantly to the electricity substitution effect, encompassing regions such as Qinghai, Gansu, Xinjiang, Inner Mongolia, Ningxia, and Gansu. Comparatively, other regions exhibit a more moderate pace in PV advancement. Despite this variance, the electricity substitution effect remains a pivotal catalyst for PV growth across all provinces. The rationale behind this phenomenon is rooted in the Northwest's demographic sparseness and favorable solar irradiance, positioning it as a vanguard for governmental initiatives aimed at fostering renewable energy as a substitute for conventional energy sources. Consequently, the electricity substitution effect has emerged as a principal impetus for the rapid PV development in Northwest China, yielding commendable outcomes.

In the context of the 13th Five-Year Plan, the substitution effect of electricity and economic drivers emerged as the primary catalysts for PV development across China's provinces. Notably, beyond the Northwest region, the influence is pronounced in other pivotal areas such as Shandong, Hebei, Jiangsu, Zhejiang, Henan, Anhui, and Shaanxi. This trend can be attributed to the period's marked integration of new energy generation into the economic fabric, with the aforementioned provinces serving as linchpins in China's regional economic growth. Their advancement is contingent upon robust economic expansion and substantial energy demand. Consequently, the interplay of electricity substitution and economic stimuli has solidified their position as the principal impetuses for the advancement of PV technology.

In the realm of wind energy development, the 12th Five-Year Plan period in Northwest China witnessed electricity substitution effects and economic catalysts as the predominant influences on the sector's growth, notably in regions such as Inner Mongolia, Shanxi, Hebei, Ningxia, Gansu, and Shandong. The primary rationale for this advancement is attributed to the region's endowment of substantial wind energy resources, with Inner Mongolia standing out as a paragon of energy transition due to its resource wealth. Furthermore, the burgeoning pursuit of a green economic transformation is amplifying the demand for clean energy sources, thereby emerging as a significant impetus for the proliferation of regional wind energy initiatives.

Throughout the 13th Five-Year Plan period, the impetuses propelling wind energy development in China's provinces generally mirrored those of the preceding 12th period. However, an emerging trend has been the discernible negative influence of support effects on the wind energy

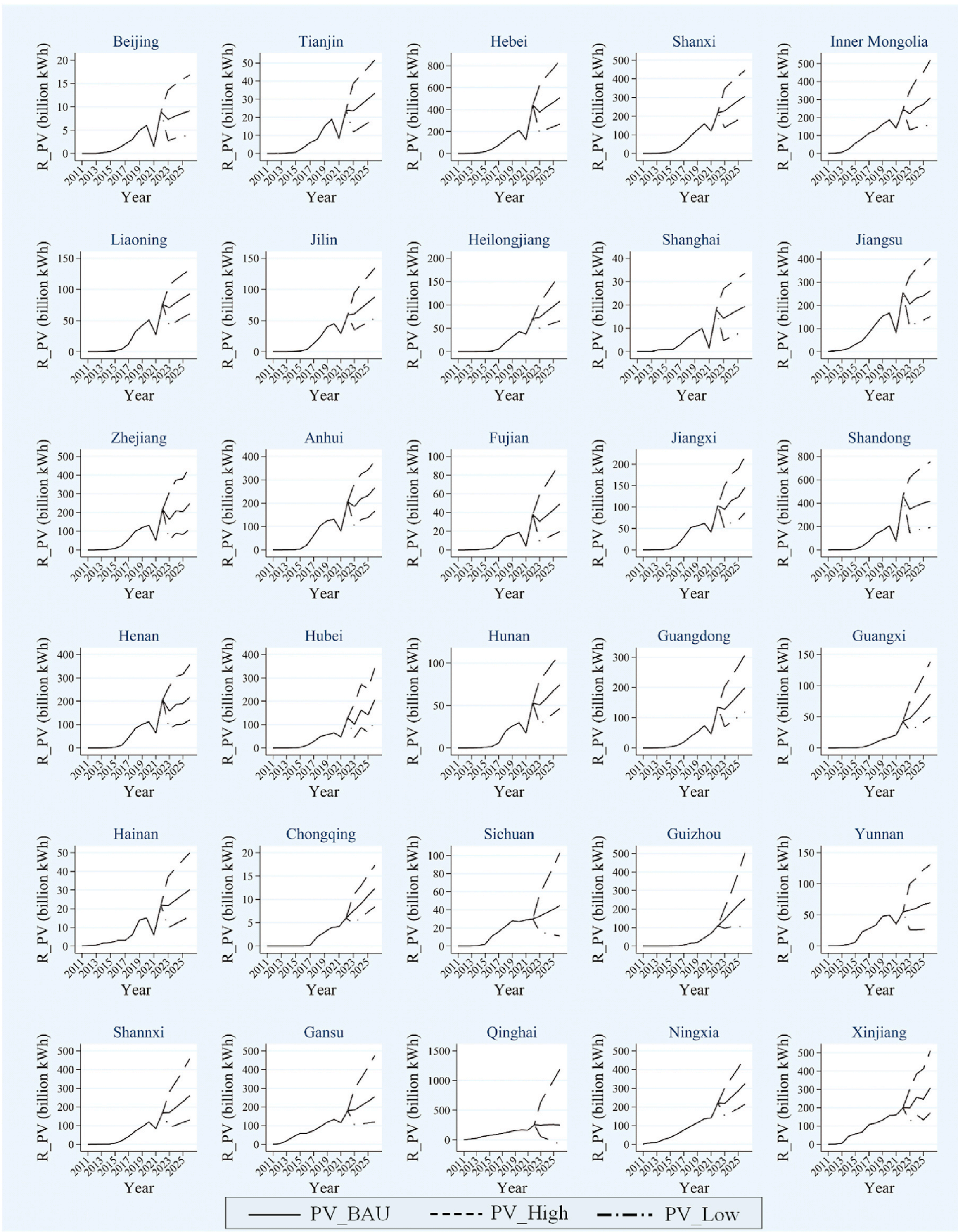


Fig. 3. Forecast results of PV development in China.
Note: where BAU is the baseline as usual, High represents the projected volume at the upper 95 % confidence interval, and Low represents the projected volume at the lower 95 % confidence interval.

sector. This adverse impact is particularly pronounced in provinces like Qinghai, Gansu, Hebei, Liaoning, and Shandong, where the prevalence of traditional energy resources and an industry-centric economic paradigm have led to significant electricity demand and the necessity for a reliable power supply. Consequently, to satisfy the substantial power load, a reliance on thermal power generation for peak capacity support has become indispensable, inadvertently exerting a counterproductive influence on the advancement of wind energy.

4.2. Forecast of renewable energy development potential

4.2.1. Photovoltaic development potential

Based on equation (18), we projected the PV power generation capacity for each region in China from 2023 to 2026, with the forecasted

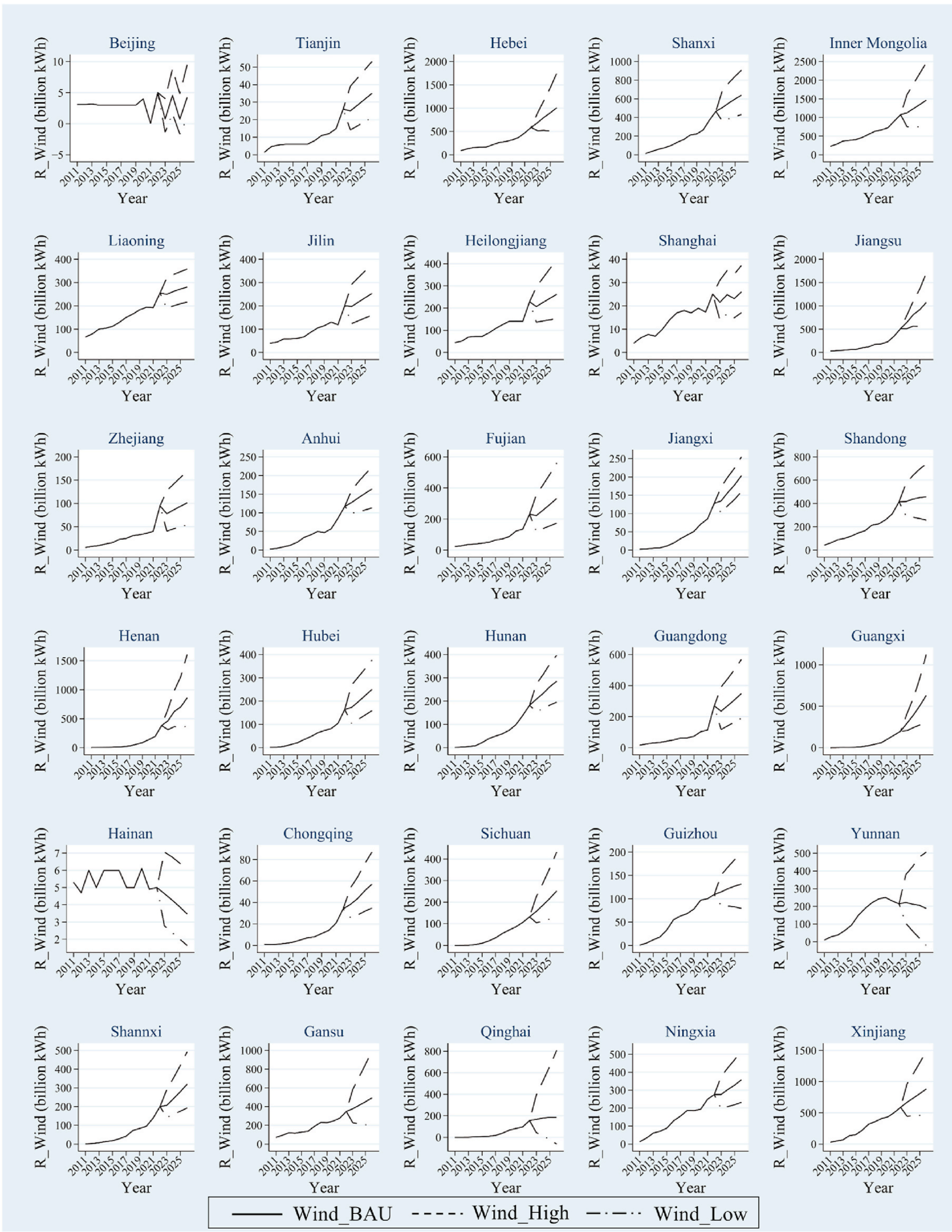


Fig. 4. Forecast results of wind energy development in China.
Note: where BAU is the baseline as usual, High represents the projected volume at the upper 95 % confidence interval, and Low represents the projected volume at the lower 95 % confidence interval.

results presented in Fig. 3. The forecasted outcomes in Fig. 3 indicate a rising trend in PV power generation across all provinces in China. Certain provinces, notably Inner Mongolia, Xinjiang, Shanxi, and Hebei, among others, are expected to experience a significant increase. Western China continues to be the primary region for future PV power generation.

4.2.2. Wind energy development potential

The wind power generation in each region of China from 2023 to 2026 has been forecasted using the forecast model, with the outcomes depicted in Fig. 4. The outcomes depicted in Fig. 4 reveal that while wind power generation in most regions of China continues to grow, certain regions, such as Hainan and Yunnan, exhibit a declining trend. This trend could be attributed to regional differences in wind energy resource availability and regional development focus.

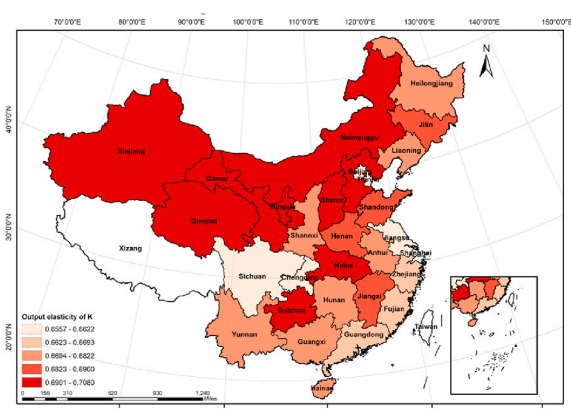
4.3. Results of factor elasticity analysis

4.3.1. Analysis of the elasticity of substitution between capital and innovation

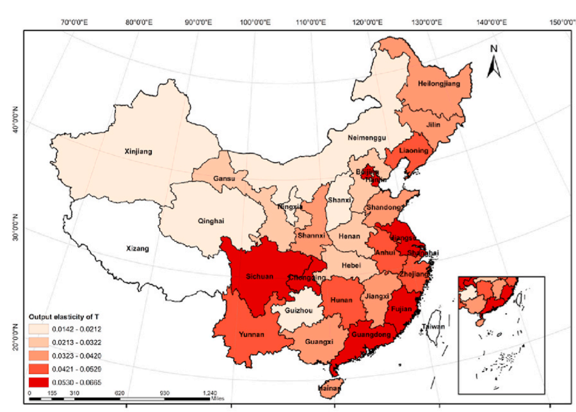
According to economic theory, the output elasticity of a factor represents the ratio of the percentage change in output to the percentage change in the input of that factor, while keeping the input of other factors constant. Through factor output elasticity, we can observe the degree of contribution of various factors to output. The output elasticities of renewable energy capital and technology factors at the provincial level in China were computed using equations (24) and (25), followed by categorizing the results into five levels using the natural breakpoint method, as illustrated in Fig. 5.

Fig. 5-a and 5-b for PV demonstrate that the output elasticity of the capital factor significantly surpasses that of the technology factor across all provinces of China. This observation suggests that PV power generation in China is predominantly driven by capital, highlighting distinct spatial distribution characteristics between capital and technology factors. The output elasticity of capital is notably higher in northwestern China compared to southeastern China, indicating that the Chinese government's capital investment in PV construction is primarily focused on the northwestern region, which boasts abundant PV resources. Additionally, the economy of northwestern China is relatively less developed. In contrast, the technical output elasticity of PV is greater in Southeastern China than in Northwestern China, with the highest values observed along the eastern coast of China. This disparity indicates a higher level of technological development for PV in Southeast China compared to Northwest China, highlighting a spatial mismatch between technological advancement and resource distribution in the PV sector.

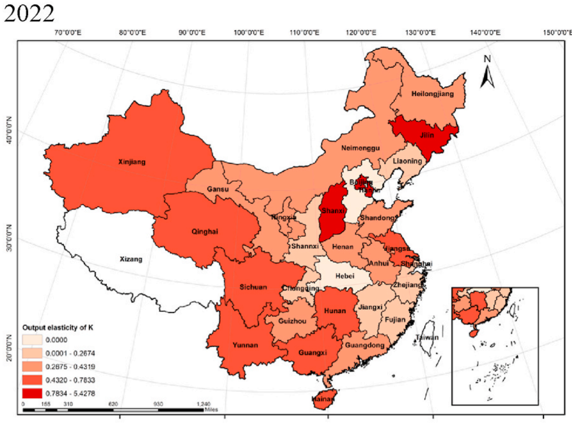
Fig. 5-c and 5-d depict the factor output elasticity of wind power generation in China, revealing that the current capital output elasticity surpasses the output elasticity of technological innovation, highlighting that China's wind power generation is primarily propelled by capital. Provinces with elevated capital output elasticity include Xinjiang, Qinghai, Sichuan, and Yunnan, mirroring the Chinese government's strategic emphasis on "Western Development" in wind energy infrastructure. Provinces with relatively elevated technical output elasticity comprise Xinjiang, Yunnan, and Jiangsu. Notably, certain provinces like Sichuan, Hunan, and Guangdong exhibit negative output elasticities for wind energy technologies, potentially stemming from overly aggressive technological investments and regional discrepancies in innovation resources. This underscores the importance for regions to carefully weigh



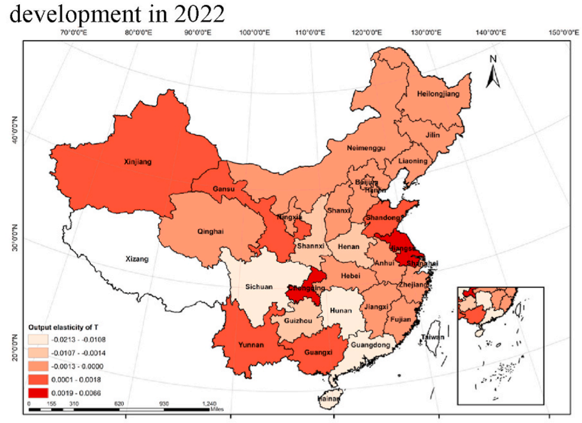
a. Capital factor output elasticity of PV development in 2022



b. Technological factor output elasticity of PV development in 2022



c. Capital factor output elasticity of wind energy development in 2022



d. Technological factor output elasticity of wind energy development in 2022

Fig. 5. Output elasticities of capital and technology factors.

the impacts of various factors when advancing renewable energy development within the dual-carbon target framework, thereby necessitating the formulation of a development strategy tailored to the unique characteristics of renewable energy in each region.

4.3.2. Analysis of the elasticity of substitution between capital and innovation

Fig. 6 illustrates the elasticity of substitution among various input factors for renewable energy in China. The elasticity of substitution between factors indicates how one factor changes in response to changes in another factor, with the possibility of both substitution and complementarity between them. In a substitution relationship, an increase in one factor leads to a decrease in the other; conversely, in a complementary relationship, an increase in one factor results in an increase in the other as well. Analyzing the elasticity of substitution between factors assists us in crafting distinct renewable energy development strategies tailored to different regions.

Fig. 6-a presents the elasticity of substitution of factors for PV power generation in China. The analysis reveals that the elasticity of substitution between capital and technology factors exceeds 1 in all provinces of China, signifying a stable substitution relationship between these factors for PV power generation. However, notable discrepancies exist in the elasticity of substitution among provinces. Northwest China exhibits a higher elasticity of substitution between PV power generation factors compared to southeast China. This observation implies that ensuring the stable growth of PV power generation can be achieved by leveraging more economically advantageous (lower-priced) factors of production, providing valuable insights for formulating PV development strategies tailored to specific regions.

Fig. 6-b illustrates the factor elasticity of substitution for wind power generation in China. The analysis clearly reveals that there is a negative elasticity of substitution between capital and technology factors in Chinese provinces, indicating a complementary relationship between these factors. This observation suggests that China's wind energy industry lacks a specific market-oriented mechanism and has not yet developed an elastic market. Therefore, the government should prioritize examining the output elasticity of the capital factor and technological factors when formulating the wind energy development strategy, especially given the simultaneous development of technological factors and the subsequent increase in the capital factor.

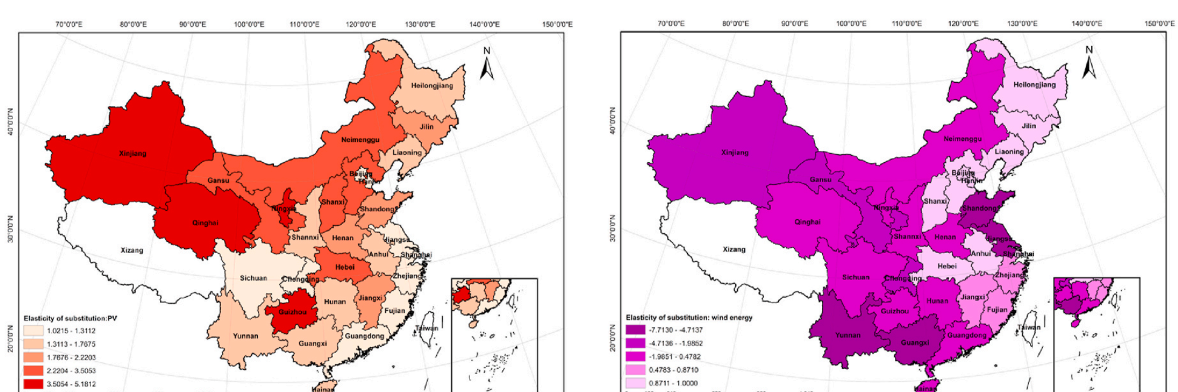
4.3.3. Identify elemental relationships and propose strategic paths for renewable energy development

Capital and technology are fundamental components for the future advancement of renewable energy in China; expanding capital is crucial for fostering a large-scale renewable energy market, while technological innovation serves as the quality assurance for sustainable long-term renewable energy development. The renewable energy development strategy should be dynamically adapted based on the interplay between capital and technology. By classifying and combining relationships as depicted in Fig. 2, we discern the strategic developmental correlations between capital and technology elements in renewable energy generation, considering the output elasticity of capital and technology elements along with the substitution elasticity between them. Subsequently, we put forth distinct development strategies for renewable energy across 30 provinces in China (as delineated in Table 4), serving as a guide for renewable energy advancement in diverse regions.

Table 4 reveals that the elasticity of substitution between capital and technology factors for PV power generation in China exceeds 1, and the output elasticity between these factors surpasses 0. Consequently, provincial governments in China should augment investments in both capital and technology factors to boost regional PV power generation capacity. Regarding elasticity of substitution, an augmentation in one factor input results in a reduction in the input of the other factor, whereas concerning factor output elasticity, the capital factor exhibits significantly greater output elasticity compared to the technology factor. This observation suggests that capital remains the predominant factor in China's current PV power generation landscape, and adopting a capital-led strategy is the preferred trajectory for the future advancement of PV power generation across all Chinese provinces. Alongside prioritizing technology research and development, local governments should concentrate on fortifying the infrastructure for PV power generation

Table 4
Strategic Options for PV and wind energy development in China.

Renewable energy types	Relationship between input elements	Output elasticity
PV wind power	Element substitution ($\sigma_{KT} > 1$) Element complementary ($\sigma_{KT} \leq 1$)	$\sigma_K > \sigma_T > 0$ $\sigma_K > \sigma_T > 0$ $\sigma_K > 0, \sigma_T < 0$
Renewable energy types	Region	Strategic path for renewable energy development
PV wind power	All provinces Beijing, Tianjin, Hebei, Shanxi, Liaoning, Jilin, Heilongjiang, Jiangsu, Shandong, Hubei, Guangxi, Chongqing, Yunnan, Gansu, Xinjiang Inner Mongolia, Shanghai, Zhejiang, Anhui, Fujian, Jiangxi, Henan, Hunan, Guangdong, Hainan, Sichuan, Guizhou, Shaanxi, Qinghai, Ningxia.	Capital-led strategy Capital-technology co-lead strategy Technology-led strategy



a. Elasticity of substitution between factors for PV development in 2022

b. Elasticity of substitution between factors for wind energy development in 2022

Fig. 6. Elasticity of substitution of capital and technology factors.

capital. For instance, they can augment the installed PV power generation capacity in each region, thereby creating a substantial capital-scale market for regional PV development.

In China's wind power generation sector, capital and technology factors complement each other, with improvements in one factor leading to enhancements in the other. Scaling up regional wind power generation requires collaborative efforts from both capital and technology factors. Thus, governments should focus on the output elasticity of capital and technology factors when devising wind power development strategies. Considering the current circumstances in China's provinces, if both the capital and technology factors exhibit positive trends, and the output elasticity of the capital factor exceeds that of the technology factor, governments should bolster both capital and technology inputs to enhance regional wind power generation capacity. Consequently, they should implement a capital-technology co-leadership strategy. However, certain provinces in China, such as Inner Mongolia, Shanghai, and Zhejiang, exhibit a negative output elasticity of the wind energy technology factor. Recognizing the complementary nature of the capital and technology factors, and acknowledging that the technology factor is a limiting factor for regional wind power generation, these provinces should prioritize a technology-led strategy. This involves mitigating the adverse effects of the technology factor through scientific allocation of innovation resources and bolstering talent acquisition to provide a robust scientific research foundation for regional renewable energy innovation.

5. Conclusions and policy implications

China currently leads the world in terms of the highest increase in global carbon emissions, and the Chinese government is steadfastly dedicated to fostering clean energy while promoting the adoption of renewable energy as an alternative path for reducing carbon emissions compared to conventional energy sources. This study aims to investigate the factors driving PV and wind power generation in China and the strategic decisions for future development at the provincial level in China. The LMDI decomposition model is employed to dissect the variations in China's PV and wind power generation into substitution, support, intensity, economic, and demographic factors, and to predict the developmental trajectory over a specific future time frame. Through analyzing the output elasticity and substitution elasticity of various renewable energy capital and technology factors, this study offers decision-making insights for different regions in formulating strategies for renewable energy development. The main conclusions that follow can be summarized as follows.

(1) The value added by PV power generation in China surged by an impressive 400.54 % from the 12th Five-Year Plan period (38.704 billion kWh) to the 13th Five-Year Plan period (193.730 billion kWh). Concerning the factors driving PV power generation, the primary driver in each region is the electricity substitution effect between PV and conventional power generation, with China's PV power sector primarily propelled by the power production segment. Nonetheless, the 13th Five-Year Plan period is witnessing a transition from production-driven growth to a model focused on joint production and consumption. Model predictions reveal a continuous growth trend in PV power generation across all Chinese provinces. Certain provinces may experience more significant growth, with the western region of China continuing to be the primary region for future PV power generation.

(2) China has established a solid foundation for wind energy development, with the value added by wind power generation surging by an impressive 102.27 % from the 12th Five-Year Plan period (111.737 billion kWh) to the 13th Five-Year Plan period (226.01 billion kWh). Analysis reveals that the substitution effect between wind energy and traditional sources, along with economic factors, serves as the primary drivers of wind power generation in China, indicating a dual-driven approach from both production and consumption aspects. Model predictions indicate a continuing growth trend in wind power generation across most regions of China, albeit with certain areas showing a potential decline.

(3) Regarding the output elasticity of capital factors across provinces, both China's PV and wind power generation are primarily propelled by capital investments. Analyzing the elasticity of substitution between capital and technology factors in provinces, China's photovoltaic power generation exhibits a stable substitution dynamic between these factors, whereas the wind power industry in China lacks a well-defined market mechanism, resulting in a non-elastic market and a complementary relationship between capital and technology factors. Considering both factor output elasticity and substitution elasticity, adopting a capital-led strategy emerges as an optimal approach for future PV power generation development across Chinese provinces. Wind energy development should be tailored to specific circumstances to formulate strategic pathways. In cases where both capital and technology factors are positive, and the output elasticity of capital surpasses that of technology, a capital-technology co-led strategy is recommended. Provinces exhibiting negative technology output elasticity should prioritize a technology-led strategy initially to address the adverse effects of technology factors, thereby enhancing the strategic allocation of innovation resources.

Drawing from the study's findings, this paper puts forth the following policy recommendations: Given that the electricity substitution effect between renewable energy and traditional thermal power is the primary driver of renewable energy generation in China, implementing energy policies that promote fuel switching at the provincial level will facilitate the continued growth of renewable energy generation. Furthermore, recognizing the significance of economic factors in driving wind power generation, both central and local governments should prioritize economic development initiatives, boost the share of wind energy in energy consumption, mitigate the abandonment rate of wind power generation across provinces, and integrate wind energy into the socio-economic energy landscape.

Furthermore, we recommend that both central and local governments adjust their investments in capital and technology factors based on their output elasticity. This will enable the formulation of a development strategy that aligns with the current state of renewable energy in the region. Capital-led and technology-led approaches can fulfill distinct roles in regional renewable energy development. Given that renewable energy is a capital-intensive industry, particularly in the initial stages of regional development, where capital factor's output elasticity is highest, the government should adopt a capital-led strategy. This entails increasing financial support for renewable energy investment and implementing subsidy and tax reduction measures for renewable energy enterprises, thereby accelerating the expansion of the renewable energy market scale. Moreover, renewable energy falls under the high-tech sector, where technology serves as the linchpin for sustainable development in the renewable energy industry. In the course of renewable energy development, local governments should prioritize enhancing scientific and technological innovation. This includes implementing robust talent protection policies, fostering inter-regional exchanges in renewable energy technology, safeguarding intellectual property rights, and bolstering the efficacy of technical elements during the latter stages of new energy development.

This research acknowledges its inherent limitations, which warrant further exploration in subsequent studies. Initially, the absence of comprehensive new energy data constrained the analysis to photovoltaic and wind energy sectors. Nonetheless, the study has established a foundational and illuminating framework for future inquiries into the dynamics of new energy drivers. As new energy data resources become increasingly available, it is envisioned that future research will broaden the scope to encompass a diverse array of energy sources, including biomass, geothermal, nuclear, and hydrogen energy. Furthermore, the current research delves into the interplay between capital and technology as pivotal components within the context of new energy strategic pathways. It acknowledges that, beyond these two domains, a constellation of additional factors—such as labor, the policy landscape, and international trade dynamics—significantly influences energy production outcomes. These multifaceted considerations are anticipated to catalyze innovative and leading-edge avenues for future scholarly inquiry.

CRediT authorship contribution statement

Yubao Wang: Supervision, Resources, Investigation, Funding acquisition, Conceptualization. **Junjie Zhen:** Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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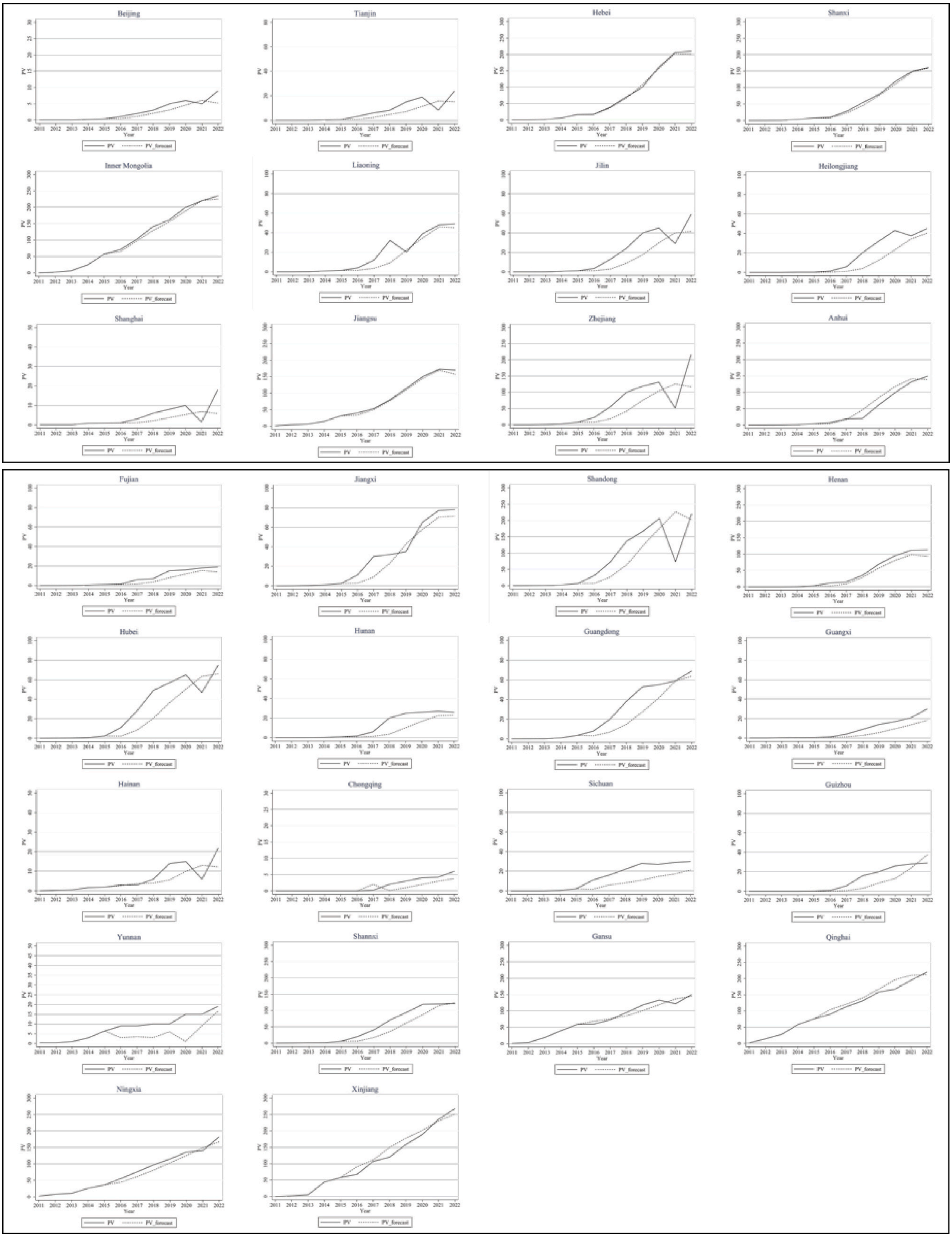
Appendix A

Appendix table 1
The specific IPC classification code.

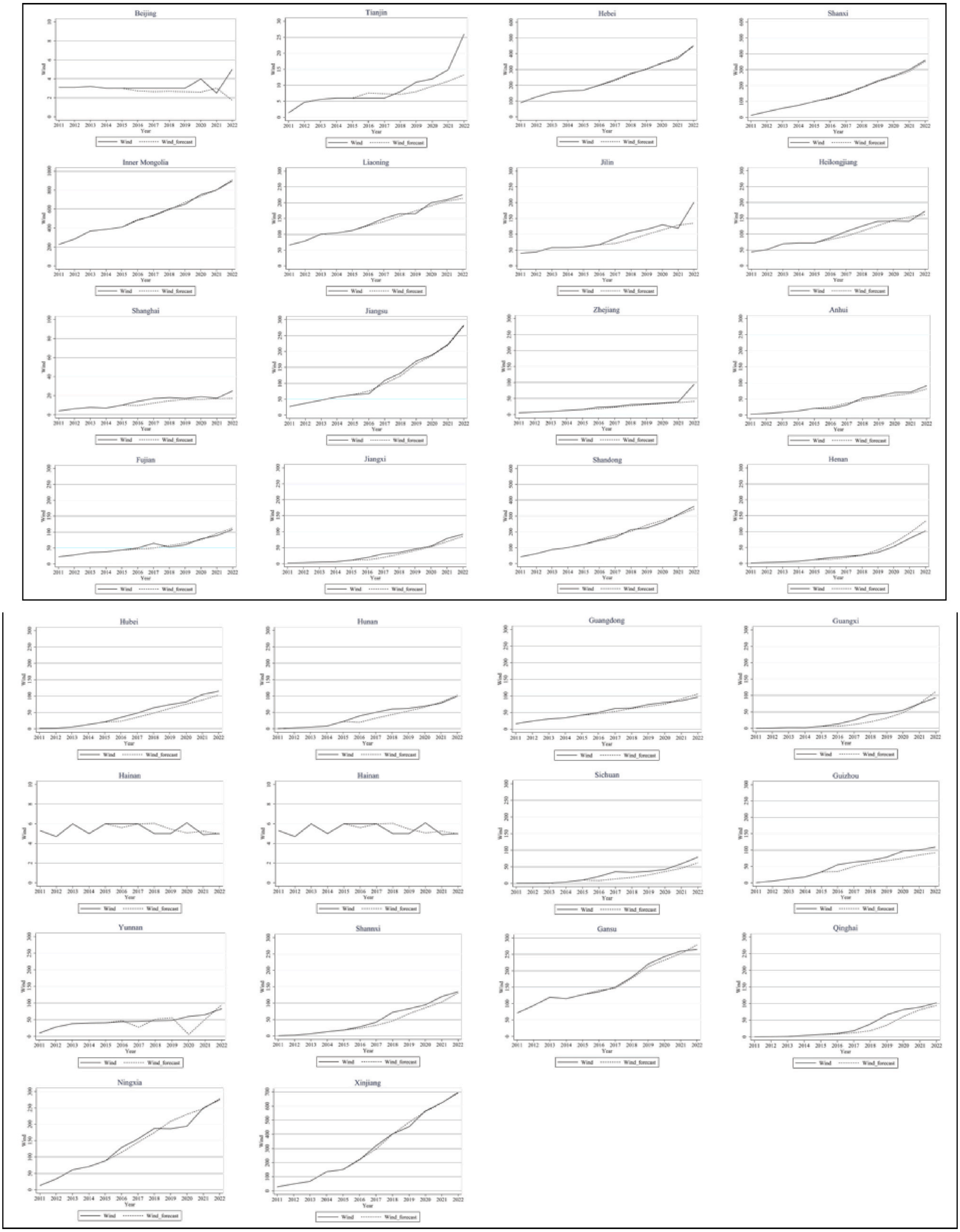
Renewable energy	Description	IPC Classes
PV	Heat captured from the sun may be used for residential heating, industrial processes or thermal power generation. Technologies involved in solar thermal energy production include solar heat collection, heat storage, systems control, and system design technologies. Specially adapted semiconductor devices are used to convert solar radiation into electrical current. Related technologies include solar cell design, storage batteries, and power conversion technologies.	F03G6/00; F03G6/06; F03G6/04; F24S; H01L27/142; H01L31/04; H01L31/041; H01L31/042; H01L31/043; H01L31/044; H01L31/0443; H01L31/0445; H01L31/046; H01L31/0463; H01L31/0465; H01L31/0468; H01L31/047; H01L31/0475; H01L31/048; H01L31/049; H01L31/05; H01L31/052; H01L31/0525; H01L31/053; H01L31/054; H01L31/055; H01L31/056; H01L31/06; H01L31/061; H01L31/062; H01L31/065; H01L31/068; H01L31/0687; H01L31/0693; H01L31/07; H01L31/072; H01L31/0725; H01L31/073; H01L31/0735; H01L31/074; H01L31/0745; H01L31/0747; H01L31/0749; H01L31/075; H01L31/078; H01L31/077; H01L31/076; H02S; E04D13/18; F03G6/02
Wind power	Wind currents can be used to generate electricity by using wing-shaped rotors to convert kinetic energy from the wind into mechanical energy and a generator to convert the resulting mechanical energy into electricity.	F03D; B60L53/52; B63B77/10; B63H13/00; B60L8/00

Appendix B

To assess the fidelity of our predictive framework, we applied the model to project the historical annual data from 2016 to 2020. The model's empirical robustness was subsequently evaluated by juxtaposing the forecasted estimates with the actual figures, with the comparative analysis graphically presented in the ensuing figure. The overall mean absolute error (MAE) of the predicted value of photovoltaic (PV) power generation is 11.9092, and that of the predicted value of wind power generation is 9.5682. It can be seen that the MAE value is relatively small and within the acceptable range, and the model predicts better.



Appendix Fig. 1. Comparison of predicted and actual results: PV.



Appendix Fig. 2. Comparison of predicted and actual results: Wind.

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