International Journal of Fuzzy System Applications
Volume 12 • Issue 1

Configuration Pathways to Enhance Green Total Factor Productivity:
A Fuzzy Set Qualitative Comparative Analysis

Yani Guo, Center for Efficiency and Productivity Research, Minjiang University, China
Yunjian Zheng, Xinhuadu Business School, Minjiang University, China*
https://orcid.org/0009-0004-7411-6046

ABSTRACT

Green total factor productivity (GTFP) is a key metric in assessing the high-quality development of the economy. The authors investigate the configuration pathways by which GTFP can be enhanced. The researchers used data from 30 provinces and municipalities in China (excluding Tibet, Hong Kong, Macau, and Taiwan) as case studies. This study demonstrates that GTFP is influenced by six factors, such as regional innovation ability and digital financial development. These factors contribute to three configuration pathways for achieving high GTFP: innovation market-oriented, economic growth-oriented, and integrated synergistic pathways. Meanwhile, there is consistency and substitutability between some factors. The innovation of this paper lies in the introduction of the fuzzy set qualitative comparative analysis (fsQCA) method into the research on GTFP. It can enrich the theoretical research in the field of GTFP and provide valuable reference and pathway options for improving GTFP in China and other countries with similar economic development patterns.

KEYWORDS

Configuration Pathways, Fuzzy Set, Green Total Factor Productivity, High-Quality Development, Qualitative Comparative Analysis

INTRODUCTION

The *Guiding Opinions on Accelerating the Establishment of a Sound Economic System with Green, Low-Carbon, and Circular Development*, released by the State Council of China in 2021, highlights the importance of harmonizing high-quality development and advanced environmental preservation efforts. Its objective is to establish an economic system that fosters green, low-carbon, and circular development, thereby guaranteeing the realization of carbon peak and carbon neutrality objectives. This strategic undertaking seeks to propel China's green development to unprecedented heights. Evidently, "green" is a crucial direction for contemporary and future economic development. For evaluating the effectiveness of economic development, most researchers widely acknowledge and employ the total factor productivity (TFP) indicator, derived from input-output calculations, as

DOI: 10.4018/IJFSA.326798 *Corresponding Author

proposed by Solow (1956). Chung et al. (1997) first introduced “undesirable” outputs, including environmental pollution, in the TFP measurement, and referred to it as green total factor productivity (GTFP). The GTFP indicator considers ecological environment and natural resources when assessing economic benefits, making it an effective measure for high-quality economic development (Chen, 2010). An enhanced GTFP is an outcome of harmonized socioeconomic, resource, and environmental development. Embracing a development approach guided by GTFP can fuel robust momentum for achieving high-quality economic growth. Finding pathways to enhance GTFP, while considering the unique characteristics of regional resource endowments, is an urgent and crucial matter that requires considerable attention.

In studies examining the factors influencing GTFP, some researchers utilized fixed effects models to empirically demonstrate that regional coordinated development (Liu et al., 2020) and green credit (Liu et al., 2023) can promote the enhancement of GTFP in China. He and Qi (2022), utilizing a two-way fixed effects approach, also demonstrated that environmental regulations (ERs) exhibit a reverse “u-shaped” impact on GTFP through effects such as innovation compensation and energy allocation. Wang et al. (2020) utilized advanced statistical methods such as generalized least squares and random effects models. Their findings indicate a substantial positive impact of technological innovation on GTFP. Based on panel data from Chinese firms, Sun et al. (2022) used the ordinary least squares method. Their findings indicate that green innovation by firms has a positive impact on GTFP.

Furthermore, researchers employed epsilon-based measure data envelopment analysis (Yang et al., 2020) and Tobit regression models (Xiao, 2021), and demonstrated the positive impact of human capital (HUM) on the efficiency of GTFP. Several researchers utilized spatial Durbin models to empirically demonstrate that digital finance (Yu et al., 2022; Zhu & Zhang, 2022) and diversified industrial structures (Ye & Xiao, 2023) can contribute to the enhancement of local city-level GTFP, while also generating significant positive spatial spillover effects. Using the geographically and temporally weighted regression model, researchers empirically demonstrated the significant promoting effects of digital development (Zhao et al., 2022), innovation investment, and urbanization level on the growth of China’s GTFP. However, scholars also observed that industrial clusters and patent applications have a dampening effect on GTFP (Xiao, 2022).

Cui and Lin (2019) utilized propensity score matching and difference-in-differences and found that the introduction of foreign direct investment contributes positively to the enhancement of firm-level GTFP. However, Xu et al. (2021), employing fixed effects models, and Dong and Xia (2022), utilizing the generalized method of moments estimation, discovered a negative correlation between foreign direct investment and China’s GTFP, providing empirical support for the “pollution haven” hypothesis. In addition, several researchers employed threshold (Han et al., 2017), mediation effect (Xie et al., 2021), and panel smooth transition regression (Wang et al., 2022) models to analyze and suggest that the enhanced marketization is instrumental in driving the enhancement of GTFP levels across different regions in China.

Qualitative comparative analysis (QCA) is an analytical method that takes a holistic perspective and focuses on the complex causal relationships between configurations of antecedent conditions and consequences (Ragin, 1989). QCA can be categorized into three types: Crisp-set qualitative comparative analysis (csQCA), multivalue qualitative comparative analysis (mvQCA), and fuzzy set qualitative comparative analysis (fsQCA), based on the type of variables. Compared to csQCA and mvQCA, fsQCA retains the advantages of qualitative data analysis and simplified configurations by transforming fuzzy-set data into truth tables (Ragin, 2009). FsQCA has been widely applied in research fields such as sociology and political science (Ragin, 2009), and has recently gained popularity in management and marketing (Misangyi et al., 2017).

Existing research on the influencing factors of GTFP mostly relies on conventional econometric models such as fixed-effects models and Tobit models. These models do not consider the combined and mutually substitutive effects of various factors on GTFP. GTFP is influenced by multiple factors that are often interrelated and jointly affect GTFP. Conventional econometric models assume independence between variables and linear causal relationships, which may result in overestimating the impact of individual factor on GTFP. FsQCA has been widely used in fields such as sociology and management. However, no literature is currently available on its application in the study of GTFP. FsQCA enables the study of multiple factors simultaneously, affecting the outcome variable through multiple concurrent mechanisms. It allows for the analysis of the interdependent impact of different factors on GTFP, facilitating the identification of optimal solutions and the exploration of configuration paths for improving GTFP.

In summary, in this study, the authors took the sample data from 30 provinces and municipalities across China and identified regional innovation capacity (TEC), digital financial development (DIGF), degree of marketization (MAR), economic development level (ECO), ER, and HUM as six key factors influencing GTFP. By innovatively introducing fsQCA into the research on GTFP, this study fills the gaps in conventional econometric models and provides theoretical insights into GTFP research. Moreover, the study provides multiple configuration pathways for achieving high GTFP and explores the consistency and substitutability among influencing factors, offering practical guidance for regions across China to select appropriate pathways for enhancing GTFP based on their resource endowments and development characteristics. Additionally, the findings of the study can serve as valuable reference for countries with similar economic development patterns as China.

RESEARCH DESIGN

Research Methods

FsQCA is a QCA tool based on Boolean algebra and set analyses. It allows to analyze complex causal phenomena and reveal asymmetric and multiple conjunctural causations (Ragin, 2009). Compared to conventional statistical methods, fsQCA can identify equivalent configuration pathways influencing the outcome variable. Additionally, it supports a holistic perspective, effectively avoiding the issue of multicollinearity among variables. The basic steps of using the fsQCA method include:

1. Selecting the antecedent conditions that influence the outcome variable.
2. Calibrating the raw sample data and constructing a table of set membership scores.
3. Testing whether each antecedent condition constitutes a necessary condition for the outcome variable.
4. Constructing a truth table by setting consistency thresholds, case frequencies, and proportional reduction in inconsistency (PRI) scores thresholds.
5. Simplifying the configuration pathways of the antecedent conditions through a QCA standardization to obtain complex solutions, simple solutions, and intermediate solutions, thus identifying the core conditions and supporting conditions that influence the outcome variable.

Variable Selection

Outcome Variable

The outcome variable in this study is the GTFP. The authors calculated the GTFP level of each province in China using the Slacks-Based Measure (SBM) directional distance function and the Global Malmquist-Luenberger (GML) index. First, the researchers used the SBM model to construct the production possibility set and the directional distance function that includes undesirable outputs, as Equations 1 and 2 illustrate:

$$P^t\left(x^t\right)=\left\{\begin{array}{c}\left(y^t,b^t\right):\sum_{k=1}^{K}Z_k^t y_{km}^t\geq y_{km}^t,\forall m;\\ \sum_{k=1}^{K}Z_{ki}^t b_{ki}^t=b_{ki}^t;\sum_{k=1}^{K}Z_k^t y_{kn}^t\leq x_{km}^t,\forall n;\sum_{k=1}^{K}Z_k^t=1,Z_k^t\geq 0,k=1,\ldots,K\end{array}\right\} \quad (1)$$

In Equation 1, t represents the time period and k represents the province or municipality, each of which represents a decision-making unit. $P^t\left(x^t\right)$ represents the production possibility set, Z_k^t represents the cross-sectional observation weights, x represents input factors, y represents desired outputs, b represents undesirable outputs; n (n= 1,...,N), m (m = 1,..., M), and i (i= 1,...,I) represent the number of input factors, desired output, and undesirable outputs, respectively:

$$S_V^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right) = \max_{S^x, S^y, S^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{S_n^x}{g_n^x} + \frac{1}{M+1}\left(\sum_{m=1}^{M}\frac{S_m^y}{g_m^y} + \sum_{i=1}^{1}\frac{S_i^b}{g_i^b}\right)}{2}$$

$$s.t. \sum_{k=1}^{K} Z_k^t x_{kn}^t + S_n^x = x_{k'n}^t, \forall n; \sum_{k=1}^{K} Z_k^t y_{km}^t - S_m^y = y_{k'm}^t, \forall m; \sum_{k=1}^{K} Z_k^t b_{ki}^t + S_i^b = b_{k'i}^t, \forall i; \quad (2)$$
$$\sum_{k=1}^{K} Z_k^t = 1, Z_k^t \geq 0, \forall n; S_m^y \geq 0, \forall m; S_i^b \geq 0, \forall i$$

In Equation 2, $S_V^G\left(x^{t,k'}, y^{t,k'}, b^{t,k'}, g^x, g^y, g^b\right)$ represents the SBM directional distance function. $\left(x^{t,k'}, y^{t,k'}, b^{t,k'}\right)$ represent the input, desired output, and undesirable output vectors for the k' th province. $\left(g^x, g^y, g^b\right)$ represents the direction vectors for input, desired output, and undesirable output, respectively. (S_n^x, S_m^y, S_i^b) represents the slack vectors of inputs and outputs.

Based on this, the authors calculated the GML index; the specific formula is as follows:

$$GML_t^{t+1} = \frac{1 + S_V^G\left(x^t, y^t, b^t; g\right)}{1 + S_V^G\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)} \quad (3)$$

GML_t^{t+1} represents the change in GTFP from period t to $t+1$. $GML_t^{t+1} > 1$ indicates an enhancement in GTFP in the $t+1$ period, compared to the t period, while the opposite indicates a decline in GTFP. Following Li et al.'s (2016) approach, the authors set the GTFP value in 2011 as 1 and, through cumulative multiplication, gradually calculated the GTFP values for each province/municipality in China between 2018 and 2020.

Table 1 presents the input-output indicators the authors used to calculate the GTFP. The calculation of capital stock follows Zhang et al.'s (2004) approach, where they conducted the estimation using the total fixed asset investment. The specific formula for calculating the capital stock is as follows:

Table 1. Input-output indicators

Variables	Primary Indicator	Secondary Indicator
GTFP	Input	Capital stock (unit: 100 million yuan).
		Total energy consumption (unit: 10,000 tons).
		End-of-year employment figure for each province (unit: 10,000 persons).
	Desired output	Gross regional product (unit: 100 million yuan).
	Undesirable output	Regional CO_2 emissions (unit: 1 million metric tons).
		Regional industrial SO_2 emissions, wastewater, and general industrial solid waste volume (unit: 10,000 metric tons).

$$\pi_{kt} = \pi_{kt-1}\left(1 - \delta_{kt}\right) + Q_{kt} \quad (4)$$

πk_t represents the capital stock of province k in year t, Q represents the total fixed asset investment, and δ is the depreciation rate of fixed capital, set at 9.6% (Zhang et al., 2004).

Condition Variables

- **Innovation Capacity:** TEC, represented by the China Regional Innovation Capacity Index (China Science and Technology Development Strategy Research Group & University China Innovation and Entrepreneurship Management Research Center, 2021), encompasses various aspects such as regional knowledge creation, knowledge acquisition, and innovation performance. Innovation can foster new business models and formats (Zheng et al., 2016). The sharing of knowledge innovation achievements between universities, firms, and research, on one side, and development institutions, on the other, enables the generation of new processes and products; the application of advanced technologies can effectively enhance the efficiency of various factors in TFP.
- **Digital Financial Development:** In the literature, the assessment of DIGF in China commonly implies the use of the China Inclusive Finance Index, jointly introduced by Peking University Digital Finance Research Center and Ant Financial. This index incorporates 33 indicators, including account coverage rate and credit services, and holds a certain level of authority and scientific significance. Therefore, in this study, the authors adopted this index to measure regional DIGF. Digital finance, as a next-generation financial service, can effectively facilitate the precise matching of fund supply and demand, expand the boundaries of financial services, and mobilize private capital. Moreover, digital financial services such as mobile payments inherently possess green attributes, contributing to the enhancement of regional GTFP.
- **Degree of Marketization:** Many scholars have used the Wang et al.'s (2021) marketization index to measure the regional MAR. This index covers various aspects such as nonstate economy, government-market relations, and product and factor markets, and has a certain representativeness in measuring the level of regional marketization. Therefore, in this study, the authors also used this index to measure the regional MAR. The advancement of marketization can help alleviate the distortion in labor and capital market factors and facilitate the optimal allocation of green resources. It plays a crucial role in enhancing the level of GTFP.
- **Economic Development Level:** ECO is represented by the regional real per capita GDP (unit: 10,000 yuan), with 2000 as the base year. When there is harmonious development between the economy and the environment, improving the ECO will also enhance GTFP.
- **Environmental Regulation:** Currently, no unified standard exists in academia for measuring the intensity of regional ER. In research literature, scholars commonly represent it by constructing composite evaluation indicators. In this study, the authors drew on Ren et al.'s (2020) approach, used the data of three waste emissions (industrial wastewater, sulfur dioxide, soot) in each province, and adopted the entropy value method to construct a composite index for evaluating the level of regional ER. The specific calculation steps were as follows.

The authors performed data standardization using the following Equations 5 and 6, where *k* represents the province (*k=1,…,30*), while *j* denotes the measurement indicator (*j=1,2,3*), X_{kj} represents the value of the *j*th indicator of the *k*th province, and X'_{kj} represents the standardized value of the *j*th indicator of the *k*th province:

Positive indicators: $X_{kj}^{'} = \dfrac{X_{kj} - \min\left\{X_j\right\}}{\max\left\{X_j\right\} - \min\left\{X_j\right\}}$ (5)

Negative indicators: $X_{kj}^{'} = \dfrac{\max\left\{X_j\right\} - X_{kj}}{\max\left\{X_j\right\} - \min\left\{X_j\right\}}$ (6)

Equation 7 illustrates the calculation of information entropy for each dimension indicator, where *u* represents the number of years (the selected ER indicator data in this study covers the years 2018-2020, and thus $u = 3$):

$$E_j = -\frac{1}{\ln(u)} \sum_{k=1}^{u} \frac{X_{kj}^{'}}{\sum X_{kj}^{'}} \ln \frac{X_{kj}^{'}}{\sum X_{kj}^{'}} \tag{7}$$

Equation (8) illustrates the calculation of weights for each indicator:

$$W_j = \frac{1 - E_j}{\sum_{j=1}^{3} \left(1 - E_j\right)} \tag{8}$$

Equation (9) shows the calculation of the composite ER index:

$$ER = \sum_{j=1}^{3} W_j X_{kj}^{'} \tag{9}$$

- **Human Capital:** HUM is represented by the average years of education in a region. Based on the educational system in China and the approach commonly used in literature: Average years of education = (number of individuals with no education * 0 + number of individuals with primary education * 6 + number of individuals with junior high school education * 9 + number of individuals with senior high school or vocational education * 12 + number of individuals with college or higher education * 16)/the total population aged 6 and above. A higher level of HUM generally indicates higher labor productivity. The level of HUM directly affects the speed of imitation and diffusion of green technologies in a region, thereby influencing the regional GTFP to some extent.

Data Description

In this study, the authors selected 30 provinces and municipalities across China as the sample cases. Due to significant data gaps in Tibet and the Hong Kong-Macao-Taiwan regions, the researchers excluded them from the sample to ensure data accuracy and availability. They sourced the data for the outcome variable and the antecedent conditions variable from various publications, including the *China Statistical Yearbook*, *China Industry Statistical Yearbook*, *China Statistical Yearbook on Environment*, and statistical bulletins or yearbooks of individual provinces/municipalities in China. The authors employed an interpolation method to fill in missing data points. The final dataset they used for fsQCA consisted of the average values of each variable between 2018 and 2020. Table 2 presents the descriptive statistics of the variables.

Data Calibration

Calibration is the process of assigning membership to a set of sample cases. In this process, three critical values must be set for the sample cases (Du et al., 2020; Schneider & Wagemann, 2012). The authors adopted the direct calibration method (Ragin, 2009), where they used the 90th, 50th, and 10th percentiles of the sample data as anchor points for full membership, crossover point, and full nonmembership, respectively (Fan et al., 2017). Table 3 presents the specific anchor point values for each data sample.

The researchers calibrated the variables using the fsQCA 3.0 software, in this study. Some calibrated samples having a membership score of 0.5 make it difficult to classify and include them in the truth table for analysis; thus, the authors followed Fiss's (2011) and Wagemann et al.'s (2016) approach by adding 0.001 to fractional values of membership scores less than 1. Table 4 presents the calibrated membership scores for the variables.

DATA ANALYSIS

Necessity Analysis

In this study, the authors conducted the necessity analysis of the antecedent conditions using the consistency and coverage indicators to examine whether each condition variable constitutes a necessary condition for high GTFP and its nonset. Equation 10 shows the calculation formula

Table 2. Descriptive statistics of variables

Variable		Mean	Std. dev	Minimum	Maximum
Outcome variable	GTFP	1.245	0.204	0.908	1.855
Condition variable	TEC	28.441	10.782	18.357	60.393
	DIGF	324.732	32.819	282.65	410.280
	MAR	7.749	2.239	3.690	12.000
	ECO	4.467	2.408	2.100	12.361
	ER	0.770	0.161	0.410	0.997
	HUM	9.373	0.927	7.903	12.782

Table 3. Variable calibration anchors

Variable		Full Membership	Crossover Point	Full Membership
Outcome variable	GTFP	1.482	1.216	1.006
Condition variable	TEC	45.896	24.612	19.488
	DIGF	364.483	318.120	292.727
	MAR	11.021	7.800	4.873
	ECO	7.525	3.496	2.259
	ER	0.965	0.788	0.534
	HUM	10.006	9.276	8.404

Table 4. Calibrated membership scores

ID	Province	GTFP	DIGF	HUM	MAR	ECO	TEC	ER
1	Beijing	1.000	0.991	1.000	0.911	0.951	0.991	0.971
2	Tianjin	0.931	0.841	1.000	0.981	0.991	0.661	0.951
3	Hebei	0.801	0.181	0.431	0.301	0.561	0.211	0.171
4	Shanxi	0.091	0.251	0.891	0.211	0.091	0.071	0.381
5	Neimenggu	0.431	0.051	0.881	0.051	0.701	0.031	0.521
6	Liaoning	0.801	0.301	0.931	0.301	0.721	0.331	0.321
7	Jilin	0.921	0.051	0.651	0.371	0.241	0.051	0.811
8	Heilongjiang	0.951	0.051	0.721	0.301	0.581	0.031	0.731
9	Shanghai	0.961	1.000	1.000	0.951	1.000	0.951	0.921
…	…	…	…	…	…	…	…	…
22	Chongqing	0.971	0.621	0.491	0.831	0.591	0.691	0.881
23	Sichuan	0.711	0.471	0.151	0.511	0.341	0.611	0.451
24	Guizhou	0.081	0.051	0.011	0.061	0.031	0.281	0.771
25	Yunnan	0.201	0.151	0.041	0.041	0.081	0.121	0.751
26	Shaanxi	0.291	0.581	0.671	0.591	0.241	0.621	0.691
27	Gansu	0.081	0.031	0.051	0.061	0.041	0.061	0.911
28	Qinghai	0.051	0.011	0.021	0.011	0.151	0.111	0.951
29	Ningxia	0.041	0.051	0.161	0.111	0.051	0.091	0.911
30	Xinjiang	0.011	0.061	0.351	0.031	0.321	0.051	0.051

for the consistency indicator, and Equation 11 illustrates the calculation formula for the coverage indicator. In the Equations, α_k represents the membership score of the antecedent variable, while β_k represents the membership score of the outcome variable. In fsQCA, it is generally understood that when the consistency threshold value is greater than 0.9, the antecedent variable can be regarded as a necessary condition for the outcome variable. This means that, whenever the outcome occurs, the specific antecedent condition will always be present. A higher coverage value indicates that a single condition or a combination of conditions α has a stronger explanatory power for the outcome β (Du et al., 2017). Table 5 presents the calculation results; all the consistency indicators have values below 0.9. This indicates that the condition variables and their nonsets are not necessary conditions for high GTFP or nonhigh GTFP. The analysis results indicate that individual condition variables have limited effects on achieving high GTFP. It is, therefore, necessary to study the combination pathways for achieving high GTFP from a configurational perspective:

$$Consistency\left(\alpha_k \leq \beta_k\right) = \frac{\min\left(\alpha_k, \beta_k\right)}{\beta_k} \tag{10}$$

$$Coverage\left(\alpha_k \leq \beta_k\right) = \frac{\min\left(\alpha_k, \beta_k\right)}{\beta_k} \tag{11}$$

Table 5. Results of necessary condition analysis

Variable	GTFP		~GTFP	
	Consistency	Coverage	Consistency	Coverage
TEC	0.685	0.788	0.443	0.484
~TEC	0.551	0.511	0.806	0.708
DIGF	0.667	0.729	0.484	0.502
~DIGF	0.545	0.527	0.739	0.678
MAR	0.738	0.795	0.443	0.452
~MAR	0.491	0.482	0.799	0.743
ECO	0.775	0.799	0.450	0.440
~ECO	0.457	0.467	0.794	0.770
ER	0.637	0.624	0.680	0.632
~ER	0.624	0.673	0.596	0.609
HUM	0.740	0.753	0.507	0.490
~HUM	0.498	0.516	0.744	0.731

Note: "~" indicates "non."

To construct the truth table, the authors drew on Fiss (2011) by setting the consistency threshold to 0.8 and the threshold of case number to 1. Moreover, Greckhamer et al. (2018) noted that configurations with PRI scores lower than 0.5 exhibit significant inconsistency. Therefore, considering the PRI scores and the specific circumstances of the sample cases, the authors set the PRI consistency threshold to 0.7 (Du & Kim, 2021; Greckhamer et al., 2018) to further refine the truth table. Table 6 presents the truth table for the sample.

Analysis of Condition Combinations

In this study, the authors employed fsQCA 3.0 software to conduct a standardized analysis of the truth table, identifying simple, intermediate, and complex solutions. Specifically, the analysis of simple solutions encompasses the widest range and includes configurations with actual observed cases and all "logical remainders." The analysis of intermediate solutions excludes the "complex" logical remainders, while complex solutions only analyze configurations with actual observed cases. Table 7 presents the results of the condition combination analysis. Among all the condition combinations in the three types of solutions, except for a few combinations with consistency below 0.8, the consistency of all other combinations is above the consistency threshold of 0.8. The total coverage of the simple solution is 0.821, indicating that the three combination pathways in the simple solution can explain 82.1% of the increase in GTFP. The total coverage of the intermediate solution is 0.776, indicating that the five combination pathways in the intermediate solution collectively explain 77.6% of the increase in GTFP.

The authors identified the configuration pathways for achieving high GTFP based on the intermediate and simple solutions. A condition variable is considered a core condition when it appears in both the intermediate and simple solutions, whereas it is considered a supporting condition (Du & Jia, 2017) if it only appears in the intermediate solution. As a result, the authors identified three main pathways for achieving high GTFP (Table 8).

Table 8 indicates that "high TEC," "high MAR," and "high ECO" appear as core conditions in both main pathways. It is evident that TEC, MAR, and ECO are important factors for enhancing GTFP in China. Moreover, a "high level of DIGF" appears as a supporting condition in Pathway

Table 6. Truth table

TEC	DIGF	MAR	ECO	ER	HUM	GTFP	Cases	Raw Consist	PRI Consist
1	1	1	1	1	1	1	5	0.978	0.962
1	0	1	1	0	1	1	4	0.989	0.958
1	1	1	1	1	0	1	3	0.964	0.853
1	0	1	0	0	0	1	2	0.957	0.845
0	0	0	1	0	1	1	2	0.924	0.818
1	1	1	0	0	0	1	2	0.951	0.813
0	0	0	1	0	0	1	2	0.928	0.811
1	1	1	1	0	0	1	1	0.951	0.808
0	0	0	1	1	1	1	1	0.898	0.743
1	1	1	1	0	1	1	1	0.906	0.723
0	1	1	0	0	0	0	1	0.915	0.686
1	1	1	0	1	1	0	1	0.865	0.599
0	0	0	0	1	1	0	1	0.798	0.588
0	0	0	0	0	1	0	1	0.787	0.535
…	…	…	…	…	…	…	…	…	…

Table 7. Results of condition combination analysis

	Condition Combination	Raw Coverage	Unique Coverage	Consistency
Complex solution	TEC*DIGF*MAR*ECO	0.601	0.232	0.865
	~TEC*~DIGF*~MAR*ECO*~ER	0.343	0.013	0.933
	~TEC*~DIGF *~MAR*ECO*HUM	0.326	0.024	0.848
	TEC*MAR*~ECO*~ER*~ HUM	0.268	0.029	0.944
	TEC*MAR*ECO* ~ER*HUM	0.347	0.007	0.910
Solution coverage				0.776
Solution consistency				0.832
Parsimonious solution	ECO	0.775	0.317	0.799
	TEC*~ER	0.474	0.004	0.793
	TEC*~HUM	0.403	0.004	0.833
Solution coverage				0.821
Solution consistency				0.772
Intermediate solution	TEC*MAR*~ECO* ~ER*~HUM	0.268	0.029	0.944
	TEC*MAR*ECO* ~ER*HUM	0.347	0.006	0.910
	TEC*DIGF*MAR*ECO	0.601	0.232	0.865
	~TEC*~DIGF*~MAR*ECO*~ER	0.343	0.013	0.933
	~TEC*~DIGF*~MAR*ECO*HUM	0.326	0.024	0.848
Solution coverage				0.776
Solution consistency				0.832

Table 8. Configurational pathways for achieving high green total factor productivity

Condition variable \ Pathways	A	B		C	
		B1	B2	C1	C2
TEC	●	⊗	⊗	●	●
DIGF		⊗	⊗		•
MAR	●	⊗	⊗	●	●
ECO	⊗	●	●	●	●
ER	⊗	⊗		⊗	
HUM	⊗		•	•	
Raw coverage	0.268	0.343	0.326	0.347	0.601
Unique coverage	0.029	0.013	0.024	0.006	0.232
Consistency	0.944	0.933	0.848	0.910	0.865
Solution coverage	0.776				
Solution consistency	0.832				

Note: ● = Core condition present; ⊗ = core condition absent; • = supporting condition present; ⊗ = supporting condition absent; "space" indicates the condition can be present or absent.

C2, contributing to the enhancement of GTFP to some extent. The condition of "high ER" does not play a significant role in any of the pathways, indicating that overly stringent ERs do not necessarily promote the enhancement of GTFP. One possible reason is that a certain level of ERs can stimulate proactive green innovation by firms. However, overly stringent ERs may divert more funds toward pollution control, leading to a "crowding-out effect" on business production and innovation. The three main pathways can be classified into the following three configurational patterns:

1. **Innovation Market-Oriented Pathway:** The configurational pattern of this main pathway is "TEC*MAR*~ECO* ~ER*~HUM," where high TEC and a high MAR are the core conditions for achieving high GTFP. Table 8 indicates that "high TEC" and "high MAR" appear simultaneously in both main pathways. Moreover, as other antecedent conditions change, "high TEC" and "high MAR" always appear together or are both absent. This indicates that the two factors have high intensity and high consistency. Technological innovation can drive energy conservation and reduce emissions in firms by incorporating cutting-edge scientific and technological advancements throughout production. This key technological pathway enhances the level of GTFP by enabling environmentally friendly production practices. A high MAR helps to reduce distortions in factor markets and promote the flow of resources to firms with high productivity and strong green TEC. Therefore, the combination of high TEC and MAR can increase regional GTFP.
2. **Economic Growth-Oriented Pathway:** This main pathway consists of two subpathways with the following configuration patterns: "~TEC*~DIGF*~MAR*ECO*~ER" and "~TEC*~DIGF*~MAR*ECO*HUM." A high ECO is a core condition for achieving high GTFP. When a country reaches a certain level of economic development, society not only focuses on the pace of economic growth, but also pays more attention to the quality of economic development. In their production processes, firms strive to balance production efficiency with energy conservation and emission reduction to enhance market competitiveness. Moreover,

consumers also become more environmentally conscious and pursue greener products. These factors significantly contribute to the enhancement of a society's GTFP.

3. **Integrated Synergistic Pathway:** This main pathway also consists of two equivalent subpathways. The configuration pattern of subpathway C1 is "TEC* MAR*ECO* ~ER*HUM," where high TEC, high MAR, and high ECO serve as core conditions, whereas high HUM level acts as a supporting condition. Subpathway C2 has the configuration pattern of "TEC*DIGF*MAR*ECO," where high TEC, high MAR, and high ECO serve as core conditions, whereas a high level of DIGF acts as a supporting condition. Subpathways C1 and C2 demonstrate that "HUM" and "DIGF" can be mutually substituted. This is because, driven by strategies such as "make China a talent-strong country," the labor force quality of Chinese firms has significantly improved in recent years, leading to the innovation in green technologies and the improved production efficiency. Green innovation research and development in firms often involves long cycles and requires substantial investment. Traditional financial institutions, to mitigate risks, are often reluctant to provide financing for such endeavors. Digital finance, through the development of green financial products and the use of technologies such as cloud computing and big data, can effectively alleviate information asymmetry issues. It can accurately identify green projects with innovation potential, thereby improving the efficiency of resource allocation for green innovation. Therefore, under the conditions of high TEC and a high MAR, the presence of high HUM or high DIGF level as supporting conditions can contribute to the enhancement of regional GTFP.

CONCLUSION

In this study, the authors employed the fsQCA method to examine the impact of TEC, DIGF, MAR, ECO, ERs, and HUM, as well as their combinations, on GTFP in 30 provinces/municipalities (excluding Tibet and Hong Kong, Macau, and Taiwan) across China. The research findings indicate that enhancing regional GTFP requires the interplay of multiple factors, and no single factor alone can serve as a necessary condition for achieving high levels of GTFP. The three pathways the authors identified, composed of the six factors mentioned above, demonstrate the diverse approaches different regions can adopt to enhance GTFP:

1. Innovation market-oriented pathway, where high TEC and MAR are the core conditions for achieving high GTFP. Furthermore, by integrating the three configuration pathways, the authors discovered a high intensity and high consistency between TEC and MAR.
2. Economic growth-oriented pathway, where a high ECO is the core condition for achieving high GTFP.
3. Integrated synergistic pathway, where high TEC, MAR, and ECO are the core conditions, while a high level of HUM or DIGF supports high GTFP. In this particular configuration, DIGF and HUM can be mutually substituted in driving high levels of regional GTFP.

Based on this finding, the authors propose the following policy recommendations.

The high-quality economic development and transition of industries cannot be achieved without a supportive regional market environment for green development. Local governments should improve regional institutional and intellectual property protection systems, cultivate a market-oriented business environment with proper regulations, and facilitate the efficient allocation of green innovation resources. Government agencies responsible for industries should concentrate research, funding, and other innovation resources to address common bottlenecks in regional green innovation, stimulate proactive engagement of enterprises with different ownerships in green innovation and creation, and foster a consensus on green innovation throughout society. Universities, research institutions, and key energy-consuming enterprises should leverage modern information technologies to establish a regional platform for the conversion and sharing of green technological achievements. This platform should aim to break information silos and facilitate the full sharing of fundamental technologies and innovative scientific achievements related to green development across different industries and enterprises. Through the synergistic development of innovation and marketization, it can promote the improvement of regional GTFP and achieve high-quality development.

Local governments should develop environmental regulatory policies that align with national requirements for high-quality economic development, taking into account the local ECO and ecological carrying capacity. These policies should focus on both administrative and market-based institutions essential for environmental governance and establish a sound environmental regulatory framework. By doing so, they can encourage energy-consuming enterprises to actively engage in green innovation and the development of green products. Enhanced coordination and cooperation among various departments in the region are needed to change the current situation where local governments separately formulate policies for economic growth and environmental governance. Efforts should be made to improve the institutional linkages between economic growth and ERs, with the aim of achieving a harmonious relationship between high-quality economic development and environmental protection. This will ensure that regional economic growth is accompanied by a simultaneous improvement in the level of GTFP.

There are regional disparities in ECO across different areas of China. Therefore, local governments should choose their configuration pathways based on regional resource endowments. Taking the development of digital finance as an example, local governments in economically developed regions can provide targeted policy support to financial institutions to expand their digital finance-related businesses. By leveraging technologies such as artificial intelligence and big data, digital finance can replace HUM and improve the efficiency of financial services for the green real economy. In underdeveloped regions, government agencies should increase investment in information infrastructure to bridge the digital divide between regions. This includes expanding the boundaries of digital financial services and improving the accessibility of digital finance for key stakeholders. Additionally, by establishing interregional digital financial service cooperation platforms, innovating composite financing methods (e.g., order financing and R&D financing), and relying on regional core enterprises to create a digital financial closed-loop ecosystem, more financing opportunities can be provided for regional traditional green industries, thereby fully leveraging the promoting role of digital finance in green development.

COMPETING INTERESTS

The authors of this publication declare that there are no competing interests.

FUNDING AGENCY

This research was supported by the Innovation Strategy Research Project of Fujian Provincial Department of Science and Technology (2022R0104).

REFERENCES

Chen, S. Y. (2010). Green Industrial Revolution in China:A perspective from the change of environmental total factor productivity. *Economic Research Journal, 45*(11), 21—34+58.

China Science and Technology Development Strategy Research Group & University China Innovation and Entrepreneurship Management Research Center. (2021). *China regional innovation capability evaluation report 2021*. Science and Technology Literature Publishing House.

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240. doi:10.1006/jema.1997.0146

Cui, X. H., & Lin, M. Y. (2019). How does foreign direct investment affect the green total factor productivity of enterprises empirical analysis based on Malmquist-Luenberger index and PSM-DID model. *Business and Management Journal*, *41*(3), 38–55. doi:10.19616/j.cnki.bmj.2019.03.003

Dong, Y. D., & Xia, W. H. (2022). Foreign direct investment and green total factor productivity in China: An empirical study based on system GMM and threshold model. *Shanghai Journal of Economics*, *407*(8), 94–106. doi:10.19626/j.cnki.cn31-1163/f.2022.08.009

Du, Y. Z., & Jia, L. D. (2017). Configurable perspective and qualitative comparative analysis (QCA): A new way of management research. *Journal of Management World*, *285*(6), 155–167. doi:10.19744/j.cnki.11-1235/f.2017.06.012

Du, Y. Z., & Kim, P. H. (2021). One size does not fit all: Strategy configurations, complex environments, and new venture performance in emerging economies. *Journal of Business Research*, *124*, 272–285. doi:10.1016/j.jbusres.2020.11.059

Du, Y. Z., Liu, Q. C., & Cheng, J. Q. (2020). What kind of business environment ecology produces high entrepreneurial activity in cities: Analysis based on institutional configuration. *Journal of Management World*, *36*(9), 141–155. doi:10.19744/j.cnki.11-1235/f.2020.0143

Fan, D., Li, Y., & Chen, L. (2017). Configuring innovative societies: The crossvergent role of cultural and institutional varieties. *Technovation*, *66*, 43–56. doi:10.1016/j.technovation.2017.05.003

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420. doi:10.5465/amj.2011.60263120

Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, *16*(4), 482–495. doi:10.1177/1476127018786487

Han, J., Liu, Y., & Zhang, X. W. (2017). The market orientation, environmental regulation and China's green economic growth. *Comparative Economic & Social Systems*, *193*(5), 105–115. 1003-3947(2017)05-0105-11

He, L. Y., & Qi, X. F. (2022). Environmental regulation and green total factor productivity: Evidence from Chinese industrial enterprises. *Economic Perspectives*, *736*(6), 97–114.

Li, B., Qi, Y., & Li, Q. (2016). Fiscal decentralization, FDI and green total factor productivity: An empirical test based on panel data dynamic GMM method. *Journal of International Trade*, *403*(7), 119–129. doi:10.13510/j.cnki.jit.2016.07.011

Liu, C. J., Zhang, S. H., & Li, X. (2023). The impact of green credit on regional green total factor productivity: An empirical test based on provincial panel data in China. *Nanjing Journal of Social Sciences*, *425*(3), 28–39. doi:10.15937/j.cnki.issn1001-8263.2023.03.004

Liu, D. D., Zhu, X. Y., & Wang, Y. F. (2020). China's agricultural green total factor productivity based on carbon emission: An analysis of evolution trend and influencing factors. *Journal of Cleaner Production*, *278*, 123692. doi:10.1016/j.jclepro.2020.123692

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing causal complexity: The emergence of a neo-configurational perspective. *Journal of Management*, *43*(1), 255–282. doi:10.1177/0149206316679252

Ragin, C. C. (1989). *The comparative method: Moving beyond qualitative and quantitative strategies*. University of California Press.

Ragin, C. C. (2009). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press., doi:10.1016/j.technovation.2017.05.003

Ren, X. S., Liu, Y. J., & Zhao, G. H. (2020). The impact and transmission mechanism of economic agglomeration on carbon intensity. *Zhongguo Renkou Ziyuan Yu Huanjing*, *30*(4), 95–106. doi:10.12062/cpre.20200113

Schneider, C. Q., & Wagemann, C. (2012). *Set-theoretic methods for the social sciences: A guide to qualitative comparative analysis*. Cambridge University Press., doi:10.1017/CBO9781139004244

Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, *70*(1), 65–94. doi:10.2307/1884513

State Council of China. (2021). *The Guiding Opinions on Accelerating the Establishment of a Sound Economic System with Green, Low-Carbon, and Circular Development* (Publication No. 2021—4).

Sun, H. A., Zhu, L. M., Wang, A. Q., Wang, S. L., & Ma, H. J. (2022). Analysis of regional social capital, enterprise green innovation and green total factor productivity—Based on Chinese a-share listed companies from 2011 to 2019. *Sustainability (Basel)*, *15*(1), 34. doi:10.3390/su15010034

Wagemann, C., Buche, J., & Siewert, M. B. (2016). QCA and business research: Work in progress or a consolidated agenda. *Journal of Business Research*, *69*(7), 2531–2540. doi:10.1016/j.jbusres.2015.10.010

Wang, M. L., Pang, S. L., Hmani, I., Hmani, I., Li, C. F., & He, Z. X. (2020). Towards sustainable development: How does technological innovation drive the increase in green total factor productivity? *Sustainable Development (Bradford)*, *29*(1), 217–227. doi:10.1002/sd.2142

Wang, S., Yang, C. Y., & Li, Z. H. (2022). Green total factor productivity growth: Policy-guided or market-driven? *International Journal of Environmental Research and Public Health*, *19*(17), 10471. doi:10.3390/ijerph191710471 PMID:36078187

Wang, X. L., Hu, L. P., & Fan, G. (2021). *Provincial marketization index report of China (2021)*. Social Sciences Academic Press.

Xiao, H., & You, J. L. (2021). The heterogeneous impacts of human capital on green total factor productivity: Regional diversity perspective. *Frontiers in Environmental Science*, *9*, 713562. doi:10.3389/fenvs.2021.713562

Xiao, S. Y., Wang, S. S., Zeng, F. H., & Huang, W. C. (2022). Spatial differences and influencing factors of industrial green total factor productivity in Chinese industries. *Sustainability (Basel)*, *14*(15), 9229. doi:10.3390/su14159229

Xie, X. J., Wang, X. F., & Ren, X. G. (2021). The impact of marketization on green total factor productivity. *Journal of Beijing Institute of Technology*, *23*(1), 67–78. doi:10.15918/j.jbitss1009-3370.2021.2604

Xu, X. F., Cui, Y. J., & Zhong, Y. D. (2021). Impact of environmental regulation and FDI on green total factor productivity: Evidence from China. *Environmental Engineering and Management Journal*, *20*(2), 177–184. doi:10.30638/eemj.2021.018

Yang, W. P., Zhao, J. K., & Bian, S. Y. (2020). The contribution of educational human capital to China's green economic growth. *Education Economics*, *36*(2), 60–69. 1003-4870(2022)02-0060-10

Ye, A. Z., & Xiao, Z. X. (2023). The impact of industrial structure diversification on urban green total factor productivity: An empirical analysis based on spatial Durbin model. *Journal of Industrial Technological Economics*, *42*(3), 33–42. doi:10.3969/j.issn.1004-910X.2023.03.004

Yu, J. T., Zhang, R., & Gong, X. Y. (2022). How does digital finance affect green total factor productivity: Characteristics of dynamic, identification of mechanism, and spatial effects? *Modern Economic Science*, *44*(6), 42–56. 1002-2848-2022(06)-0042-15

Zhang, J., Wu, G. Y., & Zhang, J. P. (2004). The estimation of China's provincial stock: 1952-2000. *Economic Research Journal*, *39*(10), 35–44.

Zhao, J. W., Zhang, Y. X., Chen, A. H., & Zhang, H. Q. (2022). Analysis on the spatio-temporal evolution characteristics of the impact of China's digitalization process on green total factor productivity. *International Journal of Environmental Research and Public Health*, *19*(22), 14941. doi:10.3390/ijerph192214941 PMID:36429659

Zheng, Y. J., Wang, Z. Y., & Sun, X. T. (2016). Analysis of the impact of entrepreneurship and innovation policies on entrepreneurial enterprises. *Chinese Public Administration*, *371*(5), 154–155. doi:10.3782/j.issn.1006-0863.2016.05.030

Zhu, Y., & Zhang, J. T. (2022). The impact of digital finance development on green and low-carbon transformation of urban economy. *Urban Problems, 327*(10), 64—71+81. 10.13239/j.bjsshkxy.cswt.221007

Yani Guo is a researcher working in the Center for Efficiency and Productivity Research of Minjiang University, China. She has her master's degree in economics from Fujian Normal University, China. Her research focuses on green economy and econometric analysis.

Yunjian Zheng is a professor at Minjiang University, China. He has his Ph. D. degree from Renmin University of China. His research focuses on industrial policy and innovation and entrepreneurship.