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Green development performance of water resources and its economic-related determinants

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Abstract

In the context of severe water shortage and pollution, enhancing the green total-factor productivity of water resources (GTFPWR) is critical for the green development of water resources. This study aims to propose a novel two-stage analytical framework, in which the GTFPWR is measured in the first stage and its economic-related determinants are examined in the second stage. In this two-stage analytical framework, we improve and integrate four classical methods, namely, the undesirable-super-slack-based measure, global Malmquist-Luenberger productivity index, system generalized method of moments and fixed-effects panel threshold models. The proposed analytical framework is capable of addressing four practical issues simultaneously: equal efficiency, undesirable outputs, impact scenarios and endogenous biases. We can thus more accurately and comprehensively evaluate the GTFPWR and its determinants. To validate the applicability and suitability of the proposed methodology, we collected the panel data about water resources across 30 provinces in China from 2005 to 2015 for an empirical study. The main findings of this study are as follows: *i*) the level of water utilization is a critical factor for the government to decide whether to increase the GTFPWR via foreign direct investment and trade; *ii*) the amount of wastewater should be effectively reduced to

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mitigate the conflicts between urbanization and the GTFPWR growth; *iii*) inland provinces, particularly Shanxi, Hainan and Yunnan, need to improve water technologies and management to increase their low-GTFPWR-growth rates. Our analytical framework is practical to evaluate water-use productivity and its determinants, while our empirical findings provide new insights into the green development of water resources and may shed light on future policies of environmental management.

Keywords

Water productivity; Two-stage framework; Economic determinants; Green development; Impact scenarios

Abbreviations

COD	Chemical Oxygen Demand
DEA	Data Envelopment Analysis
DMU	Decision-Making Unit
FDI	Foreign Direct Investment
FEPT	Fixed-Effects Panel Threshold
GMLPI	Global Malmquist-Luenberger Productivity Index
GTFPWR	Green Total-Factor Productivity of Water Resources
LWU	Level of Water Utilization
MLPI	Malmquist-Luenberger Productivity Index
PEC	Pure Efficiency Change
PPS	Production Possibility Set
PTC	Pure Technological Change
SBM	Slack-Based Measure
SEC	Scale Efficiency Change
STC	Scale Technological Change
SGMM	System Generalized Method of Moments
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
USSBM	Undesirable-Super-Slack-Based Measure
VRS	Variable Returns to Scale

1. Introduction

Water shortage is a global problem related to economic development (Fang and Chen, 2017). The Food and Agriculture Organization along with the World Water Council has reported that 40% of the world's population is facing water shortage and this proportion is expected to increase up to 67% by 2050. As the largest developing country, China's water use volume reached 601.5 billion m^3 in 2018. In particular, the agriculture, service and energy sectors consume a vast amount of freshwater (Chen and Chen, 2016; Wang et al., 2019). However, China has an insufficient water supply and its annual availability of renewable water resources per capita is only 25% of the world average (Guo et al., 2016). In addition, about 60% of the Chinese population is living in the northern provinces, where only 19% of the national water resources are stored (Kang et al., 2017). For instance, Xinjiang, Shandong, Jiangsu and Hebei provinces are facing extreme water shortage. Uneven distribution of water resources has deeply constrained the economic development in China (Fang and Chen, 2018a).

Even worse, the enormous volume of wastewater with a high proportion of chemical oxygen demand (COD) and ammonia nitrogen is directly or indirectly discharged into rivers and lakes, resulting in severe water pollution in most provinces of China. The volume of wastewater discharge reached 75.0 billion tons in 2018, while 5.5% of rivers and 16.1% of lakes were severely contaminated. Thus, efficient wastewater treatment is required to conserve a healthy environment. To address these long-existing issues, the Chinese government has implemented a variety of strategies in water supply and wastewater treatment since the late 1990s, such as the "South-to-North Water Transfer" and "Three Gorges Dam" Projects, along with the "Total Amount Control of Pollutant Emissions" policy (Bian et al., 2014). However, with rapid economic development and urbanization in recent years, it is still challenging to reduce water use and pollution.

The current context has inspired us to develop a new integrated methodology on how to achieve the green development of water resources (i.e., save water and minimize wastewater). In this study, we propose a novel two-stage integrated framework, where the green development performance of water resources is measured in the first stage and its determinants are examined in the second stage. A literature review of recent analysis methods and relevant drawbacks for a two-stage integrated framework is conducted in the following part.

In the first stage, the green development performance of water resources needs to be evaluated. Numerous studies have evaluated the green development performance of industrial sectors (Li et al., 2019; Shao et al., 2016; Yuan and Xiang, 2018) and areas, e.g., countries (Feng et al., 2017), provinces (Lin and Benjamin, 2017) and cities (Wang et al., 2018). In the literature, there are two mainstream evaluation approaches. The first approach applies weighted methods to measure the green development performance after indicator selection and data standardization. The analytic hierarchy process method (Chen et al., 2016) and entropy method (Sun et al., 2018; Wang et al., 2018) are widely used to calculate weights of indicators. After the weight assignment, the linear weighted sum method (Chen et al., 2016; Sun et al., 2018) or weighted-technique for order of preference by similarity to ideal solution (TOPSIS) method (Li et al., 2019) is used to sum up the weighted values of the indicators and obtain the final performance. The second approach implements either the data envelopment analysis (DEA) methods (Chen et al., 2019; Jin et al., 2019) or DEA-Malmquist methods (Feng et al., 2017; Lin and Benjamin, 2017; Yuan and Xiang, 2018) to evaluate the green development performance from efficiency and productivity perspectives, respectively. The DEA-Malmquist methods integrate the DEA methods with either the Malmquist productivity index or the Malmquist-Luenberger productivity index (MLPI) (Chung et al., 1997). The DEA-Malmquist methods, in which the productivity index is formulated by a ratio of two efficiencies, are more appropriate in dealing with temporal data compared with the single DEA methods.

Each approach has its own pros and cons. DEA-related methods can only use a limited number of indicators because numerous indicators generate many effective decision-making units (DMUs) and thus reduce the comparability of performances. On the contrary, the weighted methods have advantages as the number of indicators is unlimited and the indicator system can include many dimensions (e.g., economic dimension and environmental dimension). Owing to these two advantages, not only the overall performance can be comprehensively evaluated, but also its sub-performance can be presented as well. However, the weighted methods usually lack the objectivity in the following processes: determination of the dimensions of the indicator system, selection of numerous indicators, assignment of indicator weights and choice of the specific weighted method. Comparatively, the DEA-related methods are more objective because they can bypass calculations of indicator weights and data standardization. Another advantage of DEA-related methods is that their results can further be decomposed into technological development levels, resource management levels and scale effects, revealing the internal drivers of performance changes.

For evaluation content, weighted methods usually select the indicators that incorporate the classical "three factors" (i.e., economy, society and environment) (Chen et al., 2016; Li et al., 2019; Sun et al., 2018; Wang et al., 2018). In addition, several studies also include the natural system (Sun et al., 2018) and innovation indicators (Chen et al., 2016; Wang et al., 2018). Compared with weighted methods, most DEA-related methods use the "green total-factor" form (Chen et al., 2019; Feng et al., 2017; Jin et al., 2019; Lin and Benjamin, 2017; Yuan and Xiang, 2018), which includes capital stock, labour, economic output and environmental indicators.

As for the green development performance of water resources, it is appropriate to measure it by the use of DEA-related methods from the efficiency and productivity perspectives due to the following reasons: *i*) the DEA-related methods are more objective compared with the weighted methods; *ii*) the performance calculated by the DEA-related methods can be decomposed as mentioned previously;

iii) the disadvantage of a limited number of indicators is minimized as this study only focuses on water resources; *iv*) the green total-factor efficiency and productivity calculated by DEA-related methods are widely adopted to denote the green development performance (Chen et al., 2019; Feng et al., 2017; Li and Song, 2016; Lin and Benjamin, 2017; Shao et al., 2016; Yuan and Xiang, 2018).

Although the above articles have measured the green development performance from efficiency and productivity perspectives, few works have considered water resources. The following recent studies have contributed to evaluating water-use efficiency and productivity from *i*) regional perspective (e.g., provincial level (Song et al., 2018), urban level (Abbott et al., 2012)); *ii*) sectoral perspective (e.g., agricultural sector (G. Wang et al., 2015), industrial sector (Y. Wang et al., 2015)); and *iii*) systematic perspective (e.g., socio-economic system (Fang et al., 2014), multi-country system (Hoekstra and Mekonnen, 2012) and multi-sector system (Fang and Chen, 2015)). To measure the green total-factor productivity of water resources (GTFPWR), we consider the following DEA-Malmquist method, which is composed of the undesirable-slack-based measure (SBM) method (Cecchini et al., 2018) and global Malmquist-Luenberger productivity index (GMLPI) (Pastor and Lovell, 2005). The undesirable-SBM is an improved DEA method that can incorporate undesirable outputs (e.g., considering environmental impacts of water resources use), while the GMLPI is an improved MLPI that can address the existing drawbacks of traditional MLPI (see Section 3.2).

In the second stage, regression methods, especially the so-called Tobit method, are necessary for evaluating determinants of water-use productivity (Frija et al., 2009; Khoshroo et al., 2013; G. Wang et al., 2015). The reason for using the Tobit method is that the efficiency values of efficient DMUs are all equal to one when calculated by the classical DEA method, i.e., the efficiency values are censored. Due to the censored data, it is more proper to establish a DEA-Tobit two-stage analytical framework rather than other analytical frameworks to examine the determinants of efficiency and productivity. However, the classical DEA-Tobit analytical framework has two defects. First, excessive input and output indices produce many efficient DMUs with equal efficiency values in the production frontier. To avoid this defect, many studies have examined the determinants by the use of super-efficiency approach (Li and Dewan, 2017; Li and Shi, 2014). This approach can obtain uncensored efficiency values, based on which we can adopt more developed regression methods in addition to the Tobit method. Second, the classical Tobit method, without instrumental variables, fails to eliminate endogenous biases when evaluating the determinants. (Kuo and Yu, 2013; Vranken and Swinnen, 2006). In this case, the system generalized method of moments (SGMM), with fewer restrictions imposed on the error term, was recently applied to solve the endogenous biases (Biresselioglu et al., 2016). Here, we propose an improved two-stage analytical framework to simultaneously address the above two defects (i.e., equal efficiency and endogenous biases). In this framework, the SGMM (Blundell and Bond, 1998) is adopted in the second stage based on the super-efficiency values calculated by undesirable-super-slack-based measure (USSBM) in the first stage. Note that the USSBM is developed by integrating the super-efficiency approach with an undesirable-SBM method.

Regarding the determinants of water resource use, current papers have studied numerous determinants at a macro-level, including economic development (Zhang et al., 2015), urbanization (Bao and Chen, 2015), industrial structure (Shang et al., 2017), food production (Liu et al., 2019), energy production (Fang and Chen, 2018b; Urbaniec et al., 2018), technological development (Njiraini and Guthiga, 2013), population growth (Fan et al., 2017), regional spillover effect (Fang et al., 2019), foreign trade (Eisenbarth, 2017), and foreign direct investment (FDI) (Bossio et al., 2012). However, few studies have examined their effects on water resource use in different scenarios. To achieve this, we integrate the fixed-effects panel threshold (FEPT) method (Hansen, 1999) with the SGMM method in the second stage of the proposed two-stage analytical framework.

In brief, there are four existing research gaps in previous analysis methods for the green development of water resources: ignorance of undesirable outputs, inattention to equal efficiency, neglect of impact scenarios and endogenous biases. To fill these gaps, this study aims to develop a more advanced two-stage analytical framework by integrating the USSBM and the GMLPI to measure the GTFPWR in the first stage. Then, the SGMM and the FEPT methods are applied in the second stage to examine certain economic-related determinants of the green development of water resources.

The remainder of the paper is organized as follows. Section 2 explains the relationship between economic-related determinants and green development of water resources. The methodological details of the proposed two-stage analytical framework are presented in Section 3. In Section 4, the computational results are discussed through an empirical study. Finally, the conclusions are drawn in Section 5.

2. Economic-related determinants

The changes in economic structure have played a major role in water resource use since the Chinese government implemented the reform and opening-up policy in 1978. At the macro-level, the green development of water resources can be affected by multiple factors, of which this study focuses on five economic-related factors, including economic development, urbanization, FDI, foreign trade and population scale. These five factors are selected based on data availability, previous literature (Bao and Chen, 2015; Bossio et al., 2012; Eisenbarth, 2017; Fan et al., 2017; Zhao and Chen, 2014) and their critical roles in water resource use. The relevance of these factors to water resource management is presented in the following analysis, where the green development perspective (i.e., resource-saving and environmentally friendly perspective) is highlighted particularly.

Economic development

In the light of the environmental Kuznets curve (Olale et al., 2018), the green development of water resources may benefit from economic development because of the four following reasons: the higher investment in research and development, increasing water supply facilities and wastewater treatment plants, more environmentally friendly industrial structure and increased awareness of water conservation. Economic development supports a higher investment in research and development which can improve water-efficient technologies (Li et al., 2019). It also contributes to the construction of water supply facilities and wastewater treatment plants, thereby promoting the green development of water resources. Moreover, in provinces with substantial heavy industries**,** economic development usually triggers a beneficial upgrading of industrial structure, from a resource-intensive structure to a service-oriented or high-tech-intensive structure which is more environmentally friendly. In addition, economic development can raise public awareness of water conservation when material life is improved with economic development. However, according to the “Jevons paradox” (Gunderson and Yun, 2017), economic development would demand more water, intensifying water stress and thus counterbalancing the positive effects of economic development. In other words, a vicious cycle may be formed where greater efficiency in resource use leads to faster economic growth, which in turn stimulates more consumption and finally results in higher system expense for remediation. This cycle is unfavourable for the green development of water resources.

Urbanization

Urbanization has an advantageous scale effect on water resource use because urban areas usually have sufficient water supply facilities and wastewater treatment plants. In this case, water supply and pollution control can be more efficient due to centralized water processing. But on the other hand, in urban areas, there is a challenge in the green development of water resource given the rapid development of catering, entertainment and tourism industries, etc. For example, in 2016, the Chinese Environmental Minister reported that each percentage point increase in the urbanization rate resulted in 1.15 billion tons of extra sewage. In addition, urban areas with higher living standards demand more freshwater than rural areas (Li and Chen, 2009), e.g., in 2018, domestic water use per capita was 225 L/d in China's urban areas while it was 89 L/d in rural areas.

Foreign direct investment

Regions with the higher FDI may have advantages in water resource use due to increased technology transfer, person-to-person communication, encouragement of environmental practices, demonstration effects and environmental performance. FDI is a driving factor in expanding the channel of the supply chain, which is critical to the transfer of advanced water-related technology. Meanwhile, FDI promotes person-to-person communication between different countries' enterprises; this communication facilitates the diffusion of environmental tacit knowledge (Hou et al., 2014). In addition, foreign enterprises can encourage other domestic enterprises in their extended supply chain to improve their environmental practices (Albornoz et al., 2009). Similarly, some scholars have claimed that foreign enterprises can improve local environmental performance through demonstration effects, by which local enterprises can learn advanced experiences from foreign enterprises (Huber, 2008; Letchumanan and Kodama, 2000). In developing countries, foreign enterprises may adopt better environmental management and technologies to abate contamination compared with domestic enterprises (Eskeland and Harrison, 2003). This view is supported by Wang and Jin (2007) who confirmed that foreign enterprises in China have a better environmental performance than local enterprises. Despite these advantages, FDI may pollute water bodies due to the transfer of pollution-intensive industries. Developed countries usually implement stricter environmental regulations, which generate additional production costs. In this case, some foreign enterprises in developed countries shift substantial pollution-intensive industries to developing countries but adopt lower environmental standards (Tiwari et al., 2013).

Foreign trade

Foreign trade may bring about positive impacts on green development of water resources due to more learning opportunities, cleaner water technology and equipment, lower demand for domestic production as well as higher green trade barriers. Foreign trade often provides domestic enterprises with opportunities to learn about water-use practices from overseas organizations. Apart from this, foreign trade may enable developing countries to import new clean water technology and equipment. Moreover, a substantial proportion of imports minimizes the demand for domestic production and thus reduces the total amount of domestic water contamination. In addition, growing green trade barriers can force the import and export enterprises to adopt clean technology (Alvarez and López, 2005). However, some scholars believed that certain export enterprises in China are pollution-intensive (Liu and Diamond, 2005; Yan and Yang, 2010). Even worse, the export enterprises in developing countries may adopt lower environmental standards to curb their production costs, resulting in the "pollution haven" effect (Prakash and Potoski, 2006).

Population scale

On one hand, a growing population expands the scale of economic activities and thus generates the economies of scale (Li et al., 2019), which increases the water-use productivity to some extent. On the other hand, water consumption and wastewater discharge can increase rapidly with population growth as daily activities cannot be separated from the water resources (Li and Chen, 2009).

According to the above relationships between economic-related determinants and the green development of water resources, each relationship is intricate as these five determinants have both positive and negative effects in different cases. Therefore, it is necessary to examine the dominant effects by conducting an empirical analysis.

3. Methodology

In this section, an integrated and improved two-stage analytical framework is established to measure the green development performance of water resources and its economic-related determinants. In the first stage, the USSBM and GMLPI are depicted, while the SGMM and FEPT are presented in the second stage.

3.1 Undesirable-super-slack-based measure

In the first stage, an integrated USSBM model was adopted through the combination of the undesirable-SBM model and the super-SBM model. In comparison, the integrated USSBM model has advantages in simultaneously dealing with the undesirable outputs and the equal efficiency problems.

In this USSBM model, it is assumed that there are n provinces, each of which is a DMU with m inputs, q_1 desirable outputs and q_2 undesirable outputs. The input matrix X, desirable output matrix Y and undesirable output matrix B are defined as Eqs. (1)-(3):

$$X = [x_1, x_2, \dots x_n] \in R_+^{m\times n}, \tag{1}$$

$$Y = [y_1, y_2, \dots y_n] \in R_+^{q_1\times n}, \tag{2}$$

$$B = [b_1, b_2, \dots b_n] \in R_+^{q_2\times n}, \tag{3}$$

where x, y and b stands for the $m \times 1$ input vector, $q_1 \times 1$ desirable output vector and $q_2 \times 1$ undesirable output vector, respectively. The subscripts of x, y and b indicate the serial numbers of DMU and R_+ represents the set of positive real numbers. The production possibility set (PPS) is denoted as P and defined by Eq. (4):

$$P = \{(x, y, b): x\ can\ produce\ (y, b)\ |x \geq X\lambda, y \geq Y\lambda, b \geq B\lambda\}, \tag{4}$$

where λ denotes the $n \times 1$ weighted vector.

Given the above vectors, the integrated USSBM model for the k^{th} DMU was developed by the following Eqs. (5)-(10):

$$\min \quad \rho = \frac{1 + \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{h=1}^{q_2} s_h^{b-} / b_{hk}\right)} \tag{5}$$

subject to

$$\sum_{j=1, j\neq k}^{n} x_{ij}\lambda_j - s_i^- \leq x_{ik},\ i = 1, \dots, m; j = 1, \dots, n | j \neq k, \tag{6}$$

$$\sum_{j=1, j\neq k}^{n} y_{rj}\lambda_j + s_r^+ \geq y_{rk},\ r = 1, \dots, q_1; j = 1, \dots, n | j \neq k, \tag{7}$$

$$\sum_{j=1, j\neq k}^{n} b_{hj}\lambda_j - s_h^{b-} \leq b_{hk},\ h = 1, \dots, q_2; j = 1, \dots, n | j \neq k, \tag{8}$$

$$1 - \frac{1}{q_1 + q_2}\left(\sum_{r=1}^{q_1} s_r^+ / y_{rk} + \sum_{h=1}^{q_2} s_h^{b-} / b_{hk}\right) > 0,$$

$$r = 1, \dots, q_1; h = 1, \dots, q_2; j = 1, \dots, n | j \neq k, \tag{9}$$

$$\lambda, s^-, s^+, s^{b-} \geq 0, \tag{10}$$

where ρ is the efficiency value. x_{ik}, y_{rk} and b_{hk} denote the i^{th} input, r^{th} desirable output and h^{th} undesirable output for the k^{th} DMU, respectively. s_i^-, s_r^+ and s_h^{b-} represent the slacks of the i^{th} input, r^{th} desirable output and h^{th} undesirable output, respectively. x_{ij}, y_{rj} and b_{hj} signify the i^{th} input, r^{th} desirable output and h^{th} undesirable output for the j^{th} DMU. λ_j indicates the weight of the j^{th} DMU. $s^-, s^+,$ and s^{b-} stand for the $m \times 1$ vector of input slacks, $q_1 \times 1$ vector of desirable output slacks and $q_2 \times 1$ vector of undesirable output slacks.

The users have the freedom to decide their own inputs and outputs based on different real-world applications. The real-world application of this study is to measure the green development performance of water resources. For the k^{th} province, there are three inputs (x_{1k}, x_{2k}, x_{3k}), which denote the amount of capital stock, quantity of labour and volume of water use, respectively. There is one desirable output (y_{1k}) indicating the GDP, while there are two undesirable outputs (b_{1k}, b_{2k})

standing for the discharge volumes of COD and ammonia nitrogen. As a result, we can obtain water-use efficiencies by the application of the above USSBM model. The following subsection 3.2 shows how to use these efficiencies to calculate the growth rate of GTFPWR by applying the GMLPI, where the growth rate of GTFPWR represents the green development performance of water resources.

3.2 Global Malmquist-Luenberger productivity index

The classical MLPI contains multiple production possibility sets P over T periods, as defined by Eq. (11):

$$P = \{(x^t, y^t, b^t): x^t \; can\, produce \; (y^t, b^t), t = 1, 2, \ldots, T\}, \tag{11}$$

where the x^t, y^t and b^t denote the $m \times 1$ input vector, $q_1 \times 1$ desirable output vector and $q_2 \times 1$ undesirable output vector in period t.

However, the MLPI is not circular due to its geometric mean form, which may also result in an infeasible solution (Oh, 2010). On the contrary, the developed GMLPI resolves these shortcomings by adopting a single global PPS throughout the entire time horizon (Pastor and Lovell, 2005), as defined in Eq. (12):

$$P^g = P^1 \cup P^2 \cup \ldots \cup P^t \ldots \cup P^T, \tag{12}$$

where P^g denotes the global PPS consisting of all PPSs over periods, while P^t represents one PPS in period t.

By using the GMLPI, the growth rate of the GTFPWR was calculated as Eq. (13):

$$GMLPI(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}, x_k^t, y_k^t, b_k^t) = \frac{E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E^g(x_k^t, y_k^t, b_k^t)}, \tag{13}$$

where $GMPLI(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}, x_k^t, y_k^t, b_k^t)$ denotes the productivity growth rate of the k^{th} DMU from period t to period $t+1$. x_k^t, y_k^t and b_k^t represent the input vector, desirable output vector and undesirable output vector of the k^{th} DMU in period t. The superscript g indicates the efficiency obtained by adopting the global PPS. $E^g(x_k^t, y_k^t, b_k^t)$ is the efficiency value of the k^{th} DMU in periods t, determined by the USSBM model. $GMPLI > 1$ proves an increase in productivity, whereas $GMPLI < 1$ means a decrease in productivity. Two essential features of the improved GMLPI are presented as follows:

Proposition 1

If the undesirable output vector b_k^t is applied to the traditional global PPS, then the GMLPI value in a given period is equal to the multiplication of all values in sub-periods.

Analysis: In the light of Eq. (13), the circularity of MLPI is confirmed by Eq. (14):

$$\begin{aligned}
&GMLPI(x_k^{t+3}, y_k^{t+3}, b_k^{t+3}, x_k^t, y_k^t, b_k^t) \\
&\quad = \frac{E^g(x_k^{t+3}, y_k^{t+3}, b_k^{t+3})}{E^g(x_k^t, y_k^t, b_k^t)} \\
&\quad = \frac{E^g(x_k^{t+3}, y_k^{t+3}, b_k^{t+3})/E^g(x_k^{t+2}, y_k^{t+2}, b_k^{t+2})/E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E^g(x_k^{t+2}, y_k^{t+2}, b_k^{t+2})/E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})/E^g(x_k^t, y_k^t, b_k^t)} \\
&\quad = GMLPI(x_k^{t+3}, y_k^{t+3}, b_k^{t+3}, x_k^{t+2}, y_k^{t+2}, b_k^{t+2}) \times GMLPI(x_k^{t+2}, y_k^{t+2}, b_k^{t+2}, x_k^{t+1}, y_k^{t+1}, b_k^{t+1}) \times \\
&\quad\quad GMLPI(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}, x_k^t, y_k^t, b_k^t)\ . \qquad (14)
\end{aligned}$$

With the application of Proposition 1, we can determine the cumulative green productivity growth over the entire period after calculating the individual contribution of each period.

Proposition 2

If the undesirable output vector b_k^t is applied to the traditional global PPS, then the GMLPI can be decomposed into four components, i.e., pure efficiency change (PEC), scale efficiency change (SEC), pure technological change (PTC) and scale technological change (STC). This feature is shown in Eq. (15).

Analysis:

$GMLPI(x_k^{t+1}, y_k^{t+1}, b_k^{t+1}, x_k^t, y_k^t, b_k^t)$

$$= \frac{E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E^g(x_k^t, y_k^t, b_k^t)} = \frac{E^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E^t(x_k^t, y_k^t, b_k^t)} \times \left[\frac{E^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})} \times \frac{E^t(x_k^t, y_k^t, b_k^t)}{E^g(x_k^t, y_k^t, b_k^t)}\right]$$

$$= \frac{E_v^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E_v^t(x_k^t, y_k^t, b_k^t)} \times \frac{E_c^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})/E_v^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E_c^t(x_k^t, y_k^t, b_k^t)/E_v^t(x_k^t, y_k^t, b_k^t)} \times \left[\frac{E_v^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E_v^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})} \times \frac{E_v^t(x_k^t, y_k^t, b_k^t)}{E_v^g(x_k^t, y_k^t, b_k^t)}\right] \times$$

$$\left[\frac{E_c^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})/E_v^g(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})}{E_c^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})/E_v^{t+1}(x_k^{t+1}, y_k^{t+1}, b_k^{t+1})} \times \frac{E_c^t(x_k^t, y_k^t, b_k^t)/E_v^t(x_k^t, y_k^t, b_k^t)}{E_c^g(x_k^t, y_k^t, b_k^t)/E_v^g(x_k^t, y_k^t, b_k^t)}\right]$$

$$= PEC \times SEC \times PTC \times STC\,, \qquad (15)$$

where the superscripts g, t and $t+1$ of $E(x_k^t, y_k^t, b_k^t)$ denote the PPS of t period, $t+1$ period and global/entire period, respectively. The subscripts c and v of $E(x_k^t, y_k^t, b_k^t)$ stand for the constant returns to scale and variable returns to scale (VRS). The greater-than-1 PEC, SEC, PTC and STC indicate the improvement in resource management, increase in scale effect, development in technology and movement towards VRS technology, respectively (Jiménez-Sáez et al., 2013). According to Proposition 2, the individual contribution of each component of green productivity growth can be revealed by decomposing the GMLPI.

3.3 System generalized method of moments

In the second stage, determinants of the GTFPWR were examined by using regression methods, of which a static panel model was established as shown in Eq. (16):

$$GTFPWR_{i,t} = \beta_0 + \beta_1 Eco_{i,t} + \beta_2 Urb_{i,t} + \beta_3 FDI_{i,t} + \beta_4 FT_{i,t} + \beta_5 PS_{i,t} + \varepsilon_{i,t}, \qquad (16)$$

where $GTFPWR_{i,t}$ denotes the growth rate of the GTFPWR for province i in year t. β_0 is the coefficient of the constant term. $Eco_{i,t}$, $Urb_{i,t}$, $FDI_{i,t}$, $FT_{i,t}$ and $PS_{i,t}$ stand for the determinants of the GTFPWR. β_1—β_5 are the regression coefficients of the determinants. $\varepsilon_{i,t}$ represents the error term.

Note that the static panel models usually have endogeneity, thus causing a bias in the coefficient estimation (Li et al., 2018). Compared with other straightforward estimation methods, the SGMM can minimize this endogenous bias through the use of instrumental variables. Therefore, we used a two-step SGMM method to examine the determinants of the GTFPWR, as shown in Eq. (17):

$$GTFPWR_{i,t} = \beta_0 + \beta_1 Eco_{i,t} + \beta_2 Urb_{i,t} + \beta_3 FDI_{i,t} + \beta_4 FT_{i,t} + \beta_5 PS_{i,t} + \beta_6 GTFPWR_{i,t-1} + \delta_i + \varepsilon_{i,t} \,, \tag{17}$$

where $GTFPWR_{i,t-1}$ denotes the first-order lag term of the dependent variable, while β_6 is its regression coefficient. δ_i stands for the individual effects.

3.4 Fixed-effects panel threshold

For studying the impacts of the determinants in different scenarios, the usual approach is to use a variety of grouped data. In this case, it is difficult to determine the grouped criteria such as threshold values. To overcome this, the FEPT designed by Wang (2015) was applied to examine the determinants of the GTFPWR, as shown in Eq. (18):

$$GTFPWR_{i,t} = \beta_0 + \beta_1^{'} x_{i,t} \phi\left(q_{i,t} \leq \gamma\right) + \beta_2^{'} x_{i,t} \phi\left(q_{i,t} > \gamma\right) + \delta_i + \varepsilon_{i,t}, \tag{18}$$

where $\phi\left(q_{i,t} \leq \gamma\right)$ is the indicator function. If the expression is true, the value of θ is equal to 1 or 0 otherwise. $q_{i,t}$ stands for the threshold variable. γ represents the threshold parameter in two regimes with the coefficients $\beta_1^{'}$ and $\beta_2^{'}$. $x_{i,t}$ denotes the vector of independent variables of the province i in year t.

3.5 Data and variables

i. Variables and data used in the first stage

The input-output variables include capital stock input, labour input, water use input, desirable output (i.e., GDP) and undesirable outputs (i.e., COD and ammonia nitrogen). Note that the capital stock input and the labour input cannot be directly obtained, so the following equations were used to measure these inputs:

Capital stock. The perpetual inventory method was chosen to calculate the amount of capital stock, as formulated in Eq. (19):

$$K_{i,t} = K_{i,t-1} + W_{i,t} - D_{i,t} = (1-\theta_i)K_{i,t-1} + W_{i,t}, \tag{19}$$

where $K_{i,t}$ represents the amount of capital stock of province i in year t, $W_{i,t}$ denotes the amount of investment, $D_{i,t}$ stands for the amount of capital depreciation and θ_i indicates the rate of capital depreciation.

The rate of capital depreciation plays a vital role in capital stock estimation. However, most Chinese studies have failed to consider the provincial difference in the rate of capital depreciation. To fill this gap, this study adopts the data reported by Zhang et al. (2016) and applied differentiated depreciation rates for each province.

Labour. To calculate the quantity of labour, this study considered the educational level of labourers and thus adopted a definition proposed by Hall and Jones (1999). According to this definition, the education return of the first four years is 13.4%, followed by 10.1% in the next four years and 6.8% over eight years. In China, the length of schooling is six years in primary school, three years in middle school, three years in high school and 3.5 years in college/university. Based on the definition, Eqs. (20)-(23) were formulated to compute the labour input:

$$E_{i,t} = 6e_1 + 9e_2 + 12e_3 + 15.5e_4, \tag{20}$$

$$L_{i,t} = P_{i,t} \times 0.134E_{i,t} \quad \text{if } E_{i,t} < 4, \tag{21}$$

$$L_{i,t} = P_{i,t} \times (0.536 + 0.101(E_{i,t} - 8)) \quad \text{if } 4 \leq E_{i,t} < 8, \tag{22}$$

$$L_{i,t} = P_{i,t} \times (0.94 + 0.068(E_{i,t} - 8)) \quad \text{if } E_{i,t} \geq 8, \tag{23}$$

where $E_{i,t}$ denotes the average schooling length of the province i in year t. e_1, e_2, e_3 and e_4 stand for the proportions of the population in elementary school, middle school, high school and college/university, respectively. $P_{i,t}$ represents the number of employees and $L_{i,t}$ indicates the final labour input.

ii. Variables and data used in the second stage

Table 1 presents the descriptions of the variables and data used in the regression analysis.

Table 1. Variable descriptions

Type	Variable	Abbreviation	Description
Dependent variable	Green total-factor productivity of water resources	*GTFPWR*	Index variable; see Eq. (13)
Independent variables	Economic development	*ED*	GDP per capita
	Urbanization	*Urb*	Share of urban population in the total population
	Foreign direct investment	*FDI*	FDI as % of GDP
	Foreign trade	*FT*	Ratio of imports and exports to GDP
	Population scale	*PS*	Population in each province
Threshold variable	Level of water utilization	*LWU*	Wastewater discharged per unit of GDP

Table 2 shows the descriptive statistics of the dependent variable, independent variables and threshold variable.

Table 2. Descriptive statistics of variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
GTFPWR	300	1.0175	0.0484	0.7873	1.4001
ED (million yuan)	300	2.9395	1.7239	0.6000	9.1000
Urb (%)	300	0.5237	0.1389	0.2746	0.8960
FDI (%)	300	0.0257	0.0194	0.0008	0.0895
FT (%)	300	0.0481	0.0576	0.0054	0.2444
PS (billion people)	300	0.4439	0.2663	0.0548	1.0849
LWU (ton/million yuan)	300	18.6862	7.8927	6.6766	60.0106

The unit of analysis in this study is the province in China. The data were collected from the following sources: *China Statistical Yearbook*, *China Statistical Yearbook on Environment* and the statistical yearbook of each province. These sources provide real-world data from 2005 to 2015 across 30 provinces in China. All monetary variables were converted to real values as per the GDP indices. A variance inflation factor test showed that there was no severe multi-collinearity among selected independent and control variables (variance inflation factor <10). Thus, further regression analysis was statistically appropriate.

4. Results and discussion

4.1 Green development performance of water resources

In this subsection, the growth rate of the GTFPWR, which denotes the green development performance of water resources, is analyzed in detail. As shown in Fig. 1, the GTFPWR is continuously growing by 1.75% on average except in 2011, which implies that China has achieved improvements in water-use productivity to an extent. However, the growth rate of the GTFPWR declined in 2011 due to the surge of water pollution in the household sector (NBSC, 2019). In addition, the GTFPWR growth in coastal provinces is much better (i.e., 1.91% higher on average) than that in inland provinces (see Fig.1)

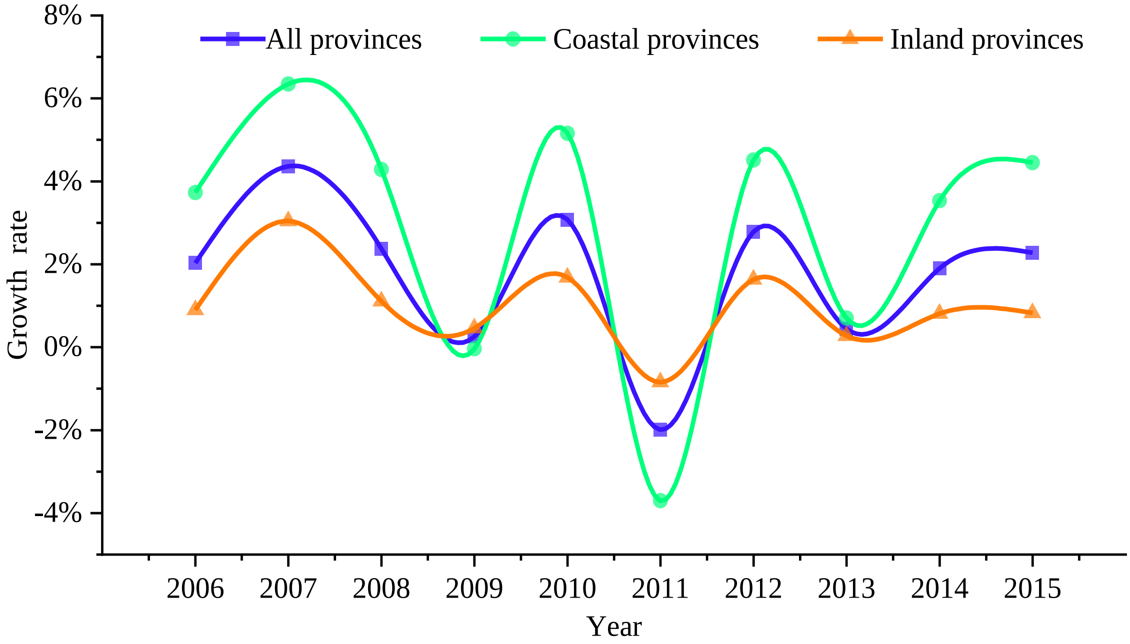

Fig. 1. Growth rates of the GTFPWR

Fig. 2 illustrates the four internal drivers of the GTFPWR growth by decomposing the productivity index. The PEC and the SEC slightly fluctuate around the 0% and then gradually converge, implying that water resource management has slowly improved. There is a small gap between the current input-output scale and the optimal scale. Moreover, the roles of PEC and SEC in the GTFPWR growth have been narrowing in recent years.

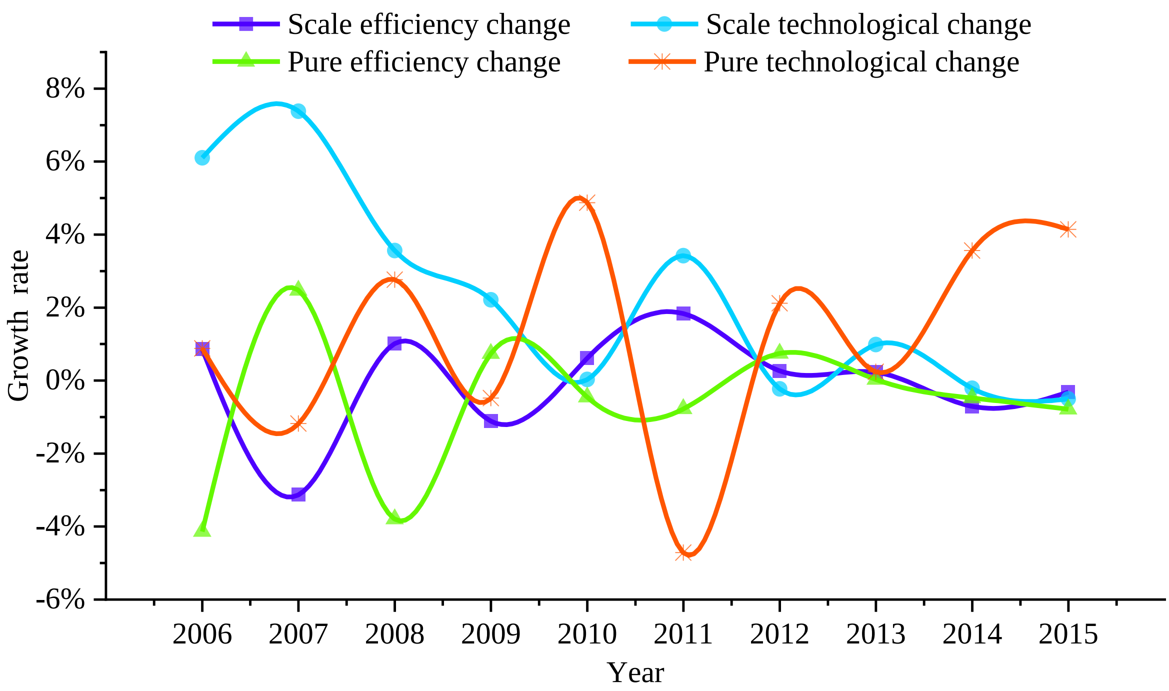

Fig. 2. Decompositions of the GTFPWR growth

Unlike the PEC and SEC, the STC was significantly higher than the 0% in the early years and the PTC has been significantly higher in recent years (e.g., from 2.78% in 2012 to 4.14% in 2015). This result implies that there was a positive association between production scales and technological development in the early years. However, in recent years, technological development has become the main driver of the GTFPWR growth (see Fig. 2).

Table 3 shows that China's GTFPWR increased by 1.75% over the last ten years on average, while twenty-seven provinces (accounting for 90%) have achieved the GTFPWR growth. Shanghai, Tianjin and Beijing have the fastest growth rates (i.e., more than 5%), whereas Shanxi, Hainan and Yunnan perform worse (i.e., less than 0%). Meanwhile, the coefficient of variation shows that the deviation in PEC is the largest, up to 3.02% on average across 30 provinces.

Table 3. Provincial GTFPWR growth and its decompositions

Province	GTFPWR	SEC	STC	PEC	PTC
Beijing	5.30%	-0.32%	4.58%	0.21%	1.09%
Tianjin	6.92%	4.63%	3.20%	0.17%	-0.15%
Hebei	0.84%	-1.72%	0.65%	-0.27%	2.53%
Shanxi	-2.02%	4.68%	4.13%	-8.15%	-0.23%
Inner Mongolia	1.38%	1.04%	1.70%	-2.11%	0.87%
Liaoning	1.32%	-1.41%	1.30%	0.10%	1.73%
Jilin	0.26%	0.79%	1.73%	-2.70%	0.74%
Heilongjiang	0.99%	0.52%	1.47%	-2.22%	1.33%
Shanghai	8.28%	0.07%	2.12%	-0.14%	6.83%
Jiangsu	4.36%	-1.80%	2.42%	6.20%	11.02%
Zhejiang	2.56%	0.74%	-2.00%	-0.23%	6.25%
Anhui	1.25%	0.86%	1.43%	-1.94%	0.99%
Fujian	1.34%	-0.38%	1.51%	-1.11%	1.54%
Jiangxi	1.65%	0.51%	2.22%	-1.14%	0.18%
Shandong	2.20%	-4.50%	1.50%	0.15%	7.30%
Henan	-0.47%	-2.56%	1.48%	-1.06%	2.11%
Hubei	1.84%	0.09%	1.36%	-0.69%	1.15%
Hunan	1.49%	0.28%	1.11%	-0.98%	1.14%
Guangdong	0.21%	-0.11%	-0.05%	0.08%	0.28%
Guangxi	0.23%	0.78%	1.15%	-2.19%	0.57%
Hainan	1.21%	-1.05%	7.81%	0.45%	-5.31%
Chongqing	3.40%	1.25%	1.84%	0.74%	0.00%
Sichuan	2.42%	-0.34%	1.69%	0.58%	1.20%
Guizhou	1.97%	0.28%	3.23%	-0.08%	-1.15%
Yunnan	-0.68%	0.55%	2.67%	-2.86%	-0.46%
Shaanxi	1.36%	0.87%	1.70%	-0.79%	0.13%
Gansu	0.97%	-0.47%	3.67%	-0.68%	-1.12%
Qinghai	1.59%	-1.55%	4.28%	2.21%	-1.54%
Ningxia	0.12%	-2.39%	5.02%	0.46%	-2.09%
Xinjiang	0.29%	-0.69%	3.34%	-1.32%	-0.38%
Average	1.75%	-0.05%	2.28%	-0.64%	1.22%
Coefficient of variation	1.78%	1.71%	2.18%	3.02%	1.78%

4.2 Effects of economic-related determinants

As shown in Table 4, different regression methods are applied to examine the economic-related determinants of the GTFPWR.

Table 4. Estimation of different regressions

Variables	(1) **POLS**	(2) **RE**	(3) **FE**	(4) **SGMM**
ED	0.0086**	0.0125***	0.0147**	0.0392***
	(2.16)	(2.99)	(2.06)	(2.90)
Urb	-0.1395**	-0.1279*	-0.3440**	-0.8532***
	(-2.03)	(-1.97)	(-2.54)	(-2.92)
FDI	0.5621***	0.4360**	0.8406**	1.6147***
	(3.20)	(2.54)	(2.01)	(2.79)
FT	0.2533***	0.1632*	0.5206*	1.027***
	(2.93)	(1.82)	(1.78)	(2.81)
PS	-0.0277**	-0.0248**	-0.0723	-0.1206
	(-2.37)	(-2.25)	(-0.25)	(-1.59)
GTFOWR(L.1)				-0.3338***
				(-2.94)
C	1.0509***	1.0397***	1.1399***	1.6529***
	(40.79)	(40.73)	(8.37)	(8.78)
N	300	300	300	270

Notes: POLS: pooled ordinary least square; RE: random effect. FE: fixed-effects. The Hansen test for SGMM ($p = 0.230$), using a robust standard error, indicates that instrumental variables are statistically valid. The AR (2) test for SGMM ($p = 0.618$) confirms that the autocorrelation does not exist.
* Significant at 10%, ** Significant at 5%, *** Significant at 1%.

Columns (1)-(4) report the results of regression analysis, showing that the effects of economic development, urbanization, FDI and foreign trade on the GTFPWR are positive and significant (p<0.1). However, the role of urbanization in the GTFPWR is negative and significant (p<0.1). Meanwhile, the effect of population scale on the GTFPWR is insignificant (p≥0.1) according to the results of FE and the SGMM, which eliminate the endogenous biases and thus are more reliable than POLS and RE.

Following the above results, the level of water utilization (LWU) is applied as the threshold value to evaluate the effects of four economic-related determinants (*ED, Urb, FDI* and *FT*) in different scenarios. Table 5 reports the statistical results of the FEPT method. It is observed that the *ED, Urb, FDI* and *FT* factors exhibit threshold effects. Based on the threshold value, provinces were classified as having either a higher-LWU ($LWU \leq 11.7$) or a lower-LWU ($LWU > 11.7$). Note that the lower calculated LWU value means the higher-LWU.

Table 5. Threshold effect test

Variable	Fstat	Prob	Critical value			Threshold	95% confidence interval
			10%	5%	1%		
Eco	16.65	0.0260	10.58	13.20	20.02	11.65	[11.56, 11.70]
Urb	20.97	0.0160	10.31	14.50	22.80	11.65	[11.56, 11.70]
FDI	12.21	0.0540	9.60	13.38	23.89	11.70	[11.58, 11.72]
FT	35.86	0.0000	9.83	12.96	23.98	11.65	[11.56, 11.70]

The results of the FEPT method are reported in Table 6, where columns (5)-(8) define *URB, ED, FDI* and *FT* as the core variables, respectively. The effect of economic development on the GTFPWR is positive and significant, regardless of whether the LWU value is above ($\gamma = 11.7$) or below ($\gamma \leq 11.7$) the threshold. The coefficient of economic development (β=0.0364) is greater in provinces with the higher-LWU value than that (β=0.0258) in provinces with the lower-LWU value. For the provinces with the lower-LWU, their technology and equipment used for saving water and treating wastewater are relatively outdated and thus have higher improvement potential (Li et al., 2019). Moreover, the provinces with the lower-LWU can achieve leapfrogging development by directly absorbing the most advanced technologies, in the light of the theory of leapfrogging (Brezis et al., 1993). Depending on whether the LWU value is above ($\gamma > 11.7$) or below ($\gamma \leq 11.7$) the threshold, the negative role of urbanization in the GTFPWR is minor (β=-0.6103) or major (β=-0.7019), respectively. Due to the lower intensity of the water use or wastewater discharge in the higher-LWU provinces, these provinces are more sensitive to the increase in the amount of water use and wastewater discharge caused by urbanization.

Table 6. Estimation results of fixed-effects panel threshold

Variables	(5) ***ED***	(6) ***Urb***	(7) ***FDI***	(8) ***FT***
$(q_{i,t} \leq \gamma)$	0.0258**	-0.7019***	-0.2164	0.1099
	(2.08)	(-2.90)	(-0.36)	(0.30)
$(q_{i,t} > \gamma)$	0.0364**	-0.6103***	1.1197**	0.7194*
	(2.12)	(-2.97)	(2.65)	(1.71)
ED		0.0340**	0.0276**	0.0321**
		(2.41)	(2.10)	(2.47)
Urb	-0.6399**		-0.5258**	-0.6417***
	(-2.62)		(-2.69)	(-2.96)
FDI	1.0294**	1.0267**		1.0008**

	(2.61)	(2.77)		(2.76)
FT	0.4669*	0.5080*	0.4222*	
	(1.79)	(1.73)	(1.77)	
PS	-0.1618	-0.1237	-0.1133	0.0776
	(-0.66)	(-0.54)	(-0.43)	(0.38)
C	1.2758***	1.2490***	1.2195***	1.1701***
	(8.11)	(9.02)	(8.19)	(9.47)
N	300	300	300	300

Note: * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

The effect of FDI on the GTFPWR is significant (p<0.05) in provinces where the LWU value is above the threshold ($\gamma > 11.7$) but insignificant (p≥0.1) in provinces where the LWU value is below the threshold ($\gamma \leq 11.7$). Water-saving and wastewater treatment technologies are more advanced in the higher-LWU provinces and the technology spillover effect caused by foreign enterprises is thus comparatively low. Moreover, foreign enterprises may lack the advantages in cleaner production compared with the local enterprises in the higher-LWU provinces. In this case, they may even have disadvantages and yield the “pollution haven” effect, which offsets the contribution of FDI. Thus, the effect of FDI on the GTFPWR is insignificant in the higher-LWU provinces. The effect of foreign trade on the GTFPWR is significant (p<0.1) in provinces where the LWU value is above the threshold (γ >11.7) and insignificant (p≥0.1) in provinces where the LWU value is below the threshold (γ ≤11.7). The higher-LWU provinces have abundant environmental knowledge and technologies; the learning effect generated by foreign trade is thus comparatively less in the higher-LWU provinces than that in the lower-LWU provinces. In addition, water contamination produced by enterprises in the higher-LWU provinces may be greater than the average level, by which this condition offsets the positive effects of foreign trade on the GTFPWR.

5. Conclusions and recommendations

Green development of water resources is a critical response to the severe water shortage and pollution. This study sought to better measure the green development performance of water resources and examine the impacts caused by economic-related determinants, providing insights on how to achieve green development.

The innovation and contribution of this research lies in the theoretical and empirical aspects. Theoretically, this study proposed a novel two-stage analytical framework for evaluating the efficiency and productivity in the first stage and examining their determinants in the second stage. In our two-stage analytical framework, the USSBM, GMLPI, SGMM and FEPT methods were integrated to address four gaps, namely, ignorance of undesirable outputs, inattention to equal efficiency, neglect of impact scenarios and endogenous biases. Existing two-stage frameworks can only address part of the aforementioned gaps, e.g., undesirable outputs (Feng et al., 2017; Lin and Benjamin, 2017), equal efficiency (Li and Dewan, 2017) or both of these two (Li and Shi, 2014; Yuan and Xiang, 2018). In contrast, our two-stage framework has incorporated all four issues within the proposed framework. Hence, the results can be more holistic by considering the undesirable outputs, more accurate by avoiding equal efficiency and endogenous biases and more comprehensive by examining the impacts of determinants in different scenarios. Empirically, this study examined whether the economic-related determinants (i.e., economic development, urbanization, foreign direct investment, foreign trade and population scale) would obstruct/promote the green development performance of water resources. More importantly, we found that the above effects changed with the level of water utilization, based on real-world data collected from 30 provinces in China during 2005-2015. These findings provide new knowledge for promoting the green development of water resources.

The empirical results reveal that China's GTFPWR grew annually (1.75% on average), while technological development of water resources became the major internal driver of the current GTFPWR growth. Meanwhile, the performance of inland provinces was much lower than that of coastal provinces, especially in Shanxi, Hainan and Yunnan where the growth rate of the GTFPWR was less than 0%. In addition, economic-related determinants including economic development, FDI and foreign trade played a positive role in the GTFPWR, but urbanization played an adverse role. Furthermore, the positive effects of FDI and foreign trade were only significant in the provinces having a low level of water utilization. A high level of water utilization significantly decreased the benefits of the above determinants. These findings provide new insights for more differentiated and efficient decision-making in the following three aspects.

First, inland provinces, particularly Shanxi, Hainan and Yunnan, ought to improve water technologies and management to increase their unsatisfactory green development performance of water resources. Preferential policy instruments including subsidy, taxation and credit should be given to support these provinces' enterprises in reducing the cost and risks of developing water-saving and wastewater treatment technologies. Moreover, governments in the inland provinces should strengthen water resource management by applying the water resource control, target responsibility and appraisal systems along with adopting treatment standards, progressive pricing, administrative penalty, environmental tax schemes. Furthermore, it is recommended that inland provinces utilize their latecomer advantages by directly adopting the cutting-edge technologies and advanced water-use management of coastal provinces, at a relatively low cost (Li et al., 2019).

Second, the amount of municipal water and wastewater should be more effectively curbed to offset the adverse effects caused by urbanization on water resource use, especially for the provinces having a higher level of water utilization. Sufficient public expenditure is suggested for constructing municipal water supply facilities and wastewater treatment plants in response to the rapidly growing urban population. The government could also accelerate urban industrial upgrading by reducing the proportion of water-intensive and polluting industries, as well as increasing the proportion of high-tech and green industries. In addition, environmental publicity and education ought to be enhanced for promoting the use of water-saving products and raising public awareness of water conservation and reuse.

Third, regions with a low level of water utilization should be open to attract even more foreign direct investment and trade because the positive effects of foreign investments and trade on water use are only significant in these regions. It is advisable to implement preferential finance, taxation and credit policies for foreign enterprises and trade enterprises in regions with a low level of water utilization. These regions also need to lower their industry access standards appropriately and establish more Sino-foreign joint venture, Sino-foreign cooperation and wholly foreign-owned enterprises.

The following topics related to the green development of water resources ought to be considered in the future to provide new insights into the green development of water resources, including the secondary pollution of water resource use (Hou et al., 2018), energy-water nexus (Duan and Chen, 2017; Liu et al., 2017; Yang et al., 2018) and the “Jevons paradox” (Gunderson and Yun, 2017) caused by the increasing water-use productivity. Moreover, further data on water pollution, in addition to traditional water quality data, will be collected to analyse the green development of water resources.

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