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Economic policy uncertainty and green economy efficiency: power or resistance?—Empirical evidence from Chinese major urban agglomerations

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ABSTRACT

Policy uncertainties have always played a critical role in shaping economic outcomes, as evidenced by the recent sluggish economic growth in many countries. Green economic efficiency (GEE) is a comprehensive index to measure economic, social, and environmental development. This paper uses the slack-based measurement (SBM) directional distance function and Luenberger productivity indicator to measure the static GEE and dynamic green total factor productivity (GTFP) of China's urban agglomerations from 2003 to 2020 under constraints of resources and environment. In order to clarify the driving mechanisms of GEE and GTFP, this paper adds the factor of economic policy uncertainty (EPU). The results show that there is a positive correlation between EPU with GEE and GTFP. The possible reason is that the market mechanism plays a decisive role in improved GEE and GTFP. Therefore, policymakers should give better play to the government's macro-control role, and play the decisive role of the market mechanism in the environmental governance system to improve GEE and GTFP in a targeted manner.

1. Introduction

Achieving sustainable development and reducing global warming and pollution emissions have prompted researchers and policymakers to focus on environmental protection and green economic development (Amri, 2018). In order to incorporate input constraints into the framework for evaluating economic performance, economists proposed to measure the regional economic performance in terms of total factor productivity (TFP). However, the traditional TFP only considers the constraints of production factors such as labour and capital, and does not consider the constraints of resources and environment, which distorts the evaluation of social welfare changes and economic performance, thereby misleading policy implications (Hailu & Veeman,

2000).With increasingly prominent problems of resources and environment in the process of economic development, researchers believe that resources and environment are not only endogenous variables, but also rigid constraints on economic development. Therefore, when evaluating economic performance by TFP, it is necessary to consider constraints of resources and environment as well as traditional factors such as capital and labour.

Green economic efficiency (GEE) is a comprehensive index to measure economic, social, and environmental development under constraints of resources and environment (Zhao et al., 2020). GEE reflects the relative relationship between each urban agglomeration and the production boundary in a given period, which is a static analysis. Green total factor productivity (GTFP) is a dynamic analysis that can analyse the relative position changes (efficiency changes) of each urban agglomeration, as well as the movement of the production boundary (technical progress). This paper chooses the SBM directional distance function to measure GEE from a static perspective, and chooses the Luenberger productivity indicator to measure GTFP from a dynamic perspective.

There are some studies on the calculation of GEE and GTFP and their influencing factors. It is worth noting that previous studies neglected the important factor of the macro-economic system closely linked to GEE and GTFP. The significance of uncertainty in policies related to economic decisions is higher than ever before in today's interconnected world (Saud & Barrak, 2019). Moreover, policy uncertainties have always played a critical role in shaping economic outcomes, as evidenced by the recent sluggish economic growth in many countries that are currently experiencing policy uncertainties. Economic policy uncertainty (EPU) will affect the external operating environment and decisions of economic entities, which in turn will affect the quality of green economy development. Therefore, GEE and GTFP is related to the EPU. This paper adopts the EPU index constructed by Baker et al. (2016) as a proxy indicator to measure EPU in China's urban agglomerations.

From the static and dynamic perspectives, this paper measures GEE and GTFP of China's 10 urban agglomerations from 2003 to 2020 under constraints of resources and environment. In order to clarify the driving mechanisms of GEE and GTFP, this paper adds the factor of EPU. We also analyse the impact of green innovation, foreign direct investment, gross regional product, endowment structure, marketisation system, and transportation infrastructure on GEE and GTFP. Compared with the existing literature, the main contributions of this paper are as follows. First, this paper uses the SBM directional distance function to measure GEE of China's urban agglomerations from a static perspective, and uses Luenberger productivity indicator to measure GTFP from a dynamic perspective. The static and dynamic analysis is helpful to comprehensively measure GEE of Chinese urban agglomerations. Second, the empirical study of the relationship between EPU and GEE in the Chinese context will help clarify the impact of institutional factors behind GEE. Third, we analyse the spatial correlation of GEE and GTFP, and use the spatial panel data model to analyse the driving mechanisms of GEE and GTFP. Fourth, this paper measures GEE and GTFP of China's 10 urban agglomerations under constraints of resources and environment, which is different from previous studies on individual urban agglomeration or cities.

Our paper is organised as follows. Section 2 reviews the literature. Section 3 describes empirical methods and materials. Section 4 interprets the results and discussion. Finally, the conclusions are presented in Section 5.

2. Literature review

In general, methods to evaluate GEE and GTFP can be divided into parametric and non-parametric approaches. As the price information of resources and environment factors is not available, traditional TFP measures cannot account for productivity under constraints of resources and environment. Although the Malmquist productivity index does not require price information, it does not calculate TFP in the presence of 'bad' output (such as SO_2 emissions). Chung et al. (1997) proposed Malmquis-Luenberger index which could measure TFP in the presence of 'bad' output. Chambers et al. (1996) proposed the Luenberger indicator with additive structure. The Luenberger indicator does not require the selection of the measurement angle, which can consider both the reduction of input and the increase of output, and also the case of minimising costs and maximising revenue. Therefore, the Luenberger indicator is a generalisation of Malmquist productivity index and Malmquis-Luenberger index (Boussemart et al., 2003).

Due to the advantages of data envelopment analysis (DEA), which does not require hypothetical function forms and can decompose productivity, many studies on GEE and GTFP basically use radial and oriented DEA to calculate the directional distance function. When there is excessive input or insufficient output, that is, there is non-zero slack in input or output, the radial DEA method will overestimate the efficiency of the evaluation object; while the oriented DEA method ignores the input or output in one aspect, the calculated efficiency results are not accurate. To overcome these two shortcomings, Tone (2001) proposed a non-radial, non-oriented slack-based measurement model (SBM). Later, Fukuyama and Weber (2009) and Fare and Grosskopf (2010) developed a more general non-radial, non-oriented directional distance function based on Tone (2001) SBM.

Scholars have attempted to incorporate byproducts/undesirable outputs into the total factor framework to measure GEE and GTFP, and drawn some useful results. For instance, incorporating CO_2 emissions into the TFP framework, Ahmed (2012), and Rusiawan et al. (2015) studied GTFP of five Southeast Asian countries and three East Asian countries, respectively. Banzhaf and Chupp (2012) used CO_2 emissions as a standard for measuring air quality pollution in the United States, and compared the degree of environmental pollution control by the environmental policies of the U.S. federal and state governments, and found that the federal government's environmental policies could improve the environmental level, but the policies of the state government did not show a clear positive effect. Zofio et al. (2013) tried to embed the traditional efficiency theory from the perspective of endogenous mapping vectors when evaluating the GEE, and modified the traditional DEA model to adapt it to the problem of unexpected output. Hampf and Kruger (2013) also used the endogenous mapping method to improve the traditional DEA model, and selected cross-country panel data to use CO_2 emissions as a standard to measure environmental pollution,

and used the modified model to measure GEE in dozens of countries in the world, and the results show that the GEE measured by this method is improved by 20% compared with other methods. Atkinson and Tsionas (2016) published two papers on the evaluation of GEE, using Bayesian analysis method and Generalised Method of Moments (GMM) to measure it, and compared with the direction distance function and the results obtained by SBM model. This analysis provides different perspectives and methods for the measurement of GEE.

In fact, resource and environment factors have been added into efficiency and productivity analysis framework to re-estimate China's GEE and GTFP in recent literature which draws many valuable conclusions (Du et al., 2019; Li & Wu, 2017; Long et al., 2020; Shen et al., 2019; Tang et al., 2017; Wang et al., 2018; Wang & Shen, 2016; Zhao et al., 2018, 2020; Zhou et al., 2019; Zhuo & Deng, 2020; Zhu et al., 2019). This paper found that most of the above-mentioned literature is mainly about the GEE and GTFP of China's inter-provincial industries and provinces or cities, and their research does not involve urban agglomerations and economic growth zones.

In the past few years, several major challenges have emerged, causing global political and economic uncertainty. The level of uncertainty is now higher and more important than ever before, since technology and globalisation have transformed the way we live (Baker et al., 2016). One of the oldest and most widely accepted uncertainty measures is the standard deviation of stock prices and stock returns. Recently, several new measures for EPU have been proposed. Manela and Moreira (2017) developed a news-based index of uncertainty using text from the Wall Street Journal. Hassan et al. (2019) developed a measure for firm-level political risk using textual analysis of quarterly earnings conference call transcripts. Baker et al. (2016) developed a proxy index for EPU that includes and measures most of the factors highlighted in earlier studies. The EPU index captures uncertainty from news, policy, market, and economic indicators. Due to the availability of the EPU index, many scholars analyse the impact of the EPU index on macro and micro levels, stock markets, corporate behaviour, and risk management (Saud & Barrak, 2019).

There is a general consensus in the literature today that EPU has adverse effects on several economic factors. However, recent studies have provided evidence that the EPU index's effects on several factors and policies are asymmetric (Bahmani-Oskooee & Maki-Nayeri, 2019; Istiak & Alam, 2019; Choudhry et al., 2020). Existing research does not empirically explore the impact of EPU on GEE and GTFP. According to efficient market hypothesis, and signal transmission theory, we believe that economic entities may increase or decrease regional pollution emissions under the influence of EPU, thereby affecting the regional GEE and GTFP.

3. Methods and materials

According to the driving mechanisms of GEE and GTFP, considering EPU factors, a theoretical and empirical analysis framework is incorporated and checked. In order to achieve this goal, a flowchart of the research framework is constructed, and is shown in Figure 1.
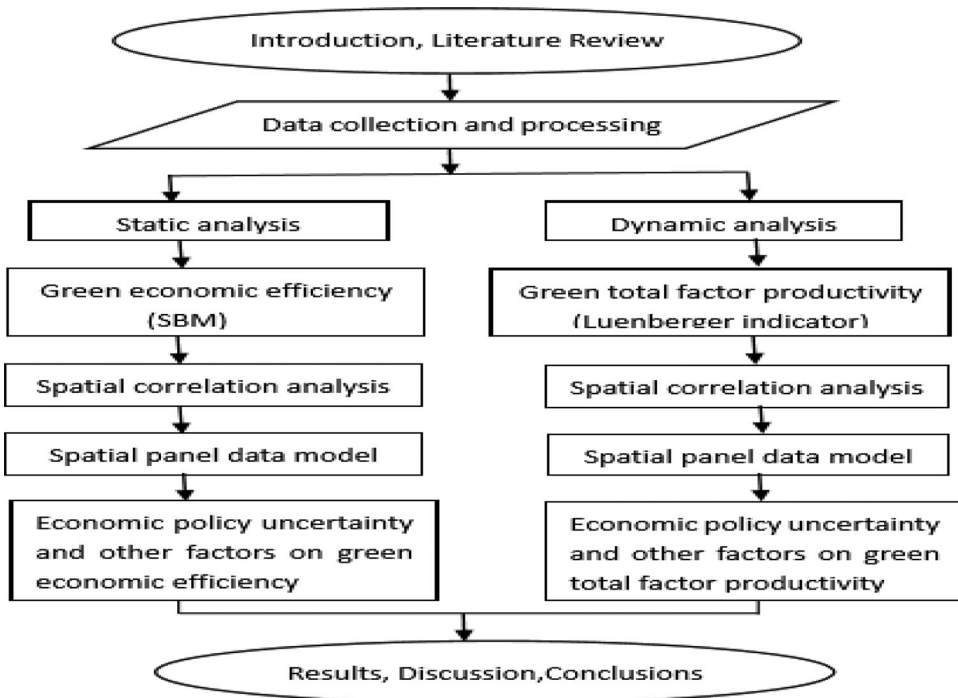
Figure 1. Flow chart of research framework. Source: The Authors

3.1. Methods for measuring GEE and GTFP—static and dynamic comprehensive perspectives

In this paper, the SBM directional distance function is used to measure GEE of Chinese urban agglomerations from a static perspective, and the Luenberger productivity indicator is used to measure GTFP from a dynamic perspective.

This paper regards each urban agglomeration as a production decision-making unit to construct the best practice boundary of Chinese production in each period. Fare et al. (2007) put both desired output (good output) and undesired output (bad output) into the production possibility set, and proposed a concept called environmental technology.

Inputs are defined by x and $x \in R_+^N$, good outputs are denoted by y and $y \in R_+^M$, and bad outputs such as CO_2 are defined as b and $b \in R_+^I$. In each period $t = 1, \ldots, T$, the input and output values of the $k = 1, \ldots K$ urban agglomeration are as (x_k^t, y_k^t, b_k^t).

When a series of assumptions of the production possibility set are satisfied, such as input and good output can be freely disposed, bad output disposability and zero-combination axiom, etc., the DEA can be used to transform the environmental technology model as follows.

$$P^t(x^t) = \left\{ (y^t, b^t) : \gamma Y \geq y_{km}^t, \forall m; \gamma B = b_{ki}^t, \forall i; \gamma X \leq x_{kn}^t, \forall n; \gamma \geq 0 \right\} \quad (1)$$

In formula (1), Y, B and X are the data of good output, bad output and input required in the process of constructing the production possibility boundary. γ is the

weight vector. In addition, if the constraint of $\gamma L = 1$ (L represents a vector whose elements are all 1) is added to the above formula, then the production technology is variable returns to scale (VRS), otherwise it is constant returns to scale (CRS).

3.1.1. SBM directional distance function-measuring static GEE

According to Tone (2001) and Fukuyama and Weber (2009), this paper defines the SBM directional distance function as follows.

$$\vec{S}_v^t\left(x_k^t, y_k^t, b_k^t, g^x, g^y, g^b\right) = max_{s^x, s^y, s^b} \frac{\frac{1}{N}\sum_{n=1}^{N}\frac{s_n^x}{g_n^x} + \frac{1}{M}\sum_{m=1}^{M}\frac{s_m^y}{g_m^y} + \frac{1}{I}\sum_{i=1}^{I}\frac{s_i^b}{g_i^b}}{3} \quad (2)$$
$$s.t. \gamma Y - s_m^y = y_{km}^t, \forall m; \ \gamma B + s_i^b = b_{ki}^t, \forall i; \gamma X + s_n^x = x_{kn}^t, \forall n;$$
$$\gamma \geq 0, \gamma l = 1; s_n^x \geq 0, s_m^y \geq 0, s_i^b \geq 0$$

In Equation (2), $\vec{S}_v^t$ represents the directional distance function under VRS. When there is no constraint that the sum of weight variables is 1, then use $\vec{S}_c^t$ to represent the directional distance function under CRS. $\left(x_k^t, y_k^t, b_k^t\right)$ represents the input and output of urban agglomeration k in the year t, $\left(g^x, g^y, g^b\right)$ represents the input and output direction vector, (s_n^x, s_m^y, s_i^b) represents slack variables of input and output. When the values of (s_n^x, s_m^y, s_i^b) are all greater than zero, it means that the actual input and pollution are greater than the boundary input and output, but the actual output is less than the output of the border. Therefore, (s_n^x, s_m^y, s_i^b) represents the overuse of input, excessive pollution emissions, and the underproduction of good output.

3.1.2. Luenberger productivity indicator-measuring dynamic GTFP

According to Chambers et al. (1996), GTFP of urban agglomeration between period t and period $t+1$ by Luenberger indicator can be expressed as follows.

$$GTFP_t^{t+1} = \frac{1}{2}\left\{\left[\vec{S}_c^t\left(x^t, y^t, b^t; g\right) - \vec{S}_c^t\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]\right.$$
$$\left. + \left[S_c^{\vec{t}+1}\left(x^t, y^t, b^t; g\right) - S_c^{\vec{t}+1}\left(x^{t+1}, y^{t+1}, b^{t+1}; g\right)\right]\right\} \quad (3)$$

where $GTFP_t^{t+1}$ represents GTFP of urban agglomeration between period t and period $t+1$. According to the ideas of Grosskopf (2003), we can further decompose GTFP into pure efficiency change (EC), pure technology change (TC), scale efficiency change (SEC), and technology scale change (TSC).

$$GTFP = EC + TC + SEC + TSC \quad (4)$$

The calculation of Luenberger indicator needs to solve four linear programs under the two assumptions of CRS and VRS to obtain eight directional distance functions.

3.2. Methods for the impact of EPU on GEE and GTFP—spatial panel data model

In order to test the relationship between EPU and GEE and GTFP, this paper uses spatial panel data model for regression analysis. The models are as follows.

$$\text{GEE}_{it} = \rho \ w_i \ \text{GEE}_t + \beta \ \text{EPU}_{it} + \theta \ X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

$$\text{GTFP}_{it} = \rho \ w_i \ \text{GTFP}_t + \beta \ \text{EPU}_{it} + \theta \ X_{it} + \mu_i + \gamma_t + \varepsilon_{it} \tag{6}$$

where GEE_{it} represents static GEE of urban agglomeration i in the year t, and $GTFP_{it}$ represents dynamic GTFP of urban agglomeration i in the year t; where w_iGEE_t, and w_iGTFP_t represent the spatial lag of GEE and GTFP, and show the spatial spillover effect of GEE and GTFP. ρ is a spatial autoregressive coefficient. w_i is the i-th row of the spatial weight matrix, W. In this paper, the geographic distance matrix of urban agglomeration is selected to form the spatial weight matrix W. The distance between the central cities of the urban agglomeration is calculated using the latitude and longitude of Chinese cities announced by the State Bureau of Surveying and Mapping of China. EPU_{it} is the economic policy uncertainty index of urban agglomeration i in the year t. X_{it} is a control variable matrix that affects GEE and GTFP, mainly including green innovation (GI) (Barbieri et al., 2016; Beltran-Esteve & Picazo-Tadeo, 2015; Constantini et al., 2016; Ghisetti & Quatraro, 2017), gross regional production (PGRP) (Adu & Denkyirah, 2018; Alam et al., 2016; Li et al., 2016), foreign direct investment (FDI) (Samia, 2016), capital-labour ratio (K/L), marketisation system (MS), transportation infrastructure (TI) (Lin & Chen, 2020). Where the K/L and MS are two variables that some authors may ignore. The K/L is a variable that effectively reflects the regional endowment structure, and can measure the impact of the upgrading of the industrial structure on GEE and GTFP. The MS can be used as a supplementary variable to the EPU, and the two variables can mutually confirm whether it is the market or the government that has the greatest impact on GEE and GTFP. θ is the corresponding coefficient matrix, μ_i is the individual effect, γ_t is the time effect, and ε_{it} is the random error term. $i = 1, 2, \ldots, 10$; $t = 2003, \ldots, 2020$.

3.3. Variable selection

The indicators involved in measuring GEE and GTFP are as follows.

'Good' output. The 'good' output is selected from the real-gross regional product (GRP) of each urban agglomeration based on 2002.

'Bad' output. Scholars chosen different pollution emissions, and examined single or multiple environmental factors. Considering that China takes the emissions of major pollutants as one of the main energy-saving and emission-reduction goals, this paper selects carbon dioxide, sulphur dioxide, smoke (dust) and industrial sewage emissions as bad output indicators.

Resources input. Since GRP is a value added indicator and resources are used as an intermediate input, traditional TFP measurement is generally not taken into

account. After considering environmental factors, some scholars have taken energy and other resource inputs into TFP measurement. This paper selects energy consumption as an indicator of resource input.

Capital input. The capital stock is estimated using Perpetual Inventory Method by Wu (2008). The basic estimation formula is as follows.

$$K_{it} = (1 - \delta_i)K_{i, t-1} + \Delta K_{it} \tag{7}$$

where K_{it} is the real value of capital stock for the region i in the year t, ΔK_{it} is the real value of incrmental capital stock, and δ_i is the rate of depreciation for the region i. Regarding the choice of depreciation rate, the relevant literature is quite different. Wu (2008) used the different depreciation rates of various regions in China for the first time to conduct research. Therefore, this paper chooses the depreciation rates of various regions in China used by Wu (2008). These depreciation rates are derived from a simulation process. The average value is about 4%, which converges to the actual depreciation values reported in the National Statistical Yearbook for each year and is also close to the value used by the World Bank.

Labour input. The labour input is measured by the total number of employed people in the urban agglomeration.

The factors affecting GEE and GTFP are as follows.

Economic policy uncertainty (EPU). EPU is the economic risk associated with undefined future government policies and regulatory frameworks. It is measured by a proxy index which is constructed by Baker et al. (2016). The EPU index captures uncertainty from news, policy, market, and economic indicators.

Green innovation(GI). This paper selects the number of green patent applications defined by the World Intellectual Property Organisation (WIPO) as the proxy variable for green innovation.

Foreign direct investment (FDI). This indicator is expressed in terms of the amount of foreign direct investment by each urban agglomeration, mainly to test the hypothesis of 'pollution paradise'.

GRP per capita (PGRP). PGRP is expressed in terms of real-GRP per capita.

Capital-labour ratio (K/L). This indicator is expressed as the ratio of capital to labour, reflecting the impact of endowment structure on GEE and GTFP.

Marketisation system (MS). This indicator is derived from the China Marketisation Index Report published by Wang et al. (2019).

Transportation infrastructure (TI). This indicator is measured by the ratio of the total length of the road, railway and inland waterway to the total land area of urban agglomerations.

3.4. Study area and data source

This paper uses panel data from 2003 to 2020 in Chinese 10 urban agglomerations. China's '13th Five-Year Plan' proposed to promote the sustainable development of 19 key urban agglomerations. This paper selects 10 urban agglomerations as study samples, such as Beijing-Tianjin-Hebei, Yangtze River delta, Pearl River delta, Shandong peninsula, west coast of the straits, central-southern of Liaoning, central

Table 1. Summary of variables.

Models		Variable	Mean	Std.	Min	Max
SBM Luenberger	Good output	GRP (RMB 100 million)	33,130	29,539	1799	160,806
	Bad	CO_2 (10,000 tons)	61,484	36,164	8165	164,622
	outputs	SO_2 (10,000 tons)	676	415	36	2000
		Smoke(dust) (10,000 tons)	37	31	4	272
		Industrial sewage (10,000 tons)	161,358	111,279	17,906	539,841
	Inputs	Labour (10,000 person)	5311	2576	2306	11,366
		Capital stock (RMB 100 million)	77,083	69,471	4688	371,740
		Energy consumption (10,000 tons)	28,151	15,362	4170	73,796
Spatial panel	GEE	GEE	0.580	0.294	0.112	1.000
data model	GTFP	GTFP	0.068	0.205	−0.634	0.884
		EPU (index value)	5.18	0.77	4.17	6.67
	Factors	GI (number)	9069	13,810	137	78,795
		FDI (USD 100 million)	385.92	644.15	4.66	2418.08
		PGRP (RMB yuan/person)	63,968	48,378	7292	256,116
		K/L (RMB 10,000/labour)	14.84	10.96	1.40	52.89
		MS (index value)	7.39	1.39	3.92	11.22
		TI (km/km2)	2.57	1.33	0.43	5.75

Source: The Authors.

plains, and middle reaches of Yangtze River, Chengdu-Chongqing, and central Shaanxi plain urban agglomerations, which include a total of 122 cities. These urban agglomerations are the most fundamental areas supporting China's land development and also play a vital role in China's participation in global competition. Geographically, these urban agglomerations involve three regions in the east, middle and west of China with gradient differences, and can better represent the economic development level and characteristics of the three regions in China.

In this paper, most statistical data were derived from the authoritative statistical yearbooks. The basic data of 'good' output, 'bad' output and input are mainly from 'China Statistical Yearbook', 'China City Statistical Yearbook', 'China Environment Statistics Yearbook', 'China Environment Yearbook' and 'China Energy Statistics Yearbook' from 2004 to 2020. The data for each variable in 2020 is predicted value. The EPU data are derived from the monthly EPU index database established by Baker et al. (2016). To be consistent with the time span of other indicators, this paper takes the arithmetic average and natural logarithm of China's monthly index to convert it as an annual EPU index.

Descriptive statistics of the data and variable are shown in Table 1.

4. Results

4.1. Static GEE and dynamic GTFP of urban agglomerations

Using the method introduced in Section 3, this paper constructs the best practice boundary of China in each year under the constraints of resources and environment, and compare GEE and GTFP of each urban agglomeration with this best practice boundary. Table 2 reports the static GEE and dynamic GTFP of Chinese urban agglomerations from 2003 to 2020 and their decomposition, mainly based on the results under the assumption of VRS.

Based on a static analysis, the average value of GEE was 0.58 in China's urban agglomerations from 2003 to 2020, indicating that excessive use of resources and

Table 2. Static GEE and dynamic GTFP of China's urban agglomerations from 2003 to 2020.

Urban agglomerations	GEE	PTE	SE	GTFP	EC	TC
Yangtze River Delta	0.663	1.000	0.663	0.075	0.000	0.075
Pearl River Delta	1.000	1.000	1.000	0.028	0.000	0.028
Beijing-Tianjin-Hebei	1.000	1.000	1.000	0.128	0.000	0.128
Central-southern of Liaoning	0.567	0.817	0.695	0.039	−0.066	0.106
Shandong Peninsula	0.423	0.553	0.764	0.030	−0.019	0.049
West Coast of the Straits	0.551	1.000	0.551	−0.035	0.000	−0.035
Central Plains	0.301	0.720	0.418	0.105	0.061	0.044
Middle reaches of Yangtze River	0.331	0.411	0.805	0.053	0.005	0.048
Central Shaanxi Plain	0.299	1.000	0.299	0.082	0.000	0.082
Chengdu-Chongqing	0.668	0.702	0.952	0.171	0.040	0.131
Average value	0.580	0.820	0.707	0.068	0.002	0.066

Source: The Authors.
Note: The values in the table are average values. PTE stands for pure technical efficiency, SE stands for scale effect, EC stands for efficiency change, and TC stands for technology change. GEE = PTE * SE; GTFP = EC + TC.

environmental pollution have caused losses to the efficiency of Chinese urban agglomerations. If explained according to the assumption that the variables change at the same rate, Chinese urban agglomerations should reduce their input by 42%, reduce their pollution emissions by 42%, and increase GRP by 42%, in order to achieve complete GEE. From the perspective of decomposition factors of GEE, pure technical efficiency is the main influencing factor. We also found that the pressure of emission reduction work is greater than that of energy conservation in China's urban agglomeration from the perspective of GEE.

Based on a dynamic analysis, GTFP of China's urban agglomerations increased by an average of 6.8% from 2003 to 2020. From the perspective of decomposition factors of GTFP, the growth of GTFP is mainly caused by the improvement of technological progress. From the mechanism point of view, technological progress can be directly through the improvement of pollution treatment technology and production technology, or indirectly by reducing the pollution intensity or energy consumption of the unit GRP, thereby reducing pollution emissions and energy use, and ultimately increasing GTFP. Due to differences in regional economic development and resources and environment, static GEE and dynamic GTFP among China's urban agglomerations is also very different.

4.2. Examination of spatial correlation of static GEE and dynamic GTFP of urban agglomerations

Moran's I is generally used to describe the variables of spatial correlation and reflect the characteristics of the clustering pattern of economic phenomena between regions. This paper also uses Moran's I to examine spatial correlation of GEE and GTFP. The formula is as follows.

$$Moran's\ I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}} \times \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(X_i-\overline{X})(X_j-\overline{X})}{\sum_{i=1}^{n}(X_i-\overline{X})^2} \tag{8}$$

where X_i is the observation value of region i; W_{ij} is the standardised spatial weight matrix. According to Equation (8), the value of Moran's I ranges from −1 to 1. At a

Table 3. Spatial autocorrelation of static GEE and dynamic GTFP.

Green economic effiency	Moran's I	Z	p-value
GEE	0.025	2.585	0.007
GTFP	0.209	4.225	0.000

Source: The Authors.

Table 4. Spatial panel data model test (static GEE) under the geospatial matrix.

	Method	Null hypothesis	Statistic	p-value	Result
SAR and SEM tests	LM-lag	No spatial lag	5.534	0.019	Reject
	R-LM-lag	No spatial lag	15.775	0.000	Reject
	LM-err	No spatial error effect	5.795	0.016	Reject
	R-LM-err	No spatial error effect	16.036	0.000	Reject
SDM fixed effect test	SFE-LR	No spatial fixed effect	−17.14	1.000	Accept
	TFE-LR	No fixed time effect	0.000	1.000	Accept
	STFE-LR	No double fixed effect			
Hausman test of SDM	Hausman	Random effect model	−8.66		Accept
Simplified test of SDM	Wald-lag	SDM can be weakened to SAR	2.3e + 09	0.000	Reject
	LR-lag	SDM can be weakened to SAR	42.16	0.000	Reject
	Wald-err	SDM can be weakened to SEM	119.97	0.000	Reject
	LR-err	SDM can be weakened to SEM	30.96	0.000	Reject

Source: The Authors.

given significance level, a value of Moran's I greater than 0 indicates a positive correlation, indicating that observations with similar attributes are spatially clustered. On the contrary, it indicates that the observations with different attributes are in a state of aggregation. This paper uses the constructed geographic distance matrix for spatial correlation analysis. Table 3 reports the Moran's I values of static GEE and dynamic GTFP in China's urban agglomerations.

It can be seen that the Moran's I values of static GEE and dynamic GTFP are both greater than 0, and both pass the significance test. This shows that whether using static or dynamic analysis methods, GEE and GTFP of China's urban agglomerations has a significant spatial correlation.

4.3. Judgment method of spatial panel data model

In order to accurately study the relationship between EPU and GEE and GTFP, further spatial measurement test is needed. This paper refers to Elhorst's (2014) test ideas, through the Lagrange multiplier (LM), likelihood ratio (LR-test), Hausman, Wald and other tests, the spatial panel data models such as spatial auto regressive model (SAR), spatial error model (SEM) and spatial Dubin model (SDM) are tested using a combination of 'specific-to-general' and 'general-to-specific'. Table 4 reports the test results of static GEE with spatial panel data model.

Using the same test methods and steps, we can also obtain the test results of dynamic GTFP with spatial panel data model. According to the selection criteria and estimation results of spatial econometric models (Anselin et al., 2004; Vega & Elhorst, 2015), the spatial panel data models for static GEE is suitable for the SDM model of random-effect, and dynamic GTFP is suitable for the SDM model of fixed-effect.

4.4. Estimation results of EPU on static GEE of urban agglomerations

In order to compare and test the robustness of the parameter estimation of each variable, this paper lists the estimation results of the OLS, SAR, SEM and SDM models. Table 5 reports estimation results of the impact of EPU on static GEE in urban agglomerations by different models.

From the spatial estimation results of static GEE, the spatial autoregressive coefficient (ρ) and spatial error coefficient (φ) in each equation are significantly positive at the 1% level, indicating that static GEE of each urban agglomeration has an obvious spatial dependence relationship. Moreover, static GEE of urban agglomerations has a significant positive spatial effect, indicating that the higher GEE in the local region is conducive to improved GEE in neighbouring regions. This may results from the diffusion effect generated by the higher GEE in the local region, which is conducive to improved GEE in neighbouring regions.

From the results of static GEE estimation, the coefficient of EPU and control variables on GEE of urban agglomerations in each equation is consistent. Synthesising statistics such as likelihood (lik) to judge and select the optimal model, SDM of random-effect is the optimal model.

According to the estimation results of SDM, EPU is positively correlated with GEE. This shows from the opposite perspective that EPU may not be conducive to the improved GEE, indicating the 'green paradox' of economic policies and environmental regulations.

According to the estimation results of control variables, GI and K/L have a significant negative effect on static GEE of urban agglomerations. FDI, PGRP, and MS have a significant positive effect. TI has a negative effect, but it does not pass the significance test.

Table 5. Estimation results of EPU on static GEE.

Model variable	(1) Random-effect SDM	(2) Fixed-effect OLS	(3) Fixed-effect SAR	(4) Fixed-effect SEM
EPU	0.1007***	0.1565***	0.1115***	0.1701***
	(3.02)	(4.91)	(3.50)	(3.69)
GI	−5.07e-06**	−2.95e-06**	−8.20e-07*	−5.87e-07**
	(−2.18)	(−2.03)	(−1.62)	(−2.33)
FDI	0.0002***	0.0002***	0.0002***	0.0002***
	(3.38)	(8.41)	(4.19)	(4.26)
PGRP	0.00001***	0.00001***	8.57e-06***	0.00001***
	(8.18)	(12.16)	(5.77)	(6.64)
K/L	−0.0627***	−0.0493***	−0.0412***	−0.0541***
	(−8.16)	(−9.97)	(−6.95)	(−7.04)
MS	0.0581***	0.0500***	0.0486***	0.0551***
	(3.13)	(4.38)	(3.49)	(3.46)
TI	−0.0409	−0.0518***	−0.0173	−0.0134
	(−1.30)	(−4.51)	(−0.84)	(−0.56)
ρ	0.1472***		0.1373***	
	(3.12)		(3.03)	
φ				0.4390***
				(4.15)
lik	101.6214		80.5429	86.1397
R2	0.7601	0.6965	0.6499	0.6615

Source: The Authors.
Note: ***, **, and * indicate significance at the 1%, 5%, and 10% level, and lik is likelihood.

4.5. Estimation results of EPU on dynamic GTFP of urban agglomerations

In order to analyse the relationship between EPU and dynamic GTFP, this paper also lists the estimation results of the OLS, SAR, SEM and SDM models. Table 6 reports the estimation results of EPU on dynamic GTFP of urban agglomerations.

From the spatial estimation results of dynamic GTFP, the spatial autoregressive coefficient (ρ) and spatial error coefficient (φ) in each equation are significantly positive at the 5% level, indicating that dynamic GTFP of each urban agglomeration has an obvious spatial dependence relationship. Moreover, dynamic GTFP of urban agglomerations has a significant positive spatial effect. The results are consistent with the estimation of static GEE.

From the results of dynamic GTFP estimation, the coefficient of EPU and control variables on GTFP of urban agglomerations in each equation is consistent. According to the selection criteria and estimation results of spatial econometric models, SDM of fixed-effect is the optimal model.

According to the estimation results of SDM, EPU is positively correlated with GTFP. This also shows from the opposite perspective that EPU may not be conducive to the improved GTFP. The results are consistent with the estimation of static GEE.

According to the estimation results of control variables, GI has a significant negative effect on GTFP of urban agglomerations, which is consistent with the estimation of static GEE. FDI and MS have a significant positive effect on GTFP, which are consistent with the estimation of static GEE. PGRP has a significant negative effect on GTFP, which is inconsistent with the estimation of static GEE. The K/L has a significant positive effect on GTFP, which is inconsistent with the estimation of static GEE. TI has a negative effect on GTFP, but it does not pass the significance test.

Table 6. Estimation results of EPU on danamic GTFP.

Model variable	(1) Fixed-effect SDM	(2) Fixed-effect OLS	(3) Fixed-effect SAR	(4) Fixed-effect SEM
EPU	0.1040***	0.1479***	0.1264***	0.1147***
	(3.09)	(4.14)	(3.34)	(2.63)
GI	−4.89e-06*	−1.82e-06	−2.41e-06	−3.45e-06
	(−1.82)	(−1.11)	(−1.34)	(−1.38)
FDI	0.00003**	0.00005*	0.00006*	0.0004
	(2.10)	(1.94)	(1.77)	(1.57)
PGRP	−6.46e-06***	−1.68e-06	−2.04e-06*	−4.69e-06**
	(−2.68)	(−1.61)	(−1.69)	(−2.08)
K/L	0.0276**	9.70e-06 (0.00)	0. 0021	0.0112
	(2.50)		(0.34)	(1.29)
MS	0.0463*	0.0392***	0.0418***	0.0397*
	(1.75)	(2.94)	(2.93)	(1.78)
TI	−0.0481	−0.0224*	−0.0253	−0.0333
	(−1.29)	(−1.71)	(−1.62)	(−1.08)
ρ	0.2158**		0.1402**	
	(1.96)		(2.25)	
φ				0.1999*
				(1.81)
lik	71.9594		52.1769	62.4807
R2	0.3269	0.2285	0.2487	0.2619

Source: The Authors.

Table 7. Research results.

		EPU	GI	FDI	PGRP	K/L	MS	TI
GEE	Correlation	Positive	Negative	Positive	Positive	Negative	Positive	Negative
	Significance	Yes	Yes	Yes	Yes	Yes	Yes	No
GTFP	Correlation	Positive	Negative	Positive	Negative	Positive	Positive	Negative
	Significance	Yes	Yes	Yes	Yes	Yes	Yes	No
Results	Consistency	Yes	Yes	Yes	No	No	Yes	Yes

Source: The Authors.

4.6. Discussion

The results of EPU on GEE and GTFP can be seen in Table 7.

From the research results, EPU has a positive correlation with GEE and GTFP. This shows from the opposite perspective that EPU may not be conducive to the improved GEE and GTFP, indicating the 'green paradox' of economic policies and environmental regulations (Gunderson & Yun, 2017; Jensen et al., 2015; Ploeg & Frederick, 2013; Svindland, 2018; Wang, 2018). In essence, EPU represents the lack of government credibility (Lam et al., 2012). The possible reason is that the government's macro-control policies do not play a precise role, or that the market mechanism plays a decisive role in improved GEE and GTFP.

GI has a negative correlation with GEE and GTFP. This result is consistent with that of Van Den Bergh et al. (2011). This is mainly because GI deteriorates environmental quality through the energy rebound effect, or the high cost makes enterprises unwilling to adopt green innovation. FDI has a positive correlation with GEE and GTFP, and does not support the 'pollution paradise' hypothesis. This may be because the host country's economic development level, political stability, and legal integrity are the key factors determining its FDI level, and environmental regulatory policies have almost no effect. PGRP has a positive correlation with GEE and negative with GTFP, and the results are inconsistent. This result is in line with the 'environmental Kuznets curve' hypothesis. When PGRP increases, environmental pollution will increase. But when PGRP reaches the 'turning point', the environmental quality will gradually improve. The K/L has a negative correlation with GEE, which is consistent with our expectations. If the K/L rises, it means that the economic structure of urban agglomerations is transforming from labour-intensive industries, which tend to be light-polluting, to capital-intensive industries, which tend to be heavily polluting. The K/L has a positive correlation with GTFP. The possible reason is that the technological progress of capital-intensive enterprises offsets its negative impact on GTFP. MS has a positive correlation with GEE and GTFP. This is consistent with the estimated results of EPU, and also shows that market mechanism plays a decisive role in improved GEE and GTFP. TI has a negative correlation with GEE and GTFP, which is inconsistent with the results of Lin and Chen (2020). The main difference may be due to the selection of research objects and efficiency measurement.

4.7. Robustness test

In this paper, the estimation results of OLS, SAR, SEM, and SDM models are listed separately, so as to compare and test the robustness of the parameter estimation of each variable.

From the spatial estimation results of static GEE and dynamic GTFP, the spatial autoregressive coefficient (ρ) and spatial error coefficient (φ) in each equation are significantly positive. This shows that no matter from a static or dynamic perspective, no matter which model is used for estimation, the parameter estimation results of each variable are robust.

From the results of static GEE and dynamic GTFP estimation, the coefficient of EPU and control variables on GEE or GTFP in each equation is consistent. This also verifies the robustness of the estimation results.

5. Conclusions

This paper uses the SBM directional distance function to measure static GEE, and adopts Luenberger productivity indicator to measure dynamic GTFP of Chinese urban agglomerations from 2003 to 2020, and empirically study the spatial driving mechanisms of EPU on static GEE and dynamic GTFP using space panel data models.

Some conclusions can be drawn as follows. First, static GEE and dynamic GTFP of urban agglomerations has a significant positive spatial effect. Second, EPU has a positive correlation with GEE and GTFP. This shows that the market mechanism plays a decisive role in improved GEE and GTFP. Third, there are differences in driving mechanisms of GEE and GTFP. EPU and MS are positive driving mechanisms for GEE and GTFP, but GI and TI are negative driving mechanisms. FDI has a positive correlation with GEE and GTFP, and does not support the 'pollution paradise' hypothesis.

In view of the above conclusions, this paper proposes policy implications. First, it is necessary to improve GEE and GTFP through technical efficiency and technological progress. Second, governments should formulate a more complete regulatory system for environmental information disclosure in areas with low environmental regulations, high carbon emissions, and unreasonable industrial structures, to alleviate the information asymmetry in the market, and ensure that investors accurately know the environmental responsibility of the enterprise, thereby preventing the reduction of green economic efficiency due to the increase in economic policy uncertainty. Third, governments should extensively use big data technology and information systems to analyse the objective environment, and make decisions with careful consideration from the perspective of sustainable development. Avoid unnecessary changes in related economic and environmental policies to increase system costs. Fourth, governments also need to pay attention to the impact of economic policy uncertainty on government credibility when formulating and changing economic policies. Fifth, we must pay attention to the negative impact of green innovation on GEE and GTFP, and take targeted corrective measures to improve GEE and GTFP. Finally, governments should consider the regional factors of urban agglomerations, and avoid 'one-size-fits-all' green economic policies, and reduce 'bad' outputs in a targeted manner to achieve improved GEE and GTFP.

However, this paper is somewhat limited and further research is needed. First, the differences in different pollution emissions may be considered. Second, the choices of

driving factors of GEE and GTFP. Different indicators and variables may be analysed, and the subjectivity of indicator selection should be avoided, so as to improve the accuracy of GEE and GTFP analysis and the persuasiveness of the conclusions for subsequent research.

Disclosure statement

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