The persistent and transient total factor carbon emission performance and its economic determinants: evidence from China's province-level panel data

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Abstract

The total factor carbon emission performance has been largely used to investigate the effectiveness of climate policies and to support the design of carbon reduction strategies. Despite the important information that this indicator is providing in relation to historical and cross-country trends, no previous studies have been specifically devoted to analyse the persistent and the transient components of the total factor carbon emission performance. By disaggregating the time-variant and the time-invariant elements of the carbon dioxide emission changes, this paper adopts, for the first time, a new methodological approach to decompose the components of the total factor carbon emission performance indicator. Using panel data for selected 30 Chinese provinces for the time-period 1997-2017, this paper combines the environmental production technology, the Shephard distance function, and the stochastic frontier models to measure and investigate the spatio-temporal evolution of the total factor carbon emission performance and to evaluate the effectiveness of Chinese policies. By providing a better understanding of the main drivers of carbon dioxide emission changes, the proposed methodology, is suitable to be replicated across regions and countries, and provides an important opportunity for international comparisons and for the design of coordinated carbon reduction strategies.

Keywords

Total factor carbon emission performance, persistent efficiency, transient efficiency, stochastic frontier analysis, China

1. Introduction

The rapid economic development that has taken place in China since the economic reforms and the open-door policy of 1978 has largely contributed to energy consumption and carbon emission increase. As depicted in Figure A1 in appendix, China has endured a rapid process of increasing carbon since its entrance into WTO. It has overtaken United States as the largest CO_2 emitter, and the per capita emissions are now larger than in European Union and UK (Figure A2 in appendix). Despite the decreasing trend in the quantity of emissions generated per unit of GDP produced, the carbon intensity of China is still larger than other countries, and even higher than the world average (Figure A3 in appendix), leaving space and pressure for further efficiency improvements (Long et al., 2018). Climate change is of broad concern with the appealing for public health and sustainable development and carbon emission is one main trigger of global warming. With the rapid economic development and urbanisation process, China endures a rough pressure to control energy consumption and curb carbon emission (Xu and Lin, 2015).

Within this context, the Chinese government has been introducing a large set of policies oriented to balance the economic growth of 1.4 billion people together with the challenges of the green development strategies. The carbon tax, the carbon quota policy, the pilot low-carbon city initiative and the mandatory constraints on carbon intensity announced since the 12th Five-Year Plan (2011-2015)[1], are examples of that reflective action (Cheng et al., 2019; Cheng et al., 2018a; Li, Y. et al., 2020). To track the progress toward a more sustainable development, the carbon intensity has been widely used to measure the carbon performances of the Chinese economy. By using panel data at different scale of analysis, a wide range of analytical models have been developed to support the design of policies oriented to curb the carbon intensity of production (Wang et al., 2020, Jiang, 2016; Li and Lin, 2015). Most of the commonly used carbon performance indicators (such as the carbon intensity and the per capita carbon emissions) have however been largely criticized for considering only some aspects of production and for the lack of systematic definition and integral measurement (Sun, 2005). In recent years, total factor carbon emission performance (TFCP) has then been proposed as alternative indicator that provide a composite measure combining information from all production factors (Wang, Q. et al., 2012; Zhou et al., 2006).

[1] In addition, there are some industry-specific policies in the Five-Year Plans, e.g. the civil aviation industry by Civil Aviation Administration of China (CAAoC) and the building code by Ministry of Housing and Urban-Rural Development (MoHURD).

For the Chinese case, total factor carbon emission performance indicators have been calculated with the application of Data Envelope Analysis (Cheng et al., 2018b; Lin and Chen, 2019) and stochastic frontier analysis (Lin and Du, 2015; Zhou et al., 2010). In the previous studies, the indicators are calculated as time varying. However, there are some elements leading the carbon performance to be long lasting or time-invariant. That is because, in most of the cases, environmental regulations are settled in a long-run period and affect carbon performance structurally. In addition, other persistent and time-invariant factors, such as institutional environment and governance structures, can also influence the carbon performance without changing over a long period. For this reason, it is reasonable to hypothesis that there are components of efficiency that does not change and others that change over time.

In previous literature, three main strands of methods have been used to measure performances by distinguishing between the long-run and the short-run efficiency. First, according to the heuristic economic concepts of (quasi-)fixed inputs, Bilodeau et al. (2004) and Ouellette and Vierstraete (2004) proposed the concept of short-run and long-run efficiency and calculated it with DEA models. However, the total factor efficiency is not only related to inputs, and other factors in the production process matter. Second, Tsionas and George Assaf (2014) proposed a new method that combined SFA and ARMA to analyze the persistence of technical efficiency. The method specifies the inefficiency term from SFA as a truncated ARMA process and then takes its steady state as long-run efficiency. However, it ignores the heterogeneity of panel individuals. Third, a series of stochastic frontier models have been used to estimate the long-run and short-run efficiency separately (Greene, 2005; Pitt and Lee, 1981), whereas Colombi et al. (2011) and Kumbhakar et al. (2014) have been among the firsts to try to decompose persistent, transient inefficiency term and heterogeneity simultaneously in one stochastic frontier model. The concepts of long-run (or persistent, time-invariant) inefficiency and short-run (or transient, time-varying) inefficiency mentioned in the present study follows the thoughts of Schmidt and Sickles (1984), Greene (2005), Colombi et al. (2011) and Kumbhakar et al. (2014). In general, the former, reveals rigidities in the production processes that are caused by institutional factors and obsolete equipment's, such as old production machines, old buildings, old road systems, and systematic behavioral failures (Filippini and Hunt, 2015). By contrast, the latter is caused by short-run factors, such as inefficient supplier selection, sub-optimal resource allocation and trial-and-error processes in unknown situations (Colombi et al., 2017).

By providing information related to the nature and the drivers of changes, the decomposition of the TFCP into the persistent and the transient components represent an important element of policy support (Badunenko and Kumbhakar, 2016; Filippini et al., 2018). For this reason, the main objective of this paper is to refine the existing TFCP decomposition approach by focusing on the nature of persistence and transient and by considering the time invariant and the time-variant factors simultaneously. The methodological innovation will then be applied to the case of China. Being characterized by energy and environmental policies usually set over a long-period of time, with a short-period tracking, the Chinese context represents the perfect case study for the methodological innovation proposed in this paper. In particular, by using panel data for selected 30 Chinese provinces over the time period 1997-2017, the following research questions will be addressed: (i) Is the low carbon emission performance of China persistent or transient?; (ii) Which are the main characteristics of TFCP in China?; (iii) Which economic factors have influenced the spatial and temporal patterns?. This study contributes to the existing literature in the following ways:

First, by using a newly developed stochastic frontier model, this paper enables to distinguish, for the first time, the persistent and transient components of the total factor carbon emission performance. By providing disaggregated information across the spatial and temporal scales this approach can provide important information supporting the design of targeted policies (Badunenko and Kumbhakar, 2016). Second, the regional disparities and the temporal evolution of the carbon emission performance are analyzed by mapping the spatial and the temporal patterns of the carbon emission performance components on the national scale. The provided evidence can support the design of policies able to consider both the regional demonstration effect and the historical experience. Third, the economic effects of the persistent and the transient carbon emission performance are modelled simultaneously. The related empirical results provide a better understanding of the economic drivers of carbon emission changes and can support the development of carbon reduction strategies.

The paper is structured as follows. Section 2 reviews the main developments in total factor carbon emission performance and stochastic frontier models. Section 3 proposes an innovative method to measure the persistent and the transient total factor carbon emission performance through stochastic frontier model and model economic effects and panel data sets. Section 4 presents the empirical results and discussion. Section 5 concludes.

2. Literature review

2.1. Defining and measuring total factor carbon emission performance

Carbon emission is usually defined as one kind of undesirable (or bad) output that is different from the desirable (or good) gross domestic production. The traditional production technology in manufacturing ignores the joint production of bad and good output. How to treat bad output becomes a question in the specification of production process and measurement of efficiency. Arabi et al. (2015) and Halkos and Petrou (2019) summarised the most common channels to treat bad output in data envelopment analysis. Among them, the adjustment of the specification of production technology set is a popular method, in which the bad output such as carbon emission, is treated in its original form mentioned above and assumed to be weak disposability by imposing an equality constraint on bad output in the production set (Färe et al., 2005). The technology dealing with undesirable output was firstly constructed by Fare et al. (1989) through imposing an assumption of weak disposability on bad outputs, and they use a multiplicative distance function. After this pioneering work, growing amounts of studies have arisen to take into consideration of bad output when measuring productivity and efficiency (Färe et al., 2001; Hernandez-Sancho et al., 2000). Fare et al. (2007) formulated environmental technology that meets the two environmental axioms incorporating weak disposability and null-jointness of outputs, and proposed an additive environmental directional distance function (DDF). For example, the weak disposability highlights the cost to reduce bad output and the null-jointness axiom means the unavoidable bad output in production. Under the constraints of these axioms, measurement of technical efficiency can be defined through Shephard distance function and directional distance functions (Table 1).

The distance functions such as Shephard distance function (Shephard, 1970) and directional distance function (Chambers, 1996; Chung et al., 1997) are commonly used to functionally represent the environmental production technology. The Shephard distance function can be viewed as a special case of directional distance function by imposing some appropriate direction vector (Chung et al., 1997; Färe et al., 2005). The directional distance function (Chambers, 1996) sets the input contraction or output expansion along the pre-specified direction vector at the same rate. Chung et al. (1997) extended the directional distance function to incorporate undesirable output and it allows expanding the good output and decreasing the bad output simultaneously. One argument on directional distance function is the choice of the direction vector, among which it can be set in some ad hoc way such as a specific direction (Macpherson et al., 2010; Wang et al., 2013), or according to the research goal (Cheng et al., 2018a). Färe et al. (2013) developed a method to estimate directional distance function in which the direction vectors are endogenously determined. When there is any slack, the efficiency measures derived from the original directional distance function may be overestimated (Fukuyama and Weber, 2009). So, the other argument about the specification of change rate between inputs and outputs, which induces radial or non-radial directional distance function (Fukuyama and Weber, 2009; Zhou et al., 2007), has been widely considered in the context of data envelopment analysis (Cheng et al., 2018b; Färe and Grosskopf, 2010; Zhang et al., 2015). Fukuyama and Weber (2010) extended the directional slack based measure of technical efficiency by Fukuyama and Weber (2009) to incorporate undesirable output. Different from the previous studies that solve the slack based inefficiency from data envelopment models, Zhou et al. (2012) defined a non-radial directional distance function normally and then energy performance index, carbon performance index and a performance index simultaneously model energy and CO_2 through some specifications on normalized weight vector and direction vector.

Data envelopment analysis (non-parametric) and stochastic frontier analysis (parametric) are the two main strands of techniques to estimate production technology and efficiency scores (Färe et al., 2005). As the rapid development of Data Envelopment Analysis (DEA) variants, plethora of empirical studies have adopted DEA to consider characteristics and properties of production process like heterogeneity (Cheng et al., 2018b). The environmental efficiency and total-factor carbon emission performance in China have been calculated from many perspectives and multiple scales, including provinces (Wang, Q. et al., 2012), fossil fuel power plants (Zhang and Choi, 2013), transportation system (Chang et al., 2013; Zhang et al., 2015; Zhou, G. et al., 2013), industrial sectors (Cheng et al., 2018b; Wang and Wei, 2014; Zhou, Y. et al., 2013), agricultural sector (Liu and Feng, 2019), commercial sector (Wang and Lin, 2018), and non-ferrous metals industry (Lin and Chen, 2019). Although DEA models, which include affluent specifications to illustrate the characteristics of production process, have the advantage to avoid the specification of production function, they have limitations and defects as they ignore the stochastic noise and cannot distinguish the persistent and transient parts of efficiency. Besides DEA and SFA, some scholars have combined the virtual of DEA and SFA in a unified framework, generating the more advanced methods namely stochastic non-smooth envelopment of data (StoNED) (Kuosmanen, 2006; Kuosmanen and Johnson, 2017; Kuosmanen and Kortelainen, 2010). This is a strand of semi-parametric approaches and it has been for example adopted to calculate cost efficiency (Li et al., 2016) and marginal abatement cost (Lee and Wang, 2019).

Stochastic Frontier Analysis (SFA) models have the advantage to express the production maximum and cost minimum, and the distance function derived via SFA is differentiable (Färe et al., 2005). The applications of SFA in carbon performance arise in recent years. Wang et al. (2013) proposed a total factor CO_2 emissions performance index (TFCP) derived from the production technology and directional distance function and adopt SFA methods to estimate it on China's province level. They find higher performance in the southeastern coastal areas than the central and western inland regions and the increasing disparity of performance between regions indicates the necessity to set different regional targets. Following the environmental performance index proposed by Tyteca (1997), Zhou et al. (2010) defined the Shephard carbon distance function and a Malmquist CO_2 emission performance index (MCPI) which is derived by solving data envelopment analysis models. Lin and Du (2015) extended the work of Zhou et al. (2010) to parametric setting by specifying the Shephard carbon distance function with SFA models. The total factor carbon emission performance in this study is defined by following the method of Lin and Du (2015) based on SFA models.

Although the environmental efficiency and total carbon emission performance of China have been investigated widely, there is no study on disentangling the persistent and transient components, that is the time-invariant and time-varying division or long-run and short-run components, and it cannot be achieved very well by using the current DEA and StoNED techniques. However, the two parts may affect the effectiveness of carbon reduction policies. This study tends to bridge this gap. Lv et al. (2020) gives an up-to-date review on the development of SFA. A series of derivative models and applications of four components SFA are constructed (Lai and Kumbhakar, 2018a; Lien et al., 2018). It is obvious that the models set by SFA present the thoughts to separate time-varying and time-invariant efficiency. However, there is a lack of theoretical support and empirical experience in the scope of economics. After the model proposed by Kumbhakar et al. (2014), the distinction between long-run and short-run efficiencies has been taken into consideration but only in some nascent studies. For example, bank's efficiency (Badunenko and Kumbhakar, 2016), Italy hospitals (Colombi et al., 2017), coal-fired electric power generating plants in the U.S. (Lai and Kumbhakar, 2018a), Swiss hydropower firms (Filippini et al., 2017), energy efficiency in the U.S. residential sector (Alberini and Filippini, 2017) and New Zealand's electricity distribution businesses (Filippini et al., 2018). Utilizing the recent proposed model of SFA, we are able to disentangle Chinese carbon performance and analyze the determinants of its different components.

Table 1 The measurement of total factor carbon emission performance.

	Production technology set	Shephard distance function	Radial or non-radial DDF
Non-parametric (DEA)	Wang, Q. et al. (2013)	Zhou et al. (2010)	Zhang et al. (2015) Wang et al. (2016)
Parametric (SFA)		Lin and Du (2015)	Wang et al. (2013)

2.2 The economic determinants of carbon emissions

According to STIRPAT (Stochastic Impacts by Regression on Population, Affluence and Technology) model, there are three classifies of factors (P-A-T) influencing environment. Based on the STIRPAT and previous literature, eight commonly investigated variables which are widely explored are frequently modelled as determinants of carbon performance (Cheng et al., 2018a; Dong et al., 2018; York et al., 2003). All these determinants can be classified to affluence, technology and population, and the theoretical mechanism of their effects on carbon performance have been widely discussed and have been explored through empirical research.

It is evident that carbon emissions are a consequence of the production process and economic growth as it is inextricably linked with energy. Per capita Gross Domestic Product is usually recognised as a crucial driver of carbon emissions and has hitherto been under discussion extensively but there has been no a unanimous conclusion as results vary among samples and empirical techniques (Bo, 2011; Dinda, 2004; Sarkodie and Strezov, 2019). The coal dominated energy structure urges the effect of economic development on carbon emissions in China (Cheng et al., 2018a). Among these studies, an important line is the Environmental Kuznets Curve hypothesis. It posits an inverted-U relationship between income and environmental pollutions, and it has been tested and discussed widely (Grossman and Krueger, 1995; Onafowora and Owoye, 2014).

The secondary industry is energy intensive and industrialization is an impetus to economic development in China, accelerating carbon emissions and carbon intensity (Dong et al., 2018; Tian et al., 2014). Xu and Lin (2015) find a nonlinear impact of industrialization on carbon emissions. However, China has realised this problem and implemented various policies to control carbon emission during industrialisation (Zhang et al., 2019). The upgrading and optimisation of industrial structure indicates the production towards the high-tech industry and modern services. The tertiary industry is regarded as an industry with less energy consumption and thus lower emissions (Shi, 2003). The percentage of value added of the third industry to GDP is taken as a proxy of the upgrading of industrial structure and has been proved to be helpful to curb carbon intensity (Cheng et al., 2018a; Lin and Zhu, 2017).

The effects of international trade on environment can be classified into scale effect, composition effect and technology effect (Grossman and Krueger, 1991). Antweiler et al. (2001) explored how international trade affects environmental pollutants in a general equilibrium model of trade. Carbon emissions embodied in international trade is mentioned in the hot discourse on the responsibility attribution of emission. Carbon emissions embodied in international trade imposes large burden on China (Lin and Sun, 2010) and as a net carbon export country, it has experienced a growth period since China entered WTO in 2001 (Long et al., 2018). Foreign direct investment (FDI) transfers and relocates products that are energy and carbon intensive worldwide through new investment and cross border merge (Huang et al., 2017). According to pollution heaven theory, host countries, especially developing countries under low environment standard and regulation, suffer from environmental deterioration brought by FDI (Sun et al., 2017). In addition, FDI is an channel to technology spillover which contributes to mitigate carbon emissions (Peterson, 2007). Overall, there are no consensus results on whether FDI is responsible for increasing carbon emission (Liu et al., 2019; Shao et al., 2019). Besides, the role of native technology progress is not clear due to rebound effect. It has been proved that technological progress is effective to reduce energy consumption under scenario analysis (Yuan et al., 2009) and curb carbon intensity (Cheng et al., 2018a; Dong et al., 2018).

After the five theorems proposed by Ehrlich and Holdren (1971) under IPAT (population, affluence, technology) model, the importance of demographic factor on environment attracts much concern. Individual consumption behavior, lifestyle and preference affect energy consumption and carbon emissions. Dalton et al. (2008) classified the demographic factors into population size (direct scale effect), population composition (indirect scale effect) and consumption patterns. They developed a theoretical framework by incorporating age structure into a dynamic computable general equilibrium model and find heterogeneous effect of aging under different scenarios in USA. In OECD countries, Liddle (2011) and Menz and Welsch (2012) identified an intensive impact of young adults (20-34) on (transportation-induced) carbon emissions and an adverse impact from other age groups. In addition, the latter study found a negative year-of-birth effect and revealed the different interaction effects between birth cohort and age structure. The population structure and consumption level are revealed to be two major impact factors of population change on carbon emissions in China (Zhu and Peng, 2012). China has entered a process of demographic transition and one significant aspect is its age structure and population aging. Zhang and Tan (2016) verify a nonlinear impact of aging on carbon emissions in China, which is more pronounced than the effect from energy intensity. Wang et al. (2017) find the effects of population aging on CO_2 emissions among Chinese regions are heterogeneous.

Additionally, urbanisation is another important aspect of population structure that cannot be ignored. Poumanyvong and Kaneko (2010) analysed the mechanisms of urbanisation on carbon emissions and identified positive relationships empirically. Finally, energy is the main source of carbon emission, especially fuel combustion. Energy efficiency is regarded as one effective policy tool to curb carbon emissions and it is widely discussed from national, regional and industrial scales (Wang et al., 2020). Energy intensity is included to represent energy efficiency.

3. Methods and data sources

3.1. New measurement of total factor carbon emission performance

This section introduces the concept of environmental production technology first (Färe et al., 2005). Then it defines the Shephard carbon distance function (Zhou et al., 2010) which can be considered as a directional distance function with a special direction vector. It adopts a translog function to represent the Shephard carbon distance function. The translog function, which is a second order differential approximation of the Taylor expansion, has the advantage to release the assumption on production function. It has been widely employed in a handful of research on China (Lin and Long, 2015; Lin and Wang, 2014) and other countries (Filippini et al., 2018). Finally, some specification of SFA models are selected to parametrically estimate the carbon performance and disentangle it.

Supposed the production process in China includes three inputs, including labor (L), capital (K) and energy (E), they can generate two kinds of production, in which the desirable one is gross domestic product (Y) and the undesirable one is carbon emissions (C). The environmental production technology is expressed as:

$$\mathrm{T} = \{(L, K, E, Y, C) : (L, K, E)\ can\ produce\ (Y, C)\} \qquad (1)$$

Here for notational simplicity, the individual index (i) and time index (t) of variables are omitted at first. As it is focused on the performance of carbon emissions, the Shephard carbon distance function (Zhou et al., 2010) is defined as follows.

$$D_C(K,L,E,Y,C) = \sup\left\{\theta : \left(K,L,E,Y,\frac{C}{\theta}\right) \in T\right\} \quad (2)$$

In this definition, it aims to find out the maximal proportion of carbon emissions reduced when keeping other inputs and output fixed, and the hypothetical amount of carbon emissions is $\frac{C}{D_C}$. Under this context, the total factor carbon emission performance (TFCP) is the ratio between the hypothetical and actual carbon emissions.

$$\text{TFCP} = \frac{\frac{C}{D_C}}{C} = \frac{1}{D_C} \quad (3)$$

It is clear that the value of TFCP is above zero and the higher value of TFCP means the smaller difference between the actual carbon emission and the hypothetical values, indicating higher efficiency (or lower inefficiency) of carbon emission in the production process. The maximum value of TFCP indicates the efficient decision unit locating at the production frontier. Now the translog transformation function, which is more flexible than Cobb-Douglas function (Coelli and Perelman, 1999; Heshmati and Kumbhakar, 2011; Lien et al., 2018), is adopted to express the Shephard distance function explicitly.

$$\ln\left(D_C(K,L,E,Y,C)\right) = \beta_0 + \sum_{n=1}^{5}\beta_n ln(X_n) + \frac{1}{2}\sum_{m=1}^{5}\sum_{n=1}^{5}\beta_{mn} ln(X_m) ln(X_n) + \vartheta = \beta_0 + \beta_L lnL + \beta_K lnK + \beta_E lnE + \beta_Y lnY + \beta_C lnC + \beta_{LK} lnLlnK + \beta_{LE} lnLlnE + \beta_{LY} lnLlnY + \beta_{LC} lnLlnC + \beta_{KE} lnKlnE + \beta_{KY} lnKlnY + \beta_{KC} lnKlnC + \beta_{EY} lnElnY + \beta_{EC} lnElnC + \beta_{KK}(lnK)^2 + \beta_{LL}(lnL)^2 + \beta_{EE}(lnE)^2 + \beta_{YY}(lnY)^2 + \beta_{CC}(lnC)^2 + \vartheta$$
(4)

Where X_i (i=1, 2, 3, 4, 5) corresponds to K, L, E, Y, C, and ϑ includes the statistical noise and measurement error. In addition to meeting the conditions that the range of Shephard distance function is (0, 1], equation (4) should also satisfy the following regularity conditions.

$$\beta_{mn} = \beta_{nm} \quad (5)$$

To estimate the functional form of Shephard distance function, we exploit its properties derived from its definition. According to the definition of Shephard distance function, it is linearly homogeneous of degree one in carbon emissions.

$$D_C(K,L,E,Y,C) = \alpha D_C\left(K,L,E,Y,\frac{C}{\alpha}\right) \qquad (6)$$

Substituting equation (4) into the logarithm of (6) and setting $\alpha = \mathrm{C}$, it generates,

$$ln\left(D_C(K,L,E,Y,C)\right) = ln(C) + ln\left(D_C(K,L,E,Y,1)\right) = lnC + \beta_0 + \beta_K lnK + \beta_L lnL + \beta_E lnE + \beta_Y lnY + \beta_{LK} lnLlnK + \beta_{LE} lnLlnE + \beta_{LY} lnLlnY + \beta_{KE} lnKlnE + \beta_{KY} lnKlnY + \beta_{EY} lnElnY + \beta_{KK}(lnK)^2 + \beta_{LL}(lnL)^2 + \beta_{EE}(lnE)^2 + \beta_{YY}(lnY)^2 + \vartheta$$

(7)

Where it uses variable name as subscripts to indicate the corresponding coefficients in (4), for example, β_{LK} is the coefficient for multiplication of lnL and lnK. Substituting equation (7) into (4) and rearranging it, we get,

$$\beta_C lnC + \beta_{LC} lnLlnC + \beta_{KC} lnKlnC + \beta_{EC} lnElnC + \beta_{YC} lnYlnC + \beta_{CC}(lnC)^2 = lnC$$

(8)

It is obvious that equation (4) can be written as,

$$\ln\left(D_C(K,L,E,Y,C)\right) = \beta_0 + \beta_K lnK + \beta_L lnL + \beta_E lnE + \beta_Y lnY + \beta_{LK} lnLlnK + \beta_{LE} lnLlnE + \beta_{LY} lnLlnY + \beta_{KE} lnKlnE + \beta_{KY} lnKlnY + \beta_{EY} lnElnY + \beta_{LL}(lnL)^2 + \beta_{KK}(lnK)^2 + \beta_{EE}(lnE)^2 + \beta_{YY}(lnY)^2 + \vartheta + lnC$$

(9)

That is,

$$-lnC = \beta_0 + \beta_K lnK + \beta_L lnL + \beta_E lnE + \beta_Y lnY + \beta_{LK} lnLlnK + \beta_{LE} lnLlnE + \beta_{LY} lnLlnY + \beta_{KE} lnKlnE + \beta_{KY} lnKlnY + \beta_{EY} lnElnY + \beta_{LL}(lnL)^2 + \beta_{KK}(lnK)^2 + \beta_{EE}(lnE)^2 + \beta_{YY}(lnY)^2 + \vartheta - \ln\left(D_C(K,L,E,Y,C)\right)$$

(10)

If denoting $\mathrm{u} = \ln\left(D_C(K, L, E, Y, C)\right)$, the specification of equation (10) is consistent with that of stochastic frontier models. Then,

$$\mathrm{TFCP} = \frac{1}{D_C} = e^{-u}. \tag{11}$$

In the following, we use the lower-case letters of variables $(\mathrm{k}, \mathrm{l}, \mathrm{e}, \mathrm{y}, \mathrm{c})$ to represent the logarithm value of variables$(lnK, lnL, lnE, lnY, lnC)$. Above all, we can obtain the TFCP scores through some stochastic frontier models. There are many possible choices of SFA models. However, there is no criteria to choose a specific one (Farsi et al., 2006). Above all, we want to discover both the persistent, transient and overall carbon performance, so for consistency and comparison, three kinds of SFA models are adopted for equation (10) in this study.

The first model is the one constructed by Schmidt and Sickles (1984) as follows.

$$-c_{it} = \beta_0 + \beta_K k_{it} + \beta_L l_{it} + \beta_E e_{it} + \beta_Y y_{it} + \beta_{LK} l_{it} k_{it} + \beta_{LE} l_{it} e_{it} + \beta_{LY} l_{it} y_{it} + \beta_{KE} k_{it} e_{it} + \beta_{KY} k_{it} y_{it} + \beta_{EY} e_{it} y_{it} + \beta_{LL} l_{it}^2 + \beta_{KK} k_{it}^2 + \beta_{EE} e_{it}^2 + \beta_{YY} y_{it}^2 + \vartheta_{it} - u_i$$

(12)

Where ϑ_{it} is the error disturbance, and u_i is the inefficiency term, which belongs to long-run inefficiency. The problem of model (11) is that it puts some unobservable time-invariant things into the inefficiency part, and mixes up the inefficiency part that relates to production technology with the pure heterogeneity that relates to the individual characteristics.

The second model is developed by Greene (2005) which is termed as true individual effects SFA models, and it separates the individual effects in the panel model while leaving time-varying inefficiency in the compounded residuals. It estimates the time-varying inefficiency, which covers only the short-run component of inefficiency.

$$-c_{it} = \beta_0 + \beta_K k_{it} + \beta_L l_{it} + \beta_E e_{it} + \beta_Y y_{it} + \beta_{LK} l_{it} k_{it} + \beta_{LE} l_{it} e_{it} + \beta_{LY} l_{it} y_{it} + \beta_{KE} k_{it} e_{it} + \beta_{KY} k_{it} y_{it} + \beta_{EY} e_{it} y_{it} + \beta_{LL} l_{it}^2 + \beta_{KK} k_{it}^2 + \beta_{EE} e_{it}^2 + \beta_{YY} y_{it}^2 + \mu_i + \vartheta_{it} - u_{it}$$

(13)

Where μ_i is the individual effect that is time-invariant, ϑ_{it} is error disturbance and u_{it} denotes the inefficiency that is time-varying. The problem in this model is that any time-invariant component is ended up in the individual effect inducing an extension of individual heterogeneity.

The last one is the four component stochastic frontier model (or termed as general true individual effects SFA model) developed by Kumbhakar et al. (2014), which is a primary effort to separate the individual effects, persistent (time-invariant, long-run) inefficiency and transient (time-varying, short-run, residual) inefficiency within one model. Besides, the overall (time-varying) inefficiency can be derived from the persistent and transient inefficiency of this model.

$$-c_{it} = \beta_0 + \beta_K k_{it} + \beta_L l_{it} + \beta_E e_{it} + \beta_Y y_{it} + \beta_{LK} l_{it} k_{it} + \beta_{LE} l_{it} e_{it} + \beta_{LY} l_{it} y_{it} + \beta_{KE} k_{it} e_{it} + \beta_{KY} k_{it} y_{it} + \beta_{EY} e_{it} y_{it} + \beta_{LL} l_{it}^2 + \beta_{KK} k_{it}^2 + \beta_{EE} e_{it}^2 + \beta_{YY} y_{it}^2 + \mu_i - u_i + \vartheta_{it} - u_{it}$$
(14)

Where μ_i is the individual effect, ϑ_{it} is error disturbance, u_i represents the persistent inefficiency and u_{it} denotes the transient inefficiency.

After the estimation of different type inefficiency scores, TFCP is derived by following the method of Jondrow et al. (1982). The long-run (time-invariant) TFCP derived from model (12) is denoted as LONG. The short-run (time-varying) TFCP derived from model (13) is denoted as SHORT. The persistent TFCP, transient TFCP and overall TFCP from model (14) are abbreviated as TRANSIENT, PERSISTENT and OVERALL.

Table 2 Abbreviations for carbon performance indicators.

Performance indicator	Abbr.
Total factor carbon performance	TFCP
long-run TFCP	LONG
short-run TFCP	SHORT
transient TFCP	TRANSIENT
persistent TFCP	PERSISTENT
overall TFCP	OVERALL

3.2. Regression modelling

To identify the response of total factor carbon emission performance to economic variables, the efficiency scores in section 3.1 are taken as dependent variables and the possible driving factors as independent variables. The definition and origination of determinants are illustrated in the Table 3. Then a full regression equation is created. It is hypothesized the factors that affect actual and hypothetical carbon emissions are possible determinants of TFCP as defined in section 3.1. The hypothetical carbon emission lies on production frontier and is affected by production technology. With these factors referred in section 2.2 in mind, an extended STIRPAT model is established in equation (15).

$$TFCP_{it} = \alpha + \beta_1 PCGRP_{it} + \beta_2 INDU_{it} + \beta_3 TERT_{it} + \beta_4 URBAN_{it} + \beta_5 \mathrm{FDI}_{it} + \beta_6 OPEN_{it} + \beta_7 TECH_{it} + \beta_8 AGING_{it} + \beta_9 EI_{it} + \varepsilon_{it} \quad (15)$$

Table 3 The selected determinants of TFCP.

Variables	Proxy	Abbr.	References
Economic growth	Per capita Gross Domestic Product	PCGRP	Cheng et al. (2018a)
Industrialization	Percentage of the industry value added to GDP	INDU	Li et al. (2018)
Industrial structure upgrading	Percentage of value added of the third industry to GDP	TERT	Lin and Zhu (2017)
Population structure	Percentage of urban population to total population	URBAN	Lv et al. (2020)
International trade openness	Percentage of import and export to GDP	OPEN	Zhang et al. (2017)
Foreign direct investment	Percentage of actual foreign investment to GDP	FDI	Huang et al. (2017)
Technology progress	Number of patents application granted	TECH	Dong et al. (2018)
Population aging	Ratio of population aged 65 and above to the total population	AGING	Wang et al. (2017)
Energy efficiency	Energy intensity	EI	Wang and Wang (2020)

3.3. Data sources

In the SFA models, five variables including three inputs and two outputs are used to calculate the total factor carbon emission performance index. The number of employed persons in urban units at the year-end measures labor. The data for capital is calculated by adopting the perpetual inventory method (PIM) and adjusted by the price index of investment of fixed assets (Zhang et al., 2004). The gross domestic product (GDP) represents the desirable output and carbon emissions is the undesirable output. As there is no official publication of carbon emissions in China, carbon emissions is derived and calculated by following the work by Shan et al. (2018). Data for labor, capital and GDP are collected from China Statistical Yearbook (1998-2018). The data for energy consumption is derived from the China Energy Statistical Yearbook (1998-2018). Due to requirement for data consistency, this study collects the data of thirty provinces of China over the period 1997 to 2017 but regions such as Tibet, Taiwan, Hong Kong and Macao are excluded because of data unavailability. Data for these variables in section 3.2 are extracted from China Statistical Yearbook (1998-2018), China Price Statistical Yearbook and Statistical Yearbook of provinces (1998-2018) and regional Statistical Yearbook (1998-2018). All variables are in logarithms to alleviate the impact of heteroscedastic and to get elasticity. In sum, descriptive statistics are presented in Table 4.

Table 4 Statistical description of variables.

Variables	Mean	SD	Min	Median	Max
l	7.5331	0.824	5.5607	7.6176	8.8198
k	9.3139	1.243	5.7941	9.3217	11.9747
e	8.9256	0.836	5.9661	8.9901	10.5687
c	5.0684	1.011	-0.2053	5.1346	7.3473
GDP	8.6292	1.109	5.3122	8.7221	11.0944
PCGRP	5.0945	0.799	3.1135	5.1523	6.7822
IND	3.6135	0.255	2.4713	3.6754	3.9710
TERT	3.7148	0.172	3.3430	3.6938	4.3890
URBAN	3.8300	0.322	3.0694	3.8410	4.4954
OPEN	0.5271	1.005	-1.7798	0.2267	2.8458
FDI	3.3932	0.902	0.9357	3.2008	6.3466
TECH	8.4912	1.715	4.0254	8.3887	12.7149
AGING	2.1442	0.241	1.3987	2.1442	2.7961
EI	0.2965	0.506	-0.9878	0.2485	1.6158

Note: Variables are in logarithm.

4. Results

4.1. Total factor carbon emission performance

The summary statistics of TFCP scores from models (11) (12) (13) are reported in

Table 5. First, the mean value of two time-invariant efficiency measurements, LONG and PERSISTENT, are 0.516 and 0.694, with different skewness of 0.258 and -1.040. The difference between them reveals the incorporation of individual heterogeneity into efficiency term when calculating efficiency scores using model (11). It verifies the necessity to separate individual effect in the panel SFA models to find out unbiased efficiency scores. Second, in the case of the three time-varying efficiency scores, TRANSISENT, SHORT and OVERALL, the statistics between TRANSISENT and SHORT are similar, as both only measures the short-run component of efficiency. Moreover, the mean value of OVERALL, which covers both the long-run and short-run component of efficiency, is lower than the other four efficiency scores, verifying the existence of different sources of inefficiency and the necessity to decompose it. This finding suggests the government to set exact policy from right direction to curb inefficiency. Third, the standard errors (SD) of SHORT and TRANSISENT are closer and much lower than that of LONG, PERSISTENT and OVERALL, indicating that there is no obvious difference in the spatial-temporal evolution of short-run component, whereas the spatial evolution of long-run part shows large diversification and disparity. It reveals that the gap of long-run efficiency between provinces is large and some provinces has much pressure to catch up. The inefficiency of carbon is a long-run problem, and the factors that related to structural rigidity and management ability should be paid more attention. Finally, the gaps of quantile values and standard error between long-run and short-run efficiency values prove the necessity to decompose efficiency which helps to make corresponding policy precisely. The larger value of standard errors of time-invariant efficiency show that long-run efficiency between provinces is more diversified than the short-run part. There is a long way to alleviate the disparity between regions and it is efficient to improve long-run efficiency to catch-up.

The pairwise (rank) correlation coefficients between the different TFCP scores are presented in Table 6. First, it is evident that the two kinds of correlation coefficients between SHORT and TRANSISENT (0.9929, 0.9969) are very high and significant positive, verifying the previous evidence. Second, the correlation coefficients between LONG and PERSISTENT are significant positive and high, as they are used mainly to measure the long-run component of efficiency. Although the time-invariant efficiency LONG includes individual effect and induces biased results, it does not affect the ranking of provinces in the long-run carbon performance here. Third, the correlation coefficients between TRANSISENT (SHORT) and PERSISTENT (LONG) are relatively low at around 0.1. The low value of Spearman's rank correlation informs a different ranking between provinces in their short-run efficiency. Finally, the correlation between OVERALL and long-run efficiency is much higher than that between OVERALL and short-run efficiency, manifesting that total efficiency is occupied by the long-run part, and indicating there is a long way to improve carbon utilization.

Figure 1 portrays the spatial-temporal evolution of two time-varying carbon emission performance, taking years 2000, 2005, 2010 and 2015 as examples. The spatial distribution has no concrete decline or increase characteristic among regions, indicating that transient carbon performance can be changed temporarily. The order of transient efficiency is unstable, indicating that it can be improved by some temporary elements. Figure 2 displays the spatial distribution of long-run efficiency based on LONG (left) and PERSISTENT (right). As the spatial distribution of OVERALL is similar to long-run efficiency, it is not displayed. The range of PERSISTENT (without the 5% extreme value) is larger than that of TRANSISENT. There is significant regional distribution (disparity and agglomeration) which is attributed to different industrial structure, economic development, local lifestyles, different development strategies and geographical characteristics (Feng et al., 2009; Wang, K. et al., 2019; Wu et al., 2016; Zhuo and Deng, 2020). It reveals that long-run (overall) efficiency is higher in the east and south regions than in the west and north regions (Cheng et al., 2018b; Liu et al., 2016; Wang, Y. et al., 2019). Both the power of more good output and less bad output improves carbon performance. The north region faces the issue of heating with coal in winter (Wu et al., 2016). The west region has lower GDP and bares the transfer of high-energy consuming and high-polluting industries from eastern region since western development of 2000. Both are possible reasons to cause low carbon performance. Although the east and south are recognized as developed with more energy demand to satisfy both residential life and economic growth, it has new and high-tech industry and large proportion of tertiary. The study of Cheng et al. (2018b) supports the role of technical progress in improving carbon efficiency in eastern region and the technology gap in inhabiting the western region. Besides, it shows similar results depicted by Ding et al. (2019). There is efficiency agglomeration and diffusion around the main municipalities (Beijing, Tianjin, Shanghai and Chongqing).

Table 5 Descriptive statistics of total factor carbon emission performance.

TFCP	Mean	SD	Min	P5	Median	P95	Max	Skewness	Kurtosis	Shapiro-Wilk
LONG	0.516	0.206	0.089	0.240	0.519	0.886	1.000	0.258(0.0086)	2.640(0.0326)	0.984(0.0000)
SHORT	0.713	0.084	0.255	0.580	0.724	0.827	0.978	-1.260(0.0000)	8.340(0.0000)	0.907(0.0000)
TRANSIENT	0.640	0.090	0.211	0.500	0.647	0.773	0.975	-0.525(0.0000)	6.650(0.0000)	0.941(0.0000)
PERSISTENT	0.694	0.182	0.145	0.390	0.762	0.898	0.912	-1.040(0.0000)	3.690(0.0042)	0.895(0.0000)
OVERALL	0.446	0.131	0.031	0.168	0.474	0.610	0.739	-0.904(0.0000)	3.550(0.0154)	0.939(0.0000)

Notes: SD is standard error. Min is minimum value. P5 is the 5% quantile value. P-values are in parentheses.

Table 6 The coefficients of correlation between TFCP scores.

	LONG	SHORT	TRANSIENT	PERSISTENT	OVERALL
LONG	1	0.0784**	0.0737*	1.0000***	0.8962***
SHORT	0.1414***	1	0.9969***	0.0784**	0.4324***
TRANSIENT	0.1006**	0.9929***	1	0.0737*	0.4289***
PERSISTENT	0.9299***	0.1785***	0.1276***	1	0.8962***
OVERALL	0.8585***	0.5024***	0.4635***	0.9271***	1

Notes: (1) Lower-triangular cells report Pearson's correlation coefficients, and upper-triangular cells are Spearman's rank correlation. (2)*** p<0.01, ** p<0.05, * p<0.1

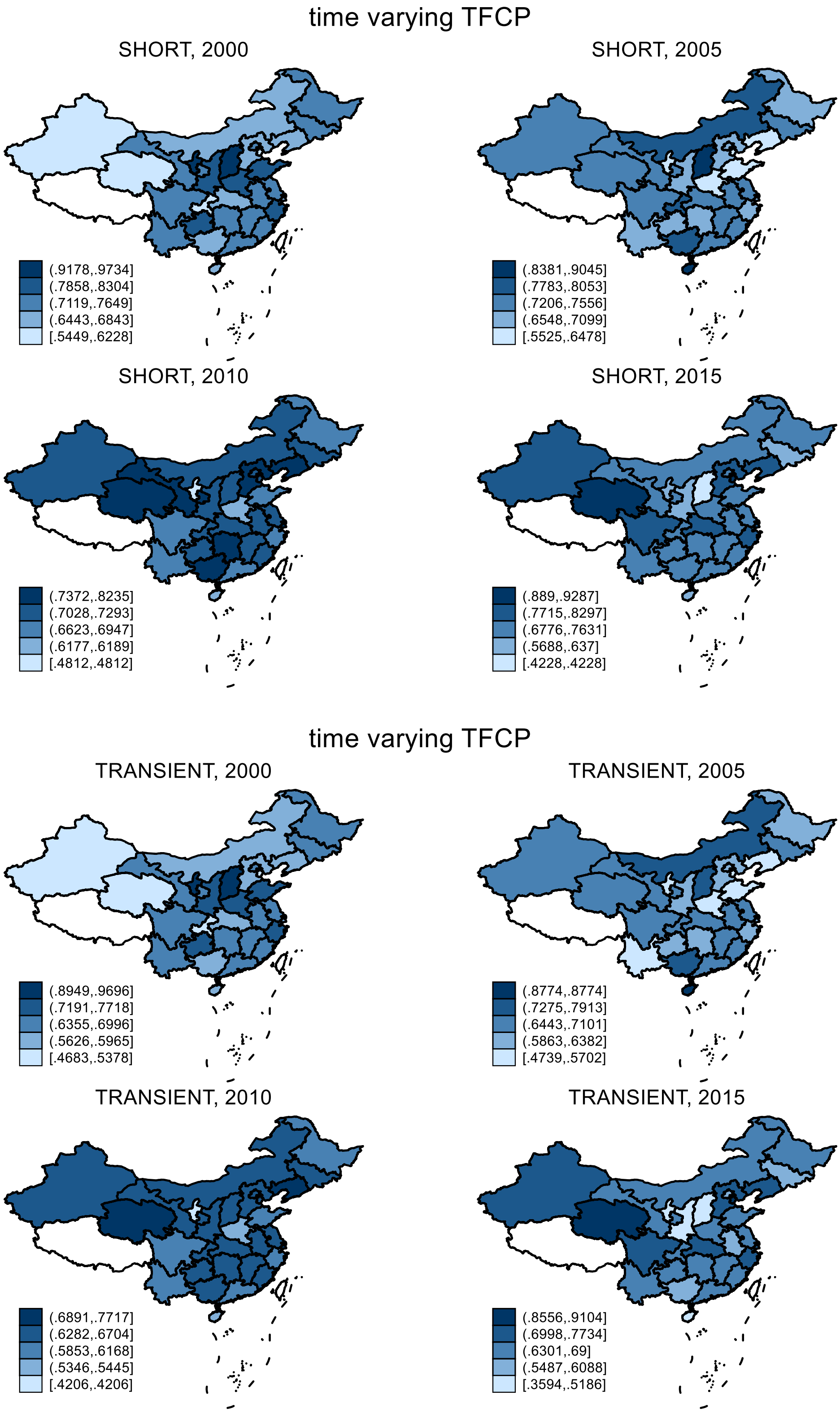

Figure 1 The spatial distribution of time-varying TFCP

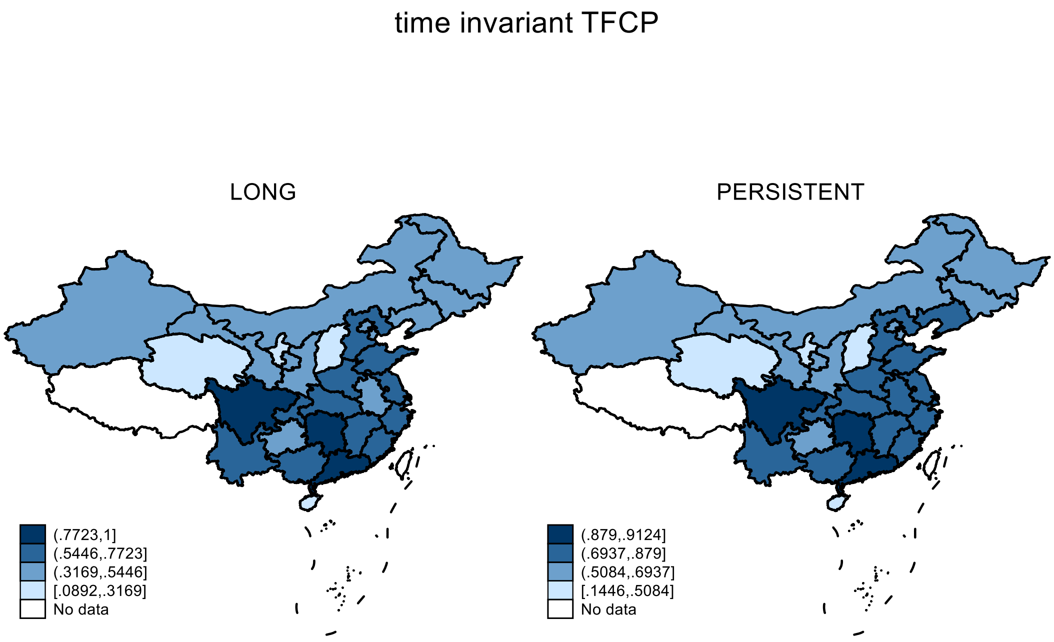

Figure 2 The spatial distribution of time-invariant TFCP

4.2. Modelling determinants of TFCP

To find out the determinants of TFCP scores, three regression models are developed. Although there are arguments with no consistent views on the data generating process of efficiency scores (Hoff, 2007; McDonald, 2009), it is common to regard the efficiency scores as censored data and adopt Tobit model to regress it on economic variables (Bai, X. et al., 2019; Ouyang et al., 2019). To derive robust result, both (panel) Tobit and linear regression models are adopted in this section. There are very limited studies exploring the determinants of persistent efficiency (Lai and Kumbhakar, 2018b; Lien et al., 2018). It should be noted that there are no natural time-invariant determinants as regressors of persistent or long-run TFCP in our sample, which is the same situation as the two previous studies. The former takes mean values of time-varying variables as determinants of persistent efficiency, and the latter explores determinants of transient inefficiency only. As the economic determinants to be sought are time varying, examining their impact on time-invariant TFCP will be problematic in terms of temporal match for modelling. Thereby, it is imperative to process data first (Lai and Kumbhakar, 2018b). However, Lai and Kumbhakar (2018b) take mean value over the full sample, which doesnot consider the temporal heterogeneous effect of a time-varying determinant on the time-invariant TFCP. That is, for example, the impact on persistent inefficiency of urbanization at different stage may be changed. In addition, Five-Year Plan is one main component of the socialist economy with Chinese characteristics, showing large disparity with the western market economy. It updates the constraint targets on carbon emissions every five years and has played top-down governance role in managing carbon emissions of China (Hu, 2016; Yuan and Zuo, 2011). Consequently, based on the data processing method in Lai and Kumbhakar (2018b), the mean values of influencing variables are calculated during 1997-2000, 2001-2005, 2006-2010, and 2011-2017, which follow the divisions of all the Five-Year Plans after 1997 in China covering the carbon constraint target since 2010. Methodologically, the sample is divided into four sub-samples and the impact is revealed with cross sectional regression. The data processing and model regressions are programmed in Stata 15 and results are shown in Table 7, with the results by Tobit regression in the upper part A and the results by linear regression in the lower part B. The values of LR chi2 and F-statistics reveal that both Tobit regression and linear regression are significant at 1% significance level, respectively. The impact of determinants on time-varying TFCP are revealed within panel regression, and results are presented in Table 8 with the results by panel Tobit in column (A) and the results by panel linear regression in column (B). The values of Wald chi2 show that the models are significant at 1% significance level. The values of chibar2 refer to the tests of individual-specific effects, using likelihood-ratio test for panel Tobit and Breusch and Pagan Lagrangian multiplier test for panel random effect regression, confirming the significance of individual-specific effects at 5% significance level. It is clear that in most cases the sign and significance of resulting time-invariant TFCP in Table 7 are consistent with the results of total performance in Table 8, confirming the dominant role of persistent carbon performance. The magnitude of coefficients is unstable between time-invariant and time-varying scores. It draws some new insights and a complete picture in the following.

As shown in Table 7, per capita GDP has insignificant impact on time invariant TFCP in all cases (Song, M. et al., 2020), indicating that the economic development has no significant pressure or improvement on carbon performance. It indicates that economic growth does not damage carbon performance in the study period. However, the increase of investment on green technology caused by economic growth does not work significantly. As China has experienced a process with high economic development but with the sacrifice of environment, it needs a long-run process of recovery. The same result happens in the situation of short-run carbon performance.

Industrialisation is recognised to have positive and significant impact (Liu and Song, 2020). Evidence on how industrialisation affects carbon emission and intensity is well established, however there is no consensus. The impact of industrialisation is found to be insignificant negative (Song, M. et al., 2020; Yang et al., 2020), significant positive (Dong et al., 2018; Huang et al., 2020; Huang et al., 2018). By comparing multi integrated assessment models, Duan et al. (2021) forecast that industrial carbon emissions will decline, which is driven by industrial structure adjustment, low-carbon transition of energy and enhancement of energy efficiency. Although result in this study is different from most others based on carbon intensity (Huang et al., 2020), it validates the effectiveness of a series of policies on industrial sectors which target at energy conservation and pollution reduction in China (Yang et al., 2020; Zhang et al., 2019). On one side, as the secondary industry accounts for 70% of carbon emission in China and leaves large potential to curb carbon. In this regard, the government has launched a wide range of energy conservation and carbon reduction policies (Feng et al., 2020; Lo et al., 2015; Zhou et al., 2014). All these programs and codes contribute to promote green production effectively. On the other side, China has paced into the post-industrialisation stage and factor substitution is highlighted in pursuing its supply-side structural reforms. As one aspect of energy substitution, inter-factor substitution is affirmed to be attributable to carbon intensity reduction in heavy industry (Liu, K. et al., 2018). In addition, the policies to shut down the high pollution enterprises and cut overcapacity contribute to carbon reduction (Chen, Z. et al., 2020).

The upgrading and optimization of industrial structure (TERT) has positive impact on persistent carbon performance, indicating the importance of industrial structure adjustment to achieve carbon reduction targets (Cheng et al., 2018a; Lin and Zhu, 2017). The Ministry of Science and Technology issues a notice on the Special Twelfth Five-Year Plan (2011-2015) of modern service industry (MOST, 2012[2]), which has the advantage of low resource consumption and environmental pollution. The development of modern service and high-tech industries are beneficial to promote low-carbon economy (Xu and Lin, 2018). The impact of industrialisation and industrial structure on TRANSIENT and SHORT (Table 8) is insignificant positive, indicating that it does not work in a transient process. As the energy conservation and emissions reduction policies has begun from the 11-th Five-Year Plan (2006-2010) with emphasis putting on the secondary industry from upgrading and optimizing industrial structure, whereas the research period covers the long-run process from 2006.

Urbanisation shows negative but insignificant effect in most cases (Table 7), which is similar to the results based on carbon intensity (Huang et al., 2020). The energy demand from urban construction and the insufficient treatment of pollutants are two main aspects that induce the increase of carbon emissions and impede carbon performance during urbanisation

[2] http://www.most.gov.cn/fggw/zfwj/zfwj2012/201202/t20120222_92619.htm

in China (Cheng et al., 2018a; Pan et al., 2020). The new-type urbanisation since 2014 in China requires ecological and environmentally friendly construction. On the consumer side, the consumption patterns and lifestyles of rural people is different from urban population (Jiang and Hardee, 2011). Urbanisation is responsible for the increase of residential carbon emissions (Bai et al., 2019). Some provinces or cities with high level of urbanisation tend to pay more attention on environmental quality. With the policy efforts and the rising environment awareness of residents, the negative effect of urbanisation shows insignificant gradually. The impact of urbanisation on TRANSISENT and SHORT (Table 8) is also insignificant negative; however, the impact on total carbon performance (Table 8) is significant negative. Overall, urbanisation hinders the improvement of carbon performance and the push effect has not aroused yet. Given the larger coefficient of persistent carbon performance and its dominant role, it is necessary to pay more attention to urbanisation driving forces that benefits to long process carbon performance.

In Table 7, the impact of openness is not significant in most cases (Yang et al., 2014). FDI has negative but not always significant impact, endorsing the pollution heaven theory. This is a result consistent with that of Cheng et al. (2018a), Liu and Song (2020) and Song et al. (2020). Although it is expected to benefit from the technology spillover, carbon emission brought by FDI and trade through scale effect and decomposition effect is dominated until now. From the perspective of scale effect, the foreign enterprises increase energy consumption and carbon emission in production process. Carbon emission embodied in international trade accounts for a large proportion and it has grown steadily in China after having joined WTO (Long et al., 2018; Ren et al., 2014; Wang and Su, 2020). In view of the relative advantage of low cost and environmental regulation standards, it tends to transfer the low-tech processing, assembly, manufacturing and resource intensive industry to China (Cheng et al., 2018a). The technology effect has not played its role well, due to the limited ability to absorb technology and the spread of managerial skills (Ang, 2009). It is believed that the role of FDI and trade on carbon emission is not isolated and it depends on some other factors, such as human capital (Lan et al., 2011) and institutional quality (Perkins and Neumayer, 2011). The impacts of FDI and openness on both persistent and transient carbon performance are insignificant or negative, indicating that the international connections impose large pressure on environment and carbon performance. There is still a long way to alleviate the side effect from outside. It is still an issue to decrease scale effect and to utilize the technology effect, not only from the short-run process but also from the long-run process.

The results state that technology progress has positive impact on time-invariant carbon performance (Cheng et al., 2018a; Huang et al., 2020). To deal with climate change and construct an environmentally friendly society, the nation encourages financing and investment on green and low-carbon technology. Although using an input indicator of technology progress, Luan et al. (2019) find domestic R&D activities is conducive to curb carbon intensity in Chinese industrial sectors. Wang, Z. et al. (2012) find the role of domestic patents for carbon-free energy technologies in carbon reduction plays well in China, whereas the domestic patents for fossil-fueled technologies do not work. In addition, technology progress, especially the development of energy innovation and clean production technology, is recognised as one pivotal way to decouple economic growth with carbon emission and achieve sustainable economic growth (Wang and Su, 2020; Wang and Wang, 2019). The impact of technology progress on transient carbon performance is positive but insignificant, which shows a little difference from the results of persistent and total performance. It should be noted that technology progress is lagged and spends long time to create working effects. Besides, although technology progress can be regarded as a significant determinant of persistent and long TFCP, there is no obvious strengthening or weakening trend between each five-year periods, indicating that the impact is nonlinear and not steady.

Aging has positive but insignificant impact, as this study focuses on a full sample different from the regional analysis of Wang et al. (2017) and the nonlinear analysis of Zhang and Tan (2016) and Yang and Wang (2020). On one hand, the Chinese older population incline to live with younger occupying less space and there are transportation policies such as bus-discount for older, inducing a different lifestyle of aging population in China from other countries (Menz and Welsch, 2012). It may cause scale of economy and contributes to the inhibitory effect of aging on carbon emission (Wang et al., 2017). On the other hand, the push effect of aging on carbon emission can be attributed to continuous labor supply and psychological factors (Zhang and Tan, 2016). In view of cost and preference, the low willingness of the elderly to applicate and accept new energy conservative products hinders the improvement of energy and carbon efficiency. The elder in developed regions tend to contribute emission more as they have higher requirement on medical and health care, which implies that the stage of aging matters (Yang and Wang, 2020). The increasing life longevity and rising recruitment age push carbon emissions emitted in the process of production and consumption. The impact of aging on transient and total carbon performance is significant positive. It indicates that aging and its effect on carbon performance happen almost simultaneously.

It shows negative effect of energy intensity on long-run carbon performance. This is reasonable as energy intensity is always used as a reciprocal indicator of energy efficiency and has been recognised to have positive impact on carbon intensity (Dong et al., 2018; Lin and Zhu, 2017; Liu and Song, 2020; Song, M. et al., 2020). The decrease of energy intensity means the growth rate of GDP is larger than that of energy input. Carbon is embodied in energy especially fossil fuels, implying that it is affected by both energy structure and energy efficiency (Dong et al., 2018). Energy intensity can be curbed by the growing development and utilization of renewable energy such as wind, solar and biomass energy, which are more efficient and environmentally friendly. The impact of energy intensity on total carbon performance is significant positive. This is a confused result proving the biased measurement of energy efficiency from side, in which energy intensity is a single-factor indicator and carbon performance is a total-factor indicator. In addition, the role of energy intensity on carbon performance relates to energy structure. Overall, there is no obvious temporal trend of the impact in different periods, showing that the impact of energy intensity on persistent TFCP is nonlinear and changing.

Table 7 Determinants of time-invariant TFCP.

	(1) Persistent 1997-2000	(2) long 1997-2000	(3) persistent 2001-2005	(4) long 2001-2005	(5) persistent 2006-2010	(6) long 2006-2010	(7) persistent 2011-2017	(8) long 2011-2017	(9) persistent 1997-2017	(10) long 1997-2017
Part A: Results from Tobit regression.										
PCGRP	-0.246	-0.318	0.114	0.235	-0.177	-0.299	-0.460	-0.553	-0.140	-0.071
	[0.21]	[0.29]	[0.26]	[0.34]	[0.27]	[0.38]	[0.28]	[0.42]	[0.28]	[0.41]
INDU	0.736***	0.756**	0.987***	0.821*	0.786**	0.495	1.103***	1.055**	1.140***	1.037**
	[0.22]	[0.31]	[0.30]	[0.40]	[0.36]	[0.51]	[0.32]	[0.48]	[0.31]	[0.45]
TERT	0.718	1.083*	1.518***	1.697**	0.648	0.388	1.104*	0.925	1.290**	1.424*
	[0.43]	[0.60]	[0.46]	[0.60]	[0.51]	[0.73]	[0.58]	[0.86]	[0.53]	[0.77]
URBAN	-0.052	-0.141	-0.666*	-1.040**	-0.125	-0.192	0.272	-0.003	-0.372	-0.735
	[0.22]	[0.31]	[0.33]	[0.44]	[0.52]	[0.74]	[0.69]	[1.02]	[0.44]	[0.64]
OPEN	0.006	-0.097	-0.168	-0.278**	0.033	-0.059	0.197*	0.152	0.048	-0.095
	[0.10]	[0.14]	[0.10]	[0.13]	[0.09]	[0.12]	[0.10]	[0.15]	[0.12]	[0.17]
FDI	-0.245**	-0.245*	-0.079	-0.024	-0.248***	-0.153	-0.317***	-0.241	-0.287***	-0.195
	[0.09]	[0.12]	[0.08]	[0.10]	[0.08]	[0.11]	[0.10]	[0.15]	[0.10]	[0.14]
TECH	0.153**	0.255***	0.193***	0.314***	0.123*	0.282***	0.067	0.158	0.078	0.208**
	[0.06]	[0.08]	[0.06]	[0.08]	[0.06]	[0.09]	[0.06]	[0.10]	[0.07]	[0.10]
AGING	0.368	0.462	-0.035	-0.099	0.400	0.314	0.371	0.398	0.353	0.263
	[0.24]	[0.34]	[0.27]	[0.36]	[0.30]	[0.42]	[0.25]	[0.37]	[0.29]	[0.43]
EI	-0.321**	-0.489**	-0.285*	-0.341	-0.325*	-0.237	-0.242	-0.273	-0.435**	-0.474*
	[0.14]	[0.19]	[0.15]	[0.20]	[0.18]	[0.25]	[0.15]	[0.22]	[0.17]	[0.25]
_cons	-4.002*	-5.573*	-9.061***	-10.088***	-4.511*	-2.797	-5.481**	-4.070	-6.894**	-7.771*
	[2.06]	[2.86]	[2.36]	[3.12]	[2.57]	[3.67]	[2.29]	[3.40]	[2.59]	[3.79]
LR chi2	49.82	46.91	47.50	47.05	43.13	39.02	47.20	40.04	49.99	43.63
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Part B: Results from linear regression.										
PCGRP	-0.246	-0.315	0.114	0.237	-0.177	-0.273	-0.460	-0.542	-0.140	-0.053
	[0.27]	[0.40]	[0.16]	[0.24]	[0.23]	[0.31]	[0.30]	[0.44]	[0.21]	[0.30]
INDU	0.736**	0.793	0.987*	0.878	0.786	0.574	1.103**	1.092*	1.140**	1.092*
	[0.34]	[0.46]	[0.55]	[0.71]	[0.54]	[0.71]	[0.47]	[0.59]	[0.48]	[0.62]
TERT	0.718	1.077	1.518*	1.735*	0.648	0.481	1.104	0.980	1.290*	1.486
	[0.67]	[0.91]	[0.77]	[0.98]	[0.78]	[1.09]	[0.78]	[1.14]	[0.74]	[0.96]
URBAN	-0.052	-0.143	-0.666**	-1.037***	-0.125	-0.221	0.272	0.007	-0.372	-0.752
	[0.18]	[0.24]	[0.27]	[0.33]	[0.57]	[0.77]	[0.75]	[1.22]	[0.37]	[0.45]
OPEN	0.006	-0.094	-0.168*	-0.277**	0.033	-0.061	0.197*	0.150	0.048	-0.097
	[0.12]	[0.15]	[0.09]	[0.13]	[0.08]	[0.11]	[0.11]	[0.18]	[0.11]	[0.17]
FDI	-0.245*	-0.235	-0.079	-0.026	-0.248**	-0.160	-0.317**	-0.249	-0.287**	-0.198
	[0.12]	[0.15]	[0.07]	[0.09]	[0.10]	[0.13]	[0.12]	[0.15]	[0.11]	[0.14]
TECH	0.153**	0.247***	0.193***	0.303***	0.123*	0.267***	0.067	0.151	0.078	0.197*
	[0.06]	[0.08]	[0.05]	[0.08]	[0.06]	[0.09]	[0.08]	[0.11]	[0.08]	[0.11]
AGING	0.368	0.426	-0.035	-0.120	0.400**	0.268	0.371	0.346	0.353	0.218
	[0.22]	[0.31]	[0.23]	[0.28]	[0.18]	[0.26]	[0.23]	[0.31]	[0.26]	[0.41]
EI	-0.321*	-0.497**	-0.285	-0.366	-0.325	-0.286	-0.242	-0.299	-0.435	-0.507
	[0.18]	[0.22]	[0.19]	[0.25]	[0.26]	[0.34]	[0.16]	[0.23]	[0.27]	[0.35]
_cons	-4.002	-5.601*	-9.061**	-10.316**	-4.511	-3.307	-5.481	-4.342	-6.894*	-8.104*
	[2.59]	[3.10]	[3.92]	[4.93]	[3.71]	[5.00]	[3.37]	[4.51]	[3.35]	[4.55]
F-statistics	35.15	26.58	9.57	7.94	10.59	10.54	10.20	9.47	12.71	9.63
	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Notes: Part A shows the results from Tobit regression and Part B shows the results from linear regression.
Standard errors for coefficients are in brackets. P-values are in parentheses.
* indicates significant at 10%, or $p < 0.10$. ** indicates significant at 5%, or $p < 0.05$. *** indicates significant at 1%, or $p < 0.01$.

Table 8 Determinants of time-varying TFCP.

	(a)transisent	(b)transisent	(a)short	(b)short	(a)overall	(b) overall
PCGRP	-0.010	-0.014	-0.009	-0.015	-0.036	-0.100**
	[0.03]	[0.03]	[0.03]	[0.02]	[0.05]	[0.04]
INDU	0.074	0.070	0.065	0.056	0.360***	0.439***
	[0.06]	[0.05]	[0.05]	[0.05]	[0.09]	[0.09]
TERT	0.083	0.075	0.069	0.053	0.399***	0.423***
	[0.09]	[0.09]	[0.08]	[0.08]	[0.12]	[0.13]
URBAN	-0.101	-0.090	-0.106	-0.086	-0.370***	-0.395***
	[0.08]	[0.07]	[0.07]	[0.06]	[0.10]	[0.10]
OPEN	0.020	0.020	0.018	0.018	0.016	0.022
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
FDI	-0.012	-0.014	-0.006	-0.010	-0.003	-0.005
	[0.02]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
TECH	0.005	0.004	0.009	0.008	0.063***	0.089***
	[0.01]	[0.01]	[0.01]	[0.01]	[0.02]	[0.02]
AGING	0.162***	0.161***	0.155***	0.153***	0.231***	0.275***
	[0.04]	[0.04]	[0.04]	[0.04]	[0.06]	[0.06]
EI	0.003	-0.002	0.017	0.006	0.145***	0.109**
	[0.03]	[0.03]	[0.03]	[0.03]	[0.05]	[0.05]
_cons	-0.902**	-0.849**	-0.743*	-0.641*	-2.969***	-2.927***
	[0.43]	[0.39]	[0.40]	[0.35]	[0.66]	[0.66]
Wald	31.38	31.38	32.84	36.36	54.48	80.21
chi2	(0.0003)	(0.0003)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
chibar2	4.25	3.52	10.05	9.42	547.06	1807.32
	(0.0200)	(0.0303)	(0.0010)	(0.0011)	(0.0000)	(0.0000)

Notes: For every model, column (A) shows the results from Tobit regression, and column (B) shows the results from linear regression.
Standard errors for coefficients are in brackets. P-value are in parentheses.
* indicates significant at 10%, or $p < 0.10$. ** indicates significant at 5%, or $p < 0.05$. *** indicates significant at 1%, or $p < 0.01$.

5. Conclusion

A clear understanding of the properties and main drivers of carbon dioxide emission changes is a fundamental element of policy design. Within this context the aim of this paper is to provide an innovative approach to disaggregate the total factor carbon emission performance between the persistent and the transient components. After an extensive literature review on the studies of total factor carbon emission performance and the linked econometric models, this paper integrates the environmental production technology and the Shephard distance function to provide an innovative way to analyse efficiency (Adom et al., 2018a; Filippini et al., 2017; Musau et al., 2020). Using panel data for 30 selected Chinese provinces for the time period 1997-2017, three SFA models are then adopted to fit the distance function and to evaluate the carbon emission performance. These models are meaningful to distinguish the individual heterogeneity and the persistent and the transient components (Adom et al., 2018a; Filippini and Zhang, 2018), where the latter two elements provide information related to the spatio-temporal evolution of the TFCP. The key findings and implications are listed as follows.

Firstly, the measurements of carbon emission performance highlight that the range of persistent carbon performance (PERSISTENT and LONG) is larger than the transient parts (TRANSIENT and SHORT), indicating that the disparity among provinces is mostly attributed to a long-run process. In light of the spatio-temporal evolution of carbon performance scores, there are two main policy implications. On one hand, it is necessary to make regional specific policies to reduce carbon emission and improve its performance according to the spatial disparity of persistent carbon performance. To make balanced development, the lagged provinces, that shows a relative low level of long-run TFCP, are suggested to emphasis policies related to long-run performance. From the country's perspective, the resource misallocation, the long-run moral hazards and the institutional quality are accounted for long-run inefficiency (Adom et al., 2018b; Colombi et al., 2017; Filippini et al., 2018). Institutional reforms, sound infrastructure governance and environmental regulations are examples of tools that can be used to improve the carbon performance and to alleviate the regional disparities (Adom et al., 2018a; Kennedy et al., 2014). Transformation of energy structure, urban planning and location choices of pollution-intensive firms, are among the policies that can contribute to improve the persistent efficiency (Wang, X. et al., 2019; Ye et al., 2015). On the other hand, these results have proved the effectiveness of the China's Five-Year Plans to manage carbon emission on national, regional and sectoral scales. However, there is still a long way to maximize carbon emission performance in China. In addition, the transient part, which is diversified without concrete spatial distribution, can be improved by temporary policies, e.g. fiscal subsidies on new energy vehicle, real time pricing, carbon information disclosure and social norms (Huber et al., 2018; Luo, 2019). On a regional scale, the following recommendations are suggested: In the northern areas where supply of winter heating is essential, it is urgent to improve the heating efficiency by retrofitting old buildings (Liu, Y. et al., 2018). In the eastern and in the coastal regions with mature economic development, it is suggested to increase the application of renewable energy and to promote more sustainable lifestyles (Feng et al., 2009). In the western and in the central areas more attentions should be devoted in adjusting the industrial structure, and in adopting the more advanced technology and human capital resources from the eastern regions. Overall, it is necessary to continue the strategy of regional coordinated development and differential environmental regulations (Shuai and Fan, 2020; Zhuo and Deng, 2020).

Secondly, referring to the determinants of carbon emission performance, the impacts of economic variables on transient, persistent and total carbon performance are not always consistent. With the growth of economy, development of urbanisation, upgrading and optimization of industrial structural, the undermining effects on carbon emission performance weakened gradually. Due to the increasing concern on environment and the urging policies to protect ecology and living conditions, the push effects of these economic activities have arisen (Lin and Benjamin, 2017), particularly on the persistent parts. It is recommended to carry on the construction of new-type urbanisation, industrialisation and industrial structure transformation. For example, at the stage of industry 4.0, it is suggested to enhance the optimization and upgrading of industrial structure (Wang et al., 2020) and to promote the integration of advanced manufacturing industry and modern service industry (Song et al., 2020). It is no doubt that urbanisation affects persistent efficiency as the urban plan and construction last long, while there are behaviors that change transiently. In the situation of new-type urbanisation, it is then urgent to alleviate its negative effect on carbon emission performance. To combat environment problems, more attention should then be devoted to the energy demand and to the carbon emission changes in different end-use sectors as their energy and carbon impacts are diversified (Lv et al., 2019). One challenge of urbanisation is the rapid construction of both residential and commercial buildings, which should highlight the importance of green construction (Li, D. et al., 2020). It takes long time to achieve low-carbon in construction industry whereas life-cycle management of building contributes to monitor and feedback the energy consumption and carbon emission conditions (Ge et al., 2020). Another challenge of new-type urbanisation is the transport issue. A major part of carbon emission come from road construction (Chen et al., 2017) and worker commuting, whereas the style of the latter has been transformed during the urbanisation, appealing the construction of public transport. Incentive polices to change transportation mode of residents and retail sector affect transient behavior (Chen and Wang, 2016; He et al., 2013). The residential sector cannot be ignored either, as energy consumption styles and preference of urban and rural residents are increasingly changing. One solution to develop low-carbon economy is the construction of smart city (Wang et al., 2019) and eco-city (Li et al., 2019).

Smart cities can promote efficient energy management (Reinisch et al., 2011), by strengthening the application of information and communication technology (ICT) (Kramers et al., 2014; Moyer and Hughes, 2012) and block-chain (Sun and Zhang, 2020) etc. during city operation and governance.

Thirdly, factors that may change production technology are revealed to be significant in improving persistent TFCP, confirming the role of technology effect. However, the technology effect on persistent and long-run TFCP is changing over periods. To improve persistent TPCP and achieve carbon neutrality, it is instrumental to find out a steady or increasing path to keep the positive technology effect. According to the insignificant impact of foreign direct investment (FDI) and trade openness on carbon emission performance, how to signify the technology spillover effect and absorb advanced technology to improve carbon performance is still an issue. A further and detailed research is required to identify whether the technology embodied in FDI or trade is green. It appeals the government to set policies to attract green FDI and import green products. Under the circumstance of globalisation, it calls for reforms of environmental institutions (Andersson, 2018), adjustment of export diversification and sophistication (Apergis et al., 2018). As proved by these empirical results, technological progress is a crucial factor in improving the performance (Jiao et al., 2020). Technology progress stems from persistent research with considerable capital. Increasing investment on innovative research and accelerating the application and transformation of new technology to industries can contribute to improve the carbon emission performance (Ang, 2009). Although research and development is a process with high input and slow effect, the significant role on persistent carbon performance and the persistent attribute of technological progress can drive enterprises in making long-term research and development strategies. For this reason, policy support should be provided in promoting R&D initiatives (Chen et al., 2020). The negative impact of energy intensity on persistent efficiency suggests to focus on both energy consumption and energy structure (Wang and Wang, 2020). Within this context, strategies to improve persistent energy efficiency can be considered as effective policy tools to increase carbon performance (Lv et al., 2020; Vieira et al., 2018).

There are some inevitable limitations in this study, which appeal for further studies on this topic. The focus of this paper is at provincial level, but analysis could be extended to the national (Zaman and Moemen, 2017), prefectural-city (Shan et al., 2017), country, industry and enterprise levels (Ren et al., 2014). Different scales of analysis and the results will be useful to gain a better understanding of the carbon trends and to optimize resource allocation and responsibility attribution. In addition, given the importance of the regional development policies (for example in Pearl River Delta and Yangtze River Delta) specific regional analysis would also be required. Despite the existing limitations and the possible analytical developments, the methodological approach presented in this paper represent one of the first attempts to disaggregate the persistent and the transient components of the TFCP. By providing a better understanding of the spatial and temporal patterns influencing the carbon dioxide emission changes and the related economic determinants, this paper can be used to support the design of carbon reduction policies at different scale of analysis. The possibility to replicate the proposed methodologies across regions and countries can also provide important opportunities for international comparisons and design of coordinated carbon reduction strategies. It should be noted that due to the property of persistent efficiency, the data processing method proposed in this study to match with Five-Year Plan is limited, particularly when applying it to Western economies. However, our approach within the specific context of Chinese economic policy-making provides comparative perspectives of understanding the complexity of economic systems, including the global challenge of carbon emission targets. Given the importance of persistent efficiency, it is imperative to develop other generalized method of processing such data and explore time-invariant determinants in the future work.

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Appendix

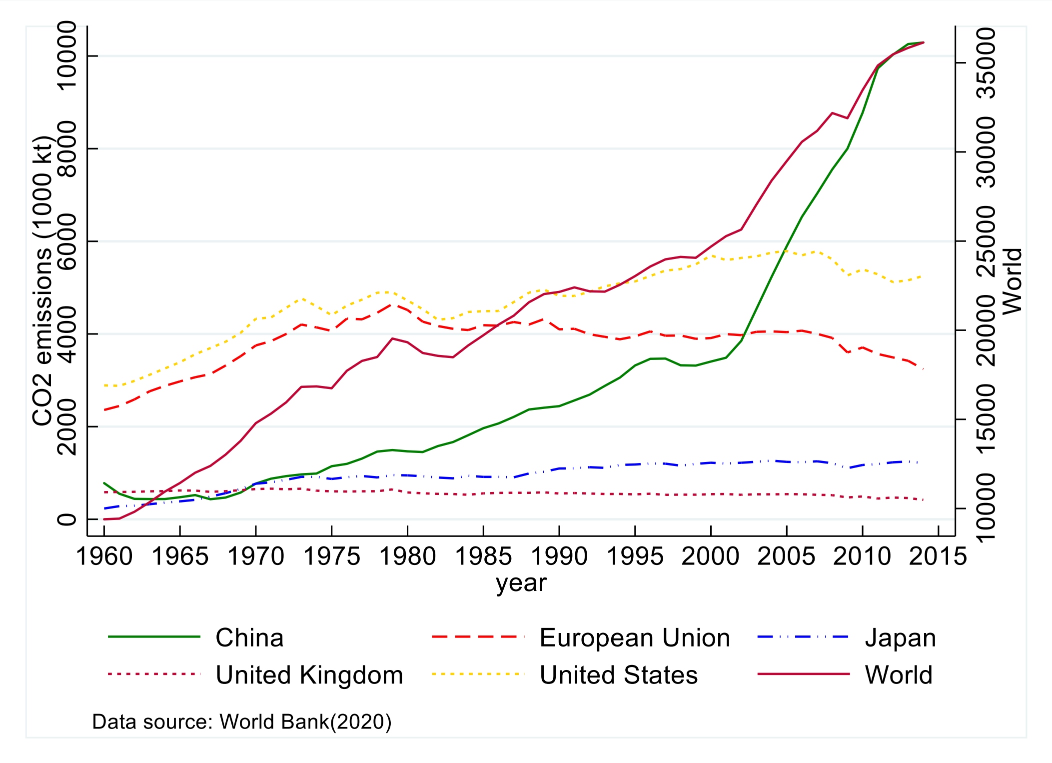

Figure A1. Total CO_2 emissions of selected countries (the world one on the right y-axis)

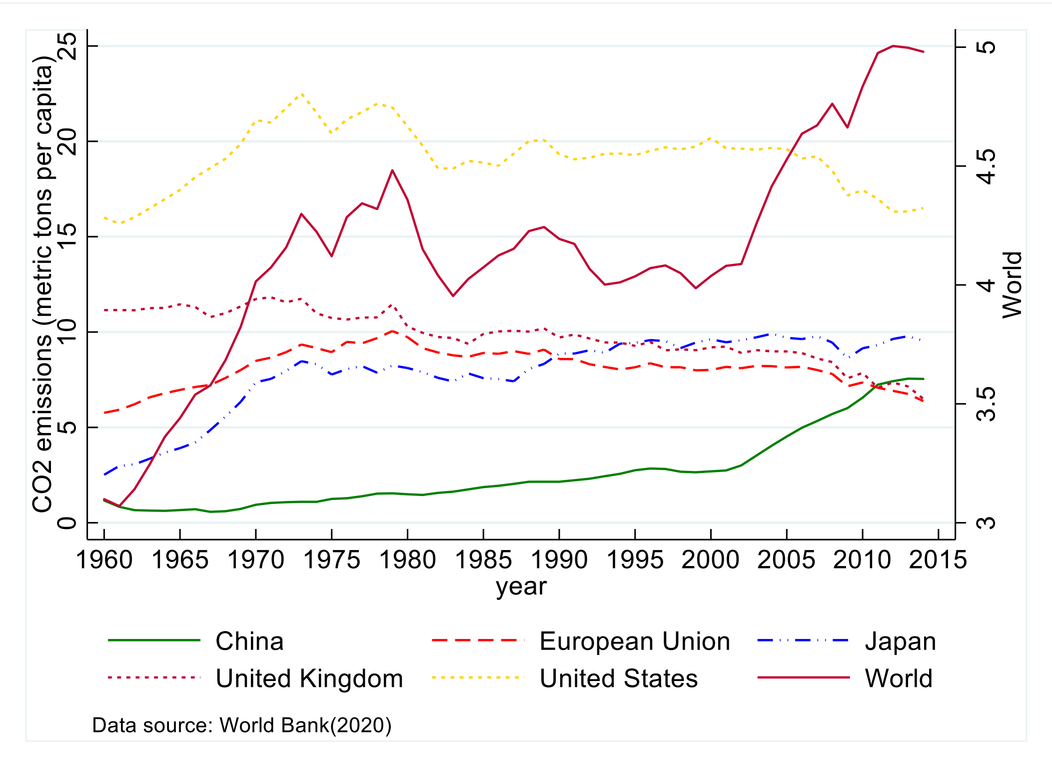

Figure A2. CO_2 emissions per capita of selected countries

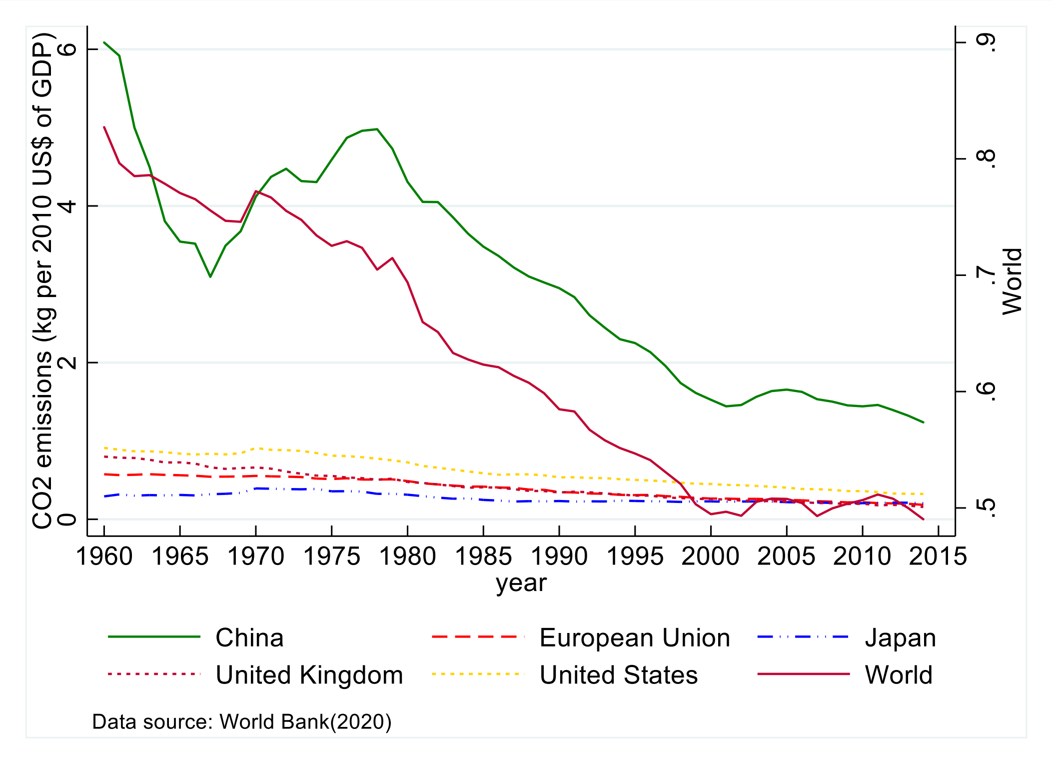

Figure A3. Carbon intensity between the selected countries and the world