Journal of Environmental Management 260 (2020) 110163

Contents lists available at ScienceDirect

Journal of Environmental Management

journal homepage: http://www.elsevier.com/locate/jenvman

Research article

Sustainability efficiency and carbon inequality of the Chinese transportation system: A Robust Bayesian Stochastic Frontier Analysis

Peter Wanke [a], Zhongfei Chen [b,c,d,*], Xi Zheng [b], Jorge Antunes [a]

[a] COPPEAD Graduate Business School, Federal University of Rio de Janeiro, Rua Paschoal Lemme, 355, Rio de Janeiro, CEP: 21949-900, Brazil
[b] School of Economics, Jinan University, No.601 Huangpu West Road, Guangzhou, Guangdong Province, China
[c] Institute of Resource, Environment and Sustainable Development Research, Jinan University, Guangzhou, Guangdong 510632, China
[d] School of Management and Economics, Beijing Institute of Technology, Beijing 100081, China

ARTICLE INFO

Keywords:
Sustainability
Transport
China
SFA
Bayesian analysis
Robust regression

ABSTRACT

This study focuses on the sustainability efficiency of the Chinese transportation system by investigating the relationship between CO_2 emission levels and the respective freight and passenger turnovers for each transportation mode from January 1999 to December 2017. A novel Robust Bayesian Stochastic Frontier Analysis (RBSFA) is developed by taking carbon inequality into account. In this model, the aggregated variance/covariance matrix for the three classical distributional assumptions of the inefficiency term—Gamma, Exponential, and Half-Normal—is minimized, yielding lower Deviance Information Criteria when compared to each classical assumption separately. Results are controlled for the impact of major macro-economic variables related to fiscal policy, monetary policy, inflationary pressure, and economic activity. Results indicate that the Chinese transportation system shows high sustainability efficiency with relatively small random fluctuations explained by macro-economic policies. Waterway, railway, and roadway transportation modes improved sustainability efficiency of freight traffic while only the railway transportation mode improved sustainability efficiency of passenger traffic. However, the air transportation mode decreased sustainability efficiency of both freight and passenger traffic. The present research helps in reaching governmental policies based not only on the internal dynamics of carbon inequality among different transportation modes, but also in terms of macro-economic impacts on the Chinese transportation sector.

1. Introduction

Sustainable transport has made significant contributions to address climate change and maintain the sustainable development of countries. As the global climate has changed dramatically, sustainable transport has become a major concern for the entire world (Greene and Wegener, 1997; Tolley, 2003; Litman and Burwell, 2006; Feng et al., 2013; Labib et al., 2018; Li et al., 2019). The World Energy Council (WEC) pointed out that 20%–25% of the global energy consumption and carbon dioxide emissions were attributed to transport based on the 2007 Global Energy Survey. Sustainable transport will effectively reduce carbon emissions caused by transportation, bringing about positive effects to further optimize transport distribution and promote sustainable economic development. The Global Sustainable Transport Conference held in December 2016 discussed the relationship between sustainable transport, climate change, and energy, pointing out that sustainable transport played a critically important role in improving transportation efficiency and reducing emissions in general.

In the past four decades, with China's rapid economic growth, its population has more disposable income to travel and visit relatives more frequently. Meanwhile, with urbanization gaining momentum, people have to commute to work by subway and automobile. Furthermore, freight transport has witnessed obvious increases in the last few years, mainly because of the fast-growing express-delivery demand driven by the emergence of e-commerce. The above-mentioned economic activities have elevated the demands for transport, which has led to the dramatic rise in pollutant emissions by transport. Referring to the IEA (International Energy Agency) statistics, carbon dioxide emissions increased from 6.15% in 1999 to 8.60% in 2014. Aiming at reducing CO_2 emissions per unit of GDP by 40%–50% by 2020, the Chinese government has launched policies to enhance managing energy emissions in the transport industry to alleviate environmental pollution and

* Corresponding author.
E-mail address: hongyeczf@163.com (Z. Chen).

https://doi.org/10.1016/j.jenvman.2020.110163
Received 16 September 2019; Received in revised form 17 January 2020; Accepted 18 January 2020
Available online 25 January 2020

Table 1
Descriptive statistics of the variable vectors used in the RSBM under six different combinations of distributional assumptions.

Variable			Units	Min	Max	Mean	SD	CV
Input	y	Total Transport CO2 Emission/Total Energy Use	100 million HP/tons	46.62	63.91	54.28	6.09	0.11
Outputs	x1	Railway Turnover of Passenger Traffic/ Railway Energy Use	100 million person*kilometers/100 million HP	8.40	54.73	25.63	6.96	0.27
	x2	Railway Turnover of Freight Traffic/Railway Energy Use	100 million tons*kilometers/100 million HP	76.53	80.01	78.72	0.52	0.01
	x3	Roadway Turnover of Passenger Traffic/ Roadway Energy Use	100 million person*kilometers/100 million HP	7.76	98.89	45.52	26.83	0.59
	x4	Roadway Turnover of Freight Traffic/ Roadway Energy Use	100 million tons*kilometers/100 million HP	65.67	72.53	69.69	2.02	0.03
	x5	Waterway Turnover of Passenger Traffic/ Waterway Energy Use	100 million person*kilometers/100 million HP	0.28	4.40	0.90	0.72	0.80
	x6	Waterway Turnover of Freight Traffic/ Waterway Energy Use	100 million tons*kilometers/100 million HP	537.30	537.61	537.57	0.05	0.00
	x7	Air Transport Turnover of Passenger Traffic/ Airway Energy Use	100 million person*kilometers/100 million HP	13.48	34.06	28.09	2.29	0.08
	x8	Air Transport Turnover of Freight Traffic/ Airway Energy Use	100 million tons*kilometers/100 million HP	0.66	2.21	1.11	0.17	0.15
Contextual		Trend	–	1.00	228.00	114.50	65.96	0.58
		Exchange rate	(RMB/USD)	6.10	8.28	7.30	0.86	0.12
		Loan rate	(%)	4.35	7.47	5.68	0.74	0.13
		Deposit rate	(%)	1.50	4.14	2.49	0.69	0.28
		CPI	(%)	−1.80	2.60	0.18	0.68	3.85
		Total trade	(100 million USD)	196.99	4089.08	1964.35	1202.97	0.61
		M2	(100 million yuan)	105500.00	1676768.54	632779.18	483581.81	0.76
		Fiscal Expenditure	(1 billion yuan)	52.98	2701.59	688.32	610.87	0.89
		Consumer Confidence Index	–	97.00	123.90	107.84	4.85	0.04
		Fixed Assets Investment	(1 million yuan)	84519.00	63168396.00	11101454.12	14282428.94	1.29

Log applied in inputs, outputs, Total trade, M2, Fiscal Expenditure and Fixed Assets Investment variables.

encourage "green commuting" (Zhang et al., 2017; Chen et al., 2019; Feng, 2019; Wang et al., 2019). China's policies have given top priority to promoting new-energy transportation vehicles in the private sector (Hu et al., 2010; Liu et al., 2013; Lin et al., 2017), but have failed to pay enough attention to traditional freight and passenger transport. Most policies have merely set stricter limits on exhaust emissions and fuel specifications to meet targets by limiting total emissions to the detriment of improving sustainability efficiency, so they have not managed to strike a balance between freight and passenger transport and sustainability efficiency.

This study examines the sustainability efficiency of the Chinese transportation system encompassing the modes of air, water, rail, and road transportation in terms of CO_2 emission levels per unit of energy based on monthly data from January 1999 to December 2017. Within the broader scope of the transportation sustainability research stream, 'sustainable transportation efficiency' deals with the productive structure of the transportation sector considering the technological specifics of each mode in moving passengers and cargo in terms of the required amount of energy to perform such a task to the detriment of fuel-burn and CO_2 emissions. Efficiency studies and transportation sustainability studies require a number of assumptions on the production frontier, or the limit of best practices, that impose technological constraints on the conversion of energy into passenger and cargo turnovers. Previous research has regarded the transportation sector as a whole, neither differentiating passenger from freight traffic nor the four distinct transportation modes. In another words, the previous body of work has ignored the inequality among different transportation modes in carbon emissions. This paper will fill the literature gap and shed some light on the potential for curbing carbon emissions for China's transportation industries, since existing research has rarely differentiated these distinct kinds of transportation modes when analyzing the entire transportation system and has failed to take into account the heterogeneity of the models. Differently from previous studies where sustainability efficiency is analyzed under traditional parametric and non-parametric efficiency models (Centobelli et al., 2017; Wanke et al., 2018a; Rashidi and Cullinane, 2019), this research proposes a novel Robust Bayesian Stochastic Frontier Analysis (RBSFA) computational model to relate the transportation sustainability efficiency in China to its turnovers in terms of freight and passenger traffic.

This novel RBSFA, differently from previous approaches, addresses epistemic uncertainty in sustainability efficiency studies by deriving a combined distributional assumption—free from collinearity—for the residual and inefficiency terms. Instead of handling four individual distribution assumptions at a time in order to decompose total error variance into its major constituents, a prior robust testing on distributional assumptions for the sustainability inefficiency is implemented, thus avoiding model misspecification by choosing one particular assumption to the detriment of the other.

Compared to traditional SFA models, the estimated sustainable efficiency is unbiased when employing the RBSFA model even with a small sample. As a matter of fact, while reducing bias, the proposed approach improves sustainable efficiency predictability in several variance reduction metrics such as R-squared, RMSE, and MAPE, as a direct consequence of mitigating epistemic uncertainty by combining different distributional assumptions. Meanwhile, our approach takes into account heterogeneity and ensures that efficiency is correctly estimated rather than assuming that all the Decision Making Units (DMUs) have the same technology (Chen et al., 2015, 2017a, b). Another distinctive feature of this paper is that major macro-economic variables are jointly taken into account for assessing sustainability efficiency levels in a given transport activity. In fact, transportation activity is strongly related to macro-economic conditions (Beyzatlar et al., 2014; Cui and Li, 2015).

Previous research on transportation freight and passenger sustainability efficiency is rather scarce (Richardson, 2005; Kelle et al., 2019). Alonso et al. (2015) developed composite indicators to evaluate the sustainability of the passenger transportation sector for 23 different cities in the European countries. They found distinct sustainability performance for medium and small cities. Wei et al. (2013) applied data envelopment analysis (DEA) to compare urban transportation systems in 34 different cities of China and found significant differences between the sustainability efficiency and the capacity efficiency for these cities, which suggests strong regional variations in transportation

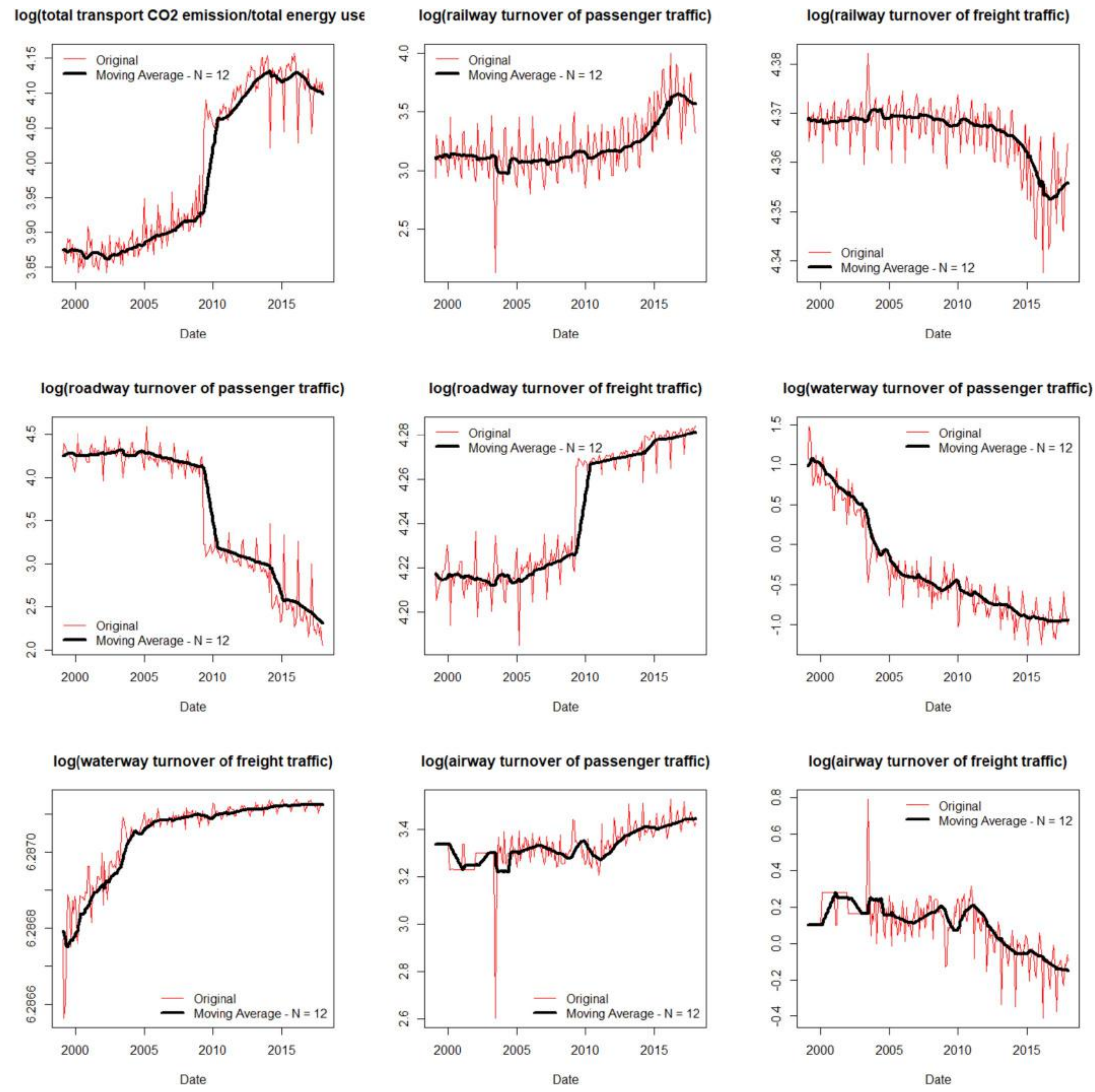

Fig. 1. Time series plots for the outputs and inputs.

development. In any case, what emerges from the above literature is that the innovative RBSFA computational model proposed here is being applied for the first time in relation to transportation sustainability efficiency and its roots in major macro-economic variables. Among the few studies in this research field that have adopted Bayesian SFA models on sustainability efficiency of transport activity are Llorca et al. (2017), who applied a random parameters stochastic frontier analysis (SFA) to estimate energy demand and efficiency of transport industry in the Latin American and Caribbean regions. Their results indicated that some of the countries that successfully improved public transport are efficient in energy consumption. Assaf (2011) also applied a Bayesian random coefficient stochastic frontier model that took into account the technological difference to estimate UK airport efficiency. He found that the new model could overcome the shortcomings of traditional SFA models and could correct the bias by allowing for heterogeneity.

Departing from previous studies, our conclusions indicate that sustainability efficiency levels would be improved when waterway, railway, and roadway are more intensively used in freight traffic. As for passenger traffic, sustainability efficiency will increase when roadway and railway are prioritized. The air transportation mode would decrease sustainability efficiency both in freight traffic and passenger traffic. Moreover, we find that certain macro-economic variables are significantly associated with sustainability efficiency.

The remainder of the paper is structured as follows: part two presents the literature review, part three introduces the methodology, part four describes the analysis and discusses the empirical results with the fifth and final part summarizing the paper's conclusions.

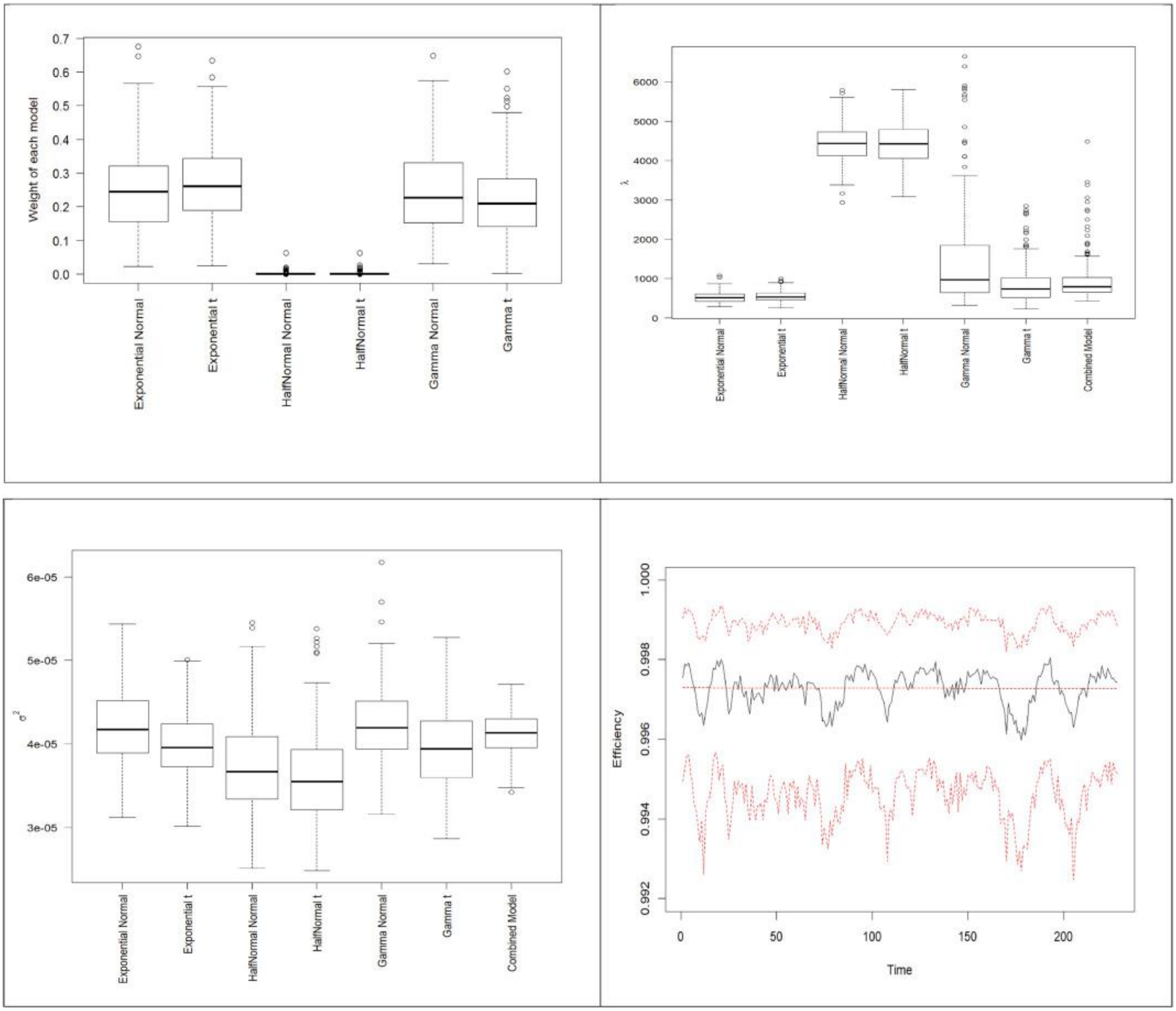

Fig. 2. RBSFA (combined model) results: differential optimization weights (top-left), lambda (top-right), sigma square (bottom-left), and time series for the efficiency scores (bottom-right).

2. Literature review

How to effectively lower CO_2 emissions and improve energy efficiency to increase the overall sustainability efficiency of the transportation sector has always been a hot topic in the respective academic fields. There are two main streams of literature for estimating sustainable efficiency: Data Envelopment Analysis (DEA) (Yu et al., 2017; Chen et al., 2017b; Park et al., 2018) and SFA (Chen et al., 2017a; Tsionas et al., 2017; Llorca et al., 2017). Furthermore, most studies thus far have only focused on one of the transportation modes separately, evaluating their sustainability efficiency for different countries or areas including road transportation (Léonardi and Baumgartner, 2004; Kuosmanen and Kortelainen, 2005; Liu et al., 2019), railway transportation (Song et al., 2016; Wanke et al., 2018b), shipping transportation (Cullinane et al., 2004; Mansouri et al., 2015; Wanke et al., 2018a), and air transportation (Li et al., 2015; Chen et al., 2017a, b; Cui, 2019).

To enhance sustainable transportation, it is important to examine which transportation mode contributes the most greenhouse gas emissions (GHGs). Hence, researchers have also conducted plenty of studies to differentiate the carbon emissions of different transportation modes and have found that they differ in terms of the respective CO_2 emissions and energy use. Among such studies, McKinnon (2007), observing UK freight data, investigated four modes of transportation: road, railway, shipping, and air. He found that 92% of the CO_2 emissions from freight transportation in the UK were caused by road transportation in 2004, while the relative environmental benefits of railway transportation were significantly underestimated. Morán and del Rio Gonzalez (2007) developed an input–output model to examine the CO_2 emission structure of road transportation in EU countries. The results indicate that the relationship between production departments and the terminal demand structure has a significant impact on the CO_2 emissions of road transportation. Lakshmanan and Han (1997) found that freight transportation rather than passenger transportation had led to the increase in energy use and carbon emissions during 1970–1991 in the U.S. transportation industry. In recent years, researchers have paid increasing attention to this issue in China. For example, Li et al. (2017) combined autoregressive distributed lag bounds testing and the vector error correction model to investigate the relationship between the transportation scale of different transportation modes and carbon emissions in the short and long term. The results indicated that the scaling up of

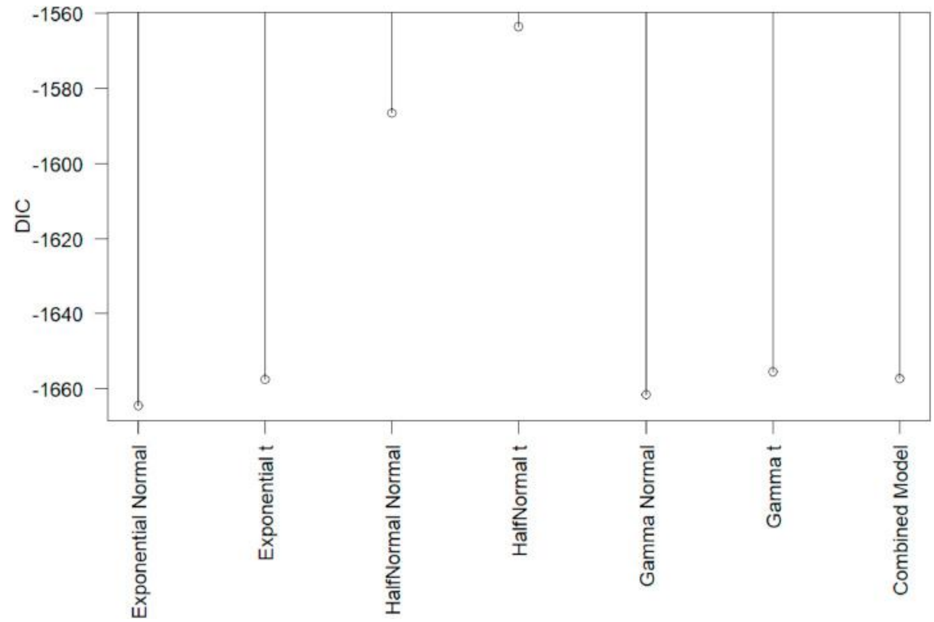

Fig. 3. Results for DIC

railway transportation, road transportation, shipping, and air transportation significantly increased carbon emissions in China during 1985–2013. The shipping mode had the greatest effect compared to the other two, and the expansion of the railway transportation saw the opposite effect on carbon emissions but during a different time range. In another words, the railway transportation will increase the emissions in the short term while reducing them in the long term. Meanwhile, Wang et al. (2011) employed the Logarithmic Mean Divisia Index and found that road transportation contributes the most to CO_2 emissions. Although a large strand of literature has been accumulated on this theme, results are inconsistent and this may be due to the different characteristics of transportation sectors in different countries. Different measurement methods may also lead to different results.

Existing studies have also paid a lot of attention to the relationship between CO_2 emissions and the macro-economic factors. Lakshmanan and Han (1997) found that the increase in travel intention, population, and GDP growth promoted an increase in energy consumption and CO_2 emissions in the US transportation sector. Meanwhile, Timilsina and Shrestha (2009) and Chandran and Tang (2013) also observed a similar situation in Asian countries. Scholl et al. (1996) noticed that an increase in tourism demand contributed to a significant raise in CO_2 emissions in the OECD countries. Some scholars have employed the co-integration test and Granger causality test to examine feedback effects between carbon dioxide emissions and macro-economic variables in the transportation sector (Huo et al., 2015; Saboori et al., 2014). Moreover, Halkos and Paizanos (2016) used the Vector autoregression (VAR) model to detect the influence of fiscal policy on CO_2 emissions in the United States and found that expansionary fiscal policies were helpful to reduce CO_2 emissions. Cui and Li (2015) applied a virtual frontier DEA model to calculate environmental efficiency of the transportation sector in 19 countries and then applied a Tobit model to identify the driving factors of carbon emission efficiency. They found that the proportion of transportation technology and low-carbon technology input in GDP is an important influencing factor. Based on the Global Change Assessment Model (GCAM), Yin et al. (2015) analyzed both China's long-term energy consumption and the country's carbon emissions and they concluded that it is more difficult for the transportation industry, which is highly dependent on fossil fuels, to curb energy consumption and CO_2 emissions compared to other industries.

A vast amount of research focuses on the sustainability efficiency of transportation industries, but a gap still remains. First of all, most studies forgo a systemic analysis and fail to break down the contribution to carbon emissions or sustainability efficiency of China's different transportation sectors. Meanwhile, the existing literature has tended to concentrate on freight transport and deemphasize passenger transport.

3. Methodology

3.1. Background on SFA

SFA, first proposed by Aigner et al. (1977) and Meeusen and van Den Broeck (1977), is a method of parametric efficiency analysis. It is used to estimate the boundary functions for a given production technology and to gauge the inherent productive or cost efficiency. There has been an increase in recent years in the number of applications of SFA models in the energy sector, although SFA applications for CO_2 emissions and other sustainable issues related to the intensive use of energy such as transportation still remain scarce (Herrala and Goel, 2012; Llorca et al., 2017). For example, Huntington (1994) estimated and compared energy efficiency and productive efficiency by employing the SFA model. Buck and Young (2007) used a parametric approach to estimate a stochastic frontier function for energy use in Canadian commercial buildings. Boyd (2008) applied the stochastic frontier function to energy use in wet corn milling plants. Additionally, Filippini and Hunt (2011) and Herrala and Goel (2012) discussed global carbon dioxide efficiency with a stochastic frontier analysis. Wang et al. (2013) used SFA to estimate the directional distance function and the total factor carbon emission performance of 28 Chinese provinces during the period from 1995 to 2009. Lin and Du (2015) adopted a fixed-effect panel stochastic frontier model and applied it to investigate the regional heterogeneity of carbon emission in 30 Chinese provinces.

In simpler SFA models, the maximum likelihood method is usually employed to compute the required parameter estimates. In recent years, as the complexity of stochastic frontiers has increased, an uptick in the use of Bayesian analysis has been evident (Liu et al., 2017; Assaf et al., 2017). In spite of its many advantages, the joint use of SFA and Bayesian analysis is still a growing field, as discussed next.

3.2. Bayesian analysis and markov-chain Monte Carlo methods

When accounting for heterogeneity in stochastic frontier models, the common method is no longer suitable for estimating the production

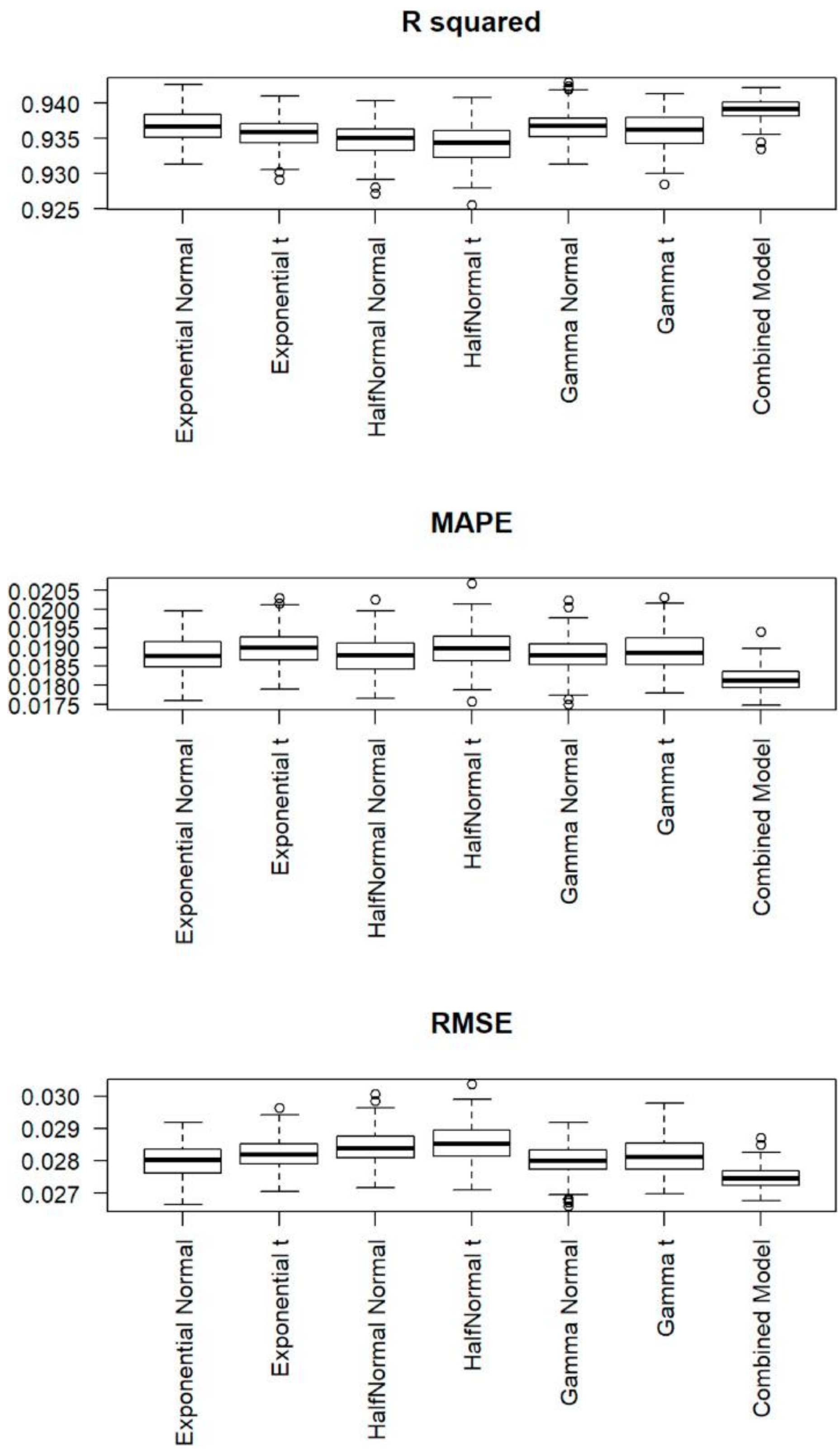

Fig. 4. Other metrics of explanatory power.

frontier. With Koop et al. (1992), the Markov Chain Monte Carlo Method (MCMC) was adopted to estimate the SFA model and has frequently been used in related literature such as Tsionas (2002), Kurkalova and Carriquiry (2002), Kumbhakar and Tsionas (2005), Goto and Makhija (2009), Souza et al. (2009), Chen et al. (2015), Chaabouni and Abednnadher (2016), and Cengiz et al. (2018). As a matter of fact, MCMC methods have become the cornerstone of Bayesian analysis.

Kim and Schmidt (2000), Huang (2004), and Ennsfellner et al. (2004) presented current developments in Bayesian SFA (BSFA) models. Griffin and Steel (2007) described MCMC methods for Bayesian estimation within the ambit of SFA model using the WinBUGS package. Tsionas and Papadakis (2010) employed a Bayesian analysis to the SFA

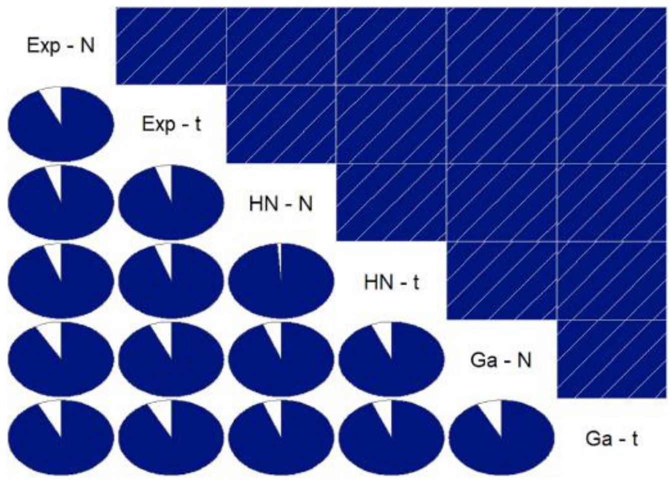

Fig. 5. Efficiency correlogram for the six distributional assumptions.

in terms of alternative simulation techniques. Using BSFA for industry applications has been widespread. For instance, Tabak and Tecles (2010) used a BSFA model to evaluate cost and profit efficiency of the banking sector in India. Tonini (2012) estimated TFP (total-factor productivity) growth in the agricultural industry for the European Union and candidate countries using SFA models with a Bayesian approach. Feng and Zhang (2012) compared the efficiency of large community banks in the US from 1997 to 2006 using BSFA. Assaf and Josiassen (2012) estimated the efficiency of health-care food-service operations with BSFA. Assaf et al. (2013) estimated the efficiency of Turkish banks during the period of 2002–2010 using BSFA. Barros (2014) used BSFA to analyze the cost efficiency of Mozambique's airports taking into account random and fixed effects.

In this related literature there is no explicit criterion when selecting the assumption on distribution for the inefficiency term in the (B)SFA model. Meeusen and van Den Broeck (1977) adopted the Exponential distribution, while Aigner et al. (1977) used the Half-Normal distribution. Gamma distributions were used by Greene (1990) and Log-normal distributions were studied by Medrano and Migon (2007). Griffin and Steel (2007) described a semiparametric modelling technique to estimate the inefficiency distribution. Alghalith (2011) described an alternative method for specifying the distribution of the inefficiency term. In fact, there are no apparent reasons for choosing one over the other of the three different forms of distributions, which all have their own pros and cons.

The major contribution of this paper is to develop a RBSFA computational model where the variances and covariances of different distributional assumptions for the sustainability inefficiency term (u) are minimized by the joint use of MCMC methods and differential optimization. As stated in the introduction, this minimization occurs against a technological frontier of best practices where fuel is burnt to generate the required amount of energy to move people and goods while polluting the environment. The goal is to minimize DIC (Deviance Information Criteria) for the combined BSFA model based on determining the optimal weights for each one of the inefficiency distributional assumptions. The RBSFA computational model is then applied to examine the sustainability efficiency of the Chinese transportation industry in terms of CO_2 emissions. Three different distributional assumptions have been considered for the inefficiency term (u), which are Half-Normal, Gamma, and Exponential and two for the error term (v): Normal and t-Student.

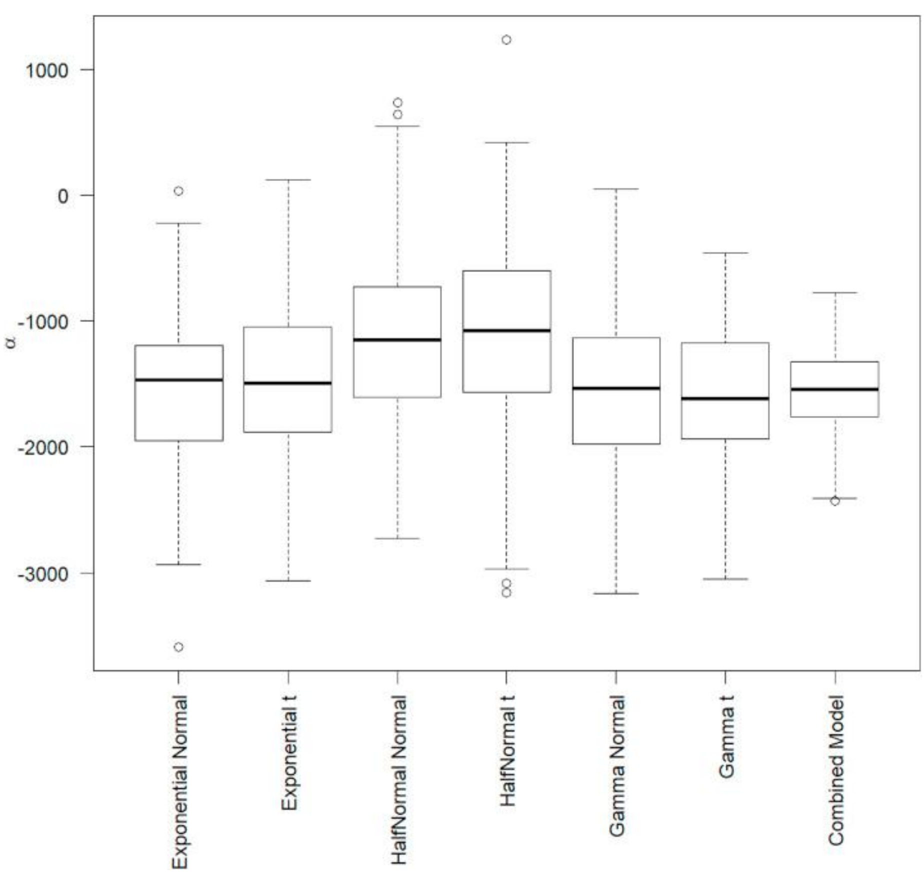

Fig. 6. Boxplots for.α

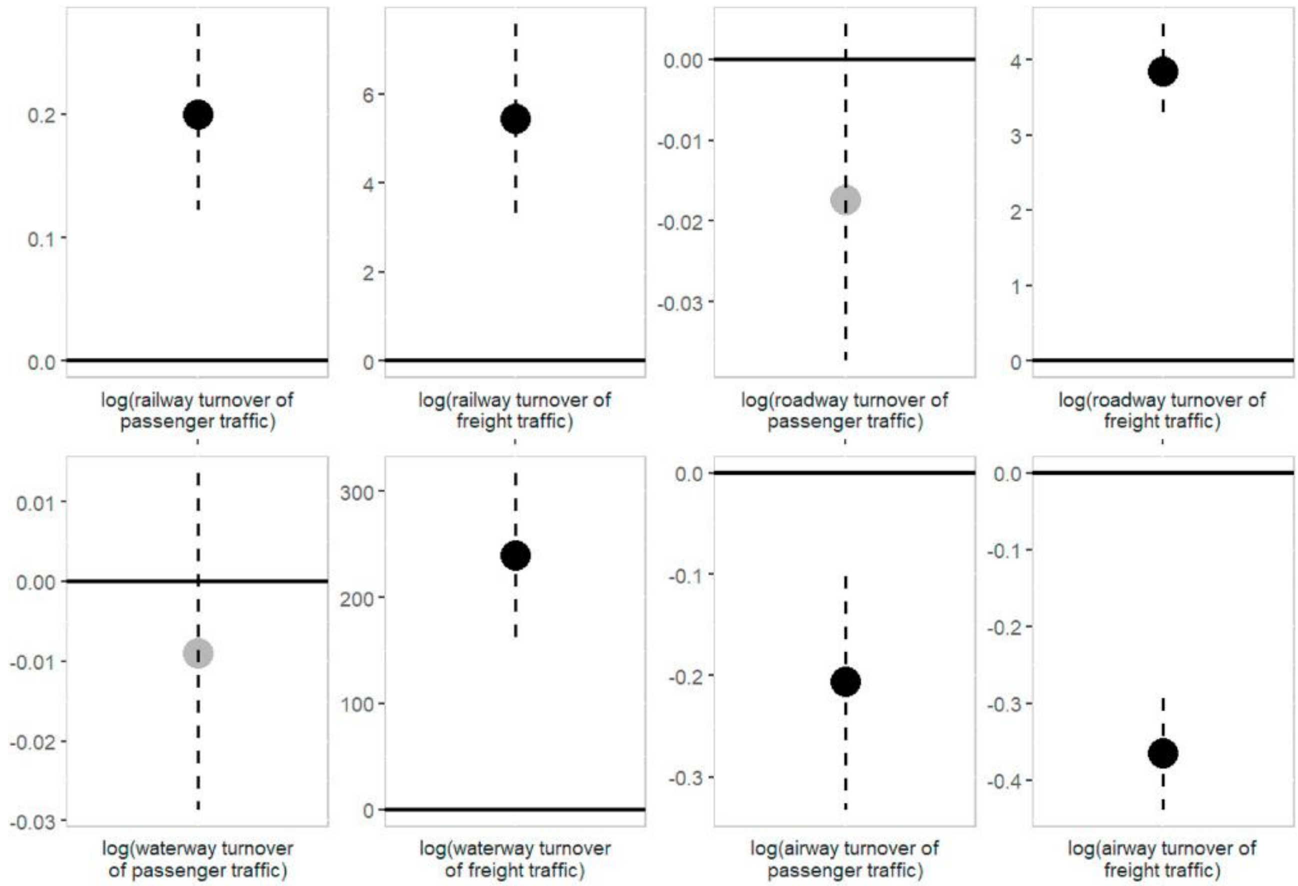

Fig. 7. Boxplots for the coefficients of the inputs and outputs.

3.3. *The RBSFA proposed*

This paper implements MCMC methods for an RBSFA computational model using codes developed in R and WinBUGS, both free statistical software. The codes developed in this paper are available to readers upon request. The basic SFA model relates the sustainability factors of pollution, energy, and cargo to a stochastic frontier of minimal production costs. Considering a panel data analysis of CO2 emissions, energy use, and freight turnovers, one possible stochastic linear model would regress the cost logarithm y_t - associated with the logarithmic ratio between CO_2 emissions and energy use at time t onto different produced quantities Q_t, that is, the $x_t$regressors. These regressors could be expressed as logarithm ratios for each transportation mode between the respective aggregate freight/passenger turnovers and the required energy used over the course of time t ($t = 1, \ldots, T$):

$$y_t \overset{ind}{\sim} N\left(\alpha + x_i'\beta + u_t,\ \sigma^2\right), \quad (1)$$

where $N(\mu, \sigma^2)$ represents a normal distribution with a unitary mean. The differences between transportation benchmarks and current CO_2 emission levels, the inefficiencies, are stochastically modelled by u_t terms that observe the one-side distribution assumption commonly used as exponential (Meeusen and van Den Broeck, 1977). Priors are required to be assigned for each one of the model's parameter vectors. Next, truncated normal distributions may be assigned to regression parameters to represent regularity conditions ($\beta \sim N(0, \sum)$), gamma distributions may be assigned to residuals to assure the prior median efficiency is r* ($\sigma^{-2} \sim G(a_0, a_1)$ with shape parameter a0 and mean $\frac{a_0}{a_1}$), and an exponential distribution may be assigned to model inefficiencies based on median efficiency $\lambda \sim \mathrm{Exp}(-\log r^*)$. Particularly the sustainability efficiency at time t can be computed as follows: $r_t = \exp(-u_t)$.

Efficiencies observed for each modal at a given month can be straightforwardly generated based on these prior distributional assumptions. Their full posterior distributions are then readily available, and variations on median efficiency levels over the course of time for each transportation mode can be captured by u_t, which are the inefficiencies of a given observation in t. Lee and Schmidt (1993) proposed a strong assumption for modelling time-dependent inefficiency by assigning a linking function between inefficiency and trend where $u_t = \beta(t)u_t$. Although this linking function can be expressed by several forms, the one proposed by Battese and Coelli (1992) has always been used so that the computations do not become cumbersome: $\beta(t) = \exp\{n(t - T)\}$.

The stochastic frontier can also be extended to handle the impact of covariates, which represent non-productive contextual variables surrounding the cost function, by further assuming that each observation can be attached to a vector of covariates, w_t for the tth observation, such as Koop et al. (1997):

$$u_t \sim \mathrm{Exp}\left(\exp\left\{w_t'\gamma\right\}\right) \quad (2)$$

where γ are coefficients of contextual variables w. These w_t covariates can both represent binary and non-binary variables. Under the former case, we can assume a priori that the distribution of inefficiency levels for each category or group should fluctuate around the same overall median efficiency r*, that is, $\exp\{\gamma_j\} \sim Exp(-\log r^*)$.

A certain distributional assumption on u is needed. Three distributional assumptions are made here from the literature on efficiency estimation: Exponential, Half-normal, and Gamma (Meeusen and van Den Broeck, 1977; Aigner et al., 1977; and Greene, 1990, respectively). We considered six alternative models based on three different inefficiency components—Half-Normal, Exponential, and Gamma

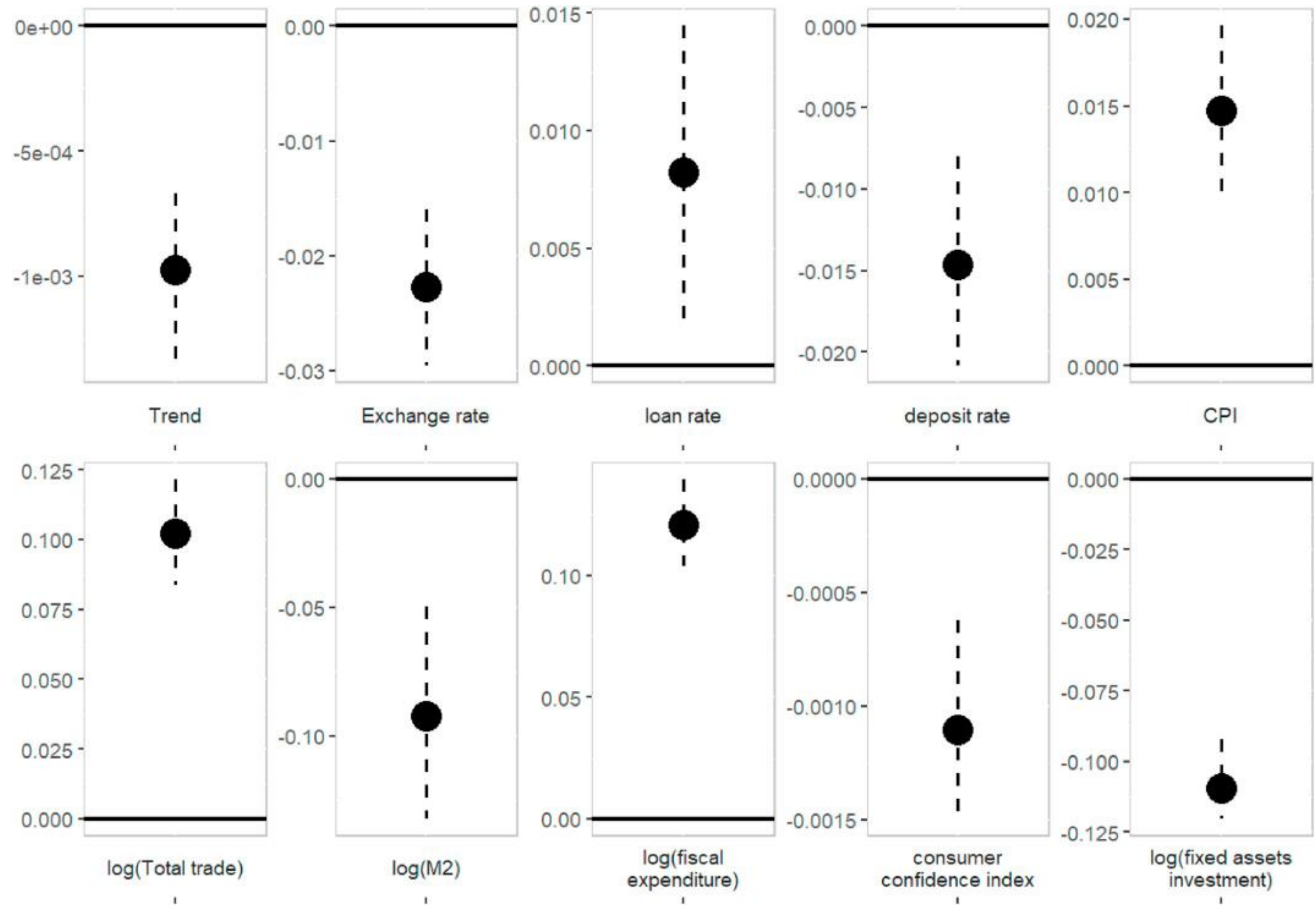

Fig. 8. Boxplots for the coefficients of the contextual variables.

distributions—as well as based on two distinct distributional assumptions for the error term: t-Student and Normal. The model proposed is specified below, regardless of the distributional assumptions in v:

$$y_t = \alpha + x_t'\beta + \beta(t) + w_t'\gamma + v_t - u_t \tag{3}$$

$$u_t \sim^{i.i.d} Exp(\lambda) \tag{3a}$$

$$u_t \sim^{i.i.d} N^{+}(0, \lambda) \tag{3b}$$

$$u_t \sim^{i.i.d} G(\varnothing, \lambda) \tag{3c}$$

The prior distributions for the parameters depicted in (3) follow the procedures presented in Griffin and Steel (2007) where all parameters are assumed to be independent. The MCMC algorithm was based on 200, 000 iterations of which the first 100,000 were disregarded for a burn-in phase.

The DIC model comparison criterion for different distributional assumptions and functional specifications (Spiegelhalter et al., 2002) trades off goodness-of-fit against a penalty that should be imposed by overfitting. In hierarchical models, the method estimates the "effective number of parameter," which is denoted by p_D. D is the posterior mean of the deviance ($-$ 2xloglikelihood), while $\widehat{D}$ is a plug-in estimate of the latter with the posterior mean of the parameters. The statistics DIC is calculated as DIC $= \overline{D} + p_D = \widehat{D} + 2p_D$. Better fitting models are those where DIC values are lower.

The relative importance of each distributional assumption for the inefficiency term u in explaining the sustainability efficiency in the Chinese transport system was explored by a robust approach where the variances of each model and the covariances between models were minimized. Variances and covariances of the inefficiency terms (u_{it}) of these six models are simultaneously minimized by a non-linear stochastic optimization problem, as presented in Eq. (4). The parameter p_i denotes the weights, which range from 0 to 1, and are assigned respectively to the inefficiency vectors of each one of the six models previously described. The model maximizes the value of p in order to minimize the variance (*Var*) and covariance (*Covar*) of the combined inefficiencies. Model (4) is solved through the differential evolution technique, which is one of several kinds of genetic algorithms mimicking the natural selection process in an evolutionary manner (Ardia et al., 2011; Mullen et al., 2011). Results are discussed in the next section.

$$\begin{aligned} &\min\left[Var\left(\sum_{i=1}^{6} p_i{*}\,u_{it}\right) + \left(\sum_{i,j=1}^{6} Covar\left(p_i{*}p_j{*}\,u_{it}{*}u_{jt}\right),\ i \neq j,\ j < i, \forall t\right)\right] \\ &s.t. \\ &\sum_{i=1}^{6} p_i = 1 \\ &0 \le p_i \le 1\ \forall i \end{aligned} \tag{4}$$

3.4. The data

The original variables used in this research are the following Chinese monthly data: (i) passenger traffic turnover (in 100 million person*km) and freight traffic turnover (in 100 million tons*km) per transport mode; (ii) energy used (in 100 million HP) and CO_2 emission (in tons) per transport mode; (iii) exchange rate at a given month (in RMB per USD); (iv) loan rate at a given month (%); (v) deposit rate at a given month

(%); (vi) inflation rate at a given month (or CPI – Consumer Price Index – in %); (vii) total foreign trade at a given month (in 100 million USD); (viii) total money supply in economy at a given month (or M2 monetary aggregate – in 100 million RMB); (ix) fiscal expenditure at a given month (in 1 billion RMB); (x) consumer confidence index (in 100 base points); (xi) fixed asset investment at a given month (in 1 million RMB); and (xii) imported crude oil price index at a given month (in RMB per barrel).This information was obtained from various sources. Variables (i) and (ii) were collected from China's National Statistics Bureau and the yearbook of China's transportation, while the other macro-economic variables were obtained from the Wind database (www.wind.com.cn). The computation of energy levels used and CO_2 emissions for each transportation mode observed average conversion factors with respect to transportation efficiency and pollutant characteristics for each mode (Zhang and Wei, 2015; Achour and Belloumi, 2016). Furthermore, an average weight of 70 kg was assigned to each passenger so that cargo and passenger freights could be set on common ground. All observations ran from January 1999 to December 2017. The descriptive statistics of the transformed variables adopted in the research (y, x, and w) are given in Table 1.

Time series plots for the outputs (log of the ratio between carbon emissions and energy use) and the inputs (logs of the freight and passenger turnovers for different transport modes) reveal a substantial increase of CO_2 emissions per energy use rate in parallel to the decline of freight transportation by rail and the corresponding increase by road. Also noteworthy is the steady increase in the airway turnover of passenger traffic as an additional driver of increased CO_2 emissions per energy use. Due to the cyclic nature of economic and transportation activities, a moving average of 12 months was also plotted in each graph in Fig. 1 to help illustrate their overall long-term trend. Structural transformations in the Chinese economy over the last 20 years may help in explaining these phenomena, including the sharply higher carbon emissions that came with the acceleration of urbanization around 2010. Meanwhile, the turnover of freight traffic by road also experienced a surge during the same period. As for the convenience of other modes of transportation, the turnover of passenger traffic via roadway and waterway has followed a falling trend over the last decades. On the other hand, the turnover for railway and airway modes saw robust growth resulting from the development of high-speed railways and airports (Wanke et al., 2017; Chen et al., 2016). Compared to roadway and waterway transportation, the freight traffic turnover of railway and airway gradually declined. Overall, with the country of China taking on the role of the "world's factory," the phenomenal volume of international trade has driven waterway transportation, which has the highest turnover, to be the busiest mode.

4. Analysis and discussion of empirical results

Estimated by the RBSFA computational model, the results are depicted in Fig. 2. Although efficiency levels appear high (bottom-right), this is due to slight inefficiency variations against the benchmark months for each transportation mode. As a matter of fact, the performance of combustion engines in terms of the amount of fuel required to generate a given amount of physical work in different transportation modes is a topic that has been continuously and exhaustively studied over the course of decades since the creation of the first modern internal combustion engine in 1876 by Nicklaus Otto. This being the case, it is worth noting that the relative performance of combustion engines is a well-established mechanical engineering discipline. Nonetheless, as a consequence of the increased interest in all things environmental, the performance of combustion engines in terms of pollutant emissions has also undergone a rigorous scrutiny over the last four decades, which enabled a better understanding of the average pollutant emissions of each transportation mode or engine design for generating the same amount of physical work. Although somewhat random variations in the performance of combustion engines may be expected at the individual level, at more aggregate levels of analysis, such as at the country level, the pooled individual impacts of random fluctuations on the performance of combustion engines can be translated into a broader sustainable efficiency analysis of the transportation sector where the technology/business specifics of each mode can be related to macroeconomic variables, economic development levels, and customer preferences. Put differently, this carry-over of slightly random fluctuations against well-established combustion engine performance benchmarks, from bottom-individual levels to top-industry levels, may help in explaining why sustainability efficiency also presents small, however significant, fluctuations around higher levels of efficiency. Besides, it is interesting to note a slight downward trend to sustainability efficiency, which may be explained by the increased use of roads for freight transportation and airlines for passenger transportation, as previously discussed. The impact of this modal shift in terms of policy formulations is further elaborated below.

The differential optimization procedure yielded higher weights for the Exponential and Gamma distributional assumptions for the inefficiency term u regardless of the distributional assumption for the random term v, whether Normal or t-Student, and to the detriment of the Half-Normal distributional assumption (top-left). Although the variance for efficiency is substantially larger than the one for random errors in each one of the six combinations tested (top-right), the Half-Normal assumption presented a higher imbalance between the total variance (sigma square) and the proportion of it explained by the inefficiency term u. In other words, the Half-Normal assumption was yielding a comparative lower total variance while assigning the larger portion to the inefficiency term u, eventually capturing some random noise v into it. Fig. 3 corroborates this fact by presenting the results for the DIC criterion for each individual model and its RBSFA computational combination. In fact, the Gamma and Exponential distributional assumptions for the inefficiency term u presented a better fit in comparison to the Half-Normal one. The RBSFA presented a fit-performance in between the Normal and t-Student v error assumptions when putting the Gamma and Exponential assumptions for inefficiency u into perspective.

As regards the well-known auxiliary metrics of explanatory power such as R-square, MAPE (Mean Average Percent Error), and RMSE (Root Mean Squared Error), the RBSFA computational model yielded superior results as expected due to the effect of pooling variances and covariances into the optimization model (See Fig. 4). In fact, although the efficiency results for the six individual models are strongly and positively correlated (cf. Fig. 5), readers should observe that optimal weights were assigned to almost zero in the extreme correlated case obtained for the Half-Normal assumptions.

Results for the RBSFA computational model are displayed in Figs. 6–8. The linear coefficient presented non-significant results for all individual models with the exception of the Gama t-Student distributional assumption combination. The RBSFA computational model not only yielded significant results for the linear coefficient, but also found the smallest dispersion during the simulation trials (cf. Fig. 6).

As regards the coefficients for the inputs, significant results were found with the exception of passenger turnovers for roadway and waterway transportation modes (cf. Fig. 7). As for the freight traffic, the results suggest that efficiency levels increase and as a consequence CO_2 emissions per energy use are lower when waterway, railway, and roadway transportation modes are more intensively used, respectively in that order. On the other hand, increased freight traffic via the air transportation mode reduces overall sustainability efficiency levels. Waterway freight transportation is a relatively clean method (Hjelle and Fridell, 2012) and has a better performance in energy combustion efficiency. Besides, the lower navigation speed of waterway freight transportation translates into lower fuel consumption (Buhaug et al., 2008; Chen et al., 2019), which enables waterway freight transportation to obtain better performance in sustainability efficiency. In recent years, the gradual improvement of the waterway network along the Yantze River Delta and Pearl River Delta has improved waterway transportation efficiency in China bringing not only lower energy consumption and CO_2 emissions, but it has also improved the sustainability efficiency of this specific transportation mode. Moreover, the recent improvements of rail and road transportation infrastructures in China have also helped explain the positive effects on the sustainability efficiency. As a matter of fact, there was a higher ratio of diesel locomotives being replaced with electric locomotives when the high-speed railways were developed (Wanke et al., 2018a,b). Different from the other three transportation modes, air transportation has the obvious advantage of time efficiency, but the higher energy consumption and CO_2 emissions bring negative impacts on the sustainability efficiency levels of this particular transportation mode (Lee et al., 2004; Chen et al., 2017b). These results are consistent with the well-consecrated literature on transportation and logistics with respect to energy efficiency and the transportation footprint of the different modes (McKinnon, 2007; Li et al., 2017).

As for passenger traffic, sustainability efficiency levels increase especially when using railway modes and present a slight decrease with air transport, which contrasts with the outcomes of several previous studies such as Dalla Chiara et al. (2017) and Qiu et al. (2017). These results are also justified by the different nature of passengers and freight traffic where the former tends to be lighter than the latter. The coefficients of the passenger turnovers for roadway and waterway transportation modes, while not significant, are negative, probably due to the continued increase of private vehicles in China, which has already led to the problems of congestion and low efficiency of energy use (Peng et al., 2016). Regardless, the number of private vehicles per capita is still low in China compared to other countries. On the other hand, waterways are rarely the passengers' first choice as waterway transportation for passenger traffic is too time consuming and therefore most useful in tourism or short-distance commuting situations, especially with the airline and railway transportation modes currently experiencing rapid development. Vis-à-vis the opposite extreme, air transportation is always linked with the shortest travel times, although this benefit is obtained to the detriment of higher carbon emissions in terms of the low passenger load factor (Papatheodorou and Lei, 2006; Bieger and Wittmer, 2006). Nonetheless, the energy consumption of the civil aviation sector has seen an annual increase of 6% during the last decade (Chen et al., 2017b).

Lastly, as regards the contextual variables (cf. Fig. 8), all were found to be significant. Higher levels of loan rate and CPI imply higher sustainability efficiency levels in Chinese transportation provided that economic activity continues to decrease due to the higher cost of money and inflationary pressures, which also diminishes the use of more expensive transportation modes such as road and air. These results may suggest the establishment of preemptive policies to keep stimulating the use of more sustainable efficiency modes when economic growth returns. As a matter of fact, cross-subsidies between air/road and rail/water tariffs could be implemented in times of accelerated economic growth to induce more investment and capital allocation in less polluting means of transportation. Similarly, total trade and fiscal expenditure also present a positive influence on the sustainability efficiency of China's transportation industry provided the supply and transport of goods inside the country diminishes to support foreign trade while inflationary pressures remain high due to higher expenditure levels. Again, countercyclical macro-economic policies based on higher sustainable transportation infrastructure investments in times of lower or decelerated economic growth could be considered to boom economic activity by means of physical capital expansion of railways and waterways. On the other hand, because inflationary pressures are high and fiscal policy should be restricted, cross-subsidies, as previously described, could be implemented to impose an economic growth soft landing while still complying with environmental issues.

On the other hand, we observe a negative impact on the trend of sustainability transportation efficiency, thus indicating a slight but continuous decrease over the course of the last two decades. Macroeconomic indicators related to the improvement of economic activity such as fixed asset investment, consumer confidence index, and monetary base supply M_2 may help in understanding the use of more expensive and less sustainable transportation modes to meet the needs of an increased demand for goods and services in the short and medium term. Furthermore, with the growth of China's middle class in the last two decades—lifting hundreds of millions out of poverty—we expect to see a greater preference for faster and more comfortable transportation modes. State media campaigns on the environmental impacts of faster transportation modes on sustainability efficiency linked to educational measures in schools and universities on the importance of saving the "last mile" of the fastest, most polluting and most expensive transportation modes, could prepare the next generation to understand why cross-subsidies among transportation modes have been implemented. Similarly, higher exchange rates and savings mean new business opportunities for investment and consumption in the Chinese economy. Meantime, foreign investments have also poured into China. With this as a backdrop, the derived demand on different modes of transportation will significantly increase. Moreover, the pursuit of time efficiency may increase the use of high-cost and unsustainable transportation methods and thus reduce sustainability efficiency. Foreign investor partners could, therefore, be attracted to tackle small, low-risk, transportation infrastructure projects to foster multi-modal passenger and freight traffic. Transshipment facilities and commuter stations are common examples of such investments to bridge the gaps between two near-by and complementary transportation modes.

5. Conclusions

In this study we proposed a novel RBSFA computational model to determine the sustainability efficiency of the Chinese transportation system. We presented a Bayesian estimator for a SFA model with a different inefficiency distribution. In contrast with the methods used in previous research, we considered three distributions of inefficiency terms in BSFA and two distributions of residual terms. By MCMC and optimizing the differences, this study determined the optimal weights of inefficiency terms in different distribution assumptions in order to find out the inefficiency terms with the lowest variance and covariance. Based on the RBSFA model and monthly data between January 1999 and December 2017 in China, our model results show that in terms of freight transportation, waterway, railway, and roadway modes would improve sustainability efficiency with waterway ranking highest, roadway second, and railway ranking third. In terms of passenger transportation, the roadway and railway modes would fundamentally improve sustainability efficiency. Meanwhile, no matter whether handling freight or passenger traffic, the air transportation mode would decrease sustainability efficiency. Moreover, macro contextual variables also have significant effects on the sustainability efficiency of the Chinese transportation system. These results indicated that the sustainability efficiency of China's transportation sector fluctuated significantly in the past two decades. The cost of credit, CPI, total trade volume, and total fiscal expenditure all played a positive role in enhancing sustainability efficiency when they increased. Macro-economic variables such as the RMB/USD exchange rate, deposit interest rates, money supply M_2, consumer confidence index, and fixed asset investment all posed a negative influence on sustainability efficiency of the transportation system in China.

These findings will help us understand the internal dynamics of carbon inequality within the transportation sector of China and how it has been affected by different factors. Rather than using Lorenz curves to illustrate carbon inequality from the consumption side, we offer the evidence from the supply side, or from inside the transportation sector. More work needs to be done to estimate and explain carbon inequality around the world, especially for a situation without a global consensus on this term and its measurement. Moreover, whereas most existing research emphasizes carbon inequality within different provinces and industries of China, we offer a more detailed breakdown and evidence in the transportation industry. Meanwhile, it is in the interest of the government authorities in China to facilitate sustainable development. This they can achieve by designing alternative policies that encompass cross-subsidies in transportation mode tariffs, educational campaigns in media and schools/universities on the importance of transportation sustainability, a closer link between transportation infrastructure investments and counter-cyclical macro-economic measure, and by building partnerships with foreign investors to boost multi-modal commutation of passengers and/or transshipment of cargoes.

Additionally, although air transportation is more time-saving and can raise the turnover efficiency of freight and passenger traffic, the carbon emission problem should be given more attention especially after IATA (the International Air Transport Association) proposed Carbon-Neutral-Growth for the civil airline industry. This is particularly relevant because the Chinese population has become richer over the last two decades and now prefers faster and more comfortable modes of transportation. Policymakers need to strike a balance between transportation efficiency and sustainability efficiency. In addition, we also noted that the transportation modes with the highest sustainability efficiency for freight and passenger traffic are different, suggesting that different policies should be adopted for freight and passenger traffic to effectively reduce carbon emissions and energy consumption and raise the overall sustainability efficiency of the transportation sector. As a matter of fact, these differences indicate that while a better link between macro-economic fiscal/monetary policy and transportation infrastructure should be established as regards cargo transportation expansion priorities, the locus of passenger transport consciousness on sustainability should be educational campaigns, cross-subsidies, and multi-modal commutation stations.

In summary, from a macro prospective, the sustainability efficiency of the transportation sector has been continuously reshaped by macro-variables, which may explain the variation of sustainability efficiency scores. In other words, the government authorities should pay attention to sustainability efficiency scores when proposing and implementing transportation policies. More importantly, with the development of new transportation infrastructures and structural changes in society and the economy, preferences for different transportation modes have also been re-ordered by a population with ever-higher purchasing power.

Research limitations of the proposed RBSFA approach are related to the fact that transportation turnovers and pollutant emissions may be temporally correlated. Future studies should address how this impacts on the inertia of transportation sustainability efficiency measurements and the respective policies for sector improvement over the course of time, as long as the beneficial impacts of such policies may take longer than expected by government and society to mature.

Author contributions section

Peter Wanke, Zhongfei Chen: Conceptualization, Methodology, Data curation, Formal analysis, Writing- Original draft preparation and etc. Xi Zheng: Resources, Investigation, Formal analysis and etc. Jorge Antunes: Software, Validation, Visualization and etc.

Acknowledgments

We thank the support provided by the National Natural Science Foundation of China (NSFC) [Grant No. 71704065], the Key Project of Philosophy and Social Sciences Research of Ministry of Education of China [Grant No. 17JZD013], the Fundamental Research Funds for the Central Universities-Ningjingzhiyuan Project of Jinan University [19JNQM21] and the China Postdoctoral Science Foundation [Grant No. 2017M620022].

References

Achour, H., Belloumi, M., 2016. Decomposing the influencing factors of energy consumption in Tunisian transportation sector using the LMDI method. Transp. Policy 52, 64–71.
Aigner, D., Lovell, C.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econom. 6 (1), 21–37.
Alghalith, M., 2011. An alternative method of stochastic optimization: the portfolio model. Appl. Math. 2 (7), 912.
Alonso, A., Monzón, A., Cascajo, R., 2015. Comparative analysis of passenger transport sustainability in European cities. Ecol. Indicat. 48, 578–592.
Ardia, D., Boudt, K., Carl, P., Mullen, K., Peterson, B.G., 2011. Differential evolution with DEoptim: an application to non-convex portfolio optimization. R Journal 3 (1), 27–34.
Assaf, A.G., Josiassen, A., 2012. Time-varying production efficiency in the health care foodservice industry: a Bayesian method. J. Bus. Res. 65 (5), 617–625.
Assaf, A.G., Matousek, R., Tsionas, E.G., 2013. Turkish bank efficiency: Bayesian estimation with undesirable outputs. J. Bank. Financ. 37 (2), 506–517.
Assaf, A.G., Oh, H., Tsionas, M., 2017. Bayesian approach for the measurement of tourism performance: a case of stochastic frontier models. J. Travel Res. 56 (2), 172–186.
Assaf, A., 2011. Accounting for technological differences in modelling the performance of airports: a Bayesian approach. Appl. Econ. 43 (18), 2267–2275.
Barros, C.P., 2014. Airports and tourism in Mozambique. Tour. Manag. 41, 76–82.
Battese, G.E., Coelli, T.J., 1992. Frontier production functions, technical efficiency and panel data: with application to paddy farmers in India. J. Prod. Anal. 3 (1–2), 153–169.
Beyzatlar, M.A., Karacal, M., Yetkiner, H., 2014. Granger-causality between transportation and GDP: a panel data approach. Transport. Res. A-Pol. 63, 43–55.
Bieger, T., Wittmer, A., 2006. Air transport and tourism-Perspectives and challenges for destinations, airlines and governments. J. Air Transp. Manag. 12 (1), 40–46.
Boyd, G.A., 2008. Estimating plant level energy efficiency with a stochastic frontier. Energy J. 29 (2), 23–43.
Buck, J., Young, D., 2007. The potential for energy efficiency gains in the Canadian commercial building sector: a stochastic frontier study. Energy 32 (9), 1769–1780.
Buhaug, Ø., Corbett, J.J., Endresen, Ø., Eyring, V., Faber, J., Hanayama, S., Pålsson, C., 2008. Updated study on greenhouse gas emissions from ships: phase I report, 1. International Maritime Organization (IMO), London, UK.
Cengiz, M.A., Dünder, E., Şenel, T., 2018. Energy performance evaluation of OECD countries using Bayesian stochastic frontier analysis and Bayesian network classifiers. J. Appl. Stat. 45 (1), 17–25.
Centobelli, P., Cerchione, R., Esposito, E., 2017. Environmental sustainability in the service industry of transportation and logistics service providers: systematic literature review and research directions. Transport. Res. D-TR. E. 53, 454–470.
Chaabouni, S., Abednnadher, C., 2016. Cost efficiency of Tunisian public hospitals: a Bayesian comparison of random and fixed frontier models. J. Knowl. Econ. 7 (3), 771–781.
Chandran, V.G.R., Tang, C.F., 2013. The impacts of transport energy consumption, foreign direct investment and income on CO_2 emissions in ASEAN-5 economies. Renew. Sustain. Energy Rev. 24, 445–453.
Chen, J., Fei, Y., Wan, Z., 2019. The relationship between the development of global maritime fleets and GHG emission from shipping. J. Environ. Manag. 242, 31–39.
Chen, Z., Barros, C.P., Borges, M.R., 2015. A Bayesian stochastic frontier analysis of Chinese fossil-fuel electricity generation companies. Energy Econ. 48, 136–144.
Chen, Z., Barros, C., Yu, Y., 2017a. Spatial distribution characteristic of Chinese airports: a spatial cost function approach. J. Air Transp. Manag. 59, 63–70.
Chen, Z., Wanke, P., Antunes, J.J.M., Zhang, N., 2017b. Chinese airline efficiency under CO2 emissions and flight delays: a stochastic network DEA model. Energy Econ. 68, 89–108.
Cui, Q., 2019. Investigating the airlines emission reduction through carbon trading under CNG2020 strategy via a Network Weak Disposability DEA. Energy 180, 763–771.
Cui, Q., Li, Y., 2015. An empirical study on the influencing factors of transportation carbon efficiency: evidences from fifteen countries. Appl. Energy 141, 209–217.
Cullinane, K., Song, D.W., Ji, P., Wang, T.F., 2004. An application of DEA windows analysis to container port production efficiency. Rev. Netw. Econ. 3 (2), 184–206.
Dalla Chiara, B., De Franco, D., Coviello, N., Pastrone, D., 2017. Comparative specific energy consumption between air transport and high-speed rail transport: a practical assessment. Transport. Res. D-TR. E. 52, 227–243.
Ennsfellner, K.C., Lewis, D., Anderson, R.I., 2004. Production efficiency in the Austrian insurance industry: a Bayesian examination. J. Risk Insur. 71 (1), 135–159.
Feng, G., Zhang, X., 2012. Productivity and efficiency at large and community banks in the US: a Bayesian true random effects stochastic distance frontier analysis. J. Bank. Financ. 36 (7), 1883–1895.
Feng, K., 2019. Drivers of peak and decline. Nat. Clim. Chang. 9 (3), 188.
Feng, K., Davis, S.J., Sun, L., Li, X., Guan, D., Liu, W., et al., 2013. Outsourcing CO2 within China. P. Natl. A. Sci. 110 (28), 11654–11659.
Filippini, M., Hunt, L.C., 2011. Energy demand and energy efficiency in the OECD countries: a stochastic demand frontier approach. Energy J. 59, 80.
Goto, M., Makhija, A.K., 2009. The impact of deregulation and corporate structure on productive efficiency: the case of the US electric utility industry, 1990–2004. In: Corporate Governance and Firm Performance. Emerald Group Publishing Limited, pp. 1–34.
Greene, D.L., Wegener, M., 1997. Sustainable transport. J. Transp. Geogr. 5 (3), 177–190.
Greene, W.H., 1990. A gamma-distributed stochastic frontier model. J. Econom. 46 (1–2), 141–163.

Griffin, J.E., Steel, M.F., 2007. Bayesian stochastic frontier analysis using WinBUGS. J. Prod. Anal. 27 (3), 163–176.
Halkos, G.E., Paizanos, E.A., 2016. The effects of fiscal policy on CO_2 emissions: evidence from the USA. Energy Policy 88, 317–328.
Herrala, R., Goel, R.K., 2012. Global CO_2 efficiency: country-wise estimates using a stochastic cost frontier. Energy Policy 45, 762–770.
Hjelle, H.M., Fridell, E., 2012. When is short sea shipping environmentally competitive?. In: Environmental Health-Emerging Issues and Practice IntechOpen.
Hu, X., Chang, S., Li, J., Qin, Y., 2010. Energy for sustainable road transportation in China: challenges, initiatives and policy implications. Energy 35 (11), 4289–4301.
Huang, H.C., 2004. Estimation of technical inefficiencies with heterogeneous technologies. J. Prod. Anal. 21, 277–296.
Huntington, H.G., 1994. Been top down so long it looks like bottom up to me. Energy Policy 22 (10), 833–839.
Huo, J., Yang, D., Zhang, W., Wang, F., Wang, G., Fu, Q., 2015. Analysis of influencing factors of CO_2 emissions in Xinjiang under the context of different policies. Environ. Sci. Policy 45, 20–29.
Kelle, P., Song, J., Jin, M., Schneider, H., Claypool, C., 2019. Evaluation of operational and environmental sustainability tradeoffs in multimodal freight transportation planning. Int. J. Prod. Econ. 209, 411–420.
Kim, Y., Schmidt, P., 2000. A review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models with panel data. J. Prod. Anal. 14 (2), 91–118.
Koop, G., Osiewalski, J., Steel, M.F., 1997. Bayesian efficiency analysis through individual effects: hospital cost frontiers. J. Econom. 76 (1–2), 77–105.
Koop, G., Steel, M.F., Osiewalski, J., 1992. In: Posterior Analysis of Stochastic Frontier Models Using Gibbs Sampling. Working paper.
Kumbhakar, S.C., Tsionas, E.G., 2005. Measuring technical and allocative inefficiency in the translog cost system: a Bayesian approach. J. Econom. 126 (2), 355–384.
Kuosmanen, T., Kortelainen, M., 2005. Measuring eco-efficiency of production with data envelopment analysis. J. Ind. Ecol. 9 (4), 59–72.
Kurkalova, L.A., Carriquiry, A., 2002. An analysis of grain production decline during the early transition in Ukraine: a Bayesian inference. Am. J. Agric. Econ. 84 (5), 1256–1263.
Labib, S.M., Neema, M.N., Rahaman, Z., Patwary, S.H., Shakil, S.H., 2018. Carbon dioxide emission and bio-capacity indexing for transportation activities: a methodological development in determining the sustainability of vehicular transportation systems. J. Environ. Manag. 223, 57–73.
Lakshmanan, T.R., Han, X., 1997. Factors underlying transportation CO_2 emissions in the USA: a decomposition analysis. Transport. Res. D-TR. E. 2 (1), 1–15.
Lee, J.J., Lukachko, S.P., Waitz, I.A., 2004. Aircraft and Energy Use. Reference Module in Earth Systems and Environmental Sciences. Encyclopedia of Energy, pp. 29–38.
Lee, Y.H., Schmidt, P., 1993. A Production Frontier Model with Flexible Temporal Variation in Technical Efficiency. The Measurement of Productive Efficiency: Techniques and Applications. Oxford press, New York, pp. 237–255.
Léonardi, J., Baumgartner, M., 2004. CO_2 efficiency in road freight transportation: status quo, measures and potential. Transport. Res. D-TR. E. 9 (6), 451–464.
Li, J., Song, X., Guo, Y., Yang, Q., Feng, K., 2019. The determinants of China's national and regional energy-related mercury emission changes. J. Environ. Manag. 246, 505–513.
Li, X., Fan, Y., Wu, L., 2017. CO_2 emissions and expansion of railway, road, airline and in-land waterway networks over the 1985–2013 period in China: a time series analysis. Transport. Res. D-TR. E 57, 130–140.
Li, Y., Wang, Y.Z., Cui, Q., 2015. Evaluating airline efficiency: an application of virtual frontier network SBM. Transport. Res. E-Log. 81, 1–17.
Lin, B., Du, K., 2015. Modeling the dynamics of carbon emission performance in China: a parametric Malmquist index approach. Energy Econ. 49, 550–557.
Lin, X., Wells, P., Sovacool, B.K., 2017. Benign mobility? Electric bicycles, sustainable transport consumption behaviour and socio-technical transitions in Nanjing, China. Transport. Res. A-Pol. 103, 223–234.
Litman, T., Burwell, D., 2006. Issues in sustainable transportation. Int. J. Glob Environ. Issues 6 (4), 331–347.
Liu, H., Wu, J., Chu, J., 2019. Environmental efficiency and technological progress of transportation industry-based on large scale data. Technol. Forecast. Soc. 144, 475–482.
Liu, J., Sickles, R., Tsionas, E., 2017. Bayesian treatments for panel data stochastic frontier models with time varying heterogeneity. Economy 5 (3), 33.
Liu, W., Lund, H., Mathiesen, B.V., 2013. Modelling the transport system in China and evaluating the current strategies towards the sustainable transport development. Energy Policy 58, 347–357.
Llorca, M., Baños, J., Somoza, J., Arbués, P., 2017. A stochastic frontier analysis approach for estimating energy demand and efficiency in the transport sector of Latin America and the Caribbean. Energy J. 38 (5).
Mansouri, S.A., Lee, H., Aluko, O., 2015. Multi-objective decision support to enhance environmental sustainability in maritime shipping: a review and future directions. Transport. Res. E-Log. 78, 3–18.
McKinnon, A., 2007. CO_2 Emissions from Freight Transport in the UK. Commission for Integrated Transport, London.
Medrano, L.A., Migon, H.S., 2007. Sampling Schemes for Asymmetric Models a Comparative Study. Relatorio técnico, Departamento de Métodos Estatısticos, 204.
Meeusen, W., van Den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. Int. Econ. Rev. 18 (2), 435–444.
Morán, M.Á.T., del Rio Gonzalez, P., 2007. Structural factors affecting land-transport CO_2 emissions: a European comparison. Transport. Res. D-TR. E. 12 (4), 239–253.
Mullen, K., Ardia, D., Gil, D.L., Windover, D., Cline, J., 2011. DEoptim: an R package for global optimization by differential evolution. J. Stat. Softw. 40 (6), 1–26.
Papatheodorou, A., Lei, Z., 2006. Leisure travel in Europe and airline business models: a study of regional airports in Great Britain. J. Air Transp. Manag. 12 (1), 47–52.
Park, Y.S., Lim, S.H., Egilmez, G., Szmerekovsky, J., 2018. Environmental efficiency assessment of US transport sector: a slack-based data envelopment analysis approach. Transport. Res. D-TR. E. 61, 152–164.
Peng, B.B., Fan, Y., Xu, J.H., 2016. Integrated assessment of energy efficiency technologies and CO_2 abatement cost curves in China's road passenger car sector. Energy Convers. Manag. 109, 195–212.
Qiu, R., Xu, J., Zeng, Z., 2017. Carbon emission allowance allocation with a mixed mechanism in air passenger transport. J. Environ. Manag. 200, 204–216.
Rashidi, K., Cullinane, K., 2019. Evaluating the sustainability of national logistics performance using Data Envelopment Analysis. Transp. Policy 74, 35–46.
Richardson, B.C., 2005. Sustainable transport: analysis frameworks. J. Transp. Geogr. 13 (1), 29–39.
Saboori, B., Sapri, M., bin Baba, M., 2014. Economic growth, energy consumption and CO_2 emissions in OECD (Organization for Economic Co-operation and Development)'s transport sector: a fully modified bi-directional relationship approach. Energy 66, 150–161.
Scholl, L., Schipper, L., Kiang, N., 1996. CO_2 emissions from passenger transport: a comparison of international trends from 1973 to 1992. Energy Policy 24 (1), 17–30.
Song, M., Zhang, G., Zeng, W., Liu, J., Fang, K., 2016. Railway transportation and environmental efficiency in China. Transport. Res. D-TR. E. 48, 488–498.
Souza, M.V.P., Souza, R.C., Baidya, T.K.N., 2009. On estimating the cost efficiency of the Brazilian electricity distribution utilities using DEA and Bayesian SFA models. In: Proceedings of the 41th Simpósio Brasileiro de Pesquisa Operacional (SOBRAPO'09).
Spiegelhalter, D.J., Best, N.G., Carlin, B.P., Van Der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. B. 64 (4), 583–639.
Tabak, B.M., Tecles, P.L., 2010. Estimating a Bayesian stochastic frontier for the Indian banking system. Int. J. Prod. Econ. 125 (1), 96–110.
Timilsina, G.R., Shrestha, A., 2009. Transport sector CO_2 emissions growth in Asia: underlying factors and policy options. Energy Policy 37 (11), 4523–4539.
Tolley, R. (Ed.), 2003. Sustainable Transport. Woodhead Publishing, UK.
Tonini, A., 2012. A Bayesian stochastic frontier: an application to agricultural productivity growth in European countries. Econ. Change Restruct. 45 (4), 247–269.
Tsionas, E.G., 2002. Stochastic frontier models with random coefficients. J. Appl. Econom. 17 (2), 127–147.
Tsionas, E.G., Papadakis, E.N., 2010. A Bayesian approach to statistical inference in stochastic DEA. Omega 38 (5), 309–314.
Tsionas, M.G., Chen, Z., Wanke, P., 2017. A structural vector autoregressive model of technical efficiency and delays with an application to Chinese airlines. Transport. Res. A-Pol. 101, 1–10.
Wang, Z., Huang, W., Chen, Z., 2019. The peak of CO_2 emissions in China: a new approach using survival models. Energy Econ. 81, 1099–1108.
Wang, W.W., Zhang, M., Zhou, M., 2011. Using LMDI method to analyze transport sector CO_2 emissions in China. Energy 36 (10), 5909–5915.
Wang, Q.W., Zhou, P., Shen, N., Wang, S.S., 2013. Measuring carbon dioxide emission performance in Chinese provinces: a parametric approach. Renew. Sustain. Energy Rev. 21, 324–330.
Wanke, P., Chen, Z., Antunes, J.J.M., Barros, C., 2018a. Malmquist productivity indexes in Chinese ports: a fuzzy GMSS DEA approach. Int. J. Shipp. Transp. Logist. (IJSTL) 10 (2), 202–236.
Wanke, P., Chen, Z., Liu, W., Antunes, J.J., Azad, M.A.K., 2018b. Investigating the drivers of railway performance: evidence from selected Asian countries. Habitat Int. 80, 49–69.
Wei, J., Xia, W., Guo, X., Marinova, D., 2013. Urban transportation in Chinese cities: an efficiency assessment. Transport. Res. D-TR. E. 23, 20–24.
Yin, X., Chen, W., Eom, J., Clarke, L.E., Kim, S.H., Patel, P.L., et al., 2015. China's transportation energy consumption and CO_2 emissions from a global perspective. Energy Policy 82, 233–248.
Yu, Y., Choi, Y., Wei, X., Chen, Z., 2017. Did China's regional transport industry enjoy better carbon productivity under regulations? J. Clean. Prod. 165, 777–787.
Zhang, N., Wei, X., 2015. Dynamic total factor carbon emissions performance changes in the Chinese transportation industry. Appl. Energy 146, 409–420.
Zhang, N., Yu, K., Chen, Z., 2017. How does urbanization affect carbon dioxide emissions? A cross-country panel data analysis. Energy Policy 107, 678–687.