Business Environment Drivers and Technical Efficiency in the Chinese Energy Industry: A Robust Bayesian Stochastic Frontier Analysis

Abstract: Improving the technical efficiency of the energy industry is a fundamental way to ensure energy security and sustainable development and is also a requirement of the supply-side structural reform of China's energy. Although the business environment plays an important role in the energy industry, this relationship between efficiency and business environment has been scarcely studied. In addition, there has been no attempt made to link the financial sector and energy industry together. To this end, a novel Robust Bayesian Stochastic Frontier Analysis (RBSFA) is developed here, where DIC (Deviance Information Criteria) is minimized by the variance/covariance optimization of three classical distributional assumptions for the inefficiency term (u): Gamma, Exponential, and Half-Normal. The goal is to develop a RBSFA model to relate the technical efficiency of the energy industry in China with major business environment performance variables (financial sector variables, energy industry variables and macroeconomic variables). Results indicate that the efficiency level of the Chinese energy industry is quite high over the examined period, although there is a large variance between different companies. Our findings further show that increases in the efficiency of the Chinese energy industry can be achieved by increasing the level of inventories and fixed assets, as well as research and development expenses. Finally, we find that the efficiency level in the Chinese energy industry is affected by the business environment. In particular, we notice that financial sector development and competition are helpful to improve the efficiency of Chinese energy companies.

Keywords: business environment; energy industry; Stochastic Frontier Analysis; Robust Bayesian analysis; Data Envelopment Analysis

1. Introduction

The energy industry plays a very important role in the economic growth of every country in the world. The energy industry is closely related to households as well as to companies. No matter who you are, where you live, what you do, households cannot live without energy and companies cannot operate well without energy. The role played by the energy sector in the economy in China is even more important. According to the data from Global Energy Statistical Yearbook (as reflected in Figure 1), over the period 2012-2015, China was the world's largest producer of energy every year. We also notice that the volume of production keeps increasing over this period, reaching a peak by the end of 2015. A similar trend is also noticed for energy consumption in China, which is the largest energy consumer in the world, with the volume of consumption reaching its highest point in 2015. Although it is noticed that the volume of trade in energy increased over the period 2012--2014, followed by a slight decline in 2015, China is still the largest importer of energy in the world. Finally, an opposite finding is noticed; compared to production, trade and consumption, the energy intensity in China kept declining over the period 2012-2015, reaching its lowest point in 2015. The statistics in the table show that energy is vital in the Chinese economy, in particular reflected from the fact that the volume of consumption is always higher than the production capacity and the volume of energy imports keeps increasing although the energy consumption per GDP capita in China keeps decreasing. Therefore, how to increase the outputs in the energy sector is a question that needs to be solved and a solution to this question will be very important for the development of the energy industry in China and would make the energy companies more competitive in the world.

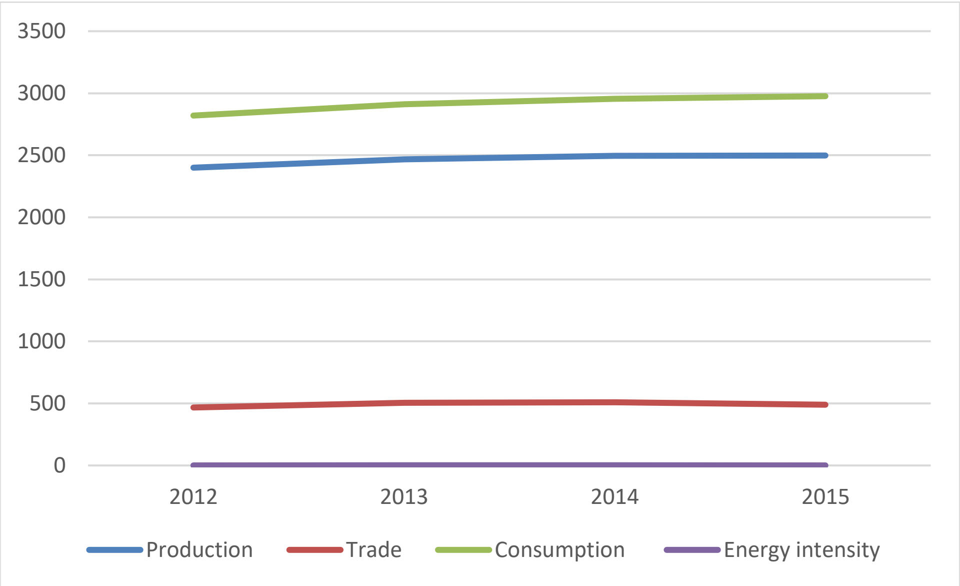

Figure 1 Statistics on the Chinese energy industry: 2012-2015[1]

[1] The unit of production trade and consumption in energy is measured by Millions of tonnes of oil equivalent (Mtoe), while the energy intensity is calculated by dividing the total energy consumption of a country to its Gross domestic product. Higher values indicate that there is a higher price or cost of converting energy into GDP. Koe/$2015p represents Kilogram oil equivalent per USD at constant exchange rate, price and purchasing power parities of the year 2015.

Note: the unit for Production, Trade and Consumption is Mtoe, while the unit for Energy intensity is koe/$2015p

Thus far, the majority of energy efficiency measurement techniques rely on the total factor energy efficiency (TFEE) concept. Some existing research has used partial factor energy efficiency, such as energy intensity, energy productivity, and the heat consumption rate (Ruzzenenti and Basosi, 2009; Duro, 2015). TFEE was first proposed by Hu and Wang (2006) to avoid the shortcomings of partial factor productivity indicators. With this respect, in terms of more comprehensive efficiency measures, the parametric and non-parametric methods should be highlighted. Typical examples include the application of Stochastic Frontier Analysis (SFA) and DEA to assess efficiency levels in the energy sector (Zhou et al., 2013). For instance, Hu and Honma (2014), Honma and Hu (2014), Lin and Du (2014), Du and Lin (2017) adopted SFA to analyze energy efficiency in different contexts. Compared with SFA, the DEA model does not need to consider a specific functional form, which cannot directly reflect the impact of contextual variables over performance. For example, Estelle et al. (2010), Zhou et al. (2013), Khalili-Damghani and Shahmir (2015), Arabi et al., (2016); Guo et al. (2017a), Hatemi-Marbini and Toloo (2017), Rezaee and Dadkhah (2019) improved the original DEA model under different circumstances of energy efficiency measurement.

Non-parametric approaches turn out to be more straightforward with the respect of the variable choice (Guo et al., 2017b; Jebali et al., 2017). During the selection of the productive resources to capture energy efficiency, most researchers consider energy, labour and capital as inputs. As regards the outputs, most researchers use GDP (Hu and Wang, 2006; Zhang et al., 2011; Li and Wang, 2014; Jebali et al., 2017), while a few consider desirable and undesirable outputs simultaneously (Wang et al., 2013; Li and Wang, 2014; Apergis et al., 2015). The selection of the undesirable output, however, is often imprecise and limited. In fact, most researchers use a single pollutant, such as CO2, to represent the undesirable outputs.

Nevertheless, spatial-temporal differences in energy efficiency is a key issue in some studies. Previous research on the impacts of regional differences on energy efficiency includes: Miketa and Mulder (2005), who studied the energy efficiency difference of 10 manufacturing sectors from 56 developed and developing countries; Honma and Hu (2007), who analyzed the TFEE difference of 47counties in Japan from 1993 to 2013; Camioto et al. (2016), who used DEA to analyze differences in energy efficiency driven by contextual variables from BRICs and G7 group. Besides these authors, Chang and Hu (2010), Song et al. (2013), Li and Zhang (2017), Huang and Zhang (2018), and Qin et al. (2018) analyzed the differences and future prospects of energy efficiency among different regions in China. On the other hand, papers on the contextual variables that may impact energy efficiency levels focus mostly on technological progress (Khazzom, 1980; Chang and Hu, 2010; Du and Lin, 2017), policy mechanisms (Geller et al., 2006; Feng et al., 2009; Zhao et al., 2010; Zhang et al., 2011;); energy prices (Fisher-Vanden et al., 2004; Hang and Tu, 2006; Zhao et al., 2010, Ouyang et al., 2018), industrial agglomeration (Chang and Hu, 2010; Liu and Meng, 2018), management levels (Cui et al., 2014), and openness levels (Li and Hu, 2012). Bian et al. (2016) used several parallel economic subsystems to evaluate energy efficiency. These authors suggested that economic development and the improvement of business conditions are energy efficiency enablers. The authors also concluded that the adjustment of the energy infrastructure to the industrial sector demands has a negative impact on energy efficiency. Watanabe and Tanaka (2007), Cui and Li (2014), and Borozan (2018) constructed different input-output indicators to measure energy efficiency and its major drivers or influencing factors. Table 1 provides a summary of literature studies described and discussed above regarding the methods used in the energy efficiency analysis, data period covered, inputs and outputs selection, assumptions and objectives of the study, as well as the main findings of the study.

Table 1 Summary of empirical literature

Author (s)	Publication year	Objectives	Data	Methods/Indicators	Inputs/Outputs selection	Main findings
Ruzzenenti and Basosi	2009	Evaluate energy efficiency in the European freight transport sector	1978-2008	Fuel economy and adjusted fuel economy under CUNA method and road test method	N/A	Energy efficiency improves, which is attributed to technological progress, the quest for more powerful vehicles and the shift of transport fleet to heavier vehicles
Hu and Wang	2006	Analyzes energy efficiencies of 29 administrative regions in China	1995-2002	Total factor energy efficiency under data envelopment analysis	Inputs: labour; capital; energy consumption; Total sown area of farm crops outputs: gross domestic product	The central area of China has the worst energy efficiency and its total adjustment of energy consumption amount is over half of China's total. Regional TFEE in China generally improved during the research period, except for the western area. A U-shape relation between the area's TFEE and per capita income in the areas of China is found
Zhou et al.,	2013	Evaluate environmental performance of industrial sectors in different provinces of China	1998-2009	Non-radial DEA approach consisting of both a static and a dynamic environmental performance index	Inputs: industrial labor force; industrial energy consumption Outputs: industrial value added; industrial carbon dioxide (CO2) emissions; industrial waste gas (IWG), industrial waste water (IWW) and industrial solid waste (ISW) for use	The environmental performance of industrial sectors in China improves by 58% in 1998–2009, mainly driven by the technological change.
Hu and Honma	2014	Estimate energy efficiency for 10	1995-2005	Total factor energy efficiency under parametric	Inputs: Labour Capital	More than half of the industries have insignificant changes in the inefficiency trend

		industries in 14 developed countries		stochastic frontier analysis	Energy intermediate input Non-energy intermediate input Outputs: Value added	construction, paper, and textile industries have significantly increasing inefficiency The metal industry is the only industry which has decreasing inefficiency
Honma and Hu	2014	Estimate energy efficiency for 47 regions across Japan	1996-2008	Total factor energy efficiency under parametric stochastic frontier analysis	Inputs:	The higher the manufacturing share and wholesale and retail trade share, the lower the energy efficiency.
Liu and Du	2014	Estimate the energy efficiency of China's provinces	1997-2010	A latent class stochastic frontier approach	Inputs: Energy consumption Labour Capital Outputs: Gross regional product	Overall energy efficiency of China's provinces is not high, with an average score of 0.632 during the period from 1997 to 2010.
Du and Lin	2017	Estimate the productivity growth in the energy sector across 123 countries (regions)	1990-2010	Malmquist energy productivity index based on the Shephard energy distance function	Inputs: Labour Capital Energy consumption Output: Gross domestic product	The energy productivity averagely increased by 34.6% from 1990 to 2010. The energy productivity growth was mainly driven by technological progress. There is no evidence of convergence of energy productivity growth in the world.
Khalili-Damghani and Shahmir	2015	Evaluate the efficiency of electricity power production and distribution processes	2006-2012	Uncertain network DEA model	Inputs: Consumption fuel cost; Specific production;	The efficiencies of production and distribution phases are determined distinctively

					Received energy from nearby companies Outputs: Specific production; Energy delivered to the distribution companies; Energy sent to the regional electricity companies; The sale of energy to industries; Emissions of power plants	
Arabi et al.,	2016	Assess the efficiency level of 52 Iranian government-owned power plants	2003-2010	Malmquist and Malmquist Luenberger indexes under a series of DEA slacks-Based models	Inputs: Fuel Capital Outputs: Generated electricity; Operational availability; Deviation from generation plan; Emission S02	there has been a significant improvement in eco-efficiency, cost efficiency and allocative efficiency of the power plants during the restructuring period
Guo et al.	2017a	Evaluate inter- temporal energy efficiency based on OECD countries and China	2000-2010	Dynamic DEA model	Inputs: Land area Population Energy use Outputs: CO2 emissions GDP	The average overall scores' efficiency is 0.78 and most countries exhibit efficiency improvement The sample countries should thus increase the volume of energy stock to improve their efficiency

					Carryover: Energy stock	
Guo et al.,	2017b	Evaluating the efficiency of regional energy saving and emission reduction of China	2011-2012	Modified Slacks-Based Measure (M-SBM) model	Inputs: *Investment completed in the treatment of wastewater and waste gas;* Coal consumption per 10,000 yuan of GDP *Electricity consumption per 10,000 yuan of GDP* Outputs: Gross domestic product *Wastewater and waste gas reduction per unit GDP* *Reduction in coal consumption reduction per 10,000 yuan of GDP* *Reduction in electricity consumption per 10,000 yuan of GDP*	Energy saving and emission reduction efficiencies of the regions in China are generally at a low level. China's regional regions performed really badly in energy saving although their emissions results are passable
Jebali et al.,	2017	Analyse the energy efficiency in the	2009-2012	DEA and two-stage double bootstrap approach	Inputs:	Energy efficiency levels in the Mediterranean countries are high and declining over time

		Mediterranean countries			Energy consumption Labour force Capital Outputs: GDP	Gross national income per capita, the population density, and the renewable energy use impact energy efficiency
Zhang et al.,	2011	Investigate energy efficiency in 23 developing countries	1980-2005	Total-factor energy efficiency using DEA window analysis.	Inputs:	Botswana, Mexico and Panama perform the best in terms of energy efficiency, whereas Kenya, Sri Lanka, Syria and the Philippines perform the worst during the entire research period A U-shaped relationship exists between total-factor energy efficiency and income per capita
Li and Wang	2014	Measure environmental efficiency in countries with different income levels	1996-2007	Slacks-based efficiency measure and the meta-frontier	Inputs: Capital Labour Energy consumption Outputs: GDP CO_2 emissions	A tremendous technology gap among income groups The international environmental efficiency difference among income groups increased over the period Economic development had a positive impact while fossil-fuel energy use and openness to trade had negative effects. Industrial structure and environmental efficiency, however, presented a "*U*"-shaped curve relationship
Wang et al.,	2013	Measure China's regional integrated energy and environmental efficiency	2006-2010	DEA based on range-adjusted measure	Inputs: Capital Labour Energy consumption Outputs: GDP CO_2 emissions	China's production efficiency slightly decreased and its emission efficiency slightly increased during 2006–2010. Most Chinese regions are recommended to rely on technology innovation for further integrated efficiency improvement.
Apergis et al.,	2015	Analyze the energy efficiency of selected OECD countries	1985-2011	Slacks-based model with undesirable output and	Inputs: Capital Labour	Efficiency levels are high but declining over time.

				Generalized linear mixed models using Markov chain Monte Carlo methods	Energy consumption Outputs: GDP CO_2 emissions	Capital-intensive countries are more energy efficient than labour-intensive countries
Miketa and Mulder	2005	Empirical analysis of energy-productivity convergence across 56 developed and developing countries, in 10 manufacturing sectors	1971-1995	Unconditional *and conditional*-convergence	N/A	Except for the non-ferrous metals sector, cross-country differences in absolute energy-productivity levels tend to decline, particularly in the less energy-intensive industries Cross-country differences in energy-productivity performance seem to be persistent Convergence is found to be local rather than global, with countries converging to different steady states and several failing to catch up
Honma and Hu	2007	Computes the regional total-factor energy efficiency (TFEE) in Japan	1993-2003	Total factor energy efficiency under DEA	Inputs: Labour Capital Energy inputs Outputs: Regional GDP	Inland regions and most regions along the Sea of Japan are efficient in energy use. Most of the inefficient prefectures that are developing mainly upon energy-intensive industries are located along the Pacific Belt Zone A U-shaped relation similar to the environmental Kuznets curve (EKC) is discovered between energy efficiency and per capita income
Camioto et al.	2016	Analyse the energy efficiency of G7 and BRICS	1993-2010	Slacks based DEA and DEA window analysis	Inputs: Capital Labour Energy consumption Outputs: GDP CO_2 emissions	Brazil has the best TFEE index in BRICS. TFEE index in BRICS ranges from 23.54% to 99.95%. All G7 countries have TFEE above 95%. patents are significant for energy efficiency in the BRICS countries; while in the G7 countries the Gross Domestic Product per capita (measured by purchasing

						power parity), life expectancy and years of schooling are significant
Chang and Hu	2010	Analyse the total-energy productivity change index in China	2000-2004	Directional distance functions	Inputs: Capital Labour Energy consumption total sown area of farm crops Outputs: real GDP	China's energy productivity was decreasing by 1.4% per year during 2000–2004. The average total-factor energy efficiency improves about 0.6% per year, while total-factor energy technical change declines progressively 2% annually. The east area has a higher TFEPI than the central and west area; increasing the development status and electricity share of energy consumption will improve the region's TFEPI performance, while increasing the proportion of GDP generated by the secondary industry deteriorates TFEPI of a region.
Song et al.	2013	Analyse the energy efficiency in China	1992-2010	Bootstrap DEA	Inputs: Capital Labour Energy consumption total sown area of farm crops outputs: real GDP	DEA direct results overestimate the energy efficiency of China for recent years China's energy efficiency are improved, that is CO2 emissions per unit of energy consumptions are reduced
Qin et al.	2018	Investigate and identify a specific and accurate evaluation of the energy efficiency in China's coastal areas	2000-2014	A virtual frontier-based global bounded adjusted measure	Inputs Labour Capital Energy consumption Outputs: GDP CO2 SO2 NOx	Hebei was always the least efficient province during our study period, followed by Guangxi and Shandong. Almost all of the inefficient scores under non-radial BAM-G were smaller than the scores under radial BAM-G. The level of production efficiency in China's coastal areas increased only slightly during the studied period, but the environmental efficiency level significantly increased.

						There was a widening gap between the high and low energy-efficient regions
Feng et al.,	2009	Investigate the relationship between energy consumption structure, economic structure and energy intensity in China	1980-2006	Energy intensity	N/A	These three variables tend to move together in the long-run There is a unidirectional causality running from energy intensity to economic structure but not vice versa
Zhao et al.,	2010	Investigate the reason for increase in the energy intensity in China	1998-2006	Energy intensity	N/A	Energy efficiency improvement in energy-intensive sectors is mainly due to the industrial policies that have been implemented in the past few years Low energy prices have directly contributed to high industrial energy consumption and indirectly to the heavy industrial structure
Fisher-Vanden et al.,	2004	Examine the reason of China's decline in energy intensity	1997-1999	Energy intensity	N/A	Rising relative energy prices, research and development expenditures, and ownership reform in the enterprise sector, as well as shifts in China's industrial structure, emerge as the principal drivers of China's declining energy intensity and use
Hang and Tu	2006	Investigate the impact of energy prices on energy intensity	1985-2004	Energy intensity	N/A	Higher relative prices of different energy types lead to the decrease in coal, oil, and aggregate energy intensities. Sectoral adjustment also drove the decrease in aggregate energy intensity.
Ouyang et al.,	2018	Measure factor price distortions and estimate their impact on energy efficiency based on an empirical analysis of 30 provinces of China	2004-2013	Stochastic frontier analysis	Inputs: Labour Capital Energy consumption Outputs: GDP	Large regional differences exist in factor price distortion and energy efficiency It is necessary to break barriers of technology transfer among regions in China.

Liu and Meng	2018	Evaluate the energy efficiency of 20 mining cities in Eastern and Central China	2010-2014	Data envelopment analysis	Inputs: total discharge of waste water total emissions of waste gas sulfur dioxide emissions, dust emissions, industrial wastes and water consumption Output: city level GDP	The level of energy efficiency in mining cities is still low China should optimize industrial structures, strengthen scientific and technological input and innovation, as well as implement energy-saving emissions reductions, and increase investment in environmental protection and ideological propaganda
Cui and Li.,	2014	Evaluate the transportation energy efficiency	2003-2012	Three-stage virtual frontier DEA	Inputs: Labour Capital Energy consumption Outputs: freight turnover volume passenger turnover volume	Transport structure and management measures have important impacts on transportation energy efficiency
Li and Hu	2012	Estimate Ecological total-factor energy efficiency of regions in China	2005-2009	Slacks-based DEA with undesirable output	Inputs: Labour Capital Energy consumption Outputs: GDP CO_2 emissions SO_2 emissions	China's regional ETFEE still remains a low level of around 0.600 and regional energy efficiency is overestimated by more than 0.100 when not looking at environmental impacts The ratio of R&D expenditure to GDP and the degree of foreign dependence have positive impacts, whereas the ratio of the secondary industry to GDP and the ratio of government subsidies for industrial pollution treatment to GDP have negative effects on the ETFEE.

Bian et al.	2016	Evaluate Energy efficiency of the economic system in China	1986-2012	A parallel slacks-based measure approach	Inputs: Labour Capital Energy consumption Outputs: GDP	1) the inefficiency of the economic system in China is mainly sourced from the lower energy performance of the secondary industry; 2) energy efficiency of the economic system increases during the study time period with an exception during 2001–2005; 3) it is better for the whole economic system to improve energy efficiency, which can help to save much more energy consumption in production in China; and 4) economic development is estimated to have positive impacts on national energy efficiency, while energy structure adjustment and industrial structure optimization have negative effects on national energy efficiency.
Watanabe and Tanaka	2007	Evaluate the energy efficiency of Chinese industries	1994-2002	Directional output distance function	Inputs: Labour Capital Material Outputs: Industrial value added Sulfur dioxide	Five coastal provinces/municipalities that have attracted a large amount of foreign direct investment are found to be the most efficient when only desirable output is considered, and also when both desirable and undesirable outputs are considered
Cui et al.	2014	Evaluate the energy efficiency and its influencing factors for nine countries	2008-2012	Data Envelopment Analysis (DEA) and Malmquist index	Inputs: Labour Energy consumption amount Energy services amount Outputs: CO2 emissions per capita	Technology indices and management indices are the main factors of energy efficiency. Management indices' effect on energy efficiency index is occurred mainly through pure technical efficiency change index. Technology indices' effect on energy efficiency index is occurred mainly through technical progress change index.

					industrial profit amount	
Borozan	2018	Estimate Technical and total factor energy efficiency of European regions	2005-2013	Data envelopment analysis	Inputs: Capital Energy consumption Employment rate Outputs: GDP	Regional differences in technical and energy efficiency are considerable, whereby most of EU regions failed to utilize efficiently all of their resources. Human capital and innovation are particularly important for improving the region's efficiency or ecological performance.

This study examines the technical efficiency of the Chinese energy industry using annual data from 2012 to 2015. The current research is from previous studies where technical efficiency is analyzed under traditional parametric and non-parametric efficiency models (Sun et al., 2017; Zeng et al., 2018). This paper proposes an innovative RBSFA computational model to assess the impact on Chinese energy industry efficiency of major business environment related variables – financial sector development (including banking sector development), stock market development, banking sector competition, macroeconomic environment (including inflation), corruption perception index, and energy industry development (including energy industry concentration) and energy industry development. Another distinctive feature of this paper is that these business environment variables are jointly taken into a single index by means of Analytic Hierarchy Process- Technique for Order Preference by Similarity to Ideal Solution (AHP-TOPSIS) rescaling and weighting (Vinodh et al., 2014; Radenovic and Veselinovic, 2017) in order not only to mitigate the collinearity issues among them, but also to make panel data repeated measures tractable.

Previous research on the efficiency of the energy industry in China is scarce (Fang et al., 2009; Rao et al., 2012; Du et al., 2013; Song et al., 2018; Kong et al., 2018). Traditional DEA CCR and BCC models are used by Fang et al. (2009) to measure and compare the technical efficiency of coal mining companies in China and the US. The results show that the technical efficiency, pure technical efficiency and scale efficiency of mining companies in China are lower than the ones in the US. Rao et al. (2012) investigate the energy efficiency of 30 regions in China over the period 2000-2009 under a slacked based DEA with labour, capital stock and energy consumption as inputs, gross domestic product as a desirable output and chemical oxygen demand and SO2 as undesirable outputs. The results show that economic development is helpful in improving efficiency levels and the eastern area has the highest level of efficiency. In comparison, the western area has more potential for industrial energy savings. Parametric stochastic frontier analysis is used by Du et al. (2013) to investigate the efficiency of China's fossil-fired power plants. The results show that when total factor productivity analysis includes fuel expenses, electricity reforms can improve the efficiency, but just in a weakly significant way, whereas, the level of technical efficiency is improved when the physical quantity includes the measurement of fuel input. A combined directional distance function and slack-based model is used by Song et al. (2018) to measure the production and safety efficiency of 18 coal mining provinces in China. The findings show that both the production efficiency and safety efficiency are quite low. Rather than using the parametric stochastic frontier analysis or the non-parametric Data Envelopment Analysis (DEA) or distance function and slack-based model, Kong et al. (2018) use the Energy Return on Investment method to investigate the production efficiency of China's natural gas hydrates located in the South Sea. The results show that the average efficiency level as reflected from energy return on investment is 0.74, while it is further suggested that when developing large scale natural gas hydrates, technological development is required. In any case, what emerges from the above literature is that the innovative RBSFA computational model proposed here is used for the first time with respect to the energy industry efficiency and its relationship with business environment variables. Among the few studies in this research field that adopted Bayesian SFA models on energy efficiency (Pereira de Souza et al., 2010; Galan and Pollitt, 2014; Chen et al., 2015; Cengiz et al., 2018; Carvalho, 2018), all of them used the traditional Bayesian SFA method and none of them addresses the issue regarding the impact of business environment on efficiency in the energy industry, in particular, the influence of financial system on the efficiency level of energy companies.

Unlike previous studies, the conclusions found here indicate that Chinese energy companies have a quite large dispersion in efficiency levels, although the average level of efficiency in the Chinese energy industry is quite high over the examined period. Our results generate interesting and important implications, from which the energy regulatory authorities in China can formulate relevant policies in order to improve efficiency levels in the Chinese energy industry. We argue that the efficiency level in the Chinese energy industry can be improved by increasing the volumes of inventories; fixed assets as well as research and development expenses. Finally, our findings show that the further developed the energy sector, stock market and banking sector in China are, the more helpful it is to improve the efficiency level in the Chinese energy industry. We also found that a higher level of competition in the Chinese banking sector has a positive impact on the efficiency level of the Chinese energy companies, whereas higher competitive condition in the energy industry (lower level of concentration), lower level of corruption and inflation promote the efficiency improvement of the Chinese energy companies.

The layout of the paper is the following: Section 2 presents the literature review. Section 3 is focused on the methodology. Section 4 outlines the analysis and discussion of results. Section 5 contains some concluding comments.

2. Literature Review and hypothesis development

2.1. *Background on SFA and energy related studies*

SFA, which was first introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), is a parametric efficiency analysis method. It is used to estimate the boundary functions for a given production technology and to measure the inherent productive efficiency. Besides, SFA helps in establishing a functional relationship between output variables, such as cost or production levels, and input variables, such as productive factors, like capital and labour and other contextual variables.

In recent years, an increased number of applications of SFA models in the energy sector is witnessed, although the SFA applications related to the energy industry and its business environment still remain scarce, as can be inferred from Table 1 (Otsuka and Goto; 2015; Sineviciene et al., 2017; Otsuka, 2017). For example, Huntington (1994) described the relationship between energy efficiency and productive efficiency using SFA. More recently, Buck and Young (2007) discussed a parametric approach to estimate a stochastic frontier function for energy use in Canadian commercial buildings. Boyd (2008) used a stochastic frontier function for energy use in wet corn milling plants. Filippini and Hunt (2011) use a panel stochastic frontier function for energy for 29 countries. Otsuka and Goto (2015) used SFA to measure the energy efficiency in Japanese regional economies and further investigate the determinants, including market access and population density as well as share of material industry. In comparison, the same method has been used by Sineviciene et al., (2017) to evaluate the energy efficiency of Eastern Europe post-communist economies and the determinant of efficiency they focused on were the macroeconomic environment, as well as energy industry indices, among others. Finally, Otsuka (2017) assessed the efficiency in residential electricity demand in China using SFA. In the second stage, they considered floor are and household size as well as ageing as the potential determinants. All the students used the panel data fixed/random effect as the econometric techniques when investigating the determinants.

2.2. Bayesian Analysis and Markov-Chain Monte Carlo Methods

The inherent complexity of SFA models makes numerical integration methods inevitable. Koop et al. (1995) firstly proposed and introduced the Markov Chain Monte Carlo (MCMC) and this method has been gradually and widely used in the empirical literature on Bayesian analysis (Kurkalova and Carriquiry, 2002; Tsionas, 2002; Huang, 2004; Kumbhakar and Tsionas, 2005; Griffin and Steel, 2007; Rimler et al., 2010; Du et al., 2011; Assaf et al., 2012; Tsionas and Assaf, 2014). As a matter of fact, MCMC methods have become the cornerstone for Bayesian analysis. Kim and Schmidt (2000), Kurkalova and Carriquiry (2002) and Ennsfellner et al. (2004) give current developments in Bayesian SFA (BSFA) models. Griffin and Steel (2007) describe MCMC methods for Bayesian analysis within the ambit of SFA models using the WinBUGS package. Tsionas and Papadakis (2010) provide a Bayesian analysis to the SFA problem in terms of alternative simulation techniques.

In this related literature, there is no explicit criterion for the selection of which distribution of the inefficiency term should be used in BSFA/SFA. Meeusen and van der Broeck (1977) and Aigner et al. (1977) use Exponential and Half-Normal distributions, respectively. Gamma distributions are used by Greene (1990) and Log-normal distributions are studied by Migon and Medrano (2004). Griffin and Steel (2007) described a semiparametric modelling technique to estimate the inefficiency distribution. Alghalith (2011) describe an alternative method for specifying the distribution of the inefficiency term (Ehlers, 2011). In fact, there are no apparent reasons for selecting one distributional form over the other and each has its pros and cons (Coelli et al., 1998).

The main contribution of this paper is to propose a RBSFA computational model where the variances and covariances of different distributional assumptions for the inefficiency term (u) are minimized by the joint use of MCMC methods and differential optimization. The goal is to minimize DIC for the combined BSFA model based on the determination of the optimal weights for each one of the inefficiency distributional assumptions. This RBSFA computational model is applied to analyze the sustainability of Chinese transportation in terms of CO2 emissions. Three different distributional assumptions have been considered for the inefficiency term (u) – Half-Normal, Gamma, and Exponential, and two for the error term (v) – Normal and t-Student.

2.3 Energy efficiency and business environment drivers- hypotheses development

As a consequence of the rapid development of China's economy over the last forty years, the total amounts of energy consumption and pollutant emissions have increased, becoming a relevant barrier to the sustainable development of China's economy. As long as energy is the cornerstone input among different productive factors, it holds a relevant and strategic position in the socio-economic development. Currently, the development of China's economy is slowing down and environmental problems caused by pollutant emissions are increasing dramatically (Zhang, 2019). Improving energy efficiency is required to achieve sustainable economic development while the pollutant emissions are reduced. The development of the energy industry in China is not only affected by the firm-specific determinants (Costa-Campi et al., 2015; Sineviciene et al., 2017)[2], but more importantly, the performance of the energy industry is significantly influenced by the

[2] The firm specific determinants mainly include firm size, firm age, investment in research and development, employee productivity, firm export, among others.

energy industry development (Craig, 2016), and the financial system (Chang, 2015) as well as the macroeconomic environment (Sharma et al., 2014) in China[3].

We contribute to the empirical literature on energy efficiency by proposing and providing systematic arguments regarding the joint impacts of the energy industry, financial system and macroeconomic environment on efficiency in the Chinese energy industry. To be more specific, we argue that the development of the banking industry[4] in China is supposed to influence efficiency in the energy industry. According to the data from China Banking Regulatory Commission (CBRC), over the period 2012-2015, the total volumes of loans granted by the Chinese banking industry to the energy sector were RMB26.7 billion, 26.8 billion, 28.4 billion and 31.6 billion, respectively. As we can see from the data, there was an increase in the demand for bank loans from the energy industry. A well-developed banking sector will provide better services to the energy companies at a lower level of cost, which will further lead to an improvement in efficiency level. Therefore, the first hypothesis of our paper is:

A well-developed banking sector is helpful to improve the efficiency level in the Chinese energy industry.

Not only is the banking industry supposed to have a significant impact on the performance of the Chinese energy companies, but we are further being the pioneer to consider and propose the potential impact of the development of the stock market on the efficiency level of the Chinese energy industry. The financial system plays an important role in the operation and development of all the economic sectors of a country. The financial systems mainly provide credits for companies' tangible investment (fixed assets, inventories, etc.) and intangible investment (research and development related expenditure). We argue that besides the banking sector, an alternative funding source for the energy companies in China will be the stock market. A well-developed stock market is supposed to provide more choices for the companies to raise funds for their investments. An increasing number of companies will engage in Initial Public Offering. This will reduce the volumes of loan businesses from banks, and the resultant reduction in demand will decrease the price of loans and further reduce the borrowing cost and improve the efficiency of energy companies. Therefore, our second hypothesis is:

A well-developed stock market leads to an increase in the efficiency level in the Chinese energy industry.

Another environmental variable we argue has a potential influence on efficiency in the energy industry is banking sector competition[5]. A higher level of competition among Chinese commercial banks will reduce the price of loans. China had completed the process of interest rate liberalization by the end of 2015. The interest rate on loans and deposit would be determined at the bank level without any influence from the government. A higher level of competition among Chinese commercial banks is supposed to decrease the interest rate on loans, and the resultant reduction in the borrowing cost

[3] The macroeconomic environment mainly includes GDP, industry total output and trade balance.

[4] Banking industry development mainly measures the importance of the banking sector to the economy in terms of providing credits to different economic sectors. It is measured by the ratio of banking industry assets to GDP; higher figures indicate a more developed banking sector (Tan and Floros, 2012)

[5] Banking sector development measures the importance of the banking industry to the economy, while banking sector competition is an indicator reflecting the interaction between different banks in the industry from a micro level. It is measured by the banking concentration ratio with higher figures indicating lower level of competition (Tan et al., 2017).

will increase the efficiency of Chinese energy companies, and therefore, our third hypothesis is:

Chinese energy companies will have a higher level of efficiency if there is stronger competition in the Chinese banking industry.

Not only will the financial sector have an impact on efficiency in the energy industry, but also we argue that the energy industry itself is supposed to influence the efficiency level of energy companies. To be more specific, we argue that energy industry concentration is supposed to affect the efficiency level of energy companies in China. A higher level of concentration in the energy sector reduces the level of competition (Ferrari and Giulietti, 2005)[6]; lower level of competition in the energy industry is supposed to reduce the managers' incentive to optimize the resources in the production process and managers will be less careful in managing inputs and outputs. This will lead to a decrease in the level of efficiency. Therefore, our fourth hypothesis is:

Chinese energy companies will have a lower level of efficiency if the energy industry is highly concentrated.

We further argue that, not only will the energy industry affect the efficiency level of energy companies, but, more importantly, energy sector development is supposed to influence the efficiency level of energy companies. Higher volumes of assets held in the energy industry, as reflected by the higher level of energy industry development, give managers more opportunities to invest money in the research and development activities. Such investments are supposed to reduce costs and further lead to an improvement in the efficiency level. Therefore, our fifth hypothesis is:

Chinese energy companies will have a higher level of efficiency if there is a well-developed energy industry.

The previous hypotheses have mainly focused on the impacts of the financial system and energy industry on the efficiency level of energy companies in China. We further argue that the macroeconomic environment is supposed to significantly affect the efficiency in the Chinese energy industry. One of the main initiatives engaged in by the current president of China, Xijipin, has been to deal with the corruption issue throughout the country. We argue anti-corruption is a very important measurement taken by the government in order to further promote a harmonious development of the society as well as healthy development of every sector of the economy. Higher levels of corruption create an environment in which all the people, including government officials, company managers and even all the staff tend to focus on building relationships and engaging in bribery. Lots of time will be wasted to engage in these activities rather than used in the production process. In other words, this environment will lead to inefficient allocation of resources and further lead to a decline in efficiency in every sector of the economy. Therefore, our sixth hypothesis is:

The efficiency level in the Chinese energy industry can be improved if the corruption level is further reduced.

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[6] If few companies occupy a relatively large amount of market share as reflected by higher concentration ratios, these companies have a higher level of market power, and it would be difficult for other companies to compete with them. Therefore, the market has a lower level of competition.

Finally, we are the first to propose and test the impact of inflation on efficiency in the energy industry. The potential impact of this macroeconomic environment on efficiency in the energy industry can be argued with the help of empirical findings from the finance literature. More specifically, Tan and Floros (2013) argue that during the inflationary period, there would be fewer people who would like to deposit their money into a bank because of value erosion of money. This will further lead to a decrease in the amount of money available in the bank for making loans. In other words, banks would normally reduce the volumes of credits granted and it would be more costly for companies to get loans. This will further lead to a reduction in the efficiency level. This argument can be further supported by Tan and Floros (2014), who argue that in a higher inflationary environment, Chinese commercial banks have lower volumes of loan loss provisions, which means inflation reduces bank risk in China. This reflects the fact that banks normally would have a much stricter requirement for granting loans and lower number of companies is able to get loans from banks. Fewer volumes of credits available in the market will increase the price of loans and further increase the costs and reduce the efficiency level. Therefore, our last hypothesis is:

Higher inflation leads to a reduction in the efficiency level in the Chinese energy industry.

Therefore, measuring the energy efficiency of Chinese energy industry controlling for the impact of business environment related variables as well as macroeconomic environment is of great theoretical significance and application value for the implementation of China's energy supply-side structural reform.

This literature review suggests that there is not a single set of contextual variables that should be included in the parametric methods to assess diverse economic impacts on energy efficiency. In fact, the available variable options are constantly increasing due to the emergence of alternative regional economic development metrics. Departing from previous studies, this paper analyses the impact of several business environment variables on the technical efficiency levels of the Chinese energy industry by means of a novel RBSFA. In particular, we fill in the gaps of the empirical literature by linking the energy industry environment, financial system and macroeconomic environment together with the efficiency in the Chinese energy industry through proposing and providing systematic arguments and establishing relevant hypotheses. As regards its production process, fixed assets, construction, inventories, and R&D expenses were considered as the financial inputs, while total income was considered as the single output of the Chinese energy industry. This paper also departs from previous energy studies that relied on parametric methods in the sense that business environment variables are jointly taken into a single index by means of AHP-TOPSIS rescaling and weighting to handle collinearity issues, as well as to properly use panel data repeated measures collected at the industry and macro levels.

3. Methodology: The Proposed RBSFA

This paper implements MCMC methods for a RBSFA computational model using codes developed in R and WinBUGS, both freely available statistical software. The codes developed in this paper are available upon request. The basic SFA model regresses a production frontier onto several distinct cost components. Considering a balanced panel dataset formed by i individuals (i= $1 \ldots I$) over the course of time t ($t = 1 \ldots T$), the

RBSFA developed in this research regresses the logarithm of total income, y_{it}, onto a vector of dependent (contextual) variables $\mathbf{x}_{it}$, which encompasses the logarithms of the fixed assets, inventory, construction, and R&D expenses for the Chinese energy industry:

$$y_{it} = \alpha + \mathbf{x}_{it}\beta + u_{it}\ ,\ y_{lt} \sim N(1\ ,\sigma^2) \tag{1}$$

where $N(\mu, \sigma^2)$ indicates a normally distributed logarithm of the total income for each company *i* over the time *t* with mean l and variance σ^2. β denotes the set of regressor coefficients while α represents the intercept. Inefficiencies are modelled by u_{it} that represents the differences between the energy industry best-practice in terms of total income and the actual total income levels for each company *i* at time *t*. Inefficiency distributions are very often supposed to be one-sided, such as the Exponential, as in the seminal paper of Meeusen and van den Broeck (1977): $u_{it} \sim \mathrm{Exp}(-\ln r^*)$, implying that the prior median efficiency is equal to r^* and that the energy efficiency of company *i* at time t is computed as $\exp(-\mathrm{u}_{it})$ (also cf. Kumbakhar and Lovell, 2003). Besides, multivariate normal censored priors are assigned to each one of the regressor coefficients - $\beta \sim N(0, \sum)$ -, while the variance reciprocal of y_{lt} are assumed to be Gamma distributed - $\sigma^{-2} \sim Ga(a_0, a_1)$ - with shape parameter a_0, scale parameter $a_1 = 1/\lambda$ and mean a_0/a_1 .

Random samples are generated for each observation and their full posterior distributions are subsequently computed. Since efficiencies may vary over the course of time, u_{it} denotes the inefficiency of a given company *i* at time *t*. One assumption presented in Lee and Schmidt (1993) considers that temporal effects over company *i* can be described by a global linking function, such as $u_{it} = \beta(t)u_i$. This parsimonious specification consists of a strong assumption with respect to the time dependence functional form. Alternative functional forms have been considered for $\beta(t)$. Specifically, Battese and Coelli (1992) suggested $\beta(t) = exp\{n(t-T)\}$ where *n* denotes a general constant trend applied to all company *i* over the course of time *t*.

Koop et al. (1997) extended the stochastic frontier modelling to consider that exponentially distributed inefficiencies maybe also dependent on contextual, business-related variables. The suggested model considered that each company *i* at time *t* is also associated to a contextual variable vector, $\mathbf{w}_{it}$. This being the case, the partial inefficiency distribution function for the contextual variable vector is given as:

$$u_{it} \sim Exp(\mathbf{w}_{it}\gamma). \tag{2}$$

where γ denotes the set of regressor coefficients for the contextual variables. This contextual variable vector $\mathbf{w}_{it}$ may be formed by non-binary variables. A tractable *a priori* assumption for this partial efficiency distribution function considers an equal median for each company *i* at time *t*, i.e., $exp(\gamma) \sim Exp(-\ln r^*)$.

A certain distributional assumption on u_{it} is needed. From the literature on efficiency estimation, three distributional assumptions are used here: Exponential (Meeusen and van der Broeck, 1977); Half-normal (Aigner et al., 1977); and a Gamma distribution (Greene, 1990). We consider six alternative models based on three different inefficiency components as the Half-Normal, the Exponential, and the Gamma distributions as well as on two distinct distributional assumptions for the error term: t-Student and Normal. The choice of these specific distributions is related to the traditional used assumptions for modelling error terms u and v, as can be found in Kumbhakar and Lovell (2001), the reference book on this subject. Very often these distributions are tested separately in different papers and researchers derive broader conclusions on the phenomenon under study. The proposed model is specified as follows, regardless of the distributional assumptions on *v*:

$$y_{it} = \alpha + \mathbf{x}_{it}\beta + \beta(t) + \mathbf{w}_{it}\gamma + v_{it} - u_{it} \tag{3}$$
$$u_{it} \sim^{i.i.d} Exp(\lambda) \tag{3a}$$
$$u_{it} \sim^{i.i.d} N^{+}(0, \lambda) \tag{3b}$$
$$u_{it} \sim^{i.i.d} Ga(\emptyset, \lambda) \tag{3c}$$

Where λ is the ratio parameter and $\emptyset$ an adequate shape parameter.

We define the prior distributions for the parameters in (3) as proposed in Griffin and Steel (2007). We assume all parameters to be independent. The MCMC algorithm involved 200,000 MCMC iterations where the first 100,000 were discarded in a burn-in phase.

The DIC model consists of a criterion for comparing different assumptions with respect to distributional and functional forms (Spiegelhalter et al. 2002). DIC trades off goodness-of-fit against a model complexity penalty. The method estimates the ''effective number of parameters'' pD. D is the posterior mean of the deviance $(-2\text{x}\log\text{likelihood})$ and $\widehat{\mathrm{D}}$ is an estimate based on the posterior mean of the parameters. The DIC is computed as $\mathrm{DIC} = \overline{\mathrm{D}} + \mathrm{p_D} = \widehat{\mathrm{D}} + 2\mathrm{p_D}$. Lower values of the criterion indicate better fitting models (Griffin and Steel, 2007).

The relative importance of each distributional assumption for the inefficiency term u in explaining the efficiency in the Chinese energy industry 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 y models are simultaneously minimized by a non-linear stochastic optimization problem, as presented in eq. (4), where p_y denote the weights assigned to the vectors of the inefficiencies of each one of the six models previously described. The values of p are determined so that the sum of the variances and covariances of the pooled inefficiencies are minimized.

$$\min \left[Var\left(\sum_{y=1}^{6} p_y * u_{ity}\right) + \left(\sum_{y,y*=1}^{6} Covar\,(p_y * p_{y*} * u_{ity} * u_{ity*}), y \neq y*, y* < y, \forall t\right)\right]$$
$$s.t.$$
$$\textstyle\sum_{y=1}^{6} p_y = 1 \tag{4}$$
$$0 \leq p_y \leq 1\ \forall y$$

Model (4) was solved using the differential evolution (DE) technique, which belongs to the research stream of genetic algorithms and mimics the natural evolutionary selection of genes The DE approach used followed the steps presented in Wanke and Leiva (2015), as reproduced next.

Let N be the number of members $\mathbf{y} \in R^n$ (tuning parameter vector) in the population, where n denotes the dimension of the vector $\mathbf{y}$, in our case given by $\mathbf{y} = (p_1..p_6) \in R^n$. The DE algorithm needs a starting population, which was obtained by sampling the objective function at multiple randomly chosen initial points (generation or solution zero (0)) for **y.** Before the population is initialized, both lower and upper bounds for each tuning parameter were set between 0 and 1. To establish the generation 0, N guesses for the optimal value of **y** were provided, using equal weights. Each generation created a new population from the current population members $\{\mathbf{y}j,g, j = 1, \ldots, N, g = 1, 2, \ldots\}$,where j indexes the tuning parameter vector that make up the population and g indexes the generation. The new generation is obtained using differential mutation of the population members. In our research, S = 100,000 denotes the number of simulated scenarios and **y** denotes the tuning parameters for $\mathbf{y} = (p_1..p_6)$. An initial mutant parameter vector $\{kj,g, j = 1, \ldots, N, g = 1, 2, \ldots\}$ was created by choosing three members of the population at random. Then the elements of the initial mutant parameter vector were generated observing a positive scale factor default of 0.8). After the first mutation operation, it continued until k mutations have been made Calculations in this paper were performed with the aid of the DEoptim package. See Storn and Price (1997) and Price et al. (2006) for more details about the algorithm, while Ardia et al. (2011) and Mullen et al. (2011) are references for further details on R implementation. Results are discussed next.

4. Analysis and Discussion of Results

The original variables used in this research are Chinese yearly information about the productive process of 128 different energy companies detailing: (i) total income (in million RMB per year); (ii) fixed assets (in million RMB); (iii) construction (in million RMB); (iv) inventories (in million RMB); (v) R&D expenditures (in million RMB per year); and (vi) investment (in million RMB). These input/output data were collected from CSMAR database, which provides comprehensive data on different economic sectors in China. The business environment related variables - banking sector development, stock market development, inflation, corruption perception index, banking sector competition, energy industry concentration, and energy industry development – were collected, respectively, from the following additional sources: 1) World Bank database; 2) China Banking Regulatory Authority; 3) National Bureau of Statistics of China; 4) Transparency International. All data range from 2012 to 2015. The descriptive statistics of the inputs, output, and business environment related variables are given in Table 2.

Table 2. Descriptive Statistics of the variable vectors used in the RSBM under six different combinations of distributional assumptions.

Variables		Min	Max	Mean	SD	CV
Inputs	Fixed Assets [million RMB]	5.39	34045.70	2879.38	5044.12	1.75
	Construction [million RMB]	0.10	14464.81	836.48	1972.83	2.36
	Inventories [million RMB]	65.58	33963.32	1836.18	4314.64	2.35
	Expenses for Research and Development [million RMB]	0.00	2706.43	87.15	349.86	4.01
Outputs	Total Income [million RMB]	3.31	38825.84	910.51	4058.01	4.46
Contextual variables	Banking Sector Development [%]	2.38	2.91	2.61	0.20	0.08
	Stock Market Development [%]	41.11	74.00	53.90	13.19	0.24
	Inflation [%]	1.44	2.62	2.15	0.50	0.23
	Corruption Perception Index [%]	36.00	40.00	38.00	1.58	0.04
	Banking Sector Competition [%]	38.43	44.04	41.56	2.37	0.06
	Energy Industry Concentration [%]	72.10	76.50	74.35	1.78	0.02
	Energy Industry Development [%]	53.00	62.00	57.00	3.25	0.06

Specifically, with respect to the business environment related variables, they are strongly and significantly correlated, as can be seen in Fig. 1. This is possibly related due to the fact that the short-length panel of collected data, altogether with country-level business environment related variables in opposition to company-level input/output data, impact on the data scales and how they can be treated. In fact, Table 3 reveals that, with only four levels each, these business-environment related variables could be regarded as belonging to the ordinal scale rather than to the metric scale.

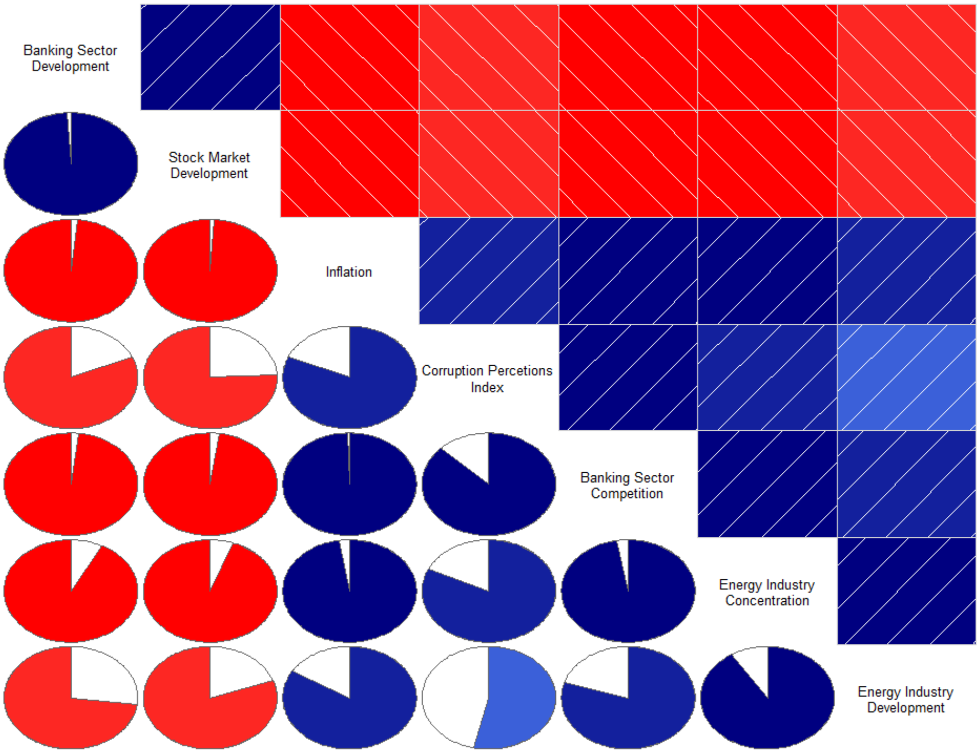

Fig. 1. Correlogram of the business environment related variables.

This being the case, this study also attempts, as a by-product of the deemed necessary data treatment, to investigate whether an AHP approach can be used to produce meaningful insights based on pairwise comparisons of the business environment related variables (after transforming them into ordinal rank data). Precisely, AHP allows the computation of a metric relevance or importance weight for each business environment variable, ranging from 0 to 1 and summing up 1, based on pairwise comparisons of ordinal data (Chen, 2006; Hou, 2016). In this paper, ordinal ranks for the business environment related variables, measured originally as indexes, were assigned as a proxy of their relative importance for each energy company in China (cf. Table 2).

Table 3. Business-environment related variables and the respective ordinal rank.

Variable	Metric ratio	Ordinal Rank
Banking Sector Development	2.38	1
	2.48	2
	2.69	3
	2.91	4
Stock Market Development	41.11	1
	43.19	2
	57.29	3
	74	4
Inflation	1.437	1
	1.922	2
	2.619	3
	2.621	4
Corruption Perception Index	36	1
	37	2
	39	3
	40	4
Banking Sector Competition	38.43	1
	40.12	2
	43.66	3
	44.04	4
Energy Industry Concentration	72.1	1
	73.2	2
	75.6	3
	76.5	4
Energy Industry Development	53	1
	56	2
	57	3
	62	4

AHP is normally considered a multistage process, but for this study, only one such stage is required. It is used as a cornerstone to transform the square matrix of pairwise ratios into normalized scores, ultimately indicating the relative weight (eigenvalues) of each business environment related variable as depicted in Table 4. These weights are often used as inputs to other multi-criteria decision-making models, such as TOPSIS, by means of which, an overall business environment performance score, ranging from 0 to 1 can be computed for each company at each year. This overall performance score synthesises the relative weighted distance of each variable to the positive and negative ideal solutions. Compared to the Weight Process (WP) and Simple Additive Weighting (SAW), AHP-TOPSIS can generate more valid results (Onder and Dag, 2013; Tyagi et al., 2014; Hadikurniawati et al., 2018).

TOPSIS also requires the signs of the relationships of each variable in terms of the positive ideal solution. Therefore, as depicted in Table 3, there are individual variables that contribute positively or negatively to an overall business environment performance index. We divide the business environment variables into three groups when discussing their impacts on the overall performance of the Chinese energy companies. First, with regard to the financial system variables, the results show that banking sector competition, banking sector development and stock market development are significantly and positively related to the efficiency in the Chinese energy industry, although we notice that banking sector competition has higher AHP weights compared to the other two. The results are in line with our hypotheses in section 2. The second group of business environment variables are energy industry related variables. The findings, as reflected from the table below, show that energy industry concentration has a significant and negative impact on the efficiency level of the Chinese energy companies, indicating that a higher level of concentration leads to a reduction in efficiency. This is also in accordance with our hypothesis. The significant and positive impact of energy industry development on the efficiency level of the Chinese energy companies can be explained by the fact that a higher developed energy industry will give the managers more opportunity to invest money for their research and development activities, the resultant advanced technology will lead to a reduction in costs and further increase the efficiency level. Finally, the macroeconomic environment, as reflected by the corruption perception index and inflation, significantly and negatively influences the efficiency level of the Chinese energy companies, indicating that higher inflation decreases the efficiency and the efficiency level will be increased if there would be a decline in the degree of corruption in China. These findings are in accordance with our hypotheses. The density plot of the overall index in given in Fig. 2. This is the solely contextual variable used in the RSBM previously described, and its multimodal characteristic may help in explaining different efficiency levels in the Chinese energy industry.

Table 4. Business-environment related variables (weights and relationship signs).

Variable	AHP Weights	TOPSIS signs
Banking Sector Development	0.107707427	+
Stock Market Development	0.107707427	+
Inflation	0.155935794	-
Corruption Perception Index	0.152982156	-
Banking Sector Competition	0.157453551	+
Energy Industry Concentration	0.159106822	-
Energy Industry Development	0.159106822	+

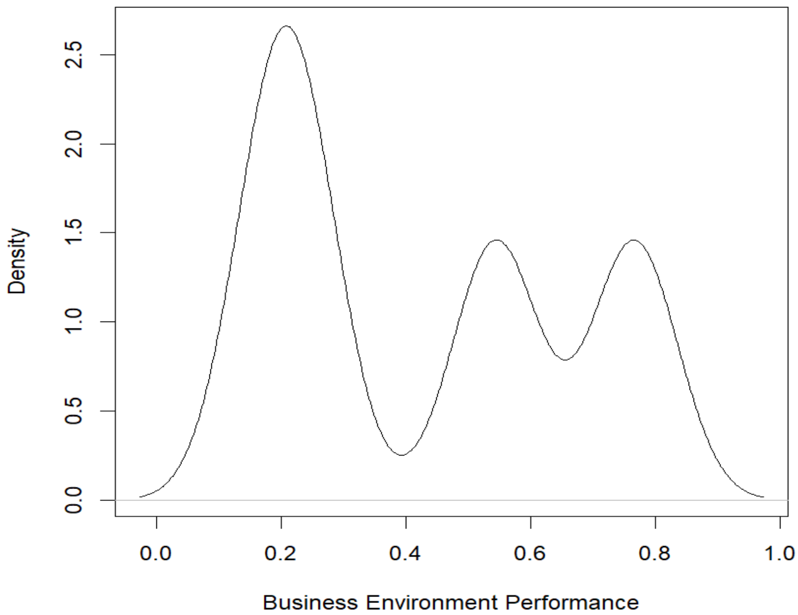

Fig. 2. TOPSIS scores for business environment performance.

Results for the RBSFA computational model are depicted in Fig. 3. Although efficiency levels appear to be high (bottom-right), their 95% confidence intervals suggest a strong dispersion, ranging from 0.70 to almost 1. The differential optimization procedure yielded higher weights for the Half-Normal distributional assumption for the inefficiency term u (regardless of the distributional assumption for the random term v, whether Normal or t-Student) to the detriment of the Gamma and Exponential distributional assumptions (top-left). Although the variance for efficiency is substantially larger than the variance for random errors only for the Half-Normal assumption (top-right), the Normal error assumption for v yielded a higher imbalance between the total variance (sigma square) and the proportion of it explained by the inefficiency term u. In other words, the t error assumption for v was yielding a comparative lower total variance thus assigning the most part of it to the inefficiency term u. This being the case, Fig. 4 corroborates this fact by presenting the results for the DIC criterion for each individual model and its RBSFA computational combination. The RBSFA presented a fitting performance in between the Normal and t-Student v error assumptions when putting the three assumptions for inefficiency u into perspective.

As regards 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 better results as expected, due to the effect of pooling variances and covariances in the optimization model. In fact, although the efficiency results for the six individual models are strongly and positively correlated (cf. Fig. 6), readers should observe that, in the extreme correlated case, obtained for the Exponential and Gamma assumptions, optimal weights were assigned to almost zero.

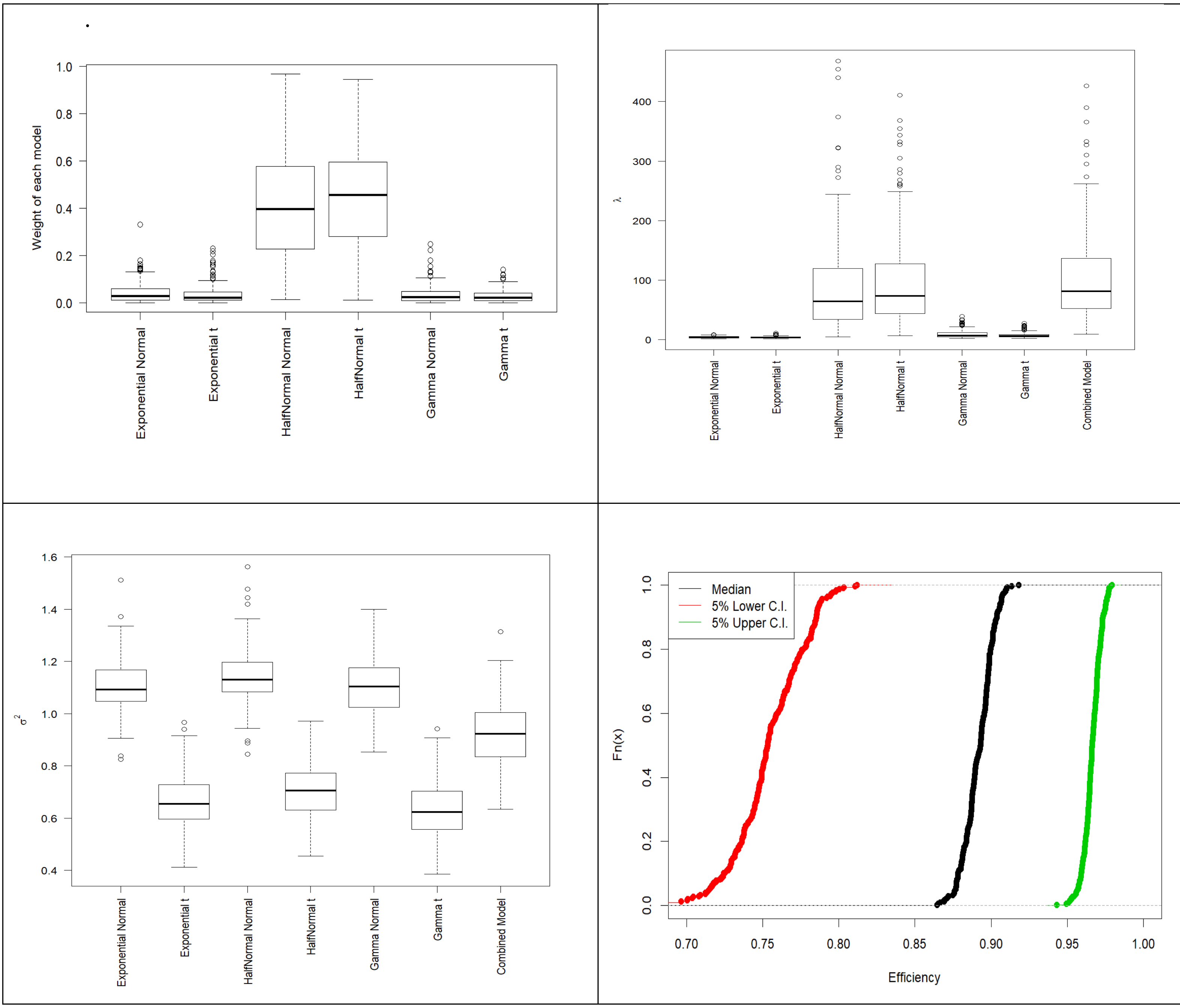

Fig. 3. RBSFA (combined model) results: differential optimization weights (top-left), lambda (top-right), sigma square (bottom-left), and the inverse cumulative efficiency scores and their confidence intervals (bottom-right).

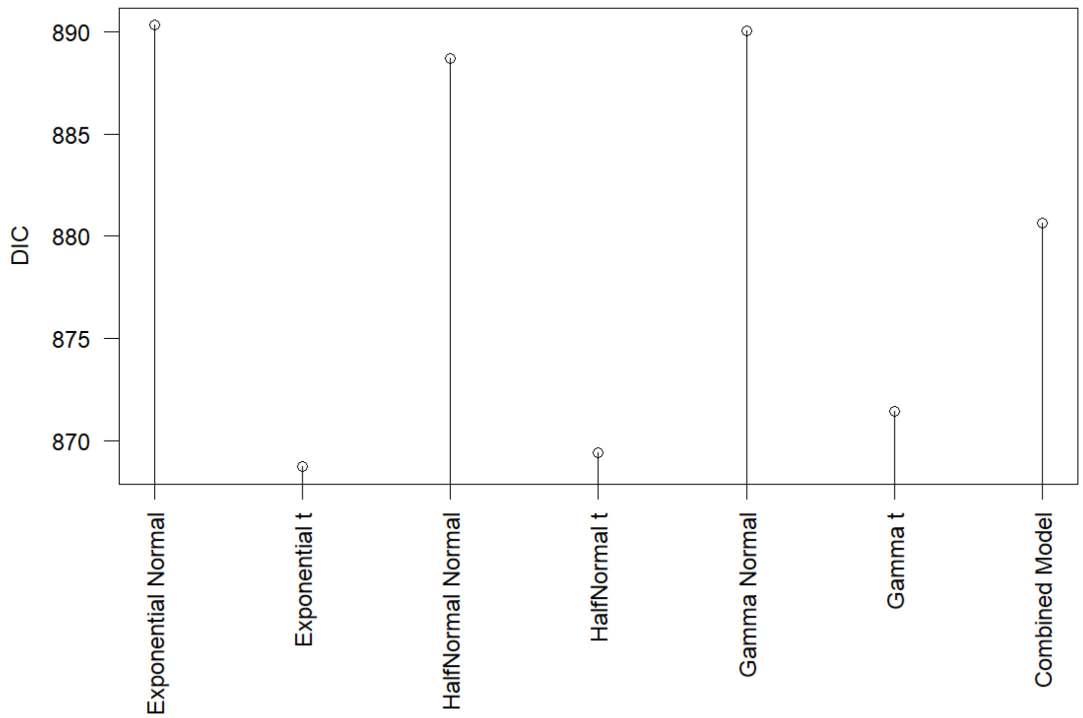

Fig. 4. Results for DIC.

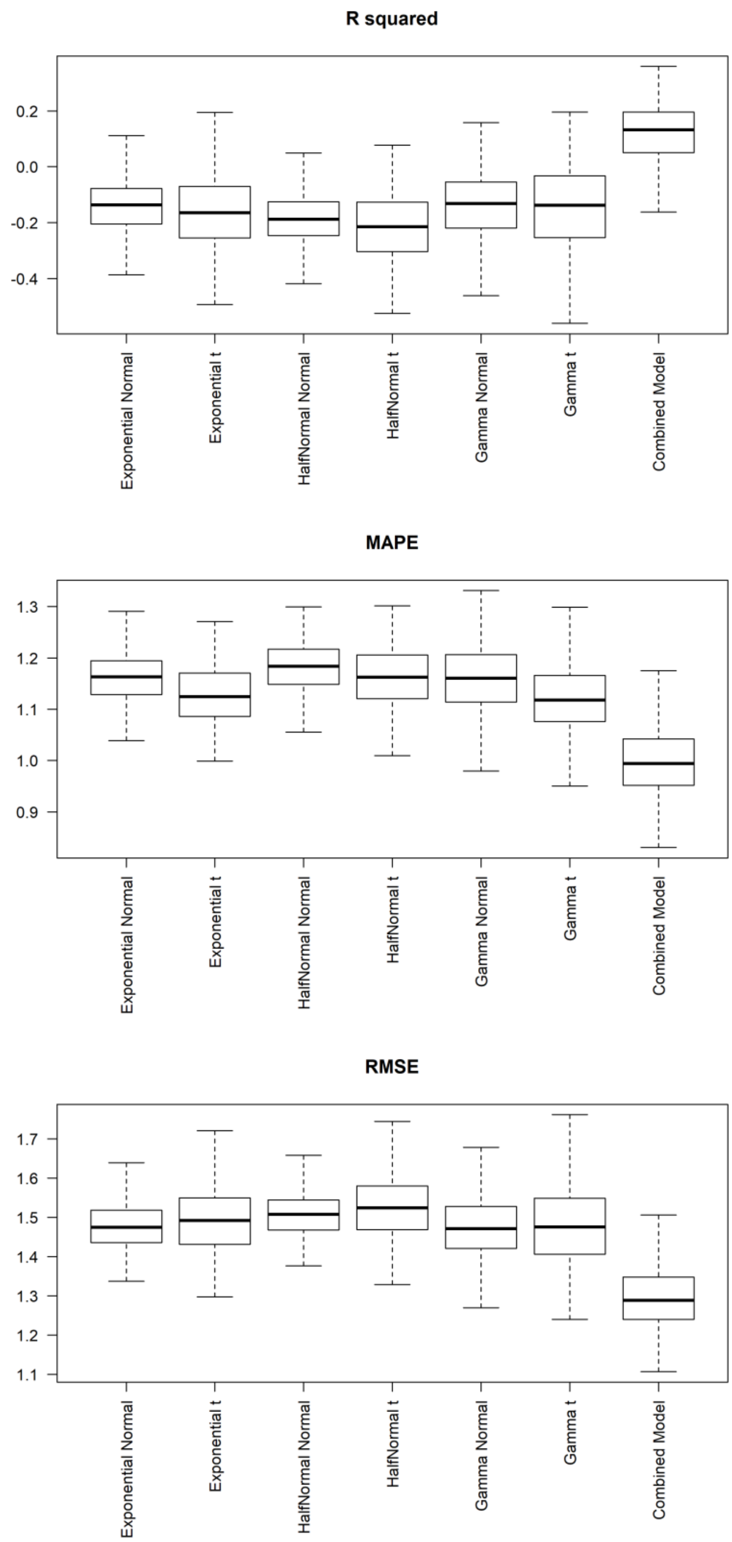

Fig. 5. Other metrics of explanatory power.

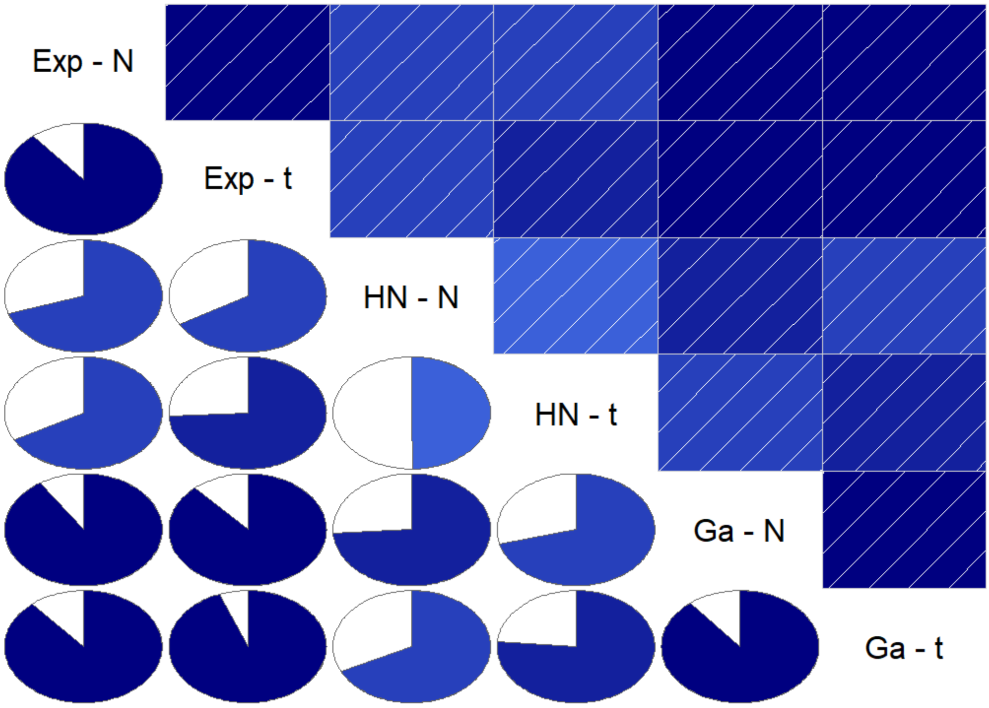

Fig. 6. Efficiency correlogram for the six distributional assumptions.

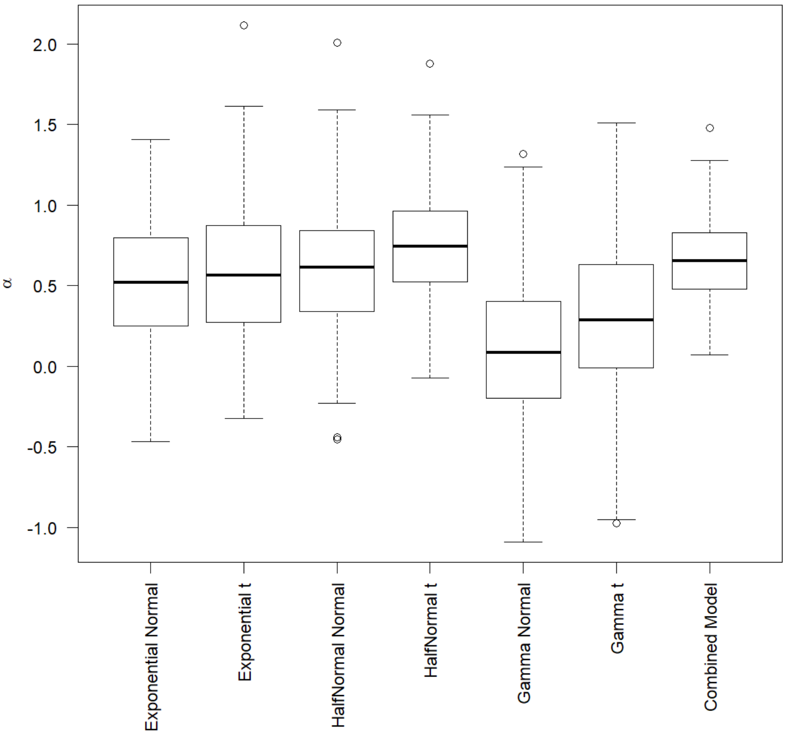

Fig. 7. Boxplots for α

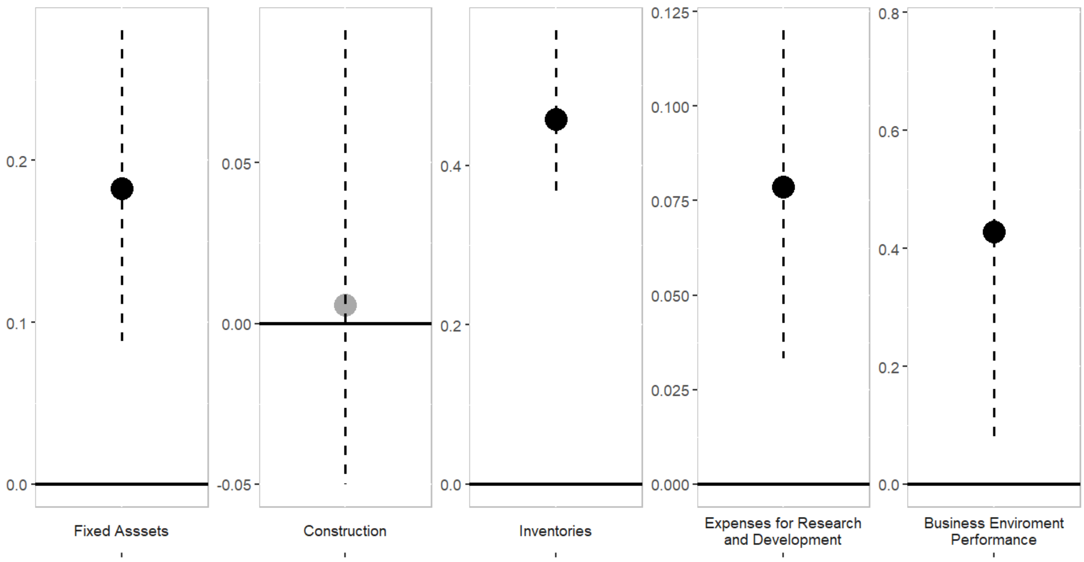

Fig. 8. Boxplots for the coefficients of the inputs and business environment performance.

Results for the RBSFA computational model are displayed in Figs. 7 and 8. The linear coefficient presented significant results only for the combined model. 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. 7). As regards the coefficients for the inputs, significant and positive results were found for all variables with the exception of the construction of new power facilities (cf. Fig. 8). Results suggest, as regards the Chinese energy industry, that efficiency levels increase when inventories, fixed assets, and R&D expenses - respectively in this order – are increased. Our results significantly contribute to the literature in estimating energy efficiency in general and significantly fill in the gap of the empirical studies of energy efficiency in China in particular (Lin and Du, 2013; Zeng et al., 2018; Wu et al., 2019) by clearly identifying the relationship between inputs and efficiency level. The generation of these results is very important due to the fact that it can be further considered and used by the Chinese energy companies to further improve their efficiency level in the future. Higher volumes of inventories will reduce borrowing costs and further lead to an improvement in efficiency. Fixed assets play an important role in providing opportunities for the employees to make and expand the production in the production process. This is supposed to be helpful in achieving the economies and scale and economies of scope, the resultant reduction in costs will further lead to an improvement in efficiency. Finally, R&D expenses are essential for companies' technology enhancement and improvement. Higher level of technology will significantly reduce the level of costs, and the cost reduction is supposed to be significantly more than the investment in R&D, which will further increase the efficiency level of the Chinese energy companies.

Finally, as regards the business environment performance (cf. Fig. 8), it also presents a positive and significant impact on the efficiency levels of Chinese energy industry. Our analysis regarding the impacts of business environment on the efficiency level of the Chinese energy companies significantly contributes to the empirical studies investigating similar issues (Costa-Campi et al., 2015; Nadeem et al., 2017; Lv et al., 2017) by firstly linking the efficiency level with the financial system in China. In general, our results show that the business environment is significantly and positively related to the efficiency level of the Chinese energy companies with the exceptions of energy industry concentration, corruption as well as inflation.

Our results provide very interesting and important implications to the Chinese energy companies in terms of improvement in the efficiency level in the future: 1) it is recommended that Chinese energy companies can further optimize the resource allocation in the production process by further increasing the volumes of inventories, fixed asset and expenses related to their R&D activities; 2) the financial system in China should be further reformed and relevant policies should be formulated to further develop the banking and stock market and also increase the competitive condition in the banking industry; 3) policies should be established to further develop the energy industry, while rules should be implemented to facilitate the equal development between different companies in the industry; 4) the Chinese government should manage the economy very well with the perspective of lower level of inflation and also further reducing the level of corruption.

5. Conclusions

In this study we propose a novel RBSFA computational model to determine the stochastic efficiency of the Chinese energy industry. We proposed a Bayesian estimator for a stochastic frontier model with different inefficient distributions.

Our study significantly contributes to the empirical literature on operational research in efficiency analysis, as well as empirical research in the determinants of energy efficiency in the following ways: 1) we innovatively propose a robust Bayesian stochastic frontier analysis, compared to the traditional Bayesian stochastic frontier analysis, we generate more robust results and produce a new method to be used in the future in the area of efficiency analysis; 2) AHP-TOPSIS analysis is used to investigate the influence of business environment on the efficiency level of the Chinese energy companies. This is supposed to be the first piece of research using this integrated method in the Chinese energy industry; 3) our study is the pioneer to link the financial system with the efficiency in the energy industry.

Future studies can be undertaken in the following areas to complement the current research: 1) the energy demand and its impact on energy efficiency can be further investigated. China's evolving approach to international energy collaboration, from securing supplies towards a more comprehensive collaboration, will have an increasing impact on its domestic energy demand. The transfer of China's industrial capacity and labour to Belt and Road Initiative countries and the establishment of new international supply chains and infrastructure will affect absolute energy consumption levels. Additionally, industrializing China's inland and border regions and the enhanced development of its low-carbon energy industry can shift its geographical patterns of energy demand and the structure of its energy mix; 2) future investigations can focus on the impact of large industries on energy efficiency because they are very significant for the energy demand as well as the willingness of Investors to enter the energy market. More specifically, *T*he manufacturing, mining, energy, and agricultural industries are China's largest industries. Manufacturing is by far the biggest industry in China, accounting for 46.8% of the country's GDP; 3). Future studies can divide China's energy industry into two subsections: fossil fuel energy and non-fossil fuel energy, and see what are the efficiency conditions between them and whether they would have similar efficiency drivers; 4) future research can use the robust Bayesian stochastic frontier analysis to estimate the efficiency level in the energy sector or other sectors of the economy and data can be updated to the most recent period to see whether our results hold; 5) Finally, data can be collected from other Asian countries and the results between different countries compared.

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