Investment efficiency of the new energy industry in China[1]

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Abstract

This paper evaluates the investment efficiency of the new energy industry in China and investigates factors that explain variations in investment efficiency across firms and over time. Applying a four-stage semi-parametric DEA analysis framework to a sample of listed new energy firms over the period 2012-2015, we find that the overall investment efficiency of the new energy industry is relatively low, with an average total technical efficiency of 44%, pure technical efficiency of 48%, and scale efficiency of 90%. We also find that new energy firms' investment efficiency is affected by both macroeconomic conditions and firm-specific characteristics. Our results are robust and have significant implications for policy makers and firm managers.

Keywords: New energy industry; semi-parametric DEA analysis; investment efficiency; China

JEL Classification: G24; G28; Q41; Q43; Q48

1. Introduction

China is the world's largest energy consumer, consuming one fifth of global energy. Thus, it will play a pivotal role in the global transition to a new era of sustainable energy. Because China relies on energy imports for more than 60% of its total energy supply, there have been growing concerns about the country's energy security and about the environmental impact of its reliance on fossil fuels. In response to these concerns, China has accelerated its development and utilization of new renewable energy sources, such as solar, wind, nuclear and biomass. The market has been expanding – with significant economic benefits – and China has become a global leader in renewable energy. The country has the world's largest capacity of both wind and hydroelectric power, owns the vast majority of solar heating and biogas facilities in the world, and has successfully developed a solar photovoltaic industry that now operates globally. In 2013, newly installed renewable energy capacity in China exceeded that of Europe and the rest of the Asia Pacific region (IRENA, 2014). China's renewable energy sector continues to grow rapidly: a new record for global investment in renewable energy was set in 2015, when the funds committed to renewable energy (excluding large hydro-electric projects) increased by 5% to USD285.9 billion. According to Bloomberg (2016), investments in renewable energy declined by 8% in developed economies but increased by 19% in developing countries. The increased investment by developing countries is largely driven by China, where investment increased by 17% to USD102.9 billion, accounting for 36% of the world's total investment in renewable energy. Against the background of this flourishing and promising development, maintaining this momentum and advancing future development is of strategic importance for policy makers and also has significant implications for new energy firms. Improving investment efficiency is the key to the success of a globally viable new energy industry in the long run; that challenge is the focus of this paper.

Domestic and international scholars have examined investment efficiency in different industries using different approaches. A common approach is the use of a multiple regression model. Richardson (2006) divides net investment into two parts. The first part is expected investment, which is determined by the expected growth of the firm as influenced by corporate structure, financial constraints and other factors. The second part is unexpected investment, that is, the difference between actual investments and ideal investments, i.e., investment model residuals, which are used to measure investment efficiency. Employing the same method, Qinglu et al. (2012) investigate the investment efficiency of private enterprises from the perspective of monetary policy. Zhao (2013) studies investment efficiency from the perspective of corporations' social capital and investment opportunities using a multivariate regression method, while Huihui et al. (2012) focus on environmental uncertainty and the investment efficiency of state-owned equity while taking into account financing constraints. The conceptualization of expected and unexpected investments is a commonly employed approach in the literature on investment efficiency. This approach relies on a multiple regression model to estimate expected (optimal) investment levels and treats under/over investment as inefficient investment. We employ an alternative approach – a semi-parametric four-stage DEA analysis – which we have embedded with frequently employed methods in efficiency studies, namely DEA and SFA. This approach enables us to obtain more accurate measures of economic efficiency and to perform a more fruitful analysis. See section 2 for a detailed discussion.

Data envelopment analysis (DEA) is a widely used method in efficiency studies, and scholars have applied it to various aspects of the new energy industry, such as technology, research and development (R&D), scale, and financing. For instance, Wang et al. (2014 b) examine energy efficiency and energy saving potential in China. Comparing equity financing efficiency among China's seven strategic emerging industries, Zhai (2012) finds that both the market and investors are attentive to the low-carbon clean technology sector, which leads to increased financial support for these industries. DEA has also been widely applied to other topics, such as environmental challenges and efficient allocation (Kim and Kim, 2012; Voltes-Dorta, et al., 2013; Sueyoshi and Goto, 2014 a; Ederer, 2015; Houshyar et al., 2012; Huang et al., 2014; Li and Lin, 2015; Mousavi-Avval et al., 2011 a; Valadkhani, et al., 2016; Vlontzos et al., 2014; Wang et al., 2014a; Sueyoshi and Goto, 2014 b; Yang and Pollitt, 2009; Mousavi-Avval et al., 2011b; Song et al., 2013; Nassiri and Singh, 2009).

More recently, researchers have employed DEA to analyze investment efficiency in different industries/sectors, such as the information technology industry (Shafer and Byrd, 2000), investment funds (Guo et al., 2012), R&D investment (Zhong et al., 2011), and the culture industry (Zeng et al., 2016). The traditional DEA model always treats the production system as a "black box," without considering any intermediate processes. Ignoring intermediate outputs yields biased efficiency scores, which make subsequent analyses (i.e., sources of inefficiency) unreliable. To address the issue, Färe and Grosskopf (1996) propose a network DEA in a two-stage setting that decomposes the manufacturing process and treats the output of a previous stage as an input in the second stage. Halkos et al. (2016) apply this method to create a composite sustainability efficiency index based on a panel of 20 countries for the period 1990–2011, and they decompose the index into production efficiency and eco-efficiency indicators. Their results suggest the existence of inequalities among countries between the two stages and that a country's higher production efficiency does not necessarily ensure high eco-efficiency performance, highlighting the importance of taking intermediate outputs into account.

However, the production process is also influenced by environmental factors and pure random noise. While some two-stage DEA models attempt to incorporate environmental factors, virtually all such models are deterministic and ignore the effect of statistical noise. Fried et al. (2002) propose a semi-parametric three-stage DEA approach with particular attention to input and output slacks. In the first stage, DEA is used to obtain initial efficiency measures and slacks. In the second stage, stochastic frontier analysis (SFA) is used to decompose slacks into three parts attributable to environmental factors, managerial inefficiencies, and statistical noise, respectively. In the third stage, input and output are adjusted by eliminating the impacts of environmental factors and statistical noise, and DEA is used to re-calculate efficiency based on adjusted input and output variables. The semi-parametric nature of this three-stage DEA approach has gained popularity and has been applied in many areas. Li and Lin (2016) adopt this approach to eliminate the effects of environmental influences and statistical noise on output slacks when measuring the effects of government policy on the green productivity growth of China's manufacturing sector during the 11th Five-Year Period (2006–2010). Huang et al. (2012) measure the technical efficiency of the high-tech industry in Beijing over the period 1995–2009 using a combined three-stage DEA and SFA model. Employing the same model, Bai and Song (2008) evaluate the technical efficiency of the thermal power industry in 30 Chinese provinces in 2004 and find that the efficiency level of thermal power in many provinces is influenced by environmental factors, such as economic development and resource endowment. Wang and Zhang (2009) conduct an analysis of the efficiency of the cultural industry in 31 provinces in China.

Perhaps due to rising concerns over climate change and energy security, the Chinese government has invested considerable resources in promoting the development of the new energy industry. This gives rise to a number of research questions: how efficient are these investments? What factors explain the differences in investment efficiency? These issues are important for policy but are under-researched in the literature, and this study aims to fill this gap. The new energy industry is a complex industry involving both innovations and government policies, and firm performance is likely to be influenced by a variety of factors. We employ a three-stage DEA approach (Fried et al., 2002) to derive the investment efficiency of listed new energy firms in China over the period 2011-2015 and examine the performance impact of environmental factors. Then, we add a fourth stage of analysis to model investment efficiency scores against a set of firm-specific variables. As such, this extended semi-parametric four-stage DEA framework allows us to (1) evaluate firms' investment efficiencies more accurately by eliminating the effect of environmental factors and random noise; (2) identify macro-level factors that characterize the environment in which new energy firms operate; and (3) investigate micro-level firm-specific factors that explain differences in investment efficiency across firms and over time.

The remainder of this paper is organized as follows. The four-stage DEA approach is elaborated in Section 2. Section 3 defines the variables and describes the data. Section 4 discusses the empirical results, and section 5 concludes.

2. Research methodology: The four-stage DEA model

We implement a four-stage analysis framework by extending Fried et al.'s (2002) three-stage DEA model. In the first stage, the DEA model is applied to outputs and inputs to obtain initial performance measures of each decision-making unit (DMU). In the second stage, the focus is on the input and output slacks of the DMUs instead of on conventional radial efficiency scores. Using stochastic frontier analysis (SFA), each slack variable is decomposed into three parts that are attributable to environmental factors, managerial inefficiency, and statistical noise. In the third stage, inputs and outputs are adjusted by removing the effects of environmental factors and the statistical noise uncovered in the second stage. Based on adjusted inputs and outputs, the DEA model is used to re-evaluate producer performance and obtain more accurate efficiency measures of DMUs. In the fourth stage, estimated efficiency scores from the third stage are regressed against a set of firm level variables to examine how the investment efficiency of DMUs varies with firm-specific characteristics.

2.1. Stage 1: The CCR and BCC DEA models

The DEA model can be simplified as in Figure 1.

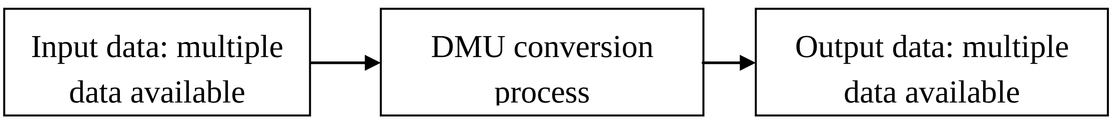

Figure 1. DEA computing model

The basic DEA model is the CCR model (Charnes et al., 1978), which addresses a technology set comprising *n* observed DMUs, where {DMU$_{j:}$ j=1, 2, …, n}. *m* indicates types of input indices x_{ij} (i =1, 2, …,m) and *s* types of output indices y_{rj} (r = 1, 2, …, s). Input indices reflect input variables, whereas output indices reflect achievement through the production process.

This model indicates that increasing the proportion of inputs can expand the scale of outputs. We can obtain the following linear programming model with an efficient frontier of constant returns to scale in equation (1) (Charnes et al., 1978).

$$\left.\begin{array}{l} \sum_{j=1}^{n} x_{ij}\lambda_j \le x_i, i=1,2, \ldots, \text{m} \\ \sum_{j=1}^{n} y_{rj}\lambda_j \ge y_r, r=1,2, \ldots, \text{s} \end{array}\right\} \qquad (1)$$

where *m* and *s* represent the number of input indices and the number of output indices.

We employ the BCC model developed by Banker et al. (1984) to measure efficiency. This model is based on the original CCR model but assumes variable returns to scale. Adding the convexity limit $\sum_{j=1}^{n}\lambda_j = 1$ to the CCR model (constant returns to scale), it evolves into the BCC model (variable returns to scale). The output-oriented variable returns to scale of the DEA model are shown in equation (2):

$$\max \phi,$$

subject to,

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{ijo} \quad i\text{=1,2,…, m;}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{rjo} \quad r\text{=1,2,…,s;}$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j \geq 0 \quad j=1,2,\ldots,n. \tag{2}$$

where $\lambda_1, \lambda_2, \ldots, \lambda_n$ and Φ are decision variables, x_{ijo} and y_{rjo} represent the ith input and the rth output of the jth DMU, respectively. s_i^- is input slacks and s_r^+ output slacks.

Input slacks represent further reduction in input while achieving the same level of output, and likewise, output slacks represent a further increase in output without increasing input. If φ*=1 and $s_i^{-*} = s_r^{+*} = 0$, the DMU is on the frontier, and current output levels cannot be expanded proportionally; if φ*<1, the DMU is dominated by the frontier, and we can obtain an efficiency score for DMU$_j$. The optimal solutions to the envelopment problem in (2) provide initial performance evaluations for each producer, including the optimal values of $\varphi \leq 1$ and the nonnegative input slacks s_i^- and output slacks s_r^+, as in equation (3):

$$s_i^- = x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij} \qquad i=1,2,\ldots, m;$$

$$s_r^+ = \sum_{j=1}^{n} \lambda_f y_{rj} - \phi^* y_{ro} \qquad r=1,2,\ldots,s; \tag{3}$$

We can obtain pure technical efficiency (PTE) from the BCC model and total technical efficiency (TTE) from the CCR model, which allow us to calculate the scale efficiency (SE) as SE=TTE/PTE. In the BCC model, when φ*=1 and $s_i^- = s_r^+$=0, the DMU is DEA-available, and the DMU$_{j0}$ has the highest technology efficiency. If φ*＜1, actual output can increase in proportion to φ*; $s_i^- \neq 0$ indicates that inputs are excessively high at the same output level, and $s_r^+ \neq 0$ correspondingly indicates that outputs are excessively low at the same input level. We should also consider the operating scale of firms while focusing on the performance evaluation indices. If $\sum_{j=1}^{n} \lambda_j > 1$, firms should scale back production; if $\sum_{j=1}^{n} \lambda_j < 1$, they should increase production; and if $\sum_{j=1}^{n} \lambda_j = 1$, then the scale profits are constant (Banker et al., 1984; Quanling, 1998).

2.2. Stage 2: Stochastic frontier analysis (SFA) to decompose input and output slacks

In this stage, the parametric SFA approach is employed to model the total slacks of each input and output and to identify the impact of environmental factors, statistical noise and managerial inefficiency. SFA was independently developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). SFA specifies a function form, and the composite error term consists of random error (v_i) and inefficiency (u_i), which are assumed to be distributed independently of each other and of z_i. The theoretical idea underlying SFA is that no economic agent can exceed the ideal best practice "frontier," and deviations from this frontier represent individual firms' inefficiencies. The composite error term is separated into inefficiencies and the classical idiosyncratic disturbance terms, based on different distributional assumptions.

SFA has become a popular tool for efficiency analysis, and a fruitful stream of research has developed many reformulations and extensions of the original SFA models, including cross-sectional or panel data models, production or cost frontiers, time-invariant or time-varying inefficiency models, and one-step or two-step models. In this study, we specify a time-varying decay model (Battese and Coelli, 1992) to regress each input slack variable against four explanatory variables that characterize the environment in which new energy firms operate. The second-stage SFA model (one for each slack) takes a general form as in equation (4), which can be estimated using the maximum likelihood estimator.

$$s_{nit} = f^n(z_{it};\ \beta^n) + v_{nit} + u_{nit}, \qquad n = 1, \ldots, N,\ i = 1, \ldots, I \tag{4}$$

where s_{nit} is a slack variable of the n[th] input variable of the i[th] MDU at time t obtained from the first phase, and n=1, 2, 3, and 4; $f^n(z_i;\beta^n)$ are deterministic feasible slack frontiers to investigate the impact of environmental factors on slacks; the composite error is separated by assuming that the $v_{nit} \sim N(0,\ \sigma^2_{vn})$ capture statistical noise and that $u_{nit} \geq 0$ $(u_{ni} \sim N^+(\mu^n, \sigma^2_{un}))$ reflect managerial inefficiency. β^n μ^n σ^2_{un} σ^2_{un} are parameters to be estimated in each regression.

All parameters may vary across the N slack regressions, that is, the impact of environmental variables, statistical noise and managerial inefficiency may differ across different inputs. The composite error terms in equation (4) are decomposed into statistical noise and managerial inefficiencies using the approach of Jondrow et al. (1982).

2.3 Stage 3: The DEA model using adjusted inputs and outputs

Based on results from the stage 2 SFA regressions, producers' inputs are adjusted upward for those who have had advantages with respect to operating environments or simply good luck. In particular, the adjustment is constructed as in equation (5):

$$x^A_{ni} = x_{ni} + [\max_i\{z_i\ \hat{\beta}^n\} - z_i\ \hat{\beta}^n] + [\max_i\{\hat{v}_{ni}\} - \hat{v}_{ni}],\ n=1, 2, \ldots, N;\ i=1, 2, \ldots, I \tag{5}$$

where x_{ni} and x^A_{ni} are observed and adjusted input values.

The first part in parentheses on the right-hand side puts all DMUs in the same operating environment (the least favorable environment observed in the sample), and the second bracket puts all DMUs in the same unluckiest situation. These adjustments vary across producers and across inputs.

Applying the stage 1 DEA model in equation (2) to adjusted inputs (x_{ni}^{A}), we obtain improved DEA-based measures of investment efficiency that have eliminated the effects of the operating environment and statistical noise.

2.4. Stage 4: Firm-level determinants of investment efficiency

In stage 2, we considered the impact of environmental factors on firms' investment efficiency at the industrial level via their influences on input slacks. In stage 4, our main goal is to identify firm-specific factors that affect investment efficiency. The findings from stage 2 are more relevant for policy makers, while the findings from this stage are of particular importance for firm managers seeking to improve firm investment efficiency. As the efficiency measure is a bounded variable between 0 and 1, the Tobit model is commonly applied (Çelen, 2013; McDonald, 2009; Merkert and Hensher, 2011; Scheraga, 2004; Selim and Bursalioglu, 2013). However, Simar and Wilson (2007) provide evidence suggesting that results from the Tobit regression are catastrophic, while truncated regression estimates the model more accurately. The truncated regression model is shown in equation (6).

$$Efficiency_{jt} = \beta_0 + \beta_1 X_{jt} + \varepsilon_{jt} \qquad (6)$$

Where X_{jt} is a set of firm-specific variables, and β_s and ε are parameters to be estimated.

3. Variable definition and data

3.1 Input and output variables for the DEA model in stages 1 and 3

During empirical implementation, defining inputs and outputs is the key to evaluating firms' investment efficiency. Drawing on the literature and taking into account the nature of the new energy industry, we define a single output as total gross income, considering the primary objective of listed firms is to maximize shareholders' value. We define four inputs – fixed assets, assets under construction, inventories, and expenses for research and development (R&D) – covering both capital and non-capital investment activities. The DEA method requires isotonicity between input-output variables, that is, output does not decrease with increased input. We perform a correlation analysis for the input-output using the "Kendall tau" rank method. The analysis indicates a positive correlation between our chosen input-output variables.

3.2 Environmental variables for the SFA analysis in stage 2

Simar and Wilson (2007) indicate that environmental variables should satisfy separate hypotheses. Environmental factors can influence investment efficiency in the new energy industry, while they are beyond the subjective control of individual firms. Macroeconomic conditions affect all industries, and the new energy industry is no exception. We employ the regional GDP growth rate – *GDPR* – to proxy macroeconomic conditions. A more open macroeconomic environment is likely to provide exposure to more advanced technology, more management experience and a larger market, which may accelerate the development of the new energy industry. Such openness promotes external competition for China's new energy industry and simultaneously strengthens more efficient resource allocation. We employ a widely used openness measure and define *Open* as the ratio of total imports and exports to GDP, which reflects the degree of regional participation in globalization and in opening up to the world. The demand condition is expected to have a significant impact on firms' investment efficiency. Continuous increases in power consumption stimulate the development of the new energy industry, especially under the pressure of a shortage of conventional energy sources. To capture this effect, we define *Powerg* as the growth index of energy consumption. Innovation and technology are both crucial to the new energy industry. We define *Tech* as the ratio of R&D expenditure to GDP to measure the provincial technology level and examine its impact on investment efficiency.

3.3 Firm-specific variables for analysis in stage 4

The variations in investment efficiency across firms can also be attributed to firm-specific characteristics; we focus on firms' ownership structure, profitability and capital structure. The relationship between performance and ownership has been well documented in corporate finance literature under the principal-agent framework. We explore the ownership effect from two dimensions – ownership concentration and the nature of controlling owners. *Ownership concentration* is defined as the sum of the shareholdings of the 10 largest shareholders. Agency theory predicts a positive performance effect of ownership concentration based on the monitoring effect. Firms with a concentrated ownership structure and controlling shareholders have strong incentives to monitor management, and they possess real power to discipline underperforming managers and/or influence management decisions (Shleifer and Vishny, 1986). This helps to mitigate agency problems and improve performance (Jensen and Meckling, 1976). On the other hand, ownership concentration may have a negative performance effect due to the exploration effect and increased horizontal agency costs among shareholders. The ability of large shareholders to extract private benefits from minority shareholders (La Porta et al., 1999) induces conflicts of interest between controlling shareholders and minority shareholders and increases agency costs (Bebchuk and Weisbach, 2010; Young et al., 2008). Hence, the overall impact of ownership concentration is an empirical issue. The nature of firms' controlling owners also has a significant impact on firm performance. We classify firms by owner type into three mutually exclusive and collectively exhaustive groups: state-owned firms, domestic privately owned firms, and foreign-owned firms, proxied by three dummy variables – *State*, *Private*, and *Foreign*, respectively. As agency problems are more profound under state ownership, we expect state-owned firms to underperform private firms and foreign firms. Basic earnings per share – *EPS* – is used to examine the impact of firms' profitability on investment efficiency, as we expect more profitable firms to also engage in more efficient investment activities. *LT Debt*, defined as the ratio of firms' long-term debt to total asset ratio, is employed to investigate how new energy firms' investment efficiency varies with their financing structure. Literature is inconclusive regarding the impact of firm leverage on performance. The agency cost theory (Jensen and Meckling, 1976) indicates that managers have incentives to take excessive risks and that high debt ratios may act as a disciplinary device to reduce managerial cash flow waste (Jensen, 1986) and improve performance. However, facing the risk of default or a "debt overhang" problem, firms may underinvest (Myers, 1977), leading to low performance.

3.4 Sample construction, data sources and descriptive statistics

We collect data from multiple sources and cross-check to reduce measurement errors. Environmental data are collected from the China Statistical Yearbook (2011-2015) published by the National Bureau of Statistics of China. Firm level data are collected from the CSMAR database, which provides comprehensive data for China's listed firms from 1999 onward. Our sample consists of listed firms that are included in the computation of the CNI New Energy Index or the CSI CN Mainland New Energy Index. Our sample is a balanced dataset over a five-year period from 2011 to 2015, consisting of 74 listed firms from 16 provinces with 370 observations. The 16 provinces include Anhui, Beijing, Chongqing, Fujian, Guangdong, Hebei, Henan, Hubei, Jiangsu, Jiangxi, Liaoning, Shandong, Shanghai, Sichuan, Xinjiang, and Zhejiang. All variables are deflated by GDP deflator to the 2011 constant price level. After calculating growth variables (i.e., the growth index of the power consumption rate), Table 1 provides summary statistics for the sample over the period 2012-2015.

Table 1. Sample statistics (2012-2015)

Variables	No. Obs	Mean	Std. Dev.	Min	Max
Output and inputs					
Total income	296	910.51	4058.01	3.31	38825.84
Fixed asset	296	2879.38	5044.12	5.39	34045.70
Construction	296	836.48	1972.83	0.10	14464.81
Inventories	296	1836.18	4314.64	65.58	33963.32
R&D	296	87.15	349.86	0.00	2706.43
Environmental variables					
GDPR(GDP growth rate)	296	8.63	1.34	3.00	13.60
Open	296	60.72	40.11	8.95	143.47
Powerg (power consumption growth)	296	1.05	0.06	0.96	1.37
Technology	296	1.60	0.51	0.36	2.15
Firm-specific variables					
Ownership concentration	264	60.66	15.58	21.97	94.67

State	296	0.27	0.44	0	1
Private	296	0.66	0.47	0	1
Foreign	296	0.07	0.25	0	1
EPS	296	0.41	0.38	0.01	2.70
LT Debt	296	4.07	6.27	0.00	31.03

Note: (1) Input and output variables are in million RMB. (2) Environmental variables: openness is the total import and export as % of GDP; technological level is the R&D expenditure as % of GDP

4. Empirical analysis

4.1. First-stage DEA analysis: Investment efficiency of the new energy industry

DEA models have two broad variations – input-oriented and output-oriented models. The input-oriented DEA model aims to determine how much input use could contract and still achieve the same output level. As in any industry, investments in the new energy industry are for the long term, and the majority of investment inputs are fixed factors of production and cannot be reduced in the short term. Hence, the input-oriented DEA approach is less relevant. In contrast, the output-oriented DEA model aims to determine a firm's output potential if the given level of input is utilized efficiently. Output-oriented models are similar to the parametric stochastic production frontier approach, as they are "...very much in the spirit of neo-classical production functions defined as the maximum achievable output given input quantities" (Färe et al., 1994, p. 95). In addition, for industries with growing and promising markets, such as the new energy industry, the main concern is to maximize outputs and improve capacity utilization. As such, this paper adopts the output-oriented model.

When calculating firm efficiency, all input and output variables are mean normalized – dividing each variable by its mean to ensure minimal imbalance in the dataset. As the DEA model does not allow negative inputs and outputs, we dropped firms with negative outputs. Our final sample is a balanced sample, which ensures our results are not significantly affected by imbalances and outliers and allows us to explore the main trend in the new energy industry in China. Using STATA (user developed program), we obtain investment efficiency scores and slacks for each input and output. Table 2 reports the statistics of input and output slacks. The mean output slack is 0, and only a small number of DMUs (less than 30) have output slacks that are insufficient for reliable SFA estimation in stage 2. We conduct no further analysis of output slacks. On the other hand, the substantial magnitude of mean input slacks for each input variable points to a potential way to identify the sources of inefficiencies, which will be explored in section 4.2.

Table 2. Input and output slacks of new energy firms in China (2012-2015)

	Mean	Std. Dev.	Min	Max
Total income	0.00	0.00	0.00	0.00
Fixed asset	0.20	0.53	0.00	3.49
Construction	0.15	0.71	0.00	8.20
Inventories	0.34	1.45	0.00	11.19
R&D	0.42	1.16	0.00	8.26

Table 3 reports the stage 1 investment efficiency scores of the new energy industry in China over the period 2012-2015. The mean total technical efficiency (TTE) under constant returns to scale is 43%, and pure technical efficiency (PTE) under variable returns to scale is 47%, yielding an average scale efficiency (SE) of 92%. As we construct best practice frontiers by year, calculated efficiency scores – strictly speaking – are not comparable across years. Nevertheless, the comparison reveals whether firms, on average, are closer to or farther away from the best practice frontier each year. The results suggest that the investment efficiency level of the new energy industry is relatively stable during 2012-2014, with TTE and PTE of approximately 50% and SE of approximately 95%. In 2015, the distance between firms and the best practice frontier is enlarged, with TTE halved and

PTE reduced by more than one-third. As we have a balanced sample, it is unlikely that firms suddenly become inefficient. We argue that the reason for this change is the substantial increase in inputs in 2015. Investments in construction and R&D expenditure increased by 36% and 29%, respectively, and the corresponding figures during 2012-2014 (average) are 1.4% and 20%. This was likely motivated by supportive government policies. The State Council announced “Opinions on Further Deepening the Reform of the Electric Power System” in March 2015, and subsequently, the National Development and Reform Commission and the National Energy Bureau announced more detailed policies. Increases in inputs, especially in construction and R&D expenditure, lowered investment efficiency in 2015 while offering great potential for future improvements. We observe that the majority of our observations are either on the constant returns to scale part (159 obs) or the increasing returns to scale part (120 obs) of the frontier, and only 17 observations show diminishing returns to scale. The results are consistent with the nature of the new energy industry, which faces a growing and promising market. The evidence supports the increases in investment inputs that will lead to increases in output in the same or a higher range. In terms of ownership type, state-owned firms are the least efficient, while foreign-owned firms are the most efficient, regardless of efficiency measures. These initial results suggest a significant ownership effect, which will be explored in section 4.4.

Table 3. Investment efficiency of the new energy industry in China (2012-2015)

		Total technical efficiency		Pure technical efficiency		Scale efficiency	
		Stage 1	Stage 3	Stage 1	Stage 3	Stage 1	Stage 3
By year	2012-2015	0.43	0.44	0.47	0.48	0.92	0.90
	2012	0.48	0.48	0.50	0.51	0.95	0.95
	2013	0.48	0.52	0.51	0.54	0.96	0.97
	2014	0.51	0.51	0.55	0.55	0.94	0.94
	2015	0.24	0.23	0.31	0.30	0.83	0.75
By ownership	State	0.37	0.38	0.46	0.47	0.84	0.84
	Private	0.44	0.44	0.46	0.47	0.94	0.92
	Foreign	0.56	0.56	0.59	0.59	0.96	0.94
By region	Municipality	0.47	0.50	0.58	0.60	0.87	0.86
	Beijing	0.34	0.34	0.35	0.36	0.92	0.92
	Shanghai	0.55	0.59	0.68	0.73	0.85	0.85
	Chongqing	0.51	0.51	0.71	0.71	0.77	0.77
	Eastern	0.41	0.42	0.44	0.45	0.92	0.91
	Fujian	0.54	0.54	0.62	0.62	0.90	0.90
	Guangdong	0.41	0.42	0.45	0.45	0.90	0.89
	Hebei	0.25	0.27	0.31	0.33	0.77	0.81
	Jiangsu	0.43	0.43	0.45	0.45	0.96	0.94
	Liaoning	0.18	0.17	0.18	0.18	1.00	0.93
	Shandong	0.48	0.47	0.52	0.52	0.91	0.86
	Zhejiang	0.44	0.44	0.46	0.48	0.96	0.92
	Central	0.42	0.42	0.45	0.45	0.94	0.92
	Anhui	0.44	0.43	0.47	0.46	0.92	0.92
	Henan	0.47	0.47	0.49	0.50	0.92	0.92
	Hubei	0.48	0.47	0.51	0.51	0.95	0.88
	Jiangxi	0.22	0.23	0.23	0.24	0.97	0.96
	Western	0.50	0.47	0.52	0.50	0.94	0.89
	Sichuan	0.12	0.12	0.12	0.12	0.92	0.92
	Xinjiang	0.62	0.58	0.65	0.62	0.95	0.88
Wilcoxon sign rank test							
	Z-statistics	8.56***		-6.83***		0.46	

Note: "***" signifies the 1% significance level.

To inspect regional variations in the investment efficiencies of the new energy industry in China, we follow the government's approach and group provinces into four groups, namely municipalities and the eastern, central, and western regions. As shown in Table 3, variations in investment efficiency (both TTE and PTE) across the four regions are not substantial. The average TTE ranges from a high of 50% in the western region to a low of 41% in the eastern region, and PTE ranges from a high of 58% in the municipalities to a low of 44%, again in the eastern region. The municipalities have the lowest SE, and there is no material difference in SE across the other regions. It is worth noting that although Hebei province leads China in developing solar power, the eastern region has the lowest investment efficiency scores, which raises concerns about the sustainability of the new energy industry in the eastern region. On the other hand, investment efficiency varies significantly across provinces within each region. New energy firms in the western region have the highest volatility in TTE and PTE, while their peers in the municipalities and the central region have the lowest volatility. Xinjiang and Chongqing provinces have the highest TTE and PTE, respectively.

The new energy industry in China has promising potential for future development, but the overall investment efficiency level is still low (below 50%). Significant variations across provinces indicate great potential for inefficient firms to catch up by benchmarking best practice firms, thereby improving the investment efficiency of industry. Since China’s reform and opening up, the central government has implemented preferential development policies, such as eastern regional priority development, western development, and revitalization of the old northeast industrial base. These policies divert resources (e.g., financial and human capital) to those preferred regions and heavily promote regional economic development, leaving provinces in the central and western regions lagging behind in market operation and resource allocation (Yang and Zhu, 2007). This unbalanced regional development creates different environments, which in turn have significant implications for the investment efficiency of the new energy industry. Hence, it is important to understand how environmental factors affect firm investment efficiency and to use this knowledge to provide information to policy makers.

4.2. Second-stage SFA analysis: Impact of environmental factors on investment efficiency

In this stage, each of the input slacks are regressed against four environmental variables using the time-varying decay model (Battese and Coelli, 1992), and the results are reported in Table 4. The parameter gamma ($\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$), the share of technical inefficiency in the total square variance, is close to 1 and is significant in all regressions, indicating that the variation in technical inefficiencies is significant and that the role of random factors is relatively small. Likelihood ratio (LR) test statistics corresponding to the SFA model are significant for all input slacks, rejecting the null hypothesis of alternative ordinary least squares (OLS) regression analysis. The overall results suggest that the SFA model is appropriate to analyze the impact of environmental factors on investment efficiency.

Table 4. The impact of environmental factors on investment efficiency in the new energy industry in China

	Input slacks			
	Fixed assets	Construction	Inventories	R&D
	(1)	(2)	(3)	(4)
GDPR	-0.169**	-0.071**	-0.1031	-0.122
Open	-0.010	-0.003*	-0.018	-0.032
Powerg (power consumption growth)	-2.777***	-0.507	-5.81***	-0.731
Tech (technology level)	1.927**	0.204*	1.623	5.46*
Control for year/firm fixed effect	Y	Y	Y	Y
gamma	0.82	0.98	0.99	0.99
Log likelihood	-51.52	-139.45	-104.48	-166.26
LR one-tailed test	11.34***	59.8***	65.62***	21.6***
Number of observations	186	182	123	135
Number of firms	72	68	60	65

Note: GDPR: GDP growth rate, *** $p<0.01$, ** $p<0.05$, * $p<0.10$

The sign of the coefficients on each environmental factor are consistent for all input slack models but vary in their magnitudes and statistical significance levels. Environmental factors have significant impacts on investment efficiency in the new energy industry, and the selected environmental variables are appropriate.

The negative coefficient on *GDPR* indicates that a favorable macroeconomic environment (e.g., an increase in provincial GDP growth) reduces waste in investment inputs or decreases negative outcomes. The effect is significant for long-term investments, namely fixed assets and construction. When the regional/provincial economy grows, demands for energy increase, which provides the new energy industry with opportunities to expand. Firms tend to increase their long-term investments to boost future output potential. Moreover, during economic booms, firms are more likely to obtain financial resources to support their expansionary development strategy. Meanwhile, firms also have strong incentives to reduce inefficiencies, i.e., through better utilization of existing capacity, which brings immediate increases in output to meet market demand. The coefficient on *GDPR* is insignificant in columns (3)-(4), suggesting an insignificant impact on reducing the wastes of investment in inventories and R&D activities.

China's opening-up policy for economic development has significant implications for the new energy industry. A more open environment facilitates knowledge transfer and promotes technological progress, i.e., via imported machinery embedded with advanced technology. A growing export sector increases demand for low-cost clean energy, which in turn stimulates the development of the new energy industry. Economic opening-up intensifies competition in the industry, putting great pressure on domestic firms to improve their investment efficiency. Economic opening up also helps people develop comprehensive operational experience and managerial skills, which encourages scientific and efficient use of fixed assets and working capital, and also reduces waste. Hence, we expect openness to reduce input slacks and improve investment efficiency. However, our empirical evidence is weak. The coefficient on *Open* is negative and significant (at the 10% significance level) only in the slack model of construction. One possible reason for the insignificant impact of openness on investment efficiency is the deterioration of the export sector following the 2008 global financial crisis. The stagnant growth and debt crisis in Europe have not been resolved, the Greek sovereign debt crisis continues, and Italy has been faced with a sovereign credit downgrade. In Asia, Japan – which is China's main procurement customer – is facing yen appreciation. The slump in production and consumption, combined with a fiscal deterioration, is difficult to reverse in the short-term. The deteriorating world economic environment affects China's new energy industry with both direct shocks (e.g., the photovoltaics export market) and indirect shocks (e.g., slow growth in energy demand). This induces investment waste (i.e., under-utilization of capacity), cancelling out the potential positive impact of the industry's growth.

The coefficient on *Powerg* is negative and significant (at the 1% significance level) for slacks of fixed assets and inventories. Higher growth in power consumption (strong demand for energy) reduces input waste and improves overall investment efficiency, consistent with expectations. The impacts are economically significant, especially for inventories. Higher growth in power consumption improves the capacity utilization of fixed assets and speeds up inventory turnover, leading to higher investment efficiency. However, growth in power consumption has no significant impact on wastes in construction and R&D activities.

The level of science and technology (proxied by the ratio of R&D expenditure to GDP) has a negative impact on investment efficiency for all investment inputs, except for inventories. This can be explained by the fact that the new energy industry in China has not applied advanced technology widely and effectively. China's better-developed and well-invested sectors are solar, hydro, and wind, which are primarily dependent on natural resources and have low technical requirements. An environment characterized by a high level of technology may encourage the new energy industry to invest in technological improvements, which are not necessarily required by the industry's current stage of development. This induces redundant long-term investment in fixed assets, construction, and R&D activities and leads to investment inefficiencies. The insignificant impact on inventories supports our explanation, as it is less important for technological improvement compared with long-term investments.

4.3. Third-stage DEA analysis: Investment efficiency based on adjusted input variables

In this stage, based on results from the SFA estimation in the second stage, all input variables are adjusted by means of equation (5). This adjustment increases the input to DMUs in a suitable environment and decreases the input to poor environmental DMUs, thereby eliminating the impacts of environmental factors and random noise. Using adjusted inputs, we re-evaluate the DEA model as shown in Equation (2) to derive more accurate investment efficiency measures, and the results are reported in Table 3. We obtain a third-stage TTE of 44%, a PTE of 48%, and an SE of 90%. After accounting for the impact of environmental factors and random noise, TTE and PTE increase by 1 percentage point, while SE decreases by 2 percentage points compared with the results of the first-stage DEA analysis. In other words, TTE and PTE are underestimated when the influences of environmental factors and random noise are ignored.

We perform the Wilcoxon matched-pairs signed-ranks test to examine the equality of matched pairs of DEA efficiency scores from the first- and third-stage DEA analyses. As shown at the bottom of Table 3, the Z-statistics for TTE and PTE are above the critical value at the 1% significance level, but the Z-statistic for SE is insignificant. This evidence confirms that the differences in the outcomes of the first- and third-stage DEA analysis are significant and that environmental factors, namely macroeconomic conditions, openness, power consumption and technology level, have substantial influences on the investment efficiency of the new energy industry. These results also justify our choice of the three-stage DEA model to evaluate investment efficiency.

As shown in Table 3, the variations in TTE (0.12 -0.59) and SE (0.77-0.96) across provinces become slightly smaller, while PTE (0.12-0.73) becomes more dispersed compared with corresponding figures from the first stage DEA analysis (TTE between 0.12-0.62, SE between 0.77-1.00, and PTE between 0.12-0.71). Stage 1 and stage 3 consistently identify the same least-efficient provinces, but different best performers are identified. Sichuan province has the lowest TTE and PTE, and Chongqing has the lowest SE. The new energy industry in Shanghai is at the forefront in terms of TTE and PTE, while new energy firms in Jiangxi operate at the optimal scale but with relatively low TTE and PTE.

In the third-stage DEA analysis, 141 firms appear to operate at constant returns to scale, 142 at increasing returns to scale, and 13 at decreasing returns to scale. The corresponding figures from the first stage are 159, 120 and 17, respectively. Implications are two-fold. First, roughly half of firms in the sample operate at constant returns to scale and the other half operate at increasing returns to scale, indicating great potentials for future development of the new energy industry in China. Second, in the third stage, the number of firms operating at constant or decreasing returns to scale becomes smaller, while more firms are identified as operating at increasing returns to scale. The results indicate the importance of taking into account the environmental effects, which provide more accurate estimates of firm investment performance.

Table 5 reports the average inputs and outputs at different operational scales. Over the sample period 2012-2015, only 13 firms operate at decreasing returns scale. On average these firms' total income are 5 times that of firms operating at constant return to scale, while employing a comparable level of fixed assets (5.6 times), slightly less investment in construction (4 times), but significantly more working capital in inventory (7.3 times) and R&D investment (30 times). For these firms, working capital and investment in R&D are the main source of diseconomies of scale and improving working capital turnover and R&D efficiency can help firms move towards the optimal operating scale. Firms operating at increasing returns to scale earn total income that is less than one-third of that of firms operating at constant returns scale, while employing a similar level of all types of inputs except for much higher R&D investment (10 times). These firms have great potential to significantly increase total income without significant increases in inputs. Management attention should focus on the better utilization of existing capacity in terms of fixed assets, capital investment in construction, working capital, and improving the efficiency of R&D investment. Table 5 also shows variations in mean inputs and output over years, suggesting the dynamic nature of firms operations over time and great potential for firms to improve production efficiency. It is worth noting that firms operating at constant returns to scale consistently have a lower level of investment in R&D. In general firms operating at diseconomies of scale over-invest in R&D and improving the efficiency of R&D investment is crucial for firms operation at increasing returns to scale, while firms at decreasing returns to scale need to make efforts on avoiding waste in R&D investment.

Table 5. New energy industry in China: Mean inputs and output at different operational scales

		No. Obs	Total income	Fixed asset	Construction	Inventories	R&D
2012-2015	CRS	141	1071	2168	683	1566	13
	IRS	142	332	2734	821	1228	140
	DRS	13	5490	12228	2725	11455	397
2012	CRS	45	962	1621	725	1311	17
	IRS	24	171	2383	783	1193	139
	DRS	5	1364	8262	1523	5550	240
2013	CRS	41	1083	2532	724	1622	5
	IRS	32	337	2685	811	1135	183
	DRS	1	3985	12288	1076	19571	63
2014	CRS	31	1843	3495	987	2517	22
	IRS	41	303	2520	597	1029	143
	DRS	2	2460	6075	544	11788	45
2015	CRS	24	259	859	142	718	9
	IRS	45	440	3152	1051	1495	107
	DRS	5	11127	18644	5130	15604	761

Note: Results are from the third stage with all inputs adjusted for the effects of environmental factors.

4.4. Fourth-stage truncated regression analysis: firm-specific impact on investment efficiency

In this section, we investigate how firms' investment efficiencies vary with firm-specific characteristics. Firms' investment efficiency scores (TTE and PTE) obtained from the third stage are regressed against firms' ownership concentration, the nature of their owners, profitability, and leverage. As efficiency scores are bounded between 0 and 1, OLS will produce biased estimates. As suggested by Simar and Wilson (2007), we employ truncated regression, and the results are reported in Table 6. GDP growth is included to control for the effects of omitted time-varying factors, and it has a positive and significant impact on TTE but not on PTE. Moreover, we also control for firm and year fixed effects. In our robustness tests (not reported to save space), we use alternative definitions of relevant variables, such as profitability and ownership concentration, and the results are qualitatively consistent.

Table 6. Firm-specific impacts on investment efficiency in China's new energy industry (2012-15)

Explanatory variables	Total technical efficiency	Pure technical efficiency
Ownership concentration	0.005**	-0.003
Private	0.26**	0.180**
Foreign	0.258**	0.315***
EPS (Earnings per share)	0.466***	0.601***
LTDebt (Long-term debt ratio)	-0.018***	-0.017***
GDP	0.061*	0.004
Constant	-0.72**	0.367
sigma	0.191***	0.378***
Firm/year fixed effect	Y	Y
Observations	264	264

Note: State ownership is omitted as the default group. *** p<0.01, ** p<0.05, * p<0.10

The coefficient on ownership concentration (measured by the sum of the 10 largest shareholders' holdings) is positive for TTE, suggesting that firms with highly concentrated ownership structures are more efficient; this evidence supports the agency theory. The impact is significant on TTE but insignificant on PTE, and the magnitude is economically small.

The coefficient on *Private* is positive and significant for both TTE and PTE, that is, privately owned firms are more efficient than state-owned firms. The impact is economically stronger on TTE than on PTE. On average, private firms are more efficient than state-owned firms in terms of TTE and PTE by 26 and 18 percentage points, respectively. Foreign-owned firms only account for 7% of our sample, while evidence suggests they are significantly more efficient than state-owned firms, especially in terms of PTE. The results are consistent with the literature that generally reports underperformance associated with state ownership. Hence, we can conclude that private and foreign ownership with better corporate governance mechanisms, as expected, better resolves agency problems, and the efficiency gains are substantial in China's new energy industry.

Firms' profitability, proxied by *EPS*, is found to have a positive and significant impact on the investment efficiency of the new energy industry. An increase in firms' EPS by one standard deviation will increase TTE and PTE by 17 (0.38*0.46) and 22 (0.38*0.6) percentage points, respectively. These results are consistent with the literature. For instance, a recent study by Margaritis and Psillaki (2010) uses DEA to measure the efficiency of a sample of French manufacturing firms and finds a positive and significant effect of profitability on efficiency for all industries. Regression results show a negative and significant impact of firms' long-term debt on investment efficiency (both TTE and PTE), and evidence supports Myers' (1977) argument of "debt overhang". A decrease in firms' long-term debt to total asset ratio by one standard deviation will increase TTE and PTE by approximately 11 (6.27*0.018 or 0.017) percentage points.

5. Conclusions

This paper evaluates the investment efficiency of the new energy industry in China and investigates factors that explain variations in investment efficiency across firms and over time. Applying a four-stage semi-parametric DEA analysis framework to a balanced sample of 74 listed new energy firms over the period 2012–2015, our main findings are as follows. First, the average total technical efficiency is 44%, pure technical efficiency is 48%, and scale efficiency is 90%, after controlling for the effects of the macroeconomic environment and random noise. Second, the investment efficiency of the new energy industry in China is influenced by both national and global macroeconomic factors via their impact on input slacks. Favorable regional economic growth and rapid growth in power consumption reduces wastes in investment input and improves investment efficiency, while a higher regional technological level tends to induce blind long-term investment and lead to inefficiencies. We fail to observe the expected significant positive impact of openness on investment efficiency, perhaps due to the unfavorable economic conditions of most advanced countries after the 2008 global financial crisis and resulting declines in exports. Third, about half of sample firms operate at constant returns to scale and the other half operate at increasing returns to scale with only 13 firms operating at decreasing returns to scale. Fourth, firm-specific characteristics have significant impacts on investment efficiency. Highly concentrated firms are more efficient, while state-owned firms underperform their (domestic and foreign) private counterparts. More profitable firms tend to invest more wisely with higher efficiency, while firms with higher long-term debts are less efficient. These results are robust to different model specifications and variable definitions.

Our results have important implications for policy makers and firm mangers. The overall investment efficiency of the new energy industry is relatively low. If this industry is to become globally viable, it is important for policy makers and firms to identify sources of inefficiencies and formulate appropriate policies and strategies to improve investment efficiency. We find that investment efficiency varies significantly across firms, a variation that nevertheless offers inefficient firms the opportunity to catch up by benchmarking industry best practices. Our analysis suggests a set of firm-specific factors that have significant impacts on investment efficiency, and these factors are more likely to be under managers' control. Moreover, for firms operating at decreasing returns to scale, managers should focus on reducing the level of working capital and/or improving working capital turnover, and improving the efficiency of R&D investment. For firms operating at increasing returns to scale, in addition to improving the efficiency of R&D investment, management attention should be paid to the better utilization of existing capacity. Hence, our findings provide firm managers with useful information on how to improve efficiency by influencing firm-level characteristics, i.e., adjusting long-term debt level. Our analysis also finds that the macroeconomic environment has strong influences on investment efficiency, which points to a way for policy makers to improve investment efficiency. When formulating macroeconomic policy, the investment efficiency of the new energy industry should be taken into account.

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Conflict of interest

The authors declare that they have no conflicts of interest.

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