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Abstract: This study set out to evaluate the financing efficiency of low-carbon companies. Applying a three-stage Data Envelopment Analysis (DEA) with the data from 85 listed companies in China's low-carbon industries over the period 2011 to 2017, this study has found that the overall financing efficiency of low-carbon companies was relatively high and the pure technical efficiency was quite steady over the period. The overall financing efficiency of these low-carbon companies on average tended to change with the scale efficiency. This study has also shown that the scale efficiency was the main constraint influencing the financing efficiency of low-carbon companies in China over the period. Our results are robust and have significant implications for policy makers and corporate managers.

Keywords: China; Data Envelopment Analysis (DEA); Evaluation; Financing Efficiency; Low-carbon Industries; Public Listed Companies;

1. Introduction

Since the 1992 UN Conference on Environment and Development (UNCED) in Rio with the endorsing of the UN Framework Convention on Climate Change (UNFCCC), the global climate change and sustainable development issues have been at the forefront of policy and academic debates. The Paris Agreement, adopted in December 2015, sets out an international action plan to put the world on track to avoid dangerous climate change by limiting global warming to well below 2°C above pre-industrial levels and pursuing efforts to restrain the temperature rise to 1.5°C. In December 2018 about 200 countries reached a deal in Katowice to adopt a detailed set of rules to implement the Paris climate agreement. It is widely recognised that to tackle climate change, economic development priorities should be given to the growing of low-carbon industries across the globe. Business companies have a leading role to play in tackling climate change and transforming towards a low-carbon economy.

Thus, companies are increasingly challenged for actions on climate change (Damert and Baumgartner, 2018) and face mounting carbon constraints (Busch and Hoffmann, 2007). On the one hand, carbon regulations have been introduced in many countries, and as a result, the emission of CO_2 and other greenhouse gases (GHGs) is no longer free of charge. GHGs emission becomes an additional cost burden and eco-efficiency turns out to be more relevant for companies (Kabongo and Boiral, 2017). Companies must aim for eco-efficiency in their productive operations. This requires companies to develop their capacity to operate by using the smallest possible amount of raw materials and energy and maximising the reduction of their environmental impacts of emissions and waste production (Capece et al., 2017). On the other hand, consumer demand for low-carbon products and services is rising. Companies that can clearly demonstrate low-carbon credentials of their products and services would expect to gain significant competitive and commercial advantages.

As climate change and GHGs emission are increasingly becoming cost relevant, they are widely considered important business, financing and economic matters (Duncan, 2007; Porter and Reinhardt, 2007; Lee, 2012; Jung et al., 2018). Many low-carbon industries and projects have already demonstrated potential rewards in achieving high financial performance but have yet to reach a stage where they are treated at par with other sectors and projects because of various barriers that low-carbon industries and projects are facing. For example, a lack of appropriate financing mechanisms is a significant hurdle for low-carbon industries and projects to overcome. Numerous studies have documented that financing constitutes one of the major challenges to the deployment of low-carbon technologies (e.g., Li and Colombier, 2009; Hall et al., 2017; Polzin, 2017) and evidence shows there is a significant "financing gap" for low-carbon projects and industries (Bowen et al., 2014; Campiglio, 2016; Geddes et al., 2018). Actually, large-scale economic gain and environmental payback are possible only if sustainable financing mechanism that supports low-carbon industries and projects are devised and other obstacles (e.g., lacking of awareness and access to technology) are successfully addressed (Pinkse and Kolk, 2010; Böttcher and Müller, 2015).

Transitioning to a low-carbon economy is complex and requires significant investment over a long period by all sectors. The IPCC (2014) estimates that global investment in climate mitigation and adaption was in the range of US$343-385 billion per year in the period between 2009 and 2012. It is estimated that annual global investment in low-carbon technologies will need over US$730 billion by 2035, more than doubling the 2015 figure of US$290 billion, and will then need to have over US$1.6 trillion a year from 2030 to 2050 to meet global climate targets (Baietti et al., 2012). Such a large amount of investment requires cooperative efforts of both government agencies and private financial institutions (Geddes et al., 2018). Unfortunately, many financial institutions are unfamiliar with low-carbon companies and projects (Li and Colombier, 2009) and unwilling to fund these companies and projects (Campiglio, 2016) as little evidence is available on the financing efficiency of low-carbon sectors.

The concept of efficiency is derived from a particular interpretation of the notion of production frontier, which in its classical sense is the relationship between output, on the one hand, and the quantity of the inputs used in the production process to obtain that output on the other hand. More specifically, efficiency connotes a level of performance that portrays using the least amount of input to achieve the highest amount of output. It refers to the use of all inputs in producing any given output over a time (Halkos and Polemis, 2018). Efficiency can be classified into different sorts, including, for example technical efficiency and allocative efficiency. The technical efficiency refers to the ability to use the inputs of production effectively, by producing as much output as input usage permits, or by using as little input as output production permits. The allocative efficiency refers to the ability to combine inputs and outputs in optimal proportions in the light of prevailing prices or financial costs. Our study follows the notion of technical efficiency. A company's financing efficiency is therefore defined as the ability of a company under certain financial conditions and environments to finance the best operational performance with the use of least financial resources. Technically, it measures the use of the smallest amount of finance with an optimal proportion of various sources to achieve the best corporate performance. A company's finance comes from three broad sources: internal funds, debt and new equity (Myers and Majluf, 1984; de Jong et al., 2011).

A company's use of different sources of finance to attain financing efficiency is arguably one of its most important decisions in every business. Financing efficiency affects corporate performance and value creation, which has a significant effect on a company's competitiveness. The management of a company decide the use of financial resources with the purpose of maximising the company value. An efficient financing strategy is the one that allocates scarce financial resources to the most productive uses in the most effective way and reduces the misallocation or waste of financial resources. Financial efficiency is important for low-carbon companies as it determines the level of risk the companies face and the expense of financing the companies incur. Particularly, it is concerned with the optimal weighting of different sources of finance at the given cost of capital to achieve the company's best performance. Decisions relating to financing the highest amount of output of low-carbon companies are very crucial in determining their competitiveness. The managers are often caught in the dilemma of what the actual financing efficiency is and what the optimum combination of different sources of finance should be.

The objective of this paper is to evaluate the financing efficiency of low-carbon companies. Efficiency analysis is essential for the evaluation of a firm's performance. Data Envelopment Analysis (DEA) is one of the most successful methodologies that was designed to measure the efficiency of complex entities like companies, programmes etc. (Charnes et al., 1978). DEA was developed by Charnes, Cooper and Rhodes in 1978 to measure the performance of a decision-making unit (DMU) in multiple input and output settings. It is a popular method to evaluate the relative efficiency of a set of DMU, due to its advantages over other approaches (e.g., stochastic frontier analysis) and ease of use (Cummins et al., 2010; Apergis and Polemis, 2016; Halkos and Polemis, 2018). Particularly, DEA avoids the choice of a functional form vis-à-vis the technical, cost or revenue function and requires no distributional assumptions that often generate specification errors (Cummins et al., 2010). DEA can be used to measure efficiency by comparing each company in an industry to a "best practice" efficient frontier that is formed by the most efficient companies in the industry. A fully efficient company is measured by the efficiency score of 1.0 if it is on the frontier and a less-efficient company is measured by the efficiency score of < 1 if it is not on the frontier. However, since a DMU's efficiency could be influenced by exogenous, non-discretionary inputs, it has been widely suggested to use a three-stage DEA analysis to control for these inputs and preclude impacts from external environments and statistical noise (Fried et al., 1999; Fried et al., 2002; Zeng et al., 2016).

This study applies a three-stage DEA to evaluate the financing efficiency of low-carbon companies listed on China's stock exchanges and investigate factors that explain differences in financing efficiency across these companies and over time. Based on the data from all listed low-carbon companies in China over the period 2011 – 2017, this study has found that the overall financing efficiency of these companies was relatively high with the highest at the score of 0.967 in 2013 and the pure technical efficiency was steady at the score of 0.98 over the period. The overall financing efficiency of the low-carbon companies on average tended to change in line with the scale efficiency. This study has also shown that scale efficiency was the main constraint factor affecting the overall financing efficiency of low-carbon companies in China over the period.

This study makes two main contributions. First, using DEA with multiple input and output factors, we evaluate the financing efficiency of low-carbon companies in China, which remains largely unexplored. Our findings provide empirical evidence that help justify the financial benefits of investing in low-carbon companies and comprehend the impacts of low-carbon industries on the economic growth. Second, we analyse scale and pure technical efficiency based on DEA frontier efficiency measures to explain the financial obstacles to the development of low-carbon sectors. We find the scale efficiency was the main constraint factor influencing the financing efficiency of low-carbon companies in China. To the best of our knowledge, few analyses have been performed so far to reveal the financing efficiency of low-carbon companies. An exception is a recent study by Lyu and Shi (2018) of investigating the renewable energy industry financing efficiency. However, their study is restricted to the renewable energy industry and mainly based on external financing sources (e.g., R&D investment, stock market, venture capital and private investment, and project financing). No consideration was given to a company's capital structure and internal financing. Our study takes into account both internal and external financial resources (including paid-in capital, capital reserve, current liabilities, non-current liabilities, equity share), which makes our results more robust and reliable within complex dynamic market conditions.

The remainder of this paper is organised as follow. In the next section we review the literature and justify the significance of our study. Our methodology and data are given in Section 3. Section 4 presents the results. The final section concludes this study.

2. Literature Review

A growing number of studies have presented theoretical arguments and empirical evidence concerning the role of businesses in transferring toward a low-carbon economy and tackling climate change (e.g., McKibbin and Wilcoxen, 2002; Lee and Klassen, 2015; Czerny and Letmathe, 2017). From a legitimacy perspective, it is essential for businesses to make positive steps to respond to climate change as climate change is a major concern of various stakeholders including governments, the public, and financial markets. For example, under the UNFCCC, governmental obligations to meet emission reduction targets have become an objective of a national development plan. The public are beginning to consider low-carbon and energy-efficient products as part of their consumption decisions (Shewmake et al., 2015; Ricci et al., 2018). Meanwhile, financial markets are mounting their pressure on companies to disclose their carbon emissions via several initiatives including the Carbon Disclosure Project. Overall, the literature has largely supported the tender that business efforts to proactively incorporate climate change into corporate strategies are of interest to key stakeholders and the public at large (Weinhofer and Busch, 2012; Cadez et al., 2018).

To address the challenges that climate change and severe deficiency of resources have posed to all kinds of human organisations, the concepts of sustainable economy and carbon finance have emerged (Winn et al., 2011). Carbon finance explores financial implications of living in a carbon-constrained world where emissions of carbon dioxide and other GHGs carry a price. The financing support of low-carbon industries and projects is seen as indispensable to solve or at least abate an environmental and energy crisis (Gross and Foxon, 2003; Campiglio, 2016). It is widely acknowledged that despite the fact that policy intervention to support low-carbon industries is fully justified because of creating a low-carbon economy, the risk to finance low-carbon industries and projects is likely to be higher (Bolton et al., 2016).

The development of low-carbon industries and the increase of their efficiency are important to a country's economic growth and sustainability (Campiglio, 2016; Lee et al., 2017; Hu et al., 2019). Access to finance is critical for the development of low-carbon industries. An understanding of the determinants of efficiency of low-carbon industries would be crucial for the design of a country's development strategies and economic policies. In light of this, it becomes important to study different dimensions of efficiency of low-carbon industries and identify their impact on the economic growth and sustainable development. Indeed, global awareness of climate change and sustainable growth has created much interest in the literature on how to measure efficiency and carbon emission performance of organizations and industries (Böttcher and Müller, 2015; Brouwers et al., 2018). Specifically, the literature has largely focused on energy and technical efficiency (e.g., Lee and Zhang, 2012; Du and Mao, 2015; Zhu et al., 2018), implementing low-carbon technologies to improve economic efficiency (e.g., Gillingham and Sweeney, 2012; Jenkins, 2014), and the effectiveness of low-carbon investments and financing from financial institutions (e.g., Hanson and Laitner, 2004; Campiglio, 2016, Kameyama et al., 2016; Polzin, 2017; Mazzucato and Semieniuk, 2018). Unfortunately, performance indicators used for low-carbon industries have often been criticized for being inadequate and not conducive to analysing efficiency (Hoffmann and Busch, 2008; Lee et al., 2017; Hu et al., 2019). Although prior literature has also identified both macroeconomic conditions (e.g., interest rate, regulatory conditions, accounting system, banking structure and accessibility of banking services) and firm-specific characteristics (e.g., ownership, size, scale, financial capital, liquidity ratio) determine a firm's financing efficiency (e.g., Altunbas et al., 2000; Dietsch and Lozano-Vivas, 2000; Fries and Taci, 2005; Nan and Wen, 2014; Zeng et al., 2018), little evidence is available on the actual level of financing efficiency of low-carbon companies.

The debate on the role of low-carbon industries in an economy has been intensified in recent years (Bowen and Fankhauser, 2011; Jenkins, 2014; Campiglio, 2016). On the one hand, the benefit of low-carbon industries has been increasingly recognized in terms of their effects on climate change and potential economic advantages and competence. On the other hand, the concern of efficiency of low-carbon industries remains as little empirical evidence was presented to uphold efficiency claims. Companies in the low-carbon industry expect to demonstrate their efficiency; such a demonstration would shed lights on the future of global economy, *inter alia* the development of low-carbon industries. However, to date there has been little evidence available of the actual efficiency of low-carbon industries. Our study attempts to fill the gap by providing evidence based on the data from low-carbon companies listed on China's stock exchanges.

This study chooses China's listed low-carbon companies as the study sample because of the significance of Chinese economy and the role of the government in driving the country's sustainable development. Moving to a low-carbon economy and improving energy efficiency are already a political objective in China (CCICED, 2009; Jiang et al., 2018). According to the International Institute for Sustainable Development (IISD) (2015), a dynamic GHG and energy policy environment has been emerging in China, aiming at transitioning industrial zones to low-carbon and cleaner futures. The transition has been placed on a top priority of the authorities, pressuring on industries to respond to a growing and diverse set of demands with a view to improving energy and GHG performance. Primarily, the Chinese government has adopted the strategy of increasing regulations and offering more incentives to improve energy efficiency and enlarge the mix of low-carbon sectors in the economy. Since the 2000s, many Chinese companies have begun to adopt new technologies to become a low-carbon business (Watson et al., 2015; Kedia, 2016) and more Chinese companies have taken steps to establish internal carbon monitoring procedures. China recently launched one of the largest carbon trading markets in the world. The carbon market would expect to help reduce carbon emissions and create an opportunity to transform the Chinese economy.

3. Methodology and Data

3.1 Theoretical framework

The theoretical framework of this study is based on the work of Farrell (1957) concerning efficiency. Farrell introduced the notion of relative efficiency in which the efficiency of a particular DMU may be compared with another DMU within a given group and identified technical efficiency, allocative (price) efficiency, and economic efficiency (referred to by Farrell as overall efficiency). Technical efficiency measures the ability of a DMU to produce the maximum feasible output from a given bundle of inputs or product a given level of output using the minimum feasible amounts of inputs. The overall measure of technical efficiency can be disaggregated into: pure technical efficiency due to producing within in isoquant frontier and scale efficiency due to deviations from constant to scale. Allocative efficiency measures the ability of a technically efficient DMU to use inputs in a proportion that minimise production costs for given input prices. It is calculated as the ratio of the minimum costs required by the DMU to produce a given level of outputs and the actual costs of the DMU adjusted for technical efficiency. Overall efficiency is the product of both technical efficiency and allocative efficiency. According to Farrell (1957), a DMU is economically efficient if it is both technically and allocatively efficient.

3.2 Data envelopment analysis (DEA)

Various techniques for measuring efficiency have emerged in the literature. They can broadly be divided into two main categories based on whether a parametric or non-parametric approach is adopted. The former includes a wide range of stochastic frontier models, characterized by an econometric estimate of parameters, which define specific functional forms. The latter approach makes use of mathematical programming techniques without any assumption on the data distribution, which is widely known as DEA. Basically, DEA is a methodology that has been used to assess the efficiency of entities (e.g., organisations, industries, programmes etc.) that are responsible for utilising resources to obtain outputs of interest. DEA can easily be used to appraise the relative efficiency of a set of DMUs with multiple inputs and outputs. Since the seminal work of Charnes et al. (1978), DEA has been widely adopted and expanded in the literature with a variety of customized models. McWilliams et al. (2016), for example, present how DEA can be used to determine the trade-offs between efficiency, costs and pollution reduction, allowing managers to make and advocate socially responsible decisions. Xie et al. (2018) apply DEA to estimate corporate efficiency and examine the nonlinear relationship between corporate efficiency and environmental, social and governance disclosure.

One of the most basic DEA models is the CCR model initially proposed by Charnes, Copper and Rhoades in 1978. Charnes et al. (1978) propose that the efficiency of a DMU can be measured as the maximum of a ratio of weighted outputs to weighted inputs, subject to the condition that the same ratio for all DMUs must be less than or equal to one. To attain the relative efficiency of all DMUs, the DEA model needs to run *n* times, once for each unit. The envelopment in the CCR model is constant returns to scale, implying that a proportional increase in inputs results in a proportionate increase in outputs. Essentially, the CCR model can be used to evaluate both technical and scale efficiencies via the optimal value of the ratio form. Later, the BCC model was developed by Banker, Charnes and Copper in 1984 to estimate the pure technical efficiency of DMUs with reference to the efficient frontier, identifying whether a DMU is operating in increasing, decreasing or constant returns to scale.

Fundamentally, the CCR model is a specific type of the BCC model that does not take the variation in return to scale into consideration. The right choice of a DEA model often is a difficult decision (Dellnitz et al., 2018). The BCC model measures technical efficiency as the convexity constraint ensures that the composite unit is of similar scale size as the unit being measured. The resulting efficiency is always at least equal to the one given by the CCR model and those DMUs with the lowest input or highest output levels are rated efficient. The BCC model, unlike the CCR model, allows for variable returns to scale (Banker et al., 1984). Considering the returns to scale of each company may change over years and in order to find out the real state of returns to scale of the companies under study, we use the BCC model in an attempt to take variable returns to scale into account.

Previous literature has documented that DEA is an appropriate method to evaluate the efficiency of company financing and investment because performance evaluation is a complex issue, which requires multiple criteria to assess all DMUs simultaneously (Zhong et al., 2011; Ederer, 2015; Zeng et al., 2018). For instance, a DEA model can be used to establish which companies in a sample determine the envelopment surface or efficient production frontier against other companies that are not located on the frontier. The radial distance of a company towards its frontier provides the measurement of its efficiency. An efficiency index of one or any company/unit lying on the surface is considered efficient and identified as the best practice company/unit relative to other companies/units (Banker and Podinovski, 2017). Yet, final efficiency scores in a DEA model are relative, not absolute measures, because the score depends heavily on the performance of other companies/units in the group of samples.

Fried et al. (1999) and Fried et al. (2002) reveal that DMU technical efficiency is influenced by the outside environment and therefore suggest, in any study with the use of DEA, to evaluate the environmental effect on the change of input slack variables. Fried et al. (2002) and Zeng et al. (2016) recommend using a three-stage DEA model to consider impacts from factors like external environment or statistical noise. Considering the companies in our sample have different sizes and ownership, and locate in different cities where there are significant differences among them in energy consumption and CO_2 emissions (Wang et al., 2016; Miao, 2017), we adopt a three-stage DEA model developed by Fried et al. (2002) with a view to decomposing the environmental and statistical noise effects from efficiencies.

A three-stage model is capable of estimating and then separating the disturbing factors by means of Stochastic Frontier Analysis (SFA). In the first stage, crude efficiency score is measured using the original inputs and outputs altogether. In the second stage, the slack variables in the first stage are integrated into inputs and adjusted in accordance with the original inputs. In the third stage, the original DEA model is applied with the adjusted input variables from the second stage and the original output value from the first stage to estimate the financing efficiency. Following the three-stage process, we decompose the effects of the environmental condition and statistical noise from efficiencies and obtain the real efficiency of each DMU.

3.3 Selection and dimensionless of the variables used for evaluation

To use a DEA model, it requires to identify input and output variables. We choose two major financial indicators as output variables and five indicators as input variables, including two representing internal financing inputs and three for external financing inputs. All the input and output variables are listed in Table 1.

(Insert Table 1 here)

Operating revenue and *return on equity* are selected as output variables in our evaluation; both reflect the most useful performance information of a company. *Paid-in capital* and *capital reserve* are two commonly used financial indicators to measure internal financing. *Current liabilities*, *non-current liabilities* and *equity share* are used to measure external financing inputs, explaining the extent to which a company acquires funds outside (e.g., from the stock market, borrowing, and issuing bonds).

Then, all the data related to these variables require to be dimensionless as they contain both absolute numbers and percentages. For simplicity, we use the formula below to describe all the output and input dimensionless variables in our model:

$$x'_{ijt} = \frac{x_{ijt} - \min_j\{x_{ijt}\}}{\max_j\{x_{ijt}\} - \min_j\{x_{ijt}\}} \quad (1)$$

In Formula (1), x'_{ijt} refers to the standardised value of indicator i and sample number j in the observation period t, while x_{ijt} is the original value of the same indicator and sample during the same period of time. $\max_j\{x_{ijt}\}$ and $\min_j\{x_{ijt}\}$ refer to the maximum and minimum value of indicator i at time t within all the samples respectively.

3.4 Environment variables for SFA regression

Environment variables are indicators to reflect a company's external macroeconomic conditions and internal characteristics. *Environment variables* will be used later in the SFA regression to separate the *pooled error* in the second stage. The definition and implication of each *environment variable* are given in Table 2.

(Insert Table 2 here)

GDP growth and *financial deepening degree* are two external indicators related to the macroeconomic conditions and financial market development, which are beyond the management control of individual companies. *Equity scale* and *state-owned* variables represent the ownership characteristics of a company, which are largely subject to the company's financing strategy.

3.5 The DEA model and the assessment processing

3.5.1 The first stage: DEA evaluation and slack for each variable

In the first stage, we use the dimensionless data to evaluate the initial efficiency of the low-carbon companies. Generally, a DEA model can be divided into an input-oriented and output-oriented model. In an input-oriented model, the input efficiency at a given level of output is evaluated by using the cost function; while in an output-oriented model, the output efficiency at a fixed input level is evaluated by using the production function. In most cases, companies rely on their financing activities to fund their planned business operation. Therefore, we take an input-oriented model for our evaluation.

Next, we need to decide whether the CCR model or the BCC model is adopted. Considering the returns to scale of each company may change over years and in order to find out the real state of returns to scale of the companies under study, we use the BCC model in an attempt to take variable returns to scale into account. An input-oriented BCC model in its dual form can be expressed as follows:

$$s.t.\begin{cases} \min \theta - \varepsilon(\hat{e}^T S^- + e^T S^+) \\ \sum_{j=1}^{n} X_j \lambda_j + S^- = \theta \cdot X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \end{cases} \tag{2}$$

In Formula (2), $j = 1,2,...,n$ refers to different DMUs; X and Y are input and output vectors. The expression presents a DEA model, which is a linear programming process. In this study, we use the BCC model to assess the efficiency of every DMU in our sample based on the following guidelines:

If $\theta = 1, S^+ = S^- = 0$, the target DMU is efficient;

If $\theta = 1$, but $S^{+}, S^{-} \neq 0$, the target DMU is weak efficient;

If $\theta < 1$, the target DMU is not efficient.

The results of the BCC model include overall technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE). PTE reflects the way in which output unit resources are managed while SE establishes whether output unit operates at an optimal scale or not. The optimal scale is understood as the best situation that can achieve the output unit by increasing proportionally the quantity of all its input factors. Knowing any two of them, we can calculate the other one according to:

$$TE = PTE \cdot SE \tag{3}$$

With all the companies in the sample evaluated, we can get *slack variables* ($[x - X\lambda]$) that are not DEA efficient for each DMU. Based on these variables we can then break up *managerial inefficiencies* (MIE), *environmental effects* (EnvE) and *statistical noise* (SN) using the *environment variables* in the next stage.

3.5.2 The second stage: SFA regression, separation of the pooled error and data adjustment

Typically, *slack variables* consist mainly of MIE, EnvE and SN; they heavily influence the accuracy of evaluation. Applying SFA, we can separate these effects from *slack variables* and adjust the sample data to the same level for MIE, EnvE and SN. In our input-oriented BCC model, we can construct an SFA function used for regression as:

$$S_{ij} = f(Z_j; \beta_i) + v_{ij} + \mu_{ij}; i = 1,2,\ldots,I; j = 1,2,\ldots,n \tag{4}$$

In Formula (4), S_{ij} represents the *slack variables* of input i for sample number j; Z_j represents the *EnvE* of sample j with β_i being its coefficient; v_{ij}□N(0, σ_v^2) represents SN in the original data; μ_{ij}□N $^{+}(0, \sigma_\mu^2)$ is MIE that we are mostly interested. Following the process of the above function, we perform the SFA regression once for each input variable to obtain its EnvE and SN for the next adjustment.

After the SFA regression, we get all the values of EnvE and SN for every input variable and every DMU. EnvE is calculated with the original value of *environment variables*. For SN, we separate it from the *pooled* error, which includes MIE together with SN. The separation is conducted according to the following expression:

$$E(\mu \mid \varepsilon) = \sigma_* \left[\frac{\phi(\lambda \frac{\varepsilon}{\sigma})}{\Phi(\frac{\lambda\varepsilon}{\sigma})} + \frac{\lambda\varepsilon}{\sigma} \right] \tag{5}$$

In Formula (5), $\sigma_* = \frac{\sigma_\mu \sigma_\nu}{\sigma}, \sigma = \sqrt{\sigma_\mu^2 + \sigma_\nu^2}, \lambda = \frac{\sigma_\mu}{\sigma_\nu}$;

$$E[\nu_{ij} \mid \nu_{ij} + \mu_{ij}] = S_{ij} - f(Z_j; \beta_i) - E[\mu_{ij} \mid \nu_{ij} + \mu_{ij}] \tag{6}$$

MIE(μ) and SN (ν) can be separated following Formulas (6) and (5). Then the last procedure in stage two is to adjust the original data to the same level of external environment using the function below:

$$X_{ij}' = X_{ij} + [\max(f(Z_j; \hat{\beta}_i)) - f(Z_j; \hat{\beta}_i)] + [\max(\nu_{ij}) - \nu_{ij}] \tag{7}$$

In Formula (7), X_{ij}' refers to the final *adjusted input value*. The connotations of all other indicators in expression (7) are exactly the same as ones used in previous expressions. $\max(f(Z_j; \hat{\beta}_i)) - f(Z_j; \hat{\beta}_i)$ places all the DMUs under the same worst external environment by adding up the adjustment value to their original input, and $\max(\nu_{ij}) - \nu_{ij}$ performs the same to standardise the statistical error level.

3.5.3 The third stage: Re-evaluating the financing efficiency using adjusted data

With all the *input variables* adjusted to eliminate the impacts of SN and EnvE, we can reperform the DEA evaluation with the BCC model as described in the first stage. The next section describes our data.

3.6 Data

Our sample includes 85 low-carbon companies listed on China's A-share securities market in 2011 under the categories of energy conservation, environmental protection, emission reduction, and new energy classified by the China Securities Regulatory Commission (CSRC) in accordance with the concept of low-carbon economy. The low-carbon economy is an economic model based on low energy consumption, low pollution and low emissions with characteristics of energy efficient use, clean energy development, and the pursuit of green GDP.

All the data can be found in the company annual financial reports and RESSET database. RESSET is a database provided by Beijing Gildata Resset Data Tech Co., Ltd (http://www1.resset.cn:8080/product/index.jsp?lang=en) that is a Chinese high and new technology enterprise specialising in financial database and related investment research software. The RESSET database has been widely used by researchers to obtain financial data of Chinese listed firms (e.g., Wang and Qian, 2011; Fonseka et al. 2012; Li et al., 2015; Beladi et al., 2018). We got all the financial data relating to input and output variables listed in Table 1 from RESSET database. Appendix 1 provides a list of all the firms.

4. Results

4.1 Overall financing efficiency (OFE)

Table 3 presents the overall financing efficiency (OFE), pure technical efficiency (PTE) and scale efficiency (SE) of the companies under study. The results in Table 3 show that the OFE of listed low-carbon Chinese companies is relatively high as the efficiency scores over the period from 2011 to 2017 were above 0.875. However, the scores kept dropping since the peak in 2013.

(Insert Table 3 here)

On the whole, all efficiency measures look reasonable over the period of seven years. The highest value of OFE appeared in 2013 at 0.967 and the lowest in 2012 that was 0.875. In most years, financing efficiency of these 85 companies were distributed in the range from 0.90 to 0.96 and PTE hold steadily at over 0.97. Both OFE and SE kept dropping after 2013.

One of interesting findings is that PTE appeared to be extremely stable, which was almost a straight line as shown in Table 3 and OFE portrayed very similarly to SE, implying that under the specified macroeconomic environments over the period the relatively unstable SE was a determining factor to the financing efficiency of these listed low-carbon companies. Specifically, as the input-oriented model was used in the evaluation, and the outcome level of these companies did not change significantly over these seven years, the amount of different financial resources used could be a contributing factor to the financing efficiencies of these companies.

4.2 Superior pure technical efficiency and deteriorating scale efficiency

The above results suggest the great importance of SE. We further look at SE and determine if SE would be the main constraint in the OFE of these companies. To achieve this, we take the best year (2013) and the most recent year (2017) for further examinations. Results are shown in Figures 2 and 3 respectively.

(Insert Figure 1)

Figure 1 shows the distributions of OFE, PTE and SE for the companies in the sample in 2013. In Figure 1, OFE counts for the proportion of companies that are efficient in their financing. PTE refers to the companies that are technically efficient but not efficient in scale; apparently these companies were not included in the OFE category because of their non-efficient performance in terms of SE. Similarly, SE counts for the companies that are efficient in scale but not in PTE, thus their lack of technical efficiency could be the reason for their absence in the OFE category. The rest tagged as *Non-Efficient* are those companies that are neither efficient in SE nor in PTE. It appears there were more companies that were ‘failed’ in PTE rather than in SE in this year when our sample companies got the best performance during the whole observation window.

(Insert Figure 2 here)

Figure 2 shows the proportions of OFE, PTE and SE in 2017. It profiles a contrary phenomenon comparing to 2013. In 2017, over one third of the companies achieved technical efficiency while none attained SE. This was the second worst year during the period of this study. A possible explanation for this might be that the management of these companies remained stable in our evaluation window, but the pressure of China’s macro-economic environment during these years may have influenced the financial efficiency of these companies since the demand for finance (particularly external finance) increased enormously, while less funding was accessible over the period. The Chinese government tightened monetary policy several times over the period by raising the reserve requirement ratio and base interest rate, which had a huge impact on China’s capital market and banking system, triggering much difficulty for companies to gain external finance.

Furthermore, we analyse the distribution of technical and scale efficiency of these companies in two years. Results are shown in Figures 3 and 4 respectively.

(Insert Figures 3 and 4 here)

Similar situations can be observed through the distributions of PTE and SE of these companies in two years. Dots in Figures 3 and 4 represent companies in our evaluation. The vertical and horizontal positions of each dot reflect its scale and technical efficiency. Intuitively, there are more dots aligned to the upper edge in Figure 3 than in Figure 4, as more to the right edge in Figure 4 than in Figure 3, suggesting the distribution between SE and PTE varied from year 2013 to year 2017.

Comparing financing efficiencies between 2013 and 2017, which happened to be the best and most recent year in our time series, it is clear that the PTE performed outstanding and stable all along, but the SE was deteriorating dramatically over time. As the overall efficiency of these two years differs greatly, this could suggest that higher SE was closely related to higher OFE.

4.3 Changes in returns to scale and potential underfinancing

Apart from assessing the efficiency, we also perform an evaluation of returns to scale in this study. Applying the BCC model in stage 3, we got the returns to scale of each DMU in each year labelled as IRS (increasing returns to scale), DRS (decreasing returns to scale) and CRS (constant returns to scale). Table 4 presents the results.

(Insert Table 4 here)

Throughout the observation window, the number of IRS companies counts for the biggest part over the period except 2013, possibly implying that in most years, companies in the low-carbon industries enhanced their OFE by enlarging their financing scales. In 2013, more companies reached the status of CRS instead of IRS, which implies their best financing scale at the time. This is consistent with the fact that the best performance appeared in 2013. The increasing proportion of IRS and the fact that few companies were at the stage of DRS suggest a good prospect and market potential in the future, but the lower proportion of CRS indicates that most companies failed to reach the best financing scale.

(Insert Figure 5)

To make it more clearly, we put the proportion of returns to scale and SE on the same chart as shown in Figure 5. It reveals that SE moved significantly in the opposite direction from the proportion of IRS, and roughly in the same direction of the proportion of CRS. This finding might conjecture that most of the sample companies experienced underfunding in later years.

5. Conclusion

This study has provided an empirical assessment of the financing efficiency of low-carbon companies by applying a three-stage DEA model. We have estimated the financing efficiency of 85 list companies from the low-carbon industries in China for the period from 2011 to 2017. The results show that the overall financing efficiency of these low-carbon companies were relatively high on average. 2013 was the best year with the highest efficiency score at 0.967 and 2012 was the year with the lowest score at 0.875. The results of this study indicate that most of these companies were financially efficient. From 2013 to 2017, however, these companies mostly experienced a constant dropping in financing efficiency, and the overall financing efficiency tended to change along with the scale efficiency. The pure technical efficiency of these companies held at a score of around 0.98 during the period of seven years and many companies in our sample attained pure technical efficiency in each year. While scale efficiency varied from year to year at a lower level during the period, the number of companies that achieved pure technical efficiency each year was far more than the number of companies achieving scale efficiency, suggesting that scale efficiency is the main factor constraining the overall financing efficiency of the companies under study. Also, the study reveals that most companies were experiencing increasing returns to scale regardless whether their financing efficiency was rising or falling. An interesting finding is that scale efficiency and overall financing efficiency moved in the opposite direction. Specifically, the scale efficiency and consequently the overall efficiency on average appeared to be higher when more companies were in the status of constant returns to scale, and much lower when more companies were going through increasing returns to scale. On the whole, the study suggests that there is a scope for improvement in the financing efficiency of inefficient companies by choosing a correct input-output mix and selecting appropriate scale size.

One of the most significant current discussions in the global climate change and sustainable development is transition toward a low-carbon economy. Low carbon companies play a significant part in leading this transition. One question that needs to be asked, however, is whether low-carbon companies are efficient in terms of their financing, i.e., the use of the smallest amount of financial resources to achieve the best corporate performance. Unfortunately, the literature to date has tended to focus predominately on eco-efficiency and far too little attention has been paid to the issue of financing efficiency. The present study contributes to the literature by providing empirical evidence with respect to the financing efficiency of low-carbon companies. This is the first study reporting the assessment of financing efficiency of low-carbon companies from the largest developing economy. The assessment enhances our understanding of the overall financing efficiency of low carbon companies in China and the effect of pure technical efficiency and scale efficiency on the overall financing efficiency.

The findings of this study have a number of important implications for policy-making and corporate practice. Since financing efficiency reflects on and is affected by government policy (e.g., funding, regulation) and business decisions, understanding the impact of scale and technical efficiency on the overall financial efficiency helps policy makers and business managers to assess the ability of low-carbon companies to finance the best operational performance with the least financial resources, and to identify the strengths and weaknesses of various financing options available for low-carbon sectors. Interested stakeholders need to take into account the relationships among various dimensions of efficiency when evaluating the performance of low-carbon companies. Business managers have to decide on financial means to design viable financing strategies so as to ensure the most efficient use of financial resources.

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Table 1: Output and input variables

Symbol	Variable	Input or Output	Connotation
Incm	*Operating Revenue*	Output	Revenue generated by daily operation
ROE	*Return on Equity*	Output	Net income / Shareholders' equity
PdinCap	*Paid-in Capital*	Internal Input	Capital contributed by investors
CapRes	*Capital Reserve*	Internal Input	Resource created by accumulated capital surplus (not revenue surplus)
CL	*Current Liabilities*	External Input	Obligations must be repaid within the current period
NCL	*Non-Current Liabilities*	External Input	liability not due to be paid within the current period
EQShare	*Equity Share*	External Input	Liabilities / Shareholders' equity

Table 2: Environment variables

Symbol	Variable	Implication
GDPGrowth	*GDP Growth*	GDP growth over the previous year
FDD	*Financial Deepening Degree*	Total market capitalization / GDP
EQScale	*Equity Scale*	Total assets
STOwned	*State-Owned*	The company is owned by the state

Table 3: Evaluation results on average number

	2011	2012	2013	2014	2015	2016	2017
OFE	0.910752941	0.875152941	0.967058824	0.960411765	0.929705882	0.905964706	0.909658824
PTE	0.984988235	0.984458824	0.978164706	0.983047059	0.989211765	0.974341176	0.975764706
SE	0.924478293	0.887829993	0.98797917	0.976805403	0.939220223	0.929741945	0.932547353

Note: OFE: the overall financing efficiency; PTE: pure technical efficiency; SE: scale efficiency

Table 4: Returns to scale of each Year

	2011	2012	2013	2014	2015	2016	2017
IRS	69 (81%)	64 (75%)	33 (39%)	52 (61%)	54 (64%)	68 (80%)	74 (87%)
DRS	0 (0%)	1 (1%)	8 (9%)	6 (7%)	7 (8%)	1 (1%)	1 (1%)
CRS	16 (19%)	20 (24%)	44 (52%)	27 (32%)	24 (28%)	16 (19%)	10 (12%)

Appendix: Stocks & Names of 85 Low Carbon List Companies

No.	Stock code	Company Name
1	000009	China Baoan Group Co., Ltd.
2	000012	CSG Holding Co., Ltd.
3	000155	Sichuan New Energy Power Company Ltd.
4	000541	Foshan Electrical and Lighting Co., Ltd.
5	000601	Guangdong Shaoneng Group Co., Ltd.
6	000619	Wuhu Conch Profiles and Science Co., Ltd.
7	000652	Tianjin Teda Co., Ltd.
8	000697	Ligeance Aerospace Technology Co., Ltd.
9	000755	Shanxi Road & Bridge Co., Ltd.
10	000786	Beijing New Building Materials Public Co., Ltd.
11	000826	Tus-Sound Environmental Resources Co., Ltd.
12	000833	Guangxi Yuegui Guangye Holdings Co., Ltd.
13	000839	CITIC Guoan Information Industry Co., Ltd.
14	000862	Ning Xia Yin Xing Energy Co., Ltd.
15	000932	Hunan Valin Steel Co., Ltd.
16	000969	Advanced Technology and Materials Co., Ltd.
17	000970	Beijing Zhong Ke San Huan High-tech Co., Ltd.
18	000973	FSPG Hi-tech Co., Ltd.
19	002009	Miracle Automation Engineering Co.,Ltd
20	002011	Zhejiang Dun'an Artificial Environment Co., Ltd.
21	002028	Siyuan Electric Co., Ltd.
22	002056	Hengdian Group DMEGC Magnetics Co., Ltd.
23	002076	CNlight Co., Ltd.
24	002083	Sunvim Group Co., Ltd.
25	002088	Luyang Energy-Saving Materials Co., Ltd.
26	002091	Jiangsu Guotai International Group Guomao Co., Ltd.
27	002123	Montnets Rongxin Technology Group Co.,Ltd.
28	002145	Cnnc Hua Yuan Titanium Dioxide Co., Ltd.
29	002169	Guangzhou Zhiguang Electric Co., Ltd.
30	002202	Xinjiang Goldwind Science and Technology Co., Ltd.
31	002227	Shenzhen Auto Electric Power Plant Co., Ltd.
32	002255	Suzhou Hailu Heavy Industry Co., Ltd.
33	600010	Inner Mongolia Baotou Steel Union Co., Ltd.
34	600011	Huaneng Power International Co., Ltd.
35	600022	Shandong Iron and Steel Company Co., Ltd.
36	600089	Tebian Electric Apparatus Stock Co., Ltd.
37	600112	Guizhou Changzheng Tiancheng Holding Co., Ltd.
38	600123	Shanxi Lanhua Sci-Tech Venture Co., Ltd.
39	600131	Sichuan Minjiang Hydropower Co., Ltd.
40	600151	Shanghai Aerospace Automobile Electromechanical Co., Ltd.
41	600160	Zhejiang Juhua Co., Ltd.
42	600188	Yanzhou Coal Mining Co., Ltd.
43	600202	Harbin Air Conditioning Co., Ltd.

44	600261	Zhejiang Yankon Group Co., Ltd.
45	600282	Nanjing Iron and Steel Co., Ltd.
46	600290	Huayi Electric Co., Ltd.
47	600292	Spic Yuanda Environmental-Protection Co., Ltd.
48	600309	Wanhua Chemical Group Co., Ltd.
49	600348	Yang Quan Coal Industry (Group) Co., Ltd.
50	600360	Jilin Sino-Microelectronics Co., Ltd.
51	600366	Ningbo Yunsheng Co., Ltd.
52	600388	Fujian Longking Co., Ltd.
53	600392	Shenghe Resources Holding Co., Ltd.
54	600396	Shenyang Jinshan Energy Co., Ltd.
55	600416	Xiangtan Electric Manufacturing Co., Ltd.
56	600419	Xinjiang Tianrun Dairy Co.,Ltd.
57	600423	Liuzhou Chemical Industry Co., Ltd.
58	600426	Shandong Hualu-Hengsheng Chemical Co., Ltd.
59	600475	Wuxi Huaguang Boiler Co., Ltd.
60	600499	Keda Clean Energy Co., Ltd.
61	600509	Xinjiang Tianfu Energy Co.,Ltd.
62	600550	Baoding Tianwei Baobian Electric Co., Ltd.
63	600569	Anyang Iron and Steel Inc.
64	600578	Beijing Jingneng Power Co., Ltd.
65	600585	Anhui Conch Cement Co., Ltd.
66	600586	Shandong Jinjing Science and Technology Stock Co., Ltd.,
67	600590	Tellhow Sci-Tech Co., Ltd.
68	600636	Shanghai 3F New Materials Co., Ltd.
69	600644	Leshan Electric Power Co., Ltd.
70	600649	Shanghai Chengtou Holding Co., Ltd.
71	600720	Gansu Qilianshan Cement Group Co., Ltd.
72	600725	Yunnan Yunwei Co., Ltd.
73	600740	Shanxi Coking Co., Ltd.
74	600792	Yunnan Coal And Energy Co., Ltd.
75	600848	Shanghai Lingang Holdings Corp Ltd.
76	600863	Inner Mongolia Mengdian Huaneng Thermal Power Corp Ltd.
77	600875	Dongfang Electric Corp Ltd.
78	600884	Ningbo Shanshan Co., Ltd.
79	600970	Sinoma International Engineering Co., Ltd.
80	601005	Chongqing Iron and Steel Co., Ltd.
81	601666	Pingdingshan Tianan Coal.Mining Co., Ltd.
82	601727	Shanghai Electric Group Co., Ltd.
83	601898	China Coal Energy Co., Ltd
84	601958	Jinduicheng Molybdenum Co., Ltd.
85	601991	Datang International Power Generation Co., Ltd.

Figure 1: Proportion of OFE, PTE and SE in 2013

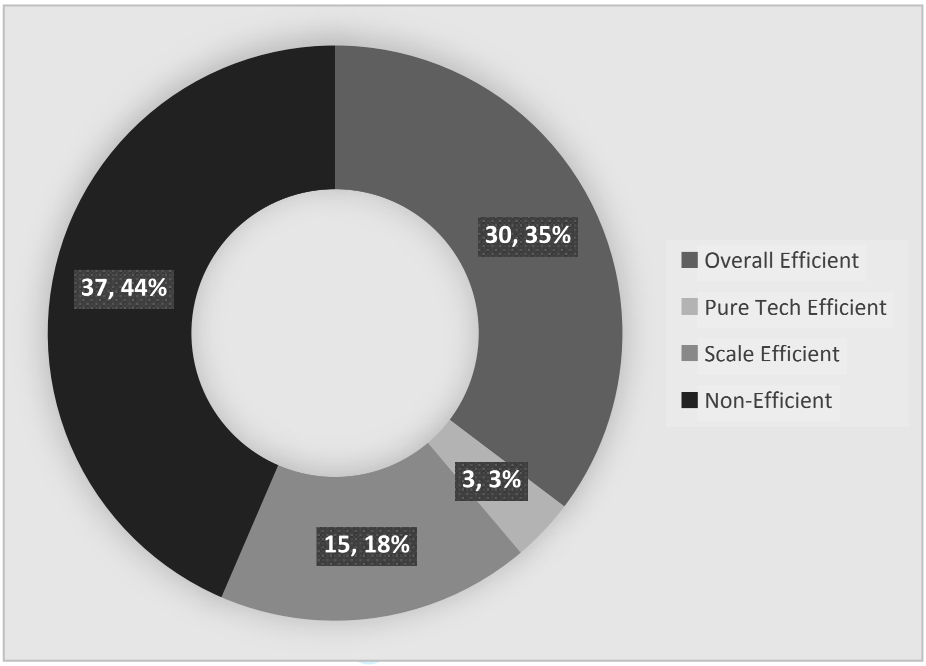

Figure 2: Proportion of OFE, PTE & SE in 2017

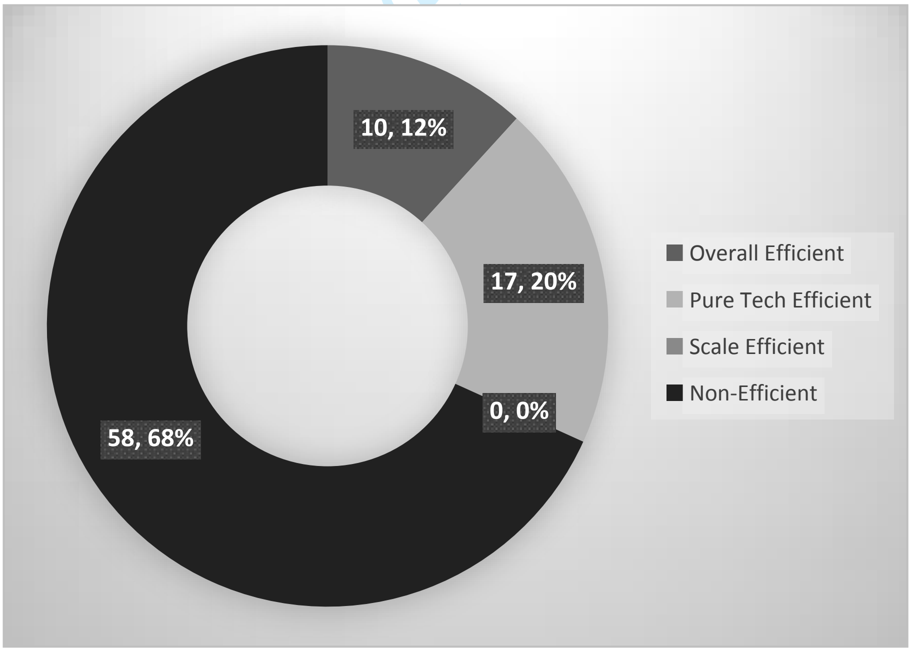

Figure 3: Distribution of technical and scale efficiency in 2013

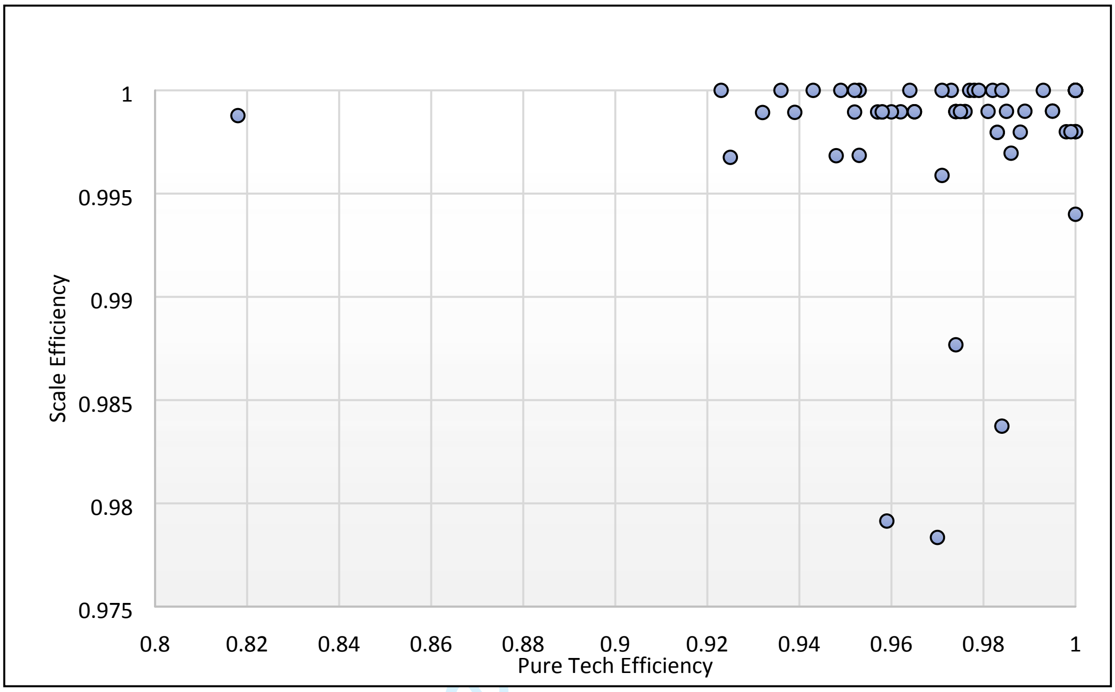

Figure 4: Distribution of technical and scale efficiency in 2017

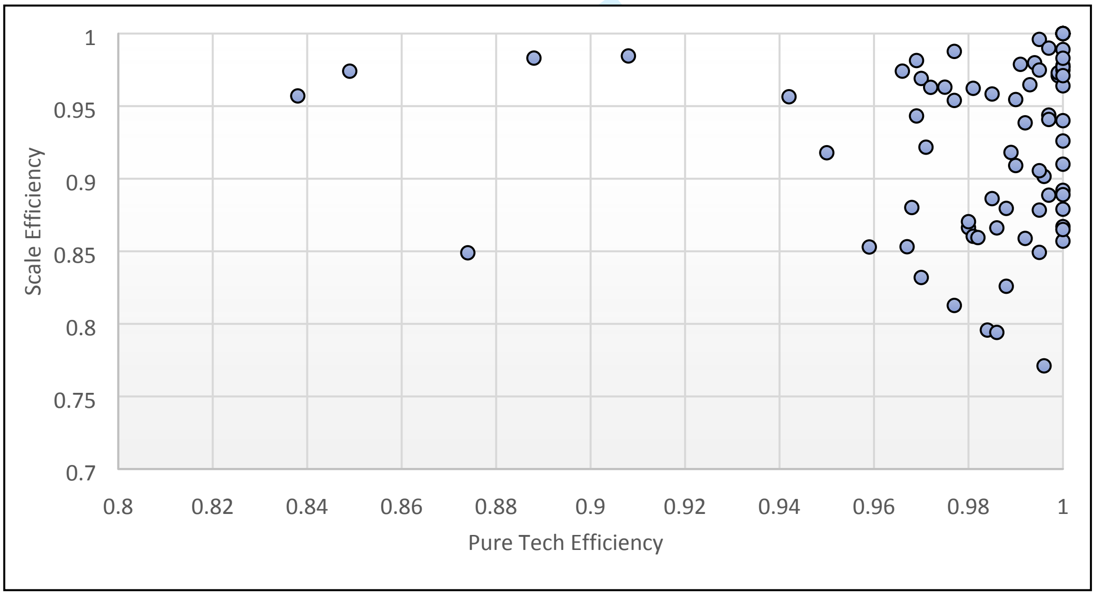

Figure 5: Proportion of increasing, decreasing & constant returns to scale