The Effects of Banks' CSR Activities on Economic Efficiency

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Abstract

This paper examines whether the engagement of corporate social responsibility (CSR) influences bank's economic efficiency. We compile different CSR scores from EIRIS database spanning 2003-2014 and estimate a directional input distance function with endogenous inputs and a cost frontier. The allocative inefficiency is found to outweigh technical inefficiency and most environmental variables significantly affect various inefficiencies. The exclusion of the environmental variables leads to under-estimation of efficiency scores. During the period of the financial crisis of 2007-2009, efficiency measures regress. Banks operating in Europe and America outperform those in Asia. Finally, the omission of undesirables incurs lower technical inefficiency estimates.

Key words: Corporate social responsibility, endogenous inputs, directional input distance function, environmental variables, cost inefficiency

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I. Introduction

Aside from pursuing profits and shareholder interests, enterprises should also take account of the benefits of their stakeholders, including consumers, creditors, minority shareholders, employees, the environment, and communities. In 2008, the Corporate Social Responsibility (CSR) Report of KPMG Sustainability Consulting showed that about 75% of the world's top 250 enterprises have incorporated CSR in their strategies and reports. Noteworthily, this proportion has risen to 92% by 2015, indicating that CSR has received considerable attention and became increasingly important.

However, Friedman (1970) objects to enterprises' engagement in CSR activities, positing that it would increase enterprise costs and could not bring substantial positive benefits. Aupperle, Carroll, and Hatfield (1985) hold the same view and assert that CSR activities reduce corporate competitiveness. Henderson and Mapp (2002) argue that while CSR activities could only enhance limited corporate reputations and require a long time to recover the costs involved, they still bring positive effects to enterprises. Furthermore, the academic community has yet to reach a consensus on whether CSR activities have tangible or intangible benefits and to determine their advantages and disadvantages, especially their effects on corporate business performance. Therefore, a comprehensive model needs to be developed.

Banks have five main functions: (1) regulating the supply of and demand for funds and enhancing fund efficiency, (2) promoting credit transactions and adjusting the flow of funds, (3) increasing savings and improving capital efficiency, (4) executing monetary policies that help boost the national economy, and (5) creating credit. They also offer financial services to local and foreign clients through international networks. Our daily lives are intimately linked with banking services, such as withdrawing cash, receiving salary, paying bills, depositing money, and getting loans. In addition, various commercial activities also rely on the banking system for trade settlement and financial scheduling. Therefore, the performance of a country's banking industry has huge effects on its national economy and people's livelihood. Hence, this paper intends to investigate this industry.

The early methods of analyzing bank performance focus on financial ratios. Since CSR activities affect the overall corporate performance, it is better to assess bank performance against some comprehensive indicators, such as technical and allocative efficiency. Technical efficiency (TE) is a comprehensive index that can be either input-oriented or output-oriented. The input-oriented TE measures the ratio of the minimum input mix to actual input mix, given an output vector. Meanwhile, the output-oriented TE measures the ratio of the actual outputs to maximum outputs, given an input vector. Both efficiencies range from zero to unity. The closer the value of TE is to unity, the more technically efficient the bank is. On the other hand, a bank's allocative efficiency (AE) reflects its ability to employ factors of production to minimize costs, where the marginal rate of technical substitution for any two factors is equal to their price ratio. Managers should enhance their managerial abilities and improve their input allocation to reduce wasting resources, save costs, and increase profits for sustainable operation.

Before we estimate TE and AE scores, it is necessary to define what the inputs and outputs are in a production process. Vitaliano and Stella (2006) consider CSR as a potential output, while Becchetti and Trovato (2011) consider CSR as an input. There are still heterogeneous opinions concerning whether CSR is a factor of input or output.[1] The CSR score of an enterprise is directly proportional to its resource consumed, which is discretionary under the control of bank managers. Therefore, this paper considers CSR as one of the input factors, which is a decision variable like other input factors. This results in the problem of endogeneity to be solved; otherwise, inconsistent coefficient estimates may be resulted. This study adopts the instrumental variables (IV) approach, proposed by Amsler, Prokhorov, and Schmidt (2016, 2017), to solve this problem. In fact, this is the first time when this method is used in literature to estimate both TE and AE. This is the first characteristic of this paper.

It is well-known that economic efficiency (EE) consists of TE and AE. Measurement of TE has been widely used to examine the performance of banking, insurance, manufacturing, hospitality, and universities. Among them, banking industry has drawn much attention of academic researchers. However, most literature emphasizes the estimation of TE, while AE is relatively less explored. This study estimates and explores the issue of EE from the cost function perspective. This is the second characteristic of this paper.

In manufacturing, the commonly produced waste in the production process includes air pollution, water pollution, and noise, known as undesirable or bad outputs. With banks engaging in fund lending, non-performing loans are inevitable and considered as an undesirable output, even if screening systems are established to carefully evaluate the credit of loan applicants. Non-performing loans can then be viewed as a bad output for banks. This output has the property of weak disposability because costs must be paid for their

[1] In order to solve the problem that CSR is a factor input or output, the network data envelopment analysis or network stochastic frontier approach should be used, according to Holod and Lewis (2011) and Huang, Lin, and Chen (2017). These two papers attempt to solve the problem of whether deposits should be regarded as an input or output. Since this topic is not the subject of this study, this paper does not choose network models for analysis.

abandonment or disposal.[2] This study uses the directional distance function proposed by Färe and Grosskopf (2005) and Färe, Grosskopf, and Weber (2006) to integrate undesirable outputs into the model. This is the third characteristic of this paper.

In summary, this study estimates the directional input distance function (DIDF) and a cost frontier in succession, while taking four factors of endogenous inputs, CSR, undesirables, and environmental variables into consideration. After estimating the TE, AE, and EE for the sample banks, this study explores the effects of the above four factors on bank performance and highlights the importance of these factors. Importantly, the results of this paper can provide a reference for bank managers and government authorities in developing business strategies and financial policies.

The remainder of this paper is organized as follows. Section II presents the literature review, Section III the econometric model, Section IV data analysis with an emphasis on the calculation and sample statistics presentation of the CSR scores, Section V the empirical analysis and the comparisons among various regression model, and Section VI the conclusion.

II. Literature Review

A. CSR Activities

CSR is firstly defined by Bowen (1953) as "the obligation of businessmen to pursue those policies, to make those decisions, or to follow those lines of action which are desirable in terms of objectives and values of our society" (p. 6). Later, Wood (1991) defines CSR as "a business organization's configuration of principles of social responsibility, processes of social responsiveness, and policies, programs, and observable outcomes as they relate to the firm's societal relationships" (p. 693). Generally, CSR should include eight aspects, including (a) employee interests and human rights, (b) consumer rights and interests, (c) corporate governance, (d) business information disclosure, (e) stockholders' equity, (f) community participation, (g) environmental protection, and (h) supplier relationship.

Firms can achieve sustainable operation, enhance social welfare, and improve employee well-being if they choose to provide employees with a comfortable work environment, educational training, good salary, and reward systems. This decision is also expected to bring higher employee productivity. In addition, four extra benefits have been identified:

2 The definition of weak disposability can be found in Färe and Grosskopf (2004).

(a) Reducing the overall operating cost

Goss and Roberts (2011) and Ghoul et al. (2011) argue that while enterprises need to pay extra costs to engage in CSR activities, firms increasing investments in CSR activities obtain low working capital from bank financing and the capital market.

(b) Strengthening consumers' willingness to buy and increasing labor productivity

Yang (2016) suggests that CSR activities could enhance people's impression of enterprises, build higher goodwill, and improve consumers' willingness in purchasing their products or increase consumers' willingness in paying higher prices. In addition, Carroll (1991) claims that CSR activities could also help enhance labor productivity.

(c) Improving corporate goodwill and images

According to Donaldson and Preston (1995) and Brammer and Pavelin (2006), although managers need to pay extra costs to participate in CSR activities, corporate images can be promoted, which are beneficial to stakeholders, such as employees, consumers, stockholders, and governments.

(d) Having an insurance function

Boutin-Dufresne and Savaria (2004), Peloza (2006), Godfrey, Merrill, and Hansen (2009), Ducassy (2013), and Shiu and Yang (2017) note that firms that engaged in more CSR activities leave positive impressions to consumers and are easily forgiven after the occurrence of unfortunate incidents, and the effects of such events on their stock prices are relatively moderate. However, the effect of positive impressions gradually wears off if the number of negative events continues to rise.

Many scholars who study the nexus between CSR and business performance compile the data obtained from the database of Kinder, Lydenberg, Domini and Co., Inc. (KLD), or Ethical Investment Research Service (EIRIS). These data are combined with accounting data such as Bankscope and Datastream for research.

Jones (1995) mentions that enterprises with higher social responsibility performance attract more customers who pay more attention to social responsibilities. Bagnoli and Watts (2003) argue that such enterprises have higher financial performance. According to Orlitzky, Schmidt, and Rynes (2003), enterprises that increase their investments in CSR activities can reduce legal and regulatory restrictions and improve their corporate reputations and brand images. These benefits are accompanied by lowering cost (Fombrun, Gardberg, and Barnett (2000)) and/or removing doubts about enterprises from the outside world (Baron (2001)).

However, previous studies on the effects of CSR activities on large enterprises' financial performances, including financial indexes and stock prices, have found inconsistent results. Moskowitz (1972) selects 14 enterprises with high corporate social responsibility performance and finds that their stock prices grow faster. However, Vance (1975) analyzes 50 enterprises between 1974 and 1975 using the same method as Moskowitz (1972) does and finds that CSR was negatively correlated with their stock return.

How can CSR performance affect corporate performance? Based on previous studies, Baron (2001) introduces three major relationships. First, for altruism, because CSR activities only increase corporate costs without bringing any benefits, it is negatively correlated with performance, as evidenced by Boyle, Higgins, and Rhee (1997). Second, for strategic choices, Friedman's statement (1970) that "the role of CSR is to maximize profits," suggests that firms invest in CSR activities to boost their own business. Hence, CSR is positively correlated with performance, consistent with the findings of Bowman and Haire (1975) and Dowell, Hart, and Yeung (2000). Third, for greenwashing, according to Frankental (2001), Dam, Koetter, and Scholtens (2009), and Wu and Shen (2013), CSR is independent of performance. Firms merely attempt to rebuild (whitewash) their corporate images by engaging in CSR activities, such as peeling away the stigma of sweatshops or enhancing the image of environmental protection and energy-saving. Their engagement in CSR activities is a false appearance and has nothing to do with business performance.

Furthermore, according to Hillman and Keim (2001), Barnett and Salomon (2006), and Brammer and Millington (2008), there may be a non-linear relationship rather than a linear relationship between CSR and corporate performance. Margolis and Walsh (2003) review 109 papers between 1993 and 2002, and explore the effects of CSR on corporate business performance. Among them, 54 papers verify that CSR has significant positive effects on bank performance, accounting for 49.5%. Meanwhile, 28 papers confirm that the effects are insignificant, 20 papers find mixed results, and 7 papers reached negative effects.

The majority of early studies focus on the relationship between CSR and financial performance. For instance, Griffin and Mahon (1997), Wright and Ferris (1997), Nelling and Webb (2009), and Wu and Shen (2013) suggest that only enterprises with high financial performance could invest in CSR activities. However, enterprises could not improve their financial performance by merely investing in CSR activities. There are fewer studies on the relationship between CSR and corporate production efficiency, including Paul and Siegel (2006), Vitaliano and Stella (2006), Dam, Koetter, and Scholtens (2009), Becchetti and Trovato (2011), and Yang (2016).

Dam, Koetter, and Scholtens (2009) first put CSR indexes into the cost function or profit function. They use the database of Kinder, Lydenberg, and Domini and Co., Inc. (KLD) to search the papers written between 1991 and 2004 and set CSR indexes of different aspects as environmental variables. However, they fail to take CSR as an input due to the absence of CSR price data. Dam, Koetter, and Scholtens (2009) explore whether the sample firms' behaviors are consistent with either one of the three hypotheses of altruism, strategic choices, or greenwashing, and find that CSR activities do increase the cost inefficiency of firms, which excludes the greenwashing hypothesis. However, CSR activities can significantly improve profit efficiency, which supports the strategic choices hypothesis. Becchetti and Trovato (2011) explore the relationship between CSR and production efficiency of 1085 firms in 13 years by the latent class stochastic frontier. They conclude that firms engaging in CSR activities conform to the strategic choices hypothesis.

In most previous studies on the effects of CSR on corporate production efficiency, cost or profit functions are used to explore technical efficiency. In this paper, endogeneity and undesirable outputs are included in the model, and allocative efficiency is added apart from technical efficiency. Given a certain output level, input-oriented TE can reflect the degree of input waste. Allocative efficiency indicates whether the current factor allocation minimizes production costs at the given output level.

B. The Nexus between Banks' CSR Activities and Performance

Wu and Shen (2013) use the database of Ethical Investment Research Service (EIRIS) to explore the correlation between CSR and financial performance with 162 banks from 22 countries in the period 2003-2009. They find that the strategic choices strategy is the motivation for the subject banks to engage in CSR activities. Yang (2016) applies the three-stage data envelopment analysis (DEA), which is able to adjust the effects of environmental factors on efficiency, and classifies the sample firms into financial and non-financial sectors to conduct empirical analysis. The results indicate that CSR activities can affect efficiencies after continuous investment over a period of time.

Zhu et al. (2017) claim that CSR activities positively impact the banking performance of banks in China through the increase in profits rather than reducing bad loans. However, this positive relationship tends to be reverse after the spending on CSR exceeds a certain limit. Huang et al. (2019) analyze the effects of banks' CSR activities on their cost efficiencies, based on the EIRIS database and Bankscope databank. Although their results fail to support greenwashing, they partially support the altruism and strategic choices hypotheses. Forgione, Laguir, and Staglianò (2020) collect the panel data of large commercial banks from 22 countries during the period 2013-2017, and examine the effects of CSR activities on efficiency. They employ the stochastic frontier approach (SFA) to estimate profit efficiency and find that more involvements in the aspects of social and environmental activities lead to lower efficiencies.

Fukuyama and Tan (2021) investigate the efficiency of Chinese banking industry between 2007 and 2017 by the output-oriented DEA and discuss its relationship with CSR. They propose three new CSR indexes, including green loan balance, SME loan, and donation. Based on the sample from 184 banks across 41 countries between 2009 and 2015, Belasri, Gomes, and Pijourlet (2020) study the effects of CSR on bank efficiency using dynamic network DEA models, and point out that CSR is positively correlated with bank efficiency only in developed countries.

C. Directional Distance Function and Undesirables

In a bank's production process, particularly granting loans, bad loans (or non-performing loans) almost inevitably occur. Some customers borrow money from banks but fail to pay interests and/or principles within the agreed time for different reasons. Banks must work hard to reduce such events to avoid losses. Adhering to the 5P principles (i.e., people, purpose, payment, protection, and perspective) for credit review before granting loans and collecting bad loans, extra costs must be paid, which increases costs and lowers efficiency. Bad loans can be considered as an undesirable output that occurs simultaneously with the loan of desirable output. Furthermore, the directional distance function is able to simultaneously increase outputs, decrease both inputs and undesirable outputs, and measure technical efficiency (Chung, Färe, and Grosskopf (1997), Seiford and Zhu (2002), Färe et al. (2005), Huang, Chiang, and Tsai (2015), and Huang and Chung (2017)).

Since the farmers' association consists of four sectors (including supply and marketing, credit, promotion, and insurance), Chen et al. (2009) construct a complete multi-sector performance evaluation DEA model in the context of directional distance function with undesirable outputs. They find that the supply and marketing, and credit sectors are more efficient than the promotion and insurance ones.

Huang and Chung (2017) describe banks' production activities by the directional distance function and discuss whether the first financial reform policy improved the technical efficiency of Taiwan's commercial banks spanning 1999-2012. Although technical inefficiency gradually increased before 2002, they find that it declined during the first financial reform and rose sharply during the Taiwan Credit Card Crisis" in 2006 and the "Subprime Mortgage Crisis" in 2008. Noteworthily, public and financial holding banks are more efficient than private and non-financial holding banks.

Huang, Lin, and Hu (2019) estimate the stochastic directional distance function by the Bayesian approach with or without environmental variables and with or without the imposition of monotonicity and curvature. They demonstrate the advantages of the directional distance function, which is capable of including undesirable outputs. Their output distance function tends to overestimate technical efficiencies for the sample countries and underestimate the rate of technical progress potentially due to the exclusion of undesirable outputs. Conversely, the results obtained by the directional distance function that imposes the restrictions of monotonicity and curvature and contains environmental variables are more reasonable.

Huang, Chiu, and Mao (2021) analyze the technical efficiencies of 51 commercial banks in Taiwan between 2002 and 2015, and probe into the effects of undesirable outputs, such as non-performing loans, on technical efficiencies. They estimate the stochastic distance function using the simultaneous regression approach, where monotonicity and curvature conditions are imposed on the function. This assures the coefficient estimates to be in line with the requirements of the economic theory.

Park and Weber (2006) explore the Luenberger productivity index of the banking industry in South Korea between 1992 and 2002 using the DEA directional distance function. They conclude that technical progress is the main driver of productivity growth. Using the data from Japan's banking industry between 2002 and 2004 and treating overdue loans as an undesirable output, Fukuyama and Weber (2008) estimate the technical efficiencies of banks and shadow prices for overdue loans by the DEA directional distance function and linear programming method. They suggest that the technical efficiency estimates obtained by the two methods are similar, while the shadow price estimates differ greatly.

Different from the above studies that adopt DEA methods, Koutsomanoli-Filippaki, Margaritis, and Staikouras (2009) utilize the stochastic directional distance function to estimate the banking efficiency and Luenberger productivity index of 10 Eastern European countries between 1998 and 2003. They claim that market competition is closely related to the banking efficiency and that the main driver of productivity gains is technical progress rather than production efficiency improvement.

Shao et al. (2020) select 25 commercial banks listed in China's stock market in 2013, 2015, and 2017 as the samples and group them into four categories of state-owned commercial banks, joint-stock commercial banks, city commercial banks, and rural commercial banks. They adopt DEA to evaluate the performance of product innovation for the four types of banks, and find that joint-stock commercial banks outperform the rest types of banks, and rural commercial banks perform the least.

D. Endogeneity Problem

If the independent variables of a regression equation are correlated with the error terms, the ordinary least squares (OLS) coefficient estimates will be inconsistent. Hence, the measurements of technical efficiencies, productivity changes, and economies of scale, calculated on the basis of these coefficient estimates, will be meaningless. Choi, Choi, and Byun (2018) point out that there are two main factors causing the endogeneity problem of the CSR index. The first factor is the selection bias, which asserts that managers' decisions on CSR activities are based on their overall policies or other internal factors, and hence, not random. Since CSR engagement may lead to higher accounting transparency, enterprises with highly reliable financial reporting are more inclined to engage in CSR activities. Therefore, the endogeneity problem needs to be properly disentangled. This paper intends to solve this problem using the instrumental variable (IV) approach recommended by Amsler, Prokhorov, and Schmidt (2016, 2017) in order to get consistent coefficient estimates.

The endogeneity problem of production factors in the stochastic frontier production frontier has received much attention from several academic researchers in the recent decade. For instance, Guan et al. (2009), Kutlu (2010), and Tran and Tsionas (2013) assume that inputs are correlated only with error terms, but not with inefficiency terms. Meanwhile, Karakaplan and Kutlu (2017b) extend the above model to allow inefficiency terms to be affected by a set of exogenous environmental variables. Tran and Tsionas (2015) consider endogenous production factors and apply maximum likelihood (ML) to estimate the likelihood function, which is derived from the copula methods, without relying on the IV approach.

Amsler, Prokhorov, and Schmidt (2016) assume that the endogenous inputs are correlated with either the error term or inefficiency term. Based on that, Amsler, Prokhorov, and Schmidt (2017) adds endogenous environmental variables that have the scaling property to propose a simulated ML to estimate the parameters of interest.

Amsler, Prokhorov, and Schmidt (2017), Kutlu (2018), Karakaplan and Kutlu (2017a), and Tsukamoto (2019) discuss endogenous inputs and endogenous environmental variables, which are assumed to be associated with random disturbances but uncorrelated with inefficiency terms. Based on the data of 128 coal-fired power plants in the United States between 2001 and 2012, Lai and Kumbhakar (2018) propose the stochastic frontier panel data model to solve the underlying endogeneity problem and to detect the determinants of inefficiency.

Kutlu, Tran, and Tsionas (2019) study the relationship between cost efficiency and profitability of large American insurance banks in the period of 1976-2007. They propose the stochastic frontier model with endogenous inputs, heterogeneous error terms, and time-varying inefficiency. Evidence is found that profitability is inversely related to cost efficiency and that their proposed model yields better estimates according to Monte Carlo simulations.

E. Technical and Allocative Efficiencies of the Banking Industry

Most empirical studies on bank performance have concentrated on technical efficiency. The topic of allocative efficiencies is relatively less investigated, probably because the price information of inputs and/or outputs is required to be additionally collected in order to estimate the allocative efficiency and is sometimes not available. There are many papers discussing both TE and AE using DEA, such as English et al. (1993), Koutsomanoli-Filippaki, Margaritis, and Staikouras (2012), Fu et al. (2016), Juo et al. (2016), Adesina (2019), Mansour and Moussawi (2020), Nair and Vinod (2019), and Simar and Wilson (2020), to mention a few. Studies that have probed the same issues by using the SFA, include Atkinson and Cornwell (1994), Kumbhakar (1997), Huang (1999), Huang (2000), Kumbhakar and Wang (2006a, 2006b), Huang et al. (2011), Huang et al. (2014), Tsionas, Assaf, and Matousek (2015), Mamatzakis et al. (2015), and Ahmad and Burki (2016). However, these papers ignore the endogeneity problem of inputs and are not conducted from the perspective of the directional distance function.

Adesina (2019) analyzes the effects of intellectual capital (IC) on technical, allocative, and cost efficiencies, using 339 commercial banks from 31 African countries spanning from 2005 to 2015. He finds that IC has positive effects on technical, allocative, and cost efficiencies of the sample banks.

III. Methodology

By considering undesirable outputs and endogenous inputs, this paper examines the effects of banks' CSR activities on their TE and AE. Almost all previous papers that use the SFA rely on a one-stage approach to estimate both TE and AE. According to Mamatzakis et al. (2015), although the one-stage approach has its advantages, it is difficult to take the problem of endogenous inputs into account because the regression model is already too complex. Färe and Grosskopf (2005) introduce the directional input distance function (DIDF) and two-stage DEA method to estimate TE and AE. However, the DEA method cannot deal with the endogeneity problem. As a result, this paper recommends the employment of the SFA to solve this problem. In the first stage, when endogenous inputs and environmental variables are considered, the DIDF is estimated to obtain TE scores for the sample banks. In the second stage, the stochastic cost frontier is estimated to yield the cost efficiency (CE) estimates.

The difference between the *CE* from the second stage and the *TE* from the first stage is defined as the *AE*.

A. Directional Input Distance Function (DIDF)

Färe, Grosskopf, and Lovell (1985) propose the directional distance function, which allows firms to expand outputs and cut both inputs and undesirables along a given direction. Chambers, Chung, and Färe (1996) demonstrate that the directional distance function is a generalized distance function of Shephard (1953) and the input and output distance functions are special functions of the directional distance function.

The input vector is defined as $x=(x_1,\dots,x_N)'\in R_+^N$, and the output vector is $y=(y_1,\dots,y_M)'\in R_+^M$. The undesirable output (b) is represented by non-performing loans, where $b\in R_+$, and has the characteristics of null-joint outputs and weak disposability.[3] Banks must pay extra costs for collecting non-performing loans by manual calling and collateral auctions.

The technology set is defined as:

$$T=\{(x, y, b): x \text{ can be used by banks to produce } (y, b)\}.$$

The input requirement set is expressed as:

$$L(y)=\{x:(x,y,b)\in T\}.$$

Let DIDF be:

$$\vec{D}_I(x,y,b;h_x)=\sup\{\beta:(x-\beta h_x,y,b)\in L(y)\}, \tag{1}$$

where $h_x\in R_+^N$ is the directional vector. Eq. (1) indicates that the firm with the existing combinations of inputs and outputs remains in the $L(y)$ set after a maximum reduction of β units along h_x direction, and thus, $\beta\geq 0$. When $\beta=0$, this means that the firm is fully technically efficient and producing at the production frontier. Hence, the lower the value of β, the higher the technical efficiency the firm. This paper sets the direction vector as a unit vector, namely $h_x=(1,\dots,1)$.

The cost function is defined as:

$$C(y,p)=\min\{px:x\in L(y)\}, p>0, \tag{2}$$

where $p\in R_+^N$ is the vector of factor prices and px is the firm's expenditure. The technical inefficiency (*TI*) measure can be calculated after estimating the DIDF of (1) and the cost inefficiency (*CI*) measure can be computed after estimating the cost function of (2). It is known that *CI* can be decomposed into two parts, i.e., *TI* and allocative inefficiencies (*AI*), as shown in Figure 1.

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3 Please refer to Färe and Grosskopf (2005) for the definitions of null-joint outputs and weak disposability.

$$CI = \overline{AD} = \overline{AB} + \overline{BD} = TI + AI. \tag{3}$$

Färe and Grosskopf (2005) suggest that the DEA can be adopted to estimate DIDF and obtain TEI, and then estimate cost function to obtain the cost (none) efficiency indicator. The difference between the above two indicators equals the AI indicators. While the same procedures are used by this paper, the SFA is undertaken, instead of the DEA. This is mainly because the mathematical programming method cannot deal with the endogeneity problem of some or all independent variables.

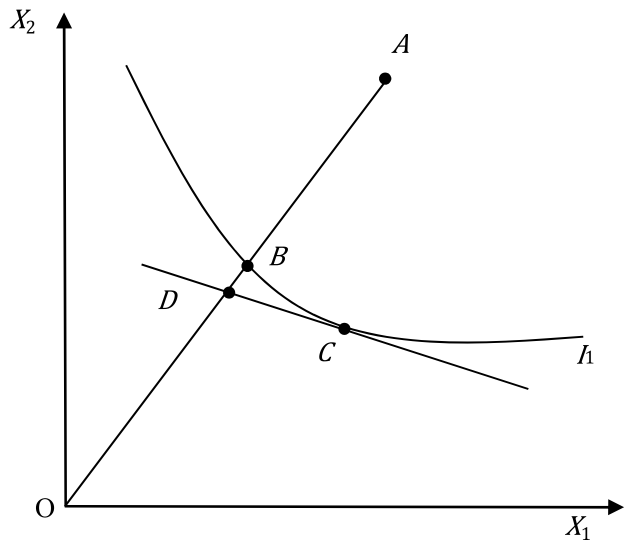

Figure 1. Technical and Allocative Efficiencies

Let the minimized cost function be $C(y,p) = px^*$, where x^* is the vector of input demands. Färe and Grosskopf (2005) define the cost inefficiency index as:

$$CI(x,y,p,h_x) = \frac{px - C(y,p)}{ph_x} = \frac{p(x-x^*)}{ph_x} \geq 0. \tag{4}$$

When $CI = 0$, this indicates that the cost inefficiency is zero because the firm has already produced at the cost frontier. Because $\{x - \vec{D}_I(x,y,b;h_x)h_x\} \in L(Y)$, the following can be derived:

$$\vec{D}_I(x,y,b;h_x) \leq \frac{px - C(y,p)}{ph_X} = CI(x,y,b;h_x).$$

The difference between the left- and right-hand sides of the above equation is the allocative inefficiency ($\overrightarrow{AI}_I$), namely,

$$CI(x,y,p;h_x) = \vec{D}_I(x,y,b;h_x) + \overrightarrow{AI}_I. \tag{5}$$

In other words, the estimate of $\vec{D}_I(x,y,b;h_x)$ is the TI measure in Eq. (3).

B. Endogenous Inputs and Environmental Variables

There are several methods in the literature to cope with the endogeneity problem, including the IV approach, two-stage least squares, three-stage least squares, generalized method of moments, and limited information maximum likelihood. The literature exploring the endogeneity problem under the stochastic frontier model includes Kutlu (2010), Karakaplan and Kutlu (2017b), and Tran and Tsionas (2013, 2015). This paper intends to utilize the IV approach proposed by Amsler, Prokhorov, and Schmidt (2016, 2017).

After the translation property and symmetry of the DIDF are considered, and a disturbance term $v_1 \sim N(0,\sigma_{v1}^2)$ added, we specify the DIDF as:

$$-x_1 = \vec{D}_I(x_2 - x_1,\ldots,x_N - x_1, y, b; h_x) + \varepsilon_1, \tag{6}$$

where $\varepsilon_1 = v_1 - u_1$ is referred to as the composed error; $TI = u_1 = \vec{D}_I(x, y, b; h_x) \sim |N(0,\sigma_{u1}^2|$ indicates the firm's technical inefficiency; v_1 is assumed to be statistically independent of u_1. Here x_1 is arbitrarily chosen for translation in Eq. (6). Other inputs can also be selected for translation.

$\vec{D}_I(x_2 - x_1,\ldots,x_N - x_1, y, b; h_x)$ is usually specified as a quadratic function. The vector of independent variable (X) contains the linear, quadratic, and cross-product terms of those translated inputs and outputs. According to Amsler, Prokhorov, and Schmidt (2016), Eq. (6) is expressed as a linear regression model:

$$-x_{1i} = \alpha + X_{1i}'\beta_1 + X_{2i}'\beta_2 + \varepsilon_{1i}, i = 1,\ldots,n, \tag{7}$$

where X_{1i} is a $j_1 \times 1$ vector of desirable and undesirable outputs and assumed to be independent of ε_{1i}; and X_{2i} is a $j_2 \times 1$ vector that consists of all inputs, except for x_{1i}. It is assumed that $E(v_{1i} | X_{2i}) \neq 0$, i.e., X_{2i} is correlated with v_{1t} but uncorrelated with u_{1t}. The elements of X_{2i} are viewed as endogenous variables.

The model of Amsler, Prokhorov, and Schmidt (2016) is extended to allow u_{1i} to be linked with a set of environmental variables, which differs from Amsler, Prokhorov, and Schmidt (2017) in two aspects. First, following the convention, u_{1i} is assumed to be statistically independent of v_{1i}. The reason is that u_{1i} signifies the firm's managerial abilities and is less likely to be correlated with the uncontrollable random variable v_{1i}. It should be noted that the required likelihood function must be re-derived. Second, without the assumption of the scaling property between u_{1i} and the environment variables, this paper assumes that $u_{1i} = \gamma_1' q_{1i} + \omega_{1i} \geq 0$, where q_{1i} denotes a group of environment variables; γ_1 is the corresponding unknown parameters to be estimated; and $\omega_{1i} (\sim N(0,\sigma_{\omega1}^2))$ is a normally distributed random variable. The variance of ω_{1i} before truncation is equal to $\sigma_{\omega1}^2$. Since $u_{1i} \geq 0$ by construction, implying $\omega_{1i} \geq -\gamma_1' q_{1i}$. Previous works, such as Huang and Liu (1994), Battese and Coelli (1995), Huang, Huang, and Liu (2014), Jiang and Sharp (2015), Lundgren and Marklund (2015), Almanidis, Karakaplan, and Kutlu (2019), and Jiang and Andrews (2020), all have a similar setup as in this paper.

Let $X_i = \begin{bmatrix} X_{1i} \\ X_{2i} \end{bmatrix}$; Eq. (7) is rewritten as:

$$\begin{aligned} -x_{1i} &= \alpha + X_i'\beta + v_{1i} - \gamma_1' q_i - \omega_{1i}, \quad i=1,\ldots,n \\ &= \alpha + X_i'\beta - \gamma_1' q_{1i} + \varepsilon_{1i}, \end{aligned} \tag{8}$$

where $\varepsilon_{1i} = v_{1i} - \omega_{1i}$.[4] It is assumed that ω_{1i} is statistically independent of v_{1i}, and all environmental variables are exogenous. Let w_i represent the vector of extra IVs and the number of instruments must be greater than or equal to the number of endogenous variables in X_{2i}. Let

$$z_i = \begin{bmatrix} 1 \\ X_{1i} \\ w_i \end{bmatrix}.$$

The reduced form of endogenous variables X_{2i} is expressed as:

$$X_{2i} = \pi_X' z_i + \eta_i, \tag{9}$$

where π_X is the vector of the reduced form coefficient. v_{1i} is allowed to be correlated with η_i, but both of them are uncorrelated with ω_{1i}. Equations (8) and (9) can be rewritten into a matrix form as follows:

$$X_2 = Z\pi_X + \eta, \tag{10}$$

$$-x_1 = \alpha + X\beta - q_1\gamma_1 - \varepsilon_1. \tag{11}$$

The joint probability density function of random variables ω_1, v_1, and η is expressed as:

$$f_{\omega_1,v_1,\eta}(\omega_1,v_1,\eta) = f_{\omega_1}(\omega_1) \times f_{v_1,\eta}(v_1,\eta) = f_{\omega_1}(\omega_1) \times f_{v_1|\eta}(v_1) \times f_\eta(\eta).$$

Then,

$$\begin{aligned} f_{\varepsilon_1,\eta}(\varepsilon_1,\eta) &= \int_{-\gamma_1' q_1}^{\infty} f_{\omega_1,v_1,\eta}(\omega_1, \varepsilon_1 + \omega_1, \eta) d\omega_1 \\ &= f_\eta(\eta) \int_{-\gamma_1' q_1}^{\infty} f_{\omega_1}(\omega_1) f_{v_1|\eta}(\varepsilon_1 + \omega_1 | \eta) d\omega_1. \end{aligned}$$

4 In order to simplify symbols, $\varepsilon_{1i} (= v_{1i} - \omega_{1i})$ is still used.

Assume that η has a joint normal distribution, and then $f_\eta(\eta)=$constant. $|\Sigma_{\eta\eta}|^{-\frac{1}{2}} \times \exp(-\frac{1}{2}\eta'\Sigma_{\eta\eta}^{-1}\eta)$, where $\Sigma_{\eta\eta}^{-1}$ is the inverse of the covariance matrix. The conditional probability density function of $v_1 | \eta$ can be proved to be a multivariate normal distribution of $N(\mu_c, \sigma_c^2)$, where $\mu_c = \Sigma_{v_1\eta}\Sigma_{\eta\eta}^{-1}\eta$ and $\sigma_c^2 = \sigma_{v1}^2 - \Sigma_{v_1\eta}\Sigma_{\eta\eta}^{-1}\Sigma_{\eta v_1}$.[5]

Thus, $\int_{-\gamma_1' q_1}^{\infty} f_{\omega_1}(\omega_1) \times f_{v_1|\eta}(\varepsilon_1 + \omega_1 | \eta) d\omega_1$ is the convolution of the half-normal distribution $|N(0, \sigma_{\omega_1}^2)|$ and normal distribution $N(\mu_c, \sigma_c^2)$. By employing the variable transformation technique and let $\tilde{\varepsilon} = \varepsilon_1 - \mu_c$, $\tilde{v} = v_1 - \mu_c$, and $\omega_1 = u_1 - \gamma_1' q_1$, the distribution of $\tilde{\varepsilon} | \eta$ can be derived from the convolution of $N(0, \sigma_c^2)$ and $N(0, \sigma_{\omega_1}^2)$, whose probability density function is $\frac{1}{\sigma \Phi\left(\frac{\gamma_1' q_1}{\sigma_{\omega_1}}\right)} \Phi(B) \Phi\left(\frac{\tilde{\varepsilon}}{\sigma}\right)$, where $\sigma^2 = \sigma_{\omega_1}^2 + \sigma_c^2, B = \frac{\gamma_1' q_1 \sigma^2 - \tilde{\varepsilon}\sigma_{\omega_1}^2}{\sigma_c \sigma_{\omega_1} \sigma}$. Finally, by reverting the above variable transformation, namely $\varepsilon_1 = \tilde{\varepsilon} + \mu_c$, the following can be obtained:

$$f_{\varepsilon_1,\eta}(\varepsilon, \eta) = \text{constant} \times |\Sigma_{\eta\eta}|^{-\frac{1}{2}} \exp(-\tfrac{1}{2}\eta'\Sigma_{\eta\eta}^{-1}\eta)\sigma^{-1}\, \Phi\left[\frac{\gamma_1' q_1}{\sigma_{\omega_1}}\right]^{-1} \Phi[B] \Phi\left(\frac{\varepsilon_1 - \mu_c}{\sigma}\right). \quad (12)$$

Taking the natural logarithm of the above equation and summing over all samples to obtain the log-likelihood function:

$$\begin{aligned}
\ln L &= \ln L_1 + \ln L_2, \\
\ln L_1 &= -\tfrac{n}{2}\ln\sigma^2 - \Sigma_i \ln\left[\Phi\left(\tfrac{\gamma_1' q_{1i}}{\sigma_{\omega 1}}\right)\right] + \Sigma_i \ln\left[\Phi(B_i)\right] \\
&\quad - \tfrac{1}{2\sigma^2}\Sigma_i(-x_{1i} - \alpha - \beta x_i' - \mu_{ci} + \gamma_1' q_{1i})^2, \\
\ln L_2 &= -\tfrac{n}{2}\ln(|\Sigma_{\eta\eta}|) - \tfrac{1}{2}\Sigma_i(\eta_i'\Sigma_{\eta\eta}^{-1}\eta_i),
\end{aligned} \quad (13)$$

where $B_i = \frac{\gamma_1' q_{1i}\sigma^2 - (-x_{1i} - \alpha - \beta x_i' - \mu_{ci} + \gamma_1' q_{1i})\sigma_{\omega 1}^2}{\sigma_c \sigma_{\omega 1}\sigma}$.

This paper utilizes the two-stage method suggested by Kutlu (2010) and Amsler, Prokhorov, and Schmidt (2016) to estimate the above model. In the first stage, Eq. (10) is estimated by the OLS to obtain the coefficient estimates of $\hat{\pi}_X$, which are used to calculate the covariance matrix $\hat{\Sigma}_{\eta\eta} = \frac{1}{n}\Sigma_i(X_{2i} - \hat{\pi}_X' z_i)(X_{2i} - \hat{\pi}_X' z_i)'$. In the second stage, Eq. (13) is estimated by ML, yielding the following parameter estimates: $\alpha, \beta, \gamma, \sigma_{\omega_1}^2, \sigma_c^2$, and $\Sigma_{v_1\eta}$.

The conditional probability density function of $\omega_1 | \tilde{\varepsilon}$ is:

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5 $\Sigma_{v_1\eta}$ is the covariance vector of the error term v_1 and η_i. In our empirical analysis, there are three endogenous inputs, meaning that vector $\Sigma_{v_1\eta}$ contains three elements, i.e., $\Sigma_{v_1\eta_1}, \Sigma_{v_1\eta_2}$, and $\Sigma_{v_1\eta_2}$.

$$f(\omega_1 \mid \tilde{\varepsilon}) = \frac{1}{\sqrt{2\pi}\,\frac{\sigma_c \sigma_{\omega 1}}{\sigma}\,\Phi[B]} \exp\left[-\frac{1}{2} \times \frac{\left(\omega_1 + \tilde{\varepsilon}\left(\frac{\sigma_{\omega 1}^2}{\sigma^2}\right)\right)^2}{\sigma_c^2 \sigma_{\omega 1}^2 / \sigma^2} \right]$$

$$= \frac{1}{\Phi\left[\frac{\gamma_1' q_1 + \mu_s}{\sigma_s}\right]\sqrt{2\pi}\sigma_s} e^{-\frac{1}{2}\left(\frac{\omega_1 - \mu_s}{\sigma_s}\right)}, \tag{14}$$

where $\mu_s = -\tilde{\varepsilon}\left(\frac{\sigma_{\omega 1}^2}{\sigma^2}\right)$ and $\sigma_s^2 = \frac{\sigma_c^2 \sigma_{\omega 1}^2}{\sigma^2}$. Eq. (14) shows that the random variable $(\omega_1 \mid \tilde{\varepsilon})$ has a truncated normal distribution $N(\mu_s, \sigma_s^2)$ at the point $-\gamma_1' q_1$. Its conditional mean can be shown to be:

$$E(\omega_1 \mid \tilde{\varepsilon}) = \mu_s + \sigma_s \frac{\phi\left[\frac{\gamma_1' q_1 + \mu_s}{\sigma_s}\right]}{\Phi\left[\frac{\gamma_1' q_1 + \mu_s}{\sigma_s}\right]}. \tag{15}$$

The coefficient estimates can be used to calculate TI measure:

$$TI = \hat{\gamma}_1' q_1 + \hat{E}(\omega_1 \mid \tilde{\varepsilon}), \tag{16}$$

where '^' denotes estimates. Hence, $\hat{E}(\omega_1 \mid \tilde{\varepsilon})$ is the estimated value of Eq. (15). The *TI* measure is calculated, according to Eq. (16). The next sub-section introduces how to estimate $CI(x, y, w, h_x)$ in Eq. (5). The measure of $\overrightarrow{AI}_I$ can be computed accordingly.

C. Cost Frontier and Environmental Variables

Let E be the actual cost of banks and p the vector of factor prices. The cost function must be a homogeneous function of degree one in input prices, as required by microeconomics. We arbitrarily choose the first input price, p_1, to normalize the cost function and formulate it as

$$\frac{E}{p_1} = C\left(\frac{p}{p_1}, y\right) + \varepsilon_2, \tag{17}$$

where y denotes the vector of output and $C(.)$ the optimal cost function in Eq. (4). To show the impacts of banks' CSR activities on their production costs, we include the CSR variable in the cost function as a quasi-fixed input. Similar to the DIDF in the previous section, $C(.)$ is set as a quadratic function of $p/p_1, y$, $p/p_1, y$, and CSR, which contains the linear, quadratic, and cross-product terms of these variables.

The composed error term of ε_2 is equal to $v_2 + u_2$. Notation $v_2 \sim N(0, \sigma_{v2}^2)$ is the statistical noise; $u_2 (= \gamma_2' q_2 + \omega_2) \geq 0$ is a non-negative random variable representing the increase in cost, incurred by technical inefficiency; $\omega_2 \sim N(0, \sigma_{\omega 2}^2)$ is a one-sided random variable, i.e., $\omega_2 \geq -\gamma_2' q_2$; q_2 denotes a set of environmental variables affecting cost inefficiency; and γ_2 is the corresponding coefficient vector. The truncated probability density function of ω_2, $f(\omega_2)$, is easily derived as $f(\omega_2)=\frac{1}{\sqrt{2\pi}\sigma_{\omega 2}}e^{\frac{-1}{2}\left(\frac{\omega_2}{\sigma_{\omega 2}}\right)^2}/\left[1-\Phi\left(\frac{\gamma_2' q_2}{\sigma_{\omega 2}}\right)\right]$, where $\Phi(.)$ is the cumulative distribution function of the standard normal distribution. The probability density function of ε_{2i}, $f(\varepsilon_{2i})$, can be written as:

$$f(\varepsilon_{2i})=\frac{\Phi(\tilde{B}_i)\phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right)}{\sigma_2\Phi\left[\frac{\gamma_2' q_{2i}}{\sigma_{\omega 2}}\right]}, \tag{18}$$

where $\tilde{B}_i=(\gamma_2' q_{2i}\sigma_2^2+\varepsilon_{2i}\sigma_{\omega 2}^2)/\sigma_{v2}\sigma_{\omega 2}\sigma_2$ and $\sigma_2=\sqrt{\sigma_{\omega 2}^2+\sigma_{v2}^2}$.

By substituting $\varepsilon_{2i}=\frac{E_i}{p_{1i}}-C\left(\frac{p_i}{p_{1i}},y_i\right)$ into Eq. (18), we have the corresponding log-likelihood function for the cost function of Eq. (17), which allows one to estimate its coefficients. The conditional probability density function of $\omega_2\,|\,\varepsilon_2$ is:

$$f(\omega_2\,|\,\varepsilon_2)=\frac{1}{\Phi\left[\frac{\gamma_2' q_2+\mu_*}{\sigma_*}\right]\sqrt{2\pi}\sigma_*}e^{-\frac{1}{2}\left(\frac{\omega_2-\mu_*}{\sigma_*}\right)^2}, \tag{19}$$

where $\mu_*=\varepsilon_2\frac{\sigma_{\omega 2}^2}{\sigma_2^2}$ and $\sigma_*^2=\frac{\sigma_{v2}^2\sigma_{\omega 2}^2}{\sigma_2^2}$. Eq. (19) is merely a truncated normal distribution $N(\mu_*,\sigma_*^2)$ at the point $-\gamma_2' q_2$ from below. Its mean value is:

$$E(\omega_2\,|\,\varepsilon_2)=\mu_*+\sigma_*\frac{\phi\left[\frac{\gamma_2' q_2+\mu_*}{\sigma_*}\right]}{\Phi\left[\frac{\gamma_2' q_2+\mu_*}{\sigma_*}\right]}. \tag{20}$$

The coefficient estimates of Eq. (17) can be used to calculate the cost inefficiency value (CIV):

$$CIV=\hat{\gamma}_2 q_2+\hat{E}(\omega_2\,|\,\varepsilon_2), \tag{21}$$

where "^" denotes estimates. Thus, $\hat{E}(\omega_2\,|\,\varepsilon_2)$ is the estimate of Eq. (20). It should be noted that the CIV is the numerator of Eq. (4), which can be translated into the cost inefficiency estimate of $CI(x,y,w,h_x)$ by dividing wh_x. Based on Eq. (5), it is clear that CI minus TI equals $\overrightarrow{AI}_I$, namely $\overrightarrow{AI}_I=CI-TI$.

IV. Data Analysis

A. The Measurement of CSR Activities

Recently, a few CSR databases have gradually emerged. For instance, the

CSR survey data from the MSCI KLD 400 index is often used in studies on American enterprises. This database only surveys the U.S. banking and non-banking industries. Using the cross-country survey data on banking industry of EIRIS database, Wu and Shen (2013) and Huang et al. (2019) investigate the relationship between CSR and banks' financial performance, and the effects of banks' CSR activities on their technical efficiencies, respectively. This paper also collects relevant CSR variables from the EIRIS database.

Brammer and Pavelin (2006) use the EIRIS dataset and categorize the questionnaire items into five dimensions, including community, environment, employee, human rights, and supply chain management. Among those dimensions, they choose communities, the environment, and employees to digitalize the text as proposed by Graves and Waddock (1994), due to incomplete data on human rights and supply chain management. Brammer and Pavelin (2006) obtain various CSR scores, where their scoring method is similar to that of Wu and Shen (2013) and Hu (2020).

In addition to the three CSR dimensions of Brammer and Pavelin (2006), this paper considers two more dimensions, such as corporate governance and stakeholders, to analyze the relationship between banks' CSR activities and their production efficiencies. The questionnaire collection rates differ among the five dimensions: (a) community: the questionnaire collection rate is 90.02%; (b) environment: three of the questions are related to banks' environmental management, policies, and reports, the collection rates of which are all 100%; (c) employee: five of the 14 questions have the collection rates above 90% and are the main cores of this dimension; (d) corporate governance: a total of 21 questions are designed, of which four have the collection rates above 90%, the four core questions are related to female board governors and banks' codes of ethics, and four other questions with the collection rates ranging from 70% to 80% are also taken into consideration to ensure the completeness of this dimension; (e) stakeholder: stakeholders refer to banks' suppliers and customers; the main contents of the EIRIS questionnaire are (i) whether banks treat stakeholders well, (ii) whether decisions are made based on stakeholders' interests, and (iii) whether banks establish good relationships with their stakeholders. Most questions in this dimension have very high collection rates.

Each question is scored on a scale of 0 to the number of options. For example, if the question has three options, then the score is recorded to be 0, 1, or 2; if the question has six options, then the score is coded to be 0, 1, 2, 3, 4, or 5. Since the number of options varies across questions, the scores are not comparable among one another. As a result, they are standardized by the equation of $\frac{x-\min}{\max-\min}\times 2+1$. The standardized scores range between 0 and 5. The scores of all dimensions are added up as the CSR index of the sample bank. The higher the index is, the more active the sample bank will engage in CSR activities.

From EIRIS databank, 287 banks across 32 countries are retrieved, spanning from 2003 to 2014. The input and output variables are taken from the accounting reports, provided by ORBIS Bank Focus (former Bankscope) of Bureau Van Dijk. After deleting non-commercial banks and the samples with missing variables and extreme values, we obtain 220 banks left with a total of 1,535 bank-year observations. Most of these samples are from developed countries or regions, with 1,480 samples from high-income countries, 52 samples from middle-high income countries, and only 3 observations from low-income countries. Moreover, there are 374 samples from the United States, 504 from Europe, 379 from Japan, 47 from South Korea, 42 from Hong Kong, and 36 from Singapore.

EIRIS only discloses bank names, countries, and regions. Users must compare these items with bank names in the ORBIS Bank Focus database to correctly retrieve relevant variables, such as inputs, outputs, and financial ratios, from the corresponding accounting statements. ORBIS provides both consolidated and unconsolidated bank statements. This paper selects consolidated statements due to its completeness, except for Japanese banks where the unconsolidated statements are used because the variable of personnel expenses is unavailable in the consolidated statements.

B. Definitions of Bank's Inputs and Outputs

Berger and Humphrey (1997) note two popular methods in defining the input and output items for the banking industry. First, the production approach holds that banks produce different types of loans and deposits using capital and labor, in which the number of transactions or the number of transaction accounts is defined as an output. Operating costs that provide financial services are treated as an input. The number of transaction accounts is not affected by inflation. However, different bank accounts require different services or costs, and the number of transaction accounts is usually not available. Parkan (1987) and Ferrier and Lovell (1990) suggest that the production approach is suitable for analyzing the performance of bank branches. Second, the intermediation approach views banks as financial intermediaries, employing labor, capital, and funds (various deposits) to produce loans, investments, and non-interest incomes (or off-balance sheet items). Because these input and output variables are easily collected, this method is wildly used by researchers and hence is exploited by the current paper.

Loans, other operating assets (investments), and non-interest incomes are defined as output items in this paper. On the other hand, input items include the number of employees, fixed assets, and deposits. A salient feature of this paper is identifying the CSR index as one of the inputs to highlight its importance in the production process of the banking industry. However, it has to be included in the cost function as a quasi-fixed input since its price is unobservable. Another feature of this paper is the inclusion of banks' undesirable outputs (i.e., non-performing loans) in the DIDF to correctly describe bank's entire production process. The four defined inputs are discretionary by bank managers and should be regarded as endogenous variables that are correlated with the disturbance term.

Table I presents descriptive statistics for the sample banks. The average value of loans (*yy*1) is equal to USD 157,648.3928 million, the average value of other earning assets (*yy*2) is equal to USD 143,844.1293 million, and the average number of employees (*x*1) equals 33,001 persons, indicating that EIRIS tends to survey large commercial banks. The average non-interest income (*yy*3) is USD 4,045.9207 million, the average fixed asset (*xx*2) is USD 2,276.3693 million, and the average deposit (*xx*3) is USD 213,962.9031 million. The average amount of non-performing loans is USD 4,965.6276 million, the average bad loan rate is 2.9724%, and the average CSR (*csrc*) score is 13.5165. All of the standard deviations of the above variables, except for the CSR score, are quite large relative to their respective mean values, indicating that those items vary substantially among the sample banks.

Table I
Sample Statistics for the DIDF

[1] Measured in millions of U.S. dollars and deflated by the consumer price indices of individual countries with base year 2010. [2] *bad_rate* is the ratio of non-performing loans to total loans.

Variable	Mean	Std. Dev.	Minimum	Maximum
Total Loans (*yy*1)[1]	157,648.3928	221,864.9067	23.1641	1,287,053.1570
Other Earning Assets (*yy*2)[1]	143,844.1293	293,915.8042	134.2420	2,362,991.7450
Non-Interest Income (*yy*3)[1]	4,045.9207	7,471.4119	0.4104	52,537.6399
Number of Employees (*x*1)	33,001.57	58,202.3515	196.0000	493,583.0000
Fixed Assets (*xx*2)[1]	2,276.3693	3,795.6923	17.9008	28,959.6658
Deposits (*xx*3)[1]	213,962.9031	333,622.3916	881.8773	2,089,566.1200
Non-Performing Loans (*bad*)[1]	4,965.6276	10,471.7261	0.0367	110,226.4198
bad_rate (%)[2]	2.9724	3.5738	0.0300	44.8900
CSR Score (*csrc*)	13.5165	4.2937	5.6000	23.3354

The correlation coefficients among the above variables are all positive, indicating a positive correlation between the input and output items. In addition, the positive correlation of non-performing loans and CSR with the inputs and outputs reveals that those two variables are correlated with banking operation and should be incorporated in the model for analysis.

The subprime mortgage crisis occurred between 2007 and 2009. This paper divides the sample period into three sub-periods, including the early (2003-2006), middle (2007-2009), and late (2010-2014) sub-periods. The sample statistics of all variables in the three sub-periods are not presented herein for brevity. The average rates of bad loans are gradually increasing over the three sub-periods, i.e., 2.0541%, 2.8488%, and 3.8026%, respectively. This implies that it takes some time to recover from the crisis, and justifies the inclusion of undesirable outputs into our model.

Table II shows the descriptive statistics of variables pertain to the cost function. The total cost is defined as the sum of personnel expenses, other operating expenses, and interest expenses. The input prices are obtained by dividing the above three expenses over the corresponding input quantities. The average total cost is equal to USD 10,696.2691 million, in which the interest expenses account for the largest proportion (48.78%), amounting to USD 5,217.8606 million. This unveils that the factor of deposits plays a key role for banking operations. The average wage (p_1) is USD 89,500. The price of capital input (p_2) is defined as the ratio of other operating expenses to fixed assets, with an average of 1.2877%. The price of deposits (p_3) is calculated as the ratio of interest expenses to total deposits, and its average value is 2.2783%. The above two factor prices can be regarded as interest rates. The standard deviations of most variables exceed the corresponding mean values, indicating that the sample banks diverge widely.

Table II
Sample Statistics for the Cost Frontier

[1] Measured in millions of U.S. dollars and deflated by the consumer price indices of individual countries with base year 2010. [2] p_1=Personnel expenses/Number of employees, which is deflated by the consumer price indices of individual countries with base year 2010. [3] p_2(%)=Other operating expenses/Fixed assets. [4] p_3(%)=Interest expenses/Deposits.

Variable	Mean	Std. Dev.	Minimum	Maximum
Total Cost[1]	10,696.2691	17,684.6083	37.8709	144,869.1685
Personnel Expenses[1]	2,873.2144	4,991.5989	14.7589	36,081.6156
Other Operating Expenses[1]	2,605.1941	4,637.2781	11.0931	36,641.0055
Interest Expenses[1]	5,217.8606	9,664.2759	10.8824	93,639.0076
Price of Labor (p_1)[2]	0.0895	0.0421	0.0061	0.5100
Price of Fixed Assets (p_2)[3]	1.2877	1.4112	0.0460	29.9858
Price of Deposits (p_3)[4]	2.2783	2.0352	0.0407	19.0610

C. The Effects of CSR Activities on Bank's Performance

This subsection discusses some hypotheses that link the motives of banks' engaging in CSR with efficiency. The three hypotheses mentioned in Section II.A are altruism, strategic choices, and greenwashing. When estimating the DIDF, some components of the CSR score are considered as a part of the environmental variables. If the component has negative effects on TE, then banks' participation in CSR activities fits the altruistic motive; if the component has positive effects on TE, then the strategic motive is confirmed; and if the component has no effects on TE, then the greenwashing motive is supported.

Similarly, when estimating the cost function, some items of the CSR score are also incorporated into the set of environmental variables. If the item has negative effects on cost (economic) efficiency, then banks' participation in CSR activities fits the altruism motive; if the item has positive effects on cost (economic) efficiency, then the strategic choice motive is confirmed; and if the item has no effects on cost (economic) efficiency, then the greenwashing motive is supported.

Based on Equations (3) and (5), AI is equal to the difference between CI and TI. Therefore, the impacts of CSR score and its components on AI depend on their effects on TI and CI. If CSR activities have negative (positive) effects on both TI and CI—that is, both fit with the altruism motive (strategic choices motive)—then the effects on AI are uncertain. On the contrary, if CSR activities have negative (positive) effects on TI and positive (negative) effects on CI, then the effects on AI are positive (negative).

D. Environmental Variables

In addition to managerial abilities, some external environmental factors could influence the efficiency of banks, such as market competition, location, and the age of banks. These environmental factors should be considered in the efficiency evaluation process so that the assessed units face the same business environment, and the resulting efficiency estimates will be fair and comparable among the sample banks. The choices of environmental variables are generally referred to previous literature, as suggested by Huang et al. (2011). This paper selects environmental variables based on Mester (1993), Allen and Rai (1996), Lozano-Vivas, Pastor, and Pastor (2002), Huang, Chiang, and Tsai (2015), and Lee and Huang (2017, 2019).

In estimating the DIDF, three environmental variables are considered. First, the market share of the top five banks ($CR5$) in the country where the sample banks are located. A high market share signifies high market concentration. In a highly concentrated financial market, if a bank is found to be technically efficient, then the quiet life hypothesis (QLH) is not supported.[6] Second, for the variable of age of bank, if an older bank outperforms a younger one, then learning effects prevail, and the managerial abilities of the sample banks are

[6] Quiet life hypothesis means that firms with dominant market power are likely to be less productive due to lack of stimulation from competitors. See, for example, Berger and Hannan (1998) and Koetter, Kolari, and Spierdijk (2012).

expected to gradually improve over time. Third, for the variable of CSR employee score (*csrc_emp*), a high score of the item means that the bank pays more attention on their employees' well-being. As a result, its employees may have high centripetal forces, which can stimulate production potential and production efficiency. This is consistent with the strategic motivation of the bank's participation in CSR activities.[7]

The environmental variables affecting banks' cost-efficiency consist of internal and external factors. The latter includes the industry-wide and macro-economic conditions, and eight environmental variables are chosen. Apart from the three variables emerging in the DIDF, five additional variables are utilized. The first two are return on assets (*ROA*) and equity to total assets ratio (*ETA*), which are commonly used to evaluate firms' performance. The higher the value of *ROA*, the higher profitability the bank, indicating better managerial abilities. On the other hand, a value of high *ETA* indicates that banks have sound capital structures and low liquidation risks. The third environmental variable is CSR corporate governance score (*csrc_gov*), which indicates the extent to which the bank observes the corporate governance principle. The above three variables belong to internal factors associated with cost efficiency. The fourth and fifth environmental variables are the ratio of total bank assets in a country to GDP (*bank_rate*) and GDP per capita (*gdp_per*), which are used by many researchers as environmental factors. High values in these two macro-variables reflect better financial environment and economic development that may improve banks' cost efficiency.

Table III shows sample statistics of the environmental variables. The average *ROA* is equal to 0.6064%, while the average *ETA* is 6.9135%, indicating that the sample banks operate with a high leverage, which is consistent with the public perception. The average value of *bank_rate* is as high as 119.0696%, implying that the banking industry plays an important role in the overall economic development of a country. The average per capita GDP over all countries is USD 41,403.2775. Furthermore, the average value of *CR*5 is 66.2786%, indicating that the banking industry of the sample countries is somewhat concentrated. The average age of the sample banks reaches 76.9857 years, reflecting that our sample banks are old. The average score of CSR employees is 2.2305, which is lower than that of corporate governance. This indicates that the sample banks should pay more attention on the well-beings of their employees.

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7 There are three motivations for enterprises to engage in CSR activities: altruism, strategic choices, and greenwashing. If enterprises are driven by altruism, CSR activities are expected to have a negative relationship with their efficiencies; if enterprises are driven by strategic choices, CSR activities are expected to have a positive relationship with their efficiencies; and if enterprises are driven by greenwashing, CSR activities are expected to have nothing to do with efficiencies. Please refer to Wu and Shen (2013).

The mean value of *ROA* in the first sample period (2003-2006) is 0.8953% and is the highest among the three sub-periods. It declined to 0.41% during the period of subprime mortgage crisis (2007-2009) and slightly increased to 0.4817% in the last sample period (2010-2014). It is noticeable that the average values of the remaining environmental variables increase over time.

V. Empirical Outcomes

In this section, subsection A reports the parameter estimates and TE scores obtained from the DIDF, where endogenous inputs and environmental variables are considered; subsection B analyzes the estimation results for the cost function, including CE and AE measures.

Table III
Descriptive Statistics of the Environmental Variables

[1] Measured in millions of U.S. dollars and deflated by the consumer price indices of individual countries with base year 2010. [2] *CR*5 denotes assets of five largest banks as a share of total commercial banking assets (%).

Variable	Mean	Std. Dev.	Minimum	Maximum
Return on Assets (*rroa*, %)	0.6064	0.9794	-13.4100	4.4300
Equity/Total Assets (*eta*, %)	6.9135	3.4299	-3.9300	32.7960
CSR_governor (*csrc_gov*)	3.4526	0.8417	1.3000	5.0000
Bank Assets/GDP (*bank_rate*, %)	119.0696	51.3779	21.7430	263.8111
GDP Per Capita (*gdp_per*)[1]	0.0414	0.0124	0.0015	0.1027
*CR*5 (%)[2]	66.2786	20.8501	31.0400	100.0000
Bank Age (*age*)	76.9857	53.5981	1.0000	232.0000
CSR_employees (*csrc_emp*)	2.2305	0.8281	1.0000	4.1133

A. Parameter Estimates of the DIDF

The reduced form equations of (10) are first estimated using the OLS. The instruments contain the three input prices and their cross-product terms, in addition to the desirable and undesirable output variables in the DIDF, as well as linear and quadratic time trends. This section does not present the coefficient estimates of the reduced form equations for brevity. Next, the likelihood function of Eq. (13) is estimated by ML to gain parameter estimates, such as $\alpha, \beta, \gamma, \sigma^2_{\omega_1}, \sigma^2_c$, and $\Sigma_{v_1\eta}$. Table IV exhibits those estimates. The dependent variable is chosen as the negative value of the number of employees.

According to Table IV, 33 out of the 45 coefficient estimates are found to be significant at the 10% significance level or above. Among the three covariance estimates, $\Sigma_{v_1\eta_1}, \Sigma_{v_1\eta_2}$, and $\Sigma_{v_1\eta_3}$, two of them are significant at the 1% level. The null hypothesis that the three covariances are jointly equal to zero is rejected by the log-likelihood ratio test since the test statistic is equal to 123.2 and exceeds the critical value even at the 1% level of significance. The null hypothesis of no endogeneity is thus rejected, indicating the presence of endogenous inputs that should be disentangled in the regression model.

Table IV
Parameter Estimates of the DIDF with Endogenous Inputs and Environmental Variables

*yy*1 is total loans, *yy*2 is other operating assets, *yy*3 is non-interest revenue, *bad* denotes non-performing loans, *x*2 denotes fixed assets, *x*3 denotes deposits, *csrc* signifies CSR score, *t* signifies time trend, *CR*5 signifies assets of five largest banks as a share of total commercial banking assets (%), *age* signifies the age of banks in number of years, and *csrc_emp* signifies the score of the item employees in CSR activities. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Parameter Estimates	Standard Error	Variable	Parameter Estimates	Standard Error
Intercept	-952.876***	180.553	$yy2\times x3$	2.74E-07	2.07E-07
$yy1$	0.0018	0.0019	$yy2\times csrc$	-5.30E-02***	1.22E-02
$yy2$	0.0102***	0.0018	$yy3\times x2$	-5.05E-05*	2.87E-05
$yy3$	0.3299***	0.0500	$yy3\times x3$	2.89E-05***	7.85E-06
bad	0.0903***	0.0216	$yy3\times csrc$	-0.0113***	0.0035
$x2$	1.0603***	0.0054	$yy1\times t$	5.66E-03	1.27E-02
$x3$	-0.0152***	0.0025	$yy2\times t$	-2.13E-03	9.05E-03
$csrc$	116.643***	21.8996	$yy3\times t$	-0.0194***	0.0034
t	-37.8907***	12.1616	$csrc\times t$	0.7303	0.9672
$yy1^2$	-2.39E+06***	4.88E+07	$bad\times x2$	-7.22E-05***	1.32E-05
$yy2^2$	1.20E-07	1.7E-07	$bad\times x3$	1.51E-05***	5.11E-06
$yy3^2$	-9.48E-04***	2.63E-04	$bad\times$csrc	-0.0041***	0.0011
bad^2	1.89E-04***	5.16E-05	$bad\times t$	-0.0053***	0.0012
$x2^2$	3.09E-05***	2.81E-06	$x2\times x3$	-2.54E-06***	7.88E-07
$x3^2$	-3.16E-06***	4.44E-07	$x2\times csrc$	-0.0013***	0.0003
$csrc^2$	-0.9740	1.4798	$x2\times t$	0.0005*	0.0003
t^2	1.7198	1.6306	$x3\times t$	0.0006***	0.0001
$yy1\times yy2$	6.24E-07***	2.37E-07	$x3\times csrc$	0.0005***	0.0002
$yy1\times yy3$	-5.44E-06*	9.97E-06	$\Sigma_{v_1\eta_1}$	-2.39E+06***	268,366
$yy1\times bad$	-2.43E-05***	4.80E-06	$\Sigma_{v_1\eta_2}$	-1.78E+06	1.19 E+06
$yy2\times yy3$	-3.14E-06	3.88E-06	$\Sigma_{v_1\eta_3}$	-464.995***	68.2368
$yy2\times bad$	-6.67E-06***	2.52E-06	σ_{ω_1}	9,612.25***	1,967.15
$yy3\times bad$	-2.60E-04***	9. 21E-05	σ_c	20.1852***	5.8106
$yy1\times x2$	-8.06E-06***	1.42E-06	Environmental Variables		
$yy1\times x3$	2.24E-06***	4.36E-07	$CR5$	-997.596***	364.794
$yy1\times csrc$	8.26E-04	1.17E-02	age	-725.076**	298.381
$yy2\times x2$	3.94E-06***	6.64E-07	$csrc\_emp$	13,501.9***	3,702.81
Number of Observations	1,535		Log-Likelihood	-12,320.	

The coefficient estimates of the three environmental variables are all significant at the 5% level or above, suggesting that they are pivotal determinants of TE. Both estimates of *CR*5 and *age* are negative. The former validates that banks operating in a highly concentrated market tend to have higher technical efficiencies. The latter reveals that older banks have higher managerial abilities due potentially to the existence of learning effects. The estimates of CSR employ score (*csrc_emp*) are positive, consistent with the altruism of Baron (2001) and Forgione, Laguir, and Staglianò (2020). Our results differ from Wu and Shen (2013) and Belasri, Gomes, and Pijourlet (2020), who argue that strategic choices are the motivation for sample banks to participate in CSR activities. Vitaliano and Stella (2006) find that the engagement of CSR activities has nothing to do with cost efficiency, supporting the greenwashing motive.

Except for *csrc_gov* and *csrc_emp*, we separately consider the other three CSR sub-variables, namely *csrc_com* (CSR community score), *csrc_env* (CSR environment score), and *csrc_stak* (CSR stakeholder score), as the environment variables in the DIDF. The parameter estimate of *csrc_com* is positive but insignificant. Both estimates of *csrc_env* and *csrc_stak* are significantly positive and, hence, supporting the altruism motive of Baron (2001).

The null hypothesis that the coefficients of the three environmental variables are jointly zero is rejected, suggesting that the DIDF incorporates environmental variables. We also estimate the DIDF without including environmental variables. The parameter estimates are not shown due to limited paper length. Moreover, we estimate the DIDF excluding the variable of CSR score. The likelihood ratio test fails to support that these coefficients of CSR score variables are jointly zero, validating the inclusion of the CSR score in the DIDF.

The coefficient estimates in Table IV and Eq. (16) are used to calculate the average TI estimates, as shown in Table V. Since the dependent variable of the DIDF is the number of employees, the unit of the TI estimates is also the number of persons. The average *TI* is equal to 1,151.3, which can be re-expressed as the average *TE Score* of 0.9257, indicating that sample banks should reduce their current input quantities by 7.43% to achieve the production frontier. The average *TE Score* from estimating the DIDF without including environmental variables equals 0.8109, leading TE measure to be under-estimated. Thus, valid business strategies to improve efficiency may be misleading. The average *TI* and *TE Score* from the model excluding the CSR score variable are equal to 1,161.56 and 0.9207, respectively, indicating a slightly overestimated *TI* and underestimated *TE*.

The sample period is divided into three sub-periods, namely 2003-2006, 2007-2009 (period of subprime mortgage crisis), and 2010-2014. Table V shows the average technical efficiency is 0.93, 0.92, and 0.93, respectively. The ANOVA test shows no significant difference in the average *TE* among the three

Table V
Estimated Technical (in)Efficiency Scores

[1] Average *TE Score*=1−*TI*/Number of employees.

	With Environmental Variables		Without Environmental Variables	
	Mean	Std. Dev.	Mean	Std. Dev.
Average *TI*	1,151.3191	2,132.6790	1,608.7813	883.9548
Average *TE Score*[1]	0.9257	0.0866	0.8109	0.2088
Different Periods				
2003-2006	0.9274	0.0827	0.8006	0.2139
2007-2009	0.9222	0.1018	0.7938	0.2270
2010-2014	0.9281	0.0800	0.8228	0.1925
Different Areas				
Europe	0.9238	0.0671	0.9011	0.1808
America	0.9726	0.0329	0.8601	0.1650
Asia	0.8797	0.1031	0.6455	0.2102

sub-periods. Although the average *TE Score* is the lowest in the sub-period of subprime mortgage crisis, it does not decrease significantly. Two possible reasons are worth mentioning. (a) As indicated in subsection II.A, CSR activities bring some benefits to banks, such as reducing operating costs, prompting consumers' willingness to buy, increasing productivity, improving corporate goodwill and images, and having an insurance-like function; (b) in the financial crisis period, governments of various countries took steps to help the distressed banks, which helps to lessen the adverse effect incurred by the financial turmoil and boost consumer confidence. As a result, the unfavorable impacts on the sample banks were trivial.

We further divide the entire sample into three regions, namely Europe, America, and Asia.[8] Table V displays their respective average technical efficiencies, which are 0.92, 0.97, and 0.88. The ANOVA test statistic is significantly different from zero, supporting heterogenous TE measures among the three regions. Moreover, according to the pairwise tests, the average *TE* of American banks is significantly higher than that of European banks, and European banks outperform Asian banks. It is known that the economic development and some institutional factors in Asia differ from those in Europe and America, which may influence banks' managerial abilities.

For the purpose of comparison, we estimate the DIDF that ignores undesirable outputs. The coefficient estimates are used to compute the average *TI* (standard deviation) and *TE Score* (standard deviation), which are 1201.2057 (2197.0767) and 0.9196 (0.0881), respectively. Those average values are apt to overestimate (underestimate) the *TI* (*TE Score*), compared with the model

8 There are only 22 observations from Africa. We choose not to include them for comparison.

including undesirable outputs. Our findings are similar to Huang and Chung (2017), who apply the directional distance function to explore the efficiency changes in Taiwan's banking industry spanning 1999-2012, which contains the first financial reform in 2002. Our results are also consistent with Chiu et al. (2016), who utilize the network DEA model to examine 42 commercial banks in Taiwan from 2004 to 2012. Park and Weber (2006) analyze the banking industry in South Korea between 1992 and 2002 and conclude that the model overlooking undesirable outputs is likely to overestimate *TI*. Huang, Chiang, and Tsai (2015) explore the TE of the banking industry in 17 central and eastern European countries from 1995 to 2008. They undertake the meta-frontier directional distance function and draw the opposite conclusion, namely that many banks producing undesirables are operating at the group frontier.

B. Cost and Allocative Efficiencies

This subsection estimates the cost frontier to calculate *CI*, from which *TI* obtained from the above subsection is subtracted. This gives the measure of *AI*. Based on microeconomics, a cost function depends on input prices and output quantities, as specified in Eq. (17). Since the factor market is assumed to be perfectly competitive, both factor prices and outputs are regarded as exogenous variables. No endogeneity problem is presented in the cost frontier. We treat CSR as a quasi-fixed input in the cost frontier since we are unable to measure the costs and prices.

Here, the cost frontier is set as a quadratic function of factor prices, outputs, CSR, and time trend, similar to the DIDF of the previous subsection. The wage of employees (p_1) is used to normalize the actual cost (E) and the prices of the other two factors (capital and funds). In this manner, the homogeneous property of degree one in input prices is imposed on the cost frontier. The parameters of Eq. (17) can be estimated by ML, and the resulting estimates can be used to calculate cost inefficiencies, based on Eq. (21).

Table VI reports the coefficient estimates of the cost frontier. Among 36 coefficient estimates, 33 reach the 1% significance level. Seven out of the eight environmental variables, except for *rroa*, are found to have significant coefficient estimates at the 1% significance level. The coefficient estimates of the two CSR sub-variables, namely *csrc_emp* and *csrc_gov*, are significantly positive at the 1% significance level, indicating that these two CSR activities depress the CE of the sample banks. This finding is consistent with the DIDF in the previous subsection and the altruistic motivation of Baron (2001) and Dam, Koetter, and Scholtens (2009). Our results are partially consistent with those of Huang et al. (2019) and Forgione, Laguir, and Staglianò (2020). In this paper, *csrc_env* and *csrc_stak* are also incorporated as the environmental variables in the cost frontier. Their coefficient estimates are found to be significantly positive, and consistent with the altruistic motive.

Table VI
Parameter Estimates of the Cost Frontier with Environmental Variables

$yy1$ is total loans, $yy2$ is other operating assets, $yy3$ is non-interest revenue, p_1=Real personnel expenses/Number of employees, p_2(%)=Other operating expenses/Fixed assets, p_3(%)=Interest expenses/Deposits, $np2$ is normalized p_2 (=p_2/p_1), $np3$ is normalized p_3(=p_3/p_1), *csrc* signifies CSR score, t signifies time trend, *rroa*(%) is return on assets, *eta*(%) is equity to total assets ratio, *CR*5 signifies assets of five largest banks as a share of total commercial banking assets (%), *age* signifies the age of banks in number of years, and *csrc_emp* signifies the score of the item employees in CSR activities. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Variable	Parameter Estimates	Standard Error	Variable	Parameter Estimates	Standard Error
Intercept	-30,832.60***	6,330.13	$np3\times yy3$	8.494***	0.1448
$np2$	537.054***	130.443	$np3\times t$	5,171.46***	377.605
$np3$	-16,625.50***	3,925.57	$yy1\times t$	0.0209***	3.99E-04
$np2^2$	0.0216	0.3759	$yy2\times t$	7.48E-03***	4.55E-04
$np3^2$	-6,226.82***	820.511	$yy3\times t$	-0.6601***	0.0197
$np2\times np3$	318.975***	31.4933	$csrc$	8,483.28***	905.143
$yy1$	0.3688***	0.0115	$csrc^2$	-707.534***	64.2135
$yy2$	-1.0626***	0.0116	$csrc\times np2$	-108.119***	8.8676
$yy3$	10.5109***	0.2856	$csrc\times np3$	-2,403***	326.652
$yy1^2$	7.64E-07***	4.43E-12	$csrc\times yy1$	-0.0389***	5.45E-04
$yy2^2$	-3.25E-07***	7.92E-13	$csrc\times yy2$	0.0509***	4.42E-04
$yy3^2$	2.50E-05***	3.94E-06	$csrc\times yy3$	-0.154***	0.010186
$yy1\times yy2$	1.52E-07***	8.95E-13	$csrc\times t$	228.319***	47.7233
$yy1\times yy3$	1.06E-06***	2.50E-09	σ_{v_2}	9,169.09***	57.7073
$yy2\times yy3$	-6.96E-07***	8.00E-10	σ_{ω_2}	66,215.4***	746.413
t	-4,493.66***	780.849	Environmental Variables		
t^2	153.682	85.186	*rroa*	3,319.15	3,720.88
$np2\times yy1$	-1.94E-03***	1.54E-04	*eta*	-13,054.50***	1,308.20
$np2\times yy2$	0.0105***	9.84E-05	*csrc_gov*	15,573.20***	4,627.35
$np2\times yy3$	0.105***	3.08E-03	*bank_rate*	-563.33***	94.4788
$np2\times t$	-2.9379	6.2381	*gdp_per*	-0.0864***	4.38E-03
$np3\times yy1$	0.7198***	3.99E-03	*CR*5	-821.426***	188.203
$np3\times yy2$	0.7037***	4.10E-03	*age*	-566.466***	60.3413
			csrc_emp	65,916.40***	5,453.56
Number of Observations	1,535		Log-Likelihood	-20,455.2	

In summary, the parameter estimates of the CSR sub-variables in both DIDF and cost frontier advocate altruism, suggesting that the engagement of those activities results in lower TE and CE. It is noteworthy that it is difficult to determine whether these CSR activities have positive or negative effects on allocative (in)efficiency, a priori, according to Eq. (5).

The remaining five coefficient estimates for the five environmental variables are all negative and reach the 1% significant level. Among them, the coefficient of *CR*5 is negative, which fails to validate the "quiet life hypothesis". The estimated coefficient of *age* is negative, confirming the existence of learning effects. Both estimation results are consistent with those of the DIDF, as mentioned in Huang and Liu (1994), Huang et al. (2011), Koetter, Kolari, and Spierdijk (2012), and Huang, Liu, and Kumbhakar (2018).

The model without environmental variables is estimated, but the parameter estimates are not shown for brevity. By using the likelihood ratio test, the null hypothesis that the eight coefficients of the environmental variables are jointly equal to zero is rejected, justifying the inclusion of the environmental variables in the cost frontier. In addition, after estimating the model without CSR score, we conduct the joint test for the null hypothesis that the CSR-related coefficients are jointly equal to zero. This hypothesis is *decisively* rejected, supporting that CSR-related variables are key determinants of CE.

Using the coefficient estimates in Table VI and Eq. (21), we are able to calculate the measures of CI, and the results are shown in the left half of Table VII. The average CI is 3,004.23 persons. As the average *TI* amounts to 1,151.32 persons, the implied average *AI* is calculated as 1,852.91(=3,004.23−1,151.32) persons. These inefficiency measures can be converted into inefficiency scores. Specially, the average *CI* score is 0.2994, the average *TI* score is 0.0743, and the average *AI* score equals 0.2251. These figures uncover that CI is mainly caused by AI, rather than TI. The sample banks should manage to reduce their production costs by 29.94%, so as to carry out production on the cost frontier. It is suggested that sample banks should first improve their AI, by means of adjusting the quantities of inputs until the ratio of input prices is equal to their marginal rate of technical substitution.[9] This can save the production costs by 22.51%. The improvement of TI can additionally save 7.43% of the production cost.

Our results are consistent with Atkinson and Cornwell (1994), Huang and Wang (2004), Lai and Kumbhakar (2019), and Kumbhakar and Tsionas (2021). There are quite a few studies reaching opposite results, such as Atkinson and Cornwell (1994), Huang (2000), Huang et al. (2011), Huang et al. (2014), Tsionas, Assaf, and Matousek (2015), and Mamatzakis et al. (2015), who suggest that TI is more serious than AI.

The average CI that excludes environmental variables from the cost frontier is equal to 3725.79, as presented in the third column of Table VII, which exceeds that of the model considering environmental variables, presented in column 1,

9 Using the coefficient estimates of the cost frontier that ignores CSR score, we can calculate the average CI, TI, and AI for the sample banks, which are equal to 2999.3, 1135.3, and 1864.0 persons, respectively. They are slightly different from those presented in the left half of Table VII.

by 721.6 persons, making the average *CI* score largely increased by 0.4794, i.e., from 0.2994 to 0.7788. The average *AI* score is increased by 0.3646, from 0.2251 to 0.5897, while the increase in the average *TI* score is relatively small, from 0.0743 to 0.1891. It is recommended that external environmental factors be included in the cost frontier; otherwise, CI and AI measures are likely to be seriously distorted.

Taking partial derivatives of Eq. (21) with respect to *csrc_gov* and *csrc_emp*, respectively, we can compute the marginal effects of the two environmental variables on CI. The average marginal effect (standard deviation) of *csrc_gov* on CI is 260.89 (60.26), and the average marginal effect of *csrc_emp* on CI is 1104.25 (255.08), indicating that for each point increase in the two variables, the average CI of the sample bank would increase by about 261 and 1104 persons, respectively. The marginal effect of the latter is much greater than that of the former.[10]

Table VII
Cost Inefficiency Estimates

	With Environmental Variables		Without Environmental Variables	
	Mean	Std. Dev.	Mean	Std. Dev.
Cost Inefficiency	3,004.2280	3,828.0133	3,725.7948	2,948.6031
TI	1,151.3191	2,132.6790	1,608.7813	883.9548
AI	1,852.9089	2,592.7723	2,635.0293	2,583.4573
CI Score	0.2994	0.4310	0.7788	1.1711
TI Score	0.0743	0.0974	0.1891	0.2088
AI Score	0.2251	0.3654	0.5897	0.9991

The sample period is divided into three sub-periods, namely 2003-2006, 2007-2009 (subprime mortgage crisis), and 2010-2014. Table VIII shows that the average *CI*, *TI*, and *AI* scores reach the highest during the subprime mortgage crisis, as expected. However, they are insignificantly different from the same measures in the other two sub-periods. In Subsection V.A, we also find that the average TI measures are not reduced considerably during the subprime mortgage crisis, which is possibly due to the benefits brought by CSR activities to banks, as mentioned in Subsection II.A. The benefits include the reduction of operating costs, strengthening consumers' willingness to buy, the increase in productivity, the improvement of corporate goodwill and images, and having an insurance-like function.

[10] We are indebted to the reviewers of this journal.

Table VIII
CI Score in Different Periods with Environmental Variables

	2003-2006		2007-2009		2010-2014	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
CI Score	0.3137	0.4224	0.3189	0.5828	0.2761	0.3198
TI Score	0.0726	0.0913	0.0777	0.1109	0.0719	0.0877
AI Score	0.2411	0.3683	0.2412	0.5014	0.2042	0.2681

Finally, we classify the data into three regions, namely Europe, America, and Asia. Table IX exhibits the various inefficiency measures. The average *AI*s of the three areas are larger than their average *TI*s, and the same applies to the average *AI* and *TI* scores. The average *CI* score of the Asian banks is found to be the highest (0.4601), followed by the European banks. The American banking industry performs the best, probably because the economic development, cultural background, and institutional factors in Asia differ substantially from those in Europe and the U.S.

Table IX
CI Estimates in Different Areas

	Europe		America		Asia	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
CI	4,597.557	5,128.570	2,123.643	1,986.638	2,332.769	3,148.498
TI	2,064.159	3,151.993	715.686	964.634	743.895	1,306.087
AI	2,533.39	3,478.604	1,407.957	1,550.312	1,588.874	2,238.681
CI Score	0.2548	0.4080	0.1606	0.4870	0.4601	0.3565
TI Score	0.0762	0.0844	0.0274	0.0251	0.1203	0.1251
AI Score	0.1786	0.3430	0.1332	0.4885	0.3398	0.3083

VI. Conclusions

Being faced with rapid economic and environmental changes, firms must pay more attention on the aspects of the environment, society, and corporate governance. This paper emphasizes the effects of CSR activities on banks' efficiency using the SFA. The DIDF is allowed for containing endogenous inputs, CSR score, undesirable outputs, and environmental variables in an attempt to appropriately characterize the production technology of banks. The parameter estimates are then used to compute TIs for different regions and sub-periods. The cost frontier is not only allowed for including CSR as a quasi-fixed input, but also a set of environmental variables. Its coefficient estimates are then used to calculate CIs that are further decomposed into the sum of TI and AI. A potential contribution of this study is that it employs the SFA to divide CI into AI and TI under the framework of DEA, thus making the endogeneity problem easier to solve. There are relatively fewer works examining both AI and TI and simultaneously taking endogenous inputs into account.

This paper adopts the IV approach, suggested by Amsler, Prokhorov, and Schmidt (2016), to deal with the endogeneity problem, which ensures that the parameter estimates are consistent. As for the environmental variables, the coefficient estimates of *CR*5 and *age* are significantly negative. The former does not support the "quiet life hypothesis," while the latter supports the presence of learning effects. Moreover, the motive of the sample banks that engage in CSR activities is congruent with the altruism hypothesis of Baron (2001).

The average *TI* is equal to 1151.32 persons and the average *TE* score equals 0.93. However, precluding the environmental variables from the DIDF results in the above two estimates to become 1608.78 persons and 0.81, respectively, thus leading to overestimated (underestimated) measure of TI (TE). If the undesirables are excluded from the DIDF, the average *TI* and *TE* are found to be 1201.2057 and 0.9196, respectively, also leading to overestimated (underestimated) measure of TI (TE), but the differences are mild.

We split the entire sample period into three sub-periods, namely 2003-2006, 2007-2009 (subprime mortgage crisis), and 2010-2014. Although the average *TE* score is the lowest during the crisis period and gradually recovered after the storm, their differences among the three sub-periods are insignificant. This may be attributed to the fact that CSR activities aid banks in reducing operating costs, reinforcing consumers' willingness to buy, promoting productivity, raising corporate goodwill and images, and having an insurance-like function. In addition, the governments of various countries offered considerable amounts of resources for relief after the financial crisis, such that the distressed banks could operate smoothly, avoid liquidation, and keep their *TE* score from heavily stepping back.

The average TE measure of American banks is found to be the highest, followed by European banks, while Asian banks perform the least. The differences among the three regions are statistically significant. This may arise from the regional differences in ethnic culture, religious belief, nationalism, economic development, and bank size.

The coefficient estimates of the environmental variables for the cost frontier are akin to those for the DIDF. For instance, the "quiet life hypothesis" is rejected, and the learning effects prevail. The coefficient estimates of CSR-related items, such as *csrc_emp* and *csrc_gov*, are positive, advocating the altruistic motivation of Baron (2001). The parameter estimates of the remaining four environmental variables, except for that of *rroa*, are significantly negative, meaning that those three variables exert positive effects on CE, in line with the existing literature.

Since the AI estimates of the sample banks are much higher than the TI estimates, it is suggested that the input allocation should be adjusted first so as to equate the ratio of input prices to their marginal rate of technical substitution. In practice, banks frequently fine-tune their organizational structures and reallocate manpower, capital, and funds. This may enhance either or both productivity and save costs. If environmental variables are omitted from the cost frontier, TI and AI are apt to be overestimated. When the data are divided into different sub-periods and regions, similar conclusions are achieved and hence ignored for avoiding repetition.

Based on the results, we suggest that endogenous inputs, undesirable outputs, and environment variables should be considered in the model whenever analyzing the effects of banks' CSR activities on their efficiencies to obtain consistent coefficient estimates and accurate TE and AE estimates. The empirical outcomes can provide useful references for managers and government authorities to draw up business strategies and financial policies aiming to improve bank efficiency.

For future research direction, we propose the use of network SFA, developed by Huang, Lin, and Chen (2017), to characterize bank production process and to gauge their TE and AE. In this context, CSR activities may be the outputs of the first production stage and the inputs of the second production stage. On the one hand, this helps to solve the dilemma of defining CSR activities as an input or output. On the other hand, the network model is supported by many researchers due to its closeness to the actual production process of banks. Although the network model can be evaluated by either DEA or SFA, only SFA can deal with the problem of endogenous inputs into account.

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銀行業從事 CSR 活動對其經濟效率之影響

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摘 要

本文探究銀行從事企業社會責任 (CSR) 活動對經濟效率之影響。CSR 分數取自 EIRIS 資料庫；同時考慮要素內生性、CSR 分數、非意欲產出與環境變數。發現成本無效率主要來自配置無效率而非技術無效率，多數環境變數對各項經濟效率有顯著影響、次貸風暴期間的效率最低、歐美地區銀行效率顯著高於亞洲地區、忽略非意欲產出易低估技術效率。

關鍵詞：企業社會責任、內生性要素、投入面方向距離函數、環境變數、成本無效率

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