

The effect of corporate social responsibility on bank performances: an application of network stochastic frontier analysis

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Abstract

This study attempts to discuss the relationship between cost efficiency and various CSR activities by taking CSR activities as the environmental variables of the network stochastic frontier model, which means that we divide the production process of the commercial banks into two stages for capturing the dual roles of deposits and corporate social responsibility (CSR) activities and for linking CSR with cost efficiency. We compile input–output data and CAMEL indices for 187 banks in 27 countries during 2003–2014 from BankScope (Bank Focus) database, as well as collect a set of CSR measures from the Ethical Investment Research and Information Service database and categorize them into seven dimensions, i.e. employee, community, environment, governance, stakeholder, anti-bribery, and ESG delivery dimensions. After controlling for banks' characteristics and their country-specific cultural factors, our empirical results reveal that banks devote themselves in “environment”, “stakeholder”, and “anti-bribery” activities would be beneficial for their efficiency performance. However, “employee”, “community”, “governance” and “ESG delivery” shows the negative relationship with banks' efficiency.

Keywords: Corporate social responsibility, Network Stochastic Frontier Analysis, Environmental variables, Window dressing, Strategic CSR, Altruistic CSR, CSR Measures

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1. Introduction

Although the relationship between corporate social responsibility (CSR) activities and firm performance has drawn considerable research attention in recent years, it is still controversial whether firms gain benefits from engaging in CSR. Some relevant studies have argued that CSR only increases firms' costs and thus reduces firms' profits; by contrast, other scholars have argued that CSR results in increased revenues for firms, which outweighs its costs.

Using corporate financial performance (CFP) indices, such as various accounting measures (e.g., return on assets) or market measures (e.g., Tobin's Q), is quite common to explore the nexus between CSR and CFP. These studies have tended to use a single CFP index as the dependent variable of a regression model, but this may be too simplistic because CSR affects firms' business activities across all aspects. Accordingly, a few papers have suggested that researchers should use efficiency scores to evaluate firms' overall performance and to explore the relationship between CSR and efficiency.

Due to the characteristics of CSR, we examine the following topics in this study:

- (1) Incorporating CSR into a bank's production process,
- (2) Linking CSR with cost efficiency,
- (3) Categorizing CSR activities,
- (4) Determining which CSR activities are beneficial for banks and which are not,
- (5) Estimating the proposed model.

To address these topics, we utilize the network structure, in which the production process of banks is split into two stages in this study. Specifically, CSR is viewed as an intermediate output in the first stage; CSR together with the other inputs is used to produce the final outputs, such as loans, investments, and noninterest income, in the second stage. As mentioned in the earlier text, we utilize the network framework to examine the role of CSR in the production process of banks.

The remaining sections are organized as follows: we review literatures concerning banks' CSR activities and its effects on CFP or efficiency performance in Section 2. In section 3, we explain how to extend two-stage network stochastic frontier proposed by Huang et al. (2017) by incorporating environmental variables into inefficiency terms. Hence, we can deal with the dual roles of deposits and CSR activities in banking industry, as well as realize the CSR effects on banks' efficiency. Sections 4 and Sections 5 are data and empirical results, and the final section is our conclusions based on the empirical results.

2. Literature Reviews

2.1 CSR and banks' activities

When referring to CSR, we often think of manufacturing industry activities. For example, automobile companies might innovate electric vehicles to reduce CO₂ emissions; chemical firms might develop less polluting products; and miners or shoe manufacturers might improve their treatment of employees and not utilize child labor. By contrast, banks have been lagged in launching CSR programs relative to the manufacturing industry. We first examine the positive effects of CSR for other industries, and we then discuss the effects of CSR on the banking industry. Lentner , Szegedi, and Tatay (2015) claimed that engaging in CSR can create the following benefits for corporates.

- (1) Increased market penetration or widen market access
- (2) Improved corporate reputation for trustworthiness among (potential) customers
- (3) Product innovation for CSR activities
- (4) Improved labor recruitment
- (5) Insurance effect

Clearly, how banks perform CSR activities is very different from how manufacturers do so. Banking products are unlikely to pollute our environment, and neither do banks hire children to operate their business. This raises the interesting questions of how and why banks should engage in socially beneficial activities, and whether these behaviors increase banks' profits.

Although the operating models of banks and manufacturers are different, the positive effects of CSR are what bank managers desire to achieve as they engage in socially beneficial activities. CSR does not totally conflict with earning profits: a corporate can incur costs in performing CSR activities and can earn profits at the same time. This raises another crucial question of which CSR activities can improve banks' performance and which incur undue costs. We answer this question in this study.

Before answering these questions, we must consider banks' main function. Banks are financial intermediaries. They absorb deposits and extend loans to those who need capital, and they earn a net interest margin from doing so. Bank operations also involve numerous types of off-balance sheet activities that result in noninterest income. These activities are intended to maximize bank profits. However, since the global financial crisis of 2008–2009, banks have faced a more challenging environment than previously in managing their business risks. Moreover, the public has become more concerned than previously about banks' trustworthiness,

anti-money laundering, and stability. As a result, banks have been forced to spend considerable money and other resources to facilitate these functions.

Lentner et al. (2015) examined Hungarian commercial banks and categorized their CSR activities. Some of the activities merely increase banks' total costs (e.g., helping disadvantaged people), whereas others are related to banks' core activities (e.g., responsible, prudent lending and risk management). This implies that different types of CSR activities result in distinct effects on banks' performance. Lee, Signal and Kang (2013) divided CSR activities into two categories based on whether they involve corporates' core operations for investigating the effects of CSR activities on CFP in the U.S. restaurant industry. They discovered that operation-related CSR activities increase restaurants' CFP, but CSR activities that are not related to the business operations have the opposite effect in economic recessions.³

2.2 The effects of CSR on banks' performances

The activities of banks can be defined in terms of social responsibility, which can affect banks behavior and the measurement of their CSR scores. Even though CSR involvement typically increases corporate costs, it also may enhance corporate revenues. Most relevant studies have supported that CSR and CFP are positively correlated, but the empirical results of some studies have revealed a negative correlation or even no relationship between them.

(1) No relationship—window dressing

Arlow and Gannon (1982) summarized seven earlier studies and concluded that

“Economic performance is not direct linked, in either positive or negative fashion, to social responsiveness.”

Some studies have analyzed highly polluting companies' CSR activities to test whether CSR has the effect of greenwashing or CSR-washing. For example, Pope and Wæraas (2016) revealed that when customers are aware of corporate CSR performance and are willing to buy CSR-linked products, corporates can take advantage of CSR to communicate with their customers and thus achieve “CSR-washing.” In addition, numerous empirical studies have questioned whether corporates engage in beneficial behavior solely to enhance their reputation. If so, then CSR activities would not alter corporate management policies, and corporates would simply engage in window dressing when undertaking CSR; if so, then CSR has no relationship with CFP.

³ Lee et al. (2013) regard operation related CSR is product quality, employee relation. And non-operation related CSR is community and environment.

(2) Positive relationship—strategic CSR

Although engaging in CSR activities results in corporates expending additional resources such as in human resources or other supportive functions, these activities can reduce legal and other operating risks, and they can even enhance banks' profitability. Corporates can improve their competitiveness and create market opportunities by pursuing appropriate CSR strategies (Husted and Allen, 2010).

In summary, CSR involvement can increase corporate profitability. Moskowitz (1972) studied 14 top CSR-ranked companies and concluded that their stock returns improved. Cochran and Wood (1984) undertook regressions of Moskowitz CSR dummy variables on three CFP measures separately and discovered the existence of a weak relationship between CSR and CFP after controlling for asset age and industry. They concluded that CSR activities alter the process of management decision-making.

(3) Negative relationship—altruistic CSR

Most relevant studies have supported a positive relationship between CSR and corporate financial performance. Vance (1975) adopted the research method of Moskowitz (1972) to investigate 50 corporates during 1974–1975 and discovered that CSR is negatively correlated with stock returns.

The hypothesis of altruism can explain this phenomenon. Corporates engage in socially beneficial activities without expecting monetary rewards, and performing these activities require corporates to incur extra costs and hence reduce their profits.

Peloza and Shang (2011) proposed that each study has measured CSR from different aspects, which explains the mixed results of the relevant literature. They suggested that researchers should classify CSR activities and analyze the effect of this classification. Some studies have used Carroll's classification (1979), such as those by Maigna, Ferrell, and Hult (1999) and Peterson (2004), but others have classified CSR activities in a more sophisticated manner that typically covers eight dimensions: (1) products, (2) employees, (3) women, (4) the environment, (5) community, (6) nuclear proliferation, (7) the military, and (8) South Africa. The KLD database, which was started in 1988, and the EIRIS database compile CSR activities mainly based on these dimensions. In this study, we extend the findings of Brammer and Pavelin (2006) to classify CSR activities into seven dimensions. Section 4 provides detailed explanations.

2.3 Efficiency analysis from network stochastic frontier

After reviewing the relevant literature, we focus on two studies that employed the SFA approach to examine the effect of CSR on efficiency. We emphasize that the possible reason to explain the three hypotheses mentioned above can be explained clearly in terms of input-output structure, or so-called efficiency analysis, as shown in Table 1.

Table 1 Three hypotheses regarding the link between CSR and efficiency

Hypothesis	Input	Output	Efficiency
Window Dressing	trivial	trivial	—
Altruistic	↑	trivial	↓
Strategic	↑	↑↑	↑

Dam, Koetter, and Scholtens (2009) collected CSR data from the KLD database to confirm which CSR theory (i.e., the altruistic, strategy-selection, or green-washing theory) holds. They regarded CSR as an environmental variable and analyzed its effect on cost inefficiency and profit inefficiency. Based on the results from the cost frontier, they discovered that CSR activities cause cost inefficiency, but based on the results from the profit frontier, they discovered that CSR activities enhance profit efficiency. Their empirical results support the strategy selection hypothesis despite the finding that CSR activity raises a DMU's operating cost. Becchetti and Trovato (2011) used a semiparametric mixture model to estimate the latent class stochastic production frontier. They explored the relationship between CSR activities and production efficiency for 1,085 firms over 15 years. One advantage of using the latent class model is that it enables researchers to estimate two or more production frontiers to distinguish different groups simultaneously. Their results revealed that firms with higher CSR involvement do not necessarily exhibit lower efficiency than firms with lower CSR involvement do.

Dam et al. (2009) was the first to incorporate a CSR indicator into the cost and profit frontiers, but their setting is very different from this study's in two aspects. First, we regard CSR activities as an output of the first production stage and as a quasi-fixed input of the second production stage. We believe that this approach captures the real role that CSR plays in the entire production process. Second, we separate CSR into seven individual activities: the employee, community, environment, corporate governance, stakeholder, bribery, and stability activities. This permits us to further analyze each CSR activity's effect on a bank's management abilities.

The study of the network SFA was pioneered recently by Huang, Lin, and Chen (2017).

They developed a network SFA model to characterize the network production process in banking and applied the model to analyze Chinese banks during 2002–2015. They assumed that banks use a portion of their labor and physical capital (i.e., fixed assets) to produce deposits in the first production stage. They thus viewed deposits as an intermediate output. In the second production stage, the remaining labor and physical capital, along with the intermediate output, are employed to produce the final outputs (i.e., loans, investments, and noninterest income). This model avoids the question of whether deposits should be regarded as an input (the intermediation approach) or an output (the production approach). Although the setting of this approach is relatively simple, it provides researchers with a feasible way to estimate the proportions of shared inputs consumed in both stages of the production process. Huang, Chen, and Lin (2018) and Huang, Lin, and Wu (2019) have followed a similar vein as that of Huang et al. (2017). The former applies the two-stage production process to estimate the efficiency of U.S. commercial banks in 2009, and the latter analyzes Taiwanese life insurance companies during 2000–2012.

This study follows the two-stage structure of the three works discussed in the preceding paragraph, but we also adopt CSR activities as an additional intermediate good and as the environmental variable. As such, we use a distance function instead of the production function used by the three papers in the first stage. In addition, we re-derive the approximate pdf of the composed error term in the second stage because environmental variables are linked with the inefficiency term.

In next section, we will discuss in greater detail the network SFA methodology developed by Huang et al. (2017) and our extension of their model to include environmental variables in the second stage. This inclusion substantially increases the difficulty of the estimation task. However, the coefficient estimates of environmental variables enable us to infer the relationship between different CSR activities and cost efficiency, which results in useful policy and managerial implications.

3. Methodologies

3.1 Network SFA

The network SFA was first developed by Huang et al. (2017). The novelty of Huang et al.'s paper (2017) is that the authors established an economic model that includes the proportions of shared inputs in a production function and a cost function, corresponding to the two production phases, such that the proportions are treated as unknown parameters and can be estimated (identified) by adding share equations that are derived from the cost function under

consideration. Critically, the estimation of the proportions does not require the availability of a sectoral dataset, which is frequently unavailable. However, their method was specially designed for a two-stage network framework with $n - 1$ shared inputs, where n represents the number of inputs. In addition, they assumed a single intermediate good and did not consider environmental variables. This study extends the findings of Huang et al. (2017) from two aspects. First, we allow for two intermediate goods. Second, we examine the relationship of environmental variables to technical inefficiency.

In the first stage, we assume that banks utilize portions of their labor and capital inputs to produce two intermediate outputs: deposits and CSR. We adopt an output-oriented distance function to characterize the first-stage production, which has been widely specified as the translog form (Färe, Grosskopf, Lovell, and Yaisawarng, 1993; O'Donnell and Coelli, 2005; Abdul-Majid, Saal, and Battisti, 2010). The output distance function is described in equation (1) after transformation by applying the homogeneity constraint on the outputs.

$$\begin{aligned}
-\ln X_3 = & b_0 + b_1 \ln \frac{CSR}{X_3} + 0.5b_2 \left(\ln \frac{CSR}{X_3}\right)^2 + b_3 \ln \alpha_1 X_1 + b_4 \ln \alpha_2 X_2 \\
& + 0.5b_5 (\ln \alpha_1 X_1)^2 + 0.5b_6 (\ln \alpha_2 X_2)^2 + b_7 \ln \alpha_1 X_1 \ln \alpha_2 X_2 \\
& + b_8 \ln \frac{CSR}{X_3} \ln \alpha_1 X_1 + b_9 \ln \frac{CSR}{X_3} \ln \alpha_2 X_2 + b_{10} t + 0.5b_{11} t^2 \\
& + b_{12} t \ln \frac{CSR}{X_3} + b_{13} t \ln \alpha_1 X_1 + b_{14} t \ln \alpha_2 X_2 + v_1 + u_1
\end{aligned} \tag{1}$$

The dependent variable is one of the two intermediate outputs (i.e., deposits), which is used to normalize the other intermediate output (i.e., CSR) on the right hand side of equation (1). Notation u_1 reflects the technical inefficiency in the first stage, which is a non-negative random variable and is assumed to have a half-normal distribution (i.e., $u_1 \sim |N(0, \sigma_{u1}^2)|$), and v_1 is the random disturbance term with a normal distribution of $N(0, \sigma_{v1}^2)$.

Because the proportions of α_1 and α_2 are additional unknown parameters, the parameters of equation (1) cannot be estimated alone. Huang et al. (2018) introduced two cost share functions derived from the cost function of the second stage, to identify α_1 and α_2 . CSR is viewed as a quasi-fixed input in a short-run cost function because a bank cannot alter its own CSR index rapidly. See, for example, Caves, Christensen, and Swanson (1981), Nelson (1985), and Schankerman and Nadiri (1986). CSR measures items that are difficult to change in the short run, such as corporate governance, managerial regulation, and employee welfare policies. Banks must invest resources into a variety of CSR activities to gradually build up their reputations.

To simplify the denotations in the second stage, the variable input vector ($\tilde{\alpha}\mathbf{X}$), the corresponding vector of input price ($\mathbf{W}$), and the vector of output ($\mathbf{Y}$) are defined as follows:

$$\tilde{\alpha}\mathbf{X} = \begin{bmatrix} \tilde{\alpha}_1 X_1 \\ \tilde{\alpha}_2 X_2 \\ \tilde{\alpha}_3 X_3 \end{bmatrix} = \begin{bmatrix} (1 - \alpha_1) X_1 \\ (1 - \alpha_2) X_2 \\ (1 - \alpha_3) X_3 \end{bmatrix} = \begin{bmatrix} (1 - \alpha_1) X_1 \\ (1 - \alpha_2) X_2 \\ X_3 \end{bmatrix}, \quad \mathbf{W} = \begin{bmatrix} W_1 \\ W_2 \\ W_3 \end{bmatrix}, \text{ and } \mathbf{Y} = \begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix}.$$

CSR does not appear in $\tilde{\alpha}\mathbf{X}$ because it is defined as a quasi-fixed input due to its lack of price information. Following Atkinson and Cornwell (1993, 1994), the production transformation function of the second stage can be expressed as $F(Y_F, CSR, b\tilde{\alpha}\mathbf{X})=0$, where b represents the technical inefficiency of the second stage and ranges between 0 and 1. The closer to 1 the value of b is, the higher the bank's technical efficiency is, and the less space the bank has to reduce inputs given a certain amount of outputs. The reverse is true for values of b that are near zero.

Within vector $\mathbf{W}$, W_1 , W_2 , and W_3 represent prices of labor, physical capital, and financial capital, respectively. The total variable cost incurred in the second stage is the sum of the three input costs (i.e., $\mathbf{W}\tilde{\alpha}\mathbf{X}$). Unfortunately, we cannot retrieve this variable cost directly from the financial reports, but we can observe the TC for a bank, as follows:

$$E = \mathbf{W}\mathbf{X} = \sum_{i=1}^3 W_i X_i. \quad (2)$$

Let the optimal cost of the second production stage be denoted by PC^* , which can be formulated as

$$\begin{aligned} PC^*\left(Y, CSR, \frac{W}{b}\right) &= \min_{b\tilde{\alpha}\mathbf{X}} \left[\frac{W'}{b} (b\tilde{\alpha}\mathbf{X}) \mid F(Y, CSR, b\tilde{\alpha}\mathbf{X}) = 0 \right] \\ &= \frac{1}{b} \min_{b\tilde{\alpha}\mathbf{X}} [W'(b\tilde{\alpha}\mathbf{X}) \mid F(Y, CSR, b\tilde{\alpha}\mathbf{X}) = 0], \\ &= \frac{1}{b} PC(Y, CSR, W) \end{aligned} \quad (3)$$

where b represents production inefficiency.

Based on Shepard's lemma and equation (3), the demand function for the i -th input can be derived as

$$X_i = \frac{1}{\alpha_i} \frac{\partial PC^*}{\partial W_i}, \quad (4)$$

and the corresponding cost share can be expressed as

$$S_i \equiv \frac{\partial \ln PC^*}{\partial \ln W_i} = \frac{\partial PC^*}{\partial W_i} \frac{W_i}{PC^*}. \quad (5)$$

Substituting equations (4) and (5) into equation (2) we obtain

$$E = \sum_{i=1}^3 W_i \frac{PC^* \times S_i}{\tilde{\alpha}_i W_i} = PC^* \sum_{i=1}^3 W_i \frac{S_i}{\tilde{\alpha}_i}. \quad (6)$$

Equation (6) can be re-expressed as

$$E = PC^* \times G(\mathbf{Y}, CSR, \mathbf{W}) = \frac{1}{b} PC \times G(\mathbf{Y}, CSR, \mathbf{W}), \quad (7)$$

where $G(\mathbf{Y}, CSR, \mathbf{W}) \equiv \sum_{i=1}^3 S_i / \tilde{\alpha}$ represents an adjustment term that balances the total expenditure (E) incurred in both sectors and the second stage cost (PC). Taking the logarithm of both sides of equation (7) and appending a random disturbance term (v_2) yields the following formula.

$$\ln E = \ln PC + \ln G(\mathbf{Y}, CSR, \mathbf{W}) + v_2 + u_2, \quad (8)$$

where $u_2 = -\ln b$ represents the increased (log) cost due to the existence of technical inefficiency.

Equation (7) is very useful because it connects the total expenditure (E), incurred in both stages with the second stage cost (PC). The term of $\ln PC$ in equation (8) is specified as a translog form subsequently. Because $\ln G$ includes the extra parameters α_1 and α_2 , the joint estimation of equations (1) and (8) does not allow us to identify all the unknown parameters. We suggest adding the two cost share equations of S_1 and S_2 to help identify α_1 and α_2 , as in the following equation.

$$\frac{W_i X_i}{E} = \frac{\frac{1}{b} PC \times \frac{S_i}{\alpha_i}}{\frac{1}{b} PC \times G(\mathbf{Y}, CSR, \mathbf{W})} + \varepsilon_{i+2} = \frac{S_i}{\alpha_i \times G(\mathbf{Y}, CSR, \mathbf{W})} + \varepsilon_{i+2}, \quad (9)$$

In equation (9), ε_{i+2} signifies statistical noise. Three cost shares are examined in this study, but one of them is deleted to avoid the problem of singularity that arises from the sum of the three shares equaling unity. In summary, to estimate the two-stage production frontiers with shared inputs and technical inefficiency under the framework of SFA, we must simultaneously estimate the following four equations:

$$-\ln X_3 = \ln D_o\left(\frac{CSR}{X_3}, \mathbf{X}\right) + \varepsilon_1, \quad (10)$$

$$\ln E = \ln PC + \ln G(\mathbf{Y}, \text{CSR}, \mathbf{W}) + \varepsilon_2, \quad (11)$$

$$\frac{W_2 X_2}{E} = \frac{S_2}{\tilde{\alpha}_2 G(Y, \text{CSR}, W)} + \varepsilon_3, \quad (12)$$

$$\frac{W_3 X_3}{E} = \frac{S_3}{\tilde{\alpha}_3 G(Y, \text{CSR}, W)} + \varepsilon_4. \quad (13)$$

Among equations (10)–(13), ε_1 and ε_2 are composed errors (i.e., $\varepsilon_1 = v_1 + u_1$ and $\varepsilon_2 = v_2 + u_2$). The terms of v_1 , v_2 , ε_3 and ε_4 are disturbance terms and follow normal distributions with zero means and respective variances. The inefficiency term u_1 follows a half-normal distribution, as mentioned previously.

In addition, because our study examines whether CSR affects banks' efficiency, we assume that u_2 is associated with a set of environmental variables ($\mathbf{D}$), which can be expressed as follows:

$$u_2 = h(\mathbf{D}) + \eta_2. \quad (14)$$

In equation (14) η_2 is a truncated normal distribution because $u_2 \geq 0$ implies that $\eta_2 \geq -h(\mathbf{D})$. We have to emphasize that since u_2 represents inefficiency term, the parameter coefficient of the environmental variable in equation (14) is negative (positive), it represents the environmental variable positively (negatively) correlated to efficiency. We take advantage of maximum likelihood method to estimate parameter coefficients, and we introduce how to derive the approximate log-likelihood function below.

3.2 Likelihood Function and Copula Method

To ensure that we can simultaneously estimate equations (10) to (13) by the maximum likelihood (ML), we derive their joint probability density function (PDF) by following Lai and Huang (2013), who adopted a Guassian copula to obtain the joint PDF. The corresponding PDF can be expressed as a Gaussian copula function multiplied by the individual marginal PDF, as follows:

$$f(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4) = c(F(\varepsilon_1), F(\varepsilon_2), F(\varepsilon_3), F(\varepsilon_4); \boldsymbol{\rho}) \times \prod_{j=1}^4 f_j(\varepsilon_j), \quad (15)$$

where the copula function, $c(\cdot)$ is assumed to be a multivariate normal PDF, and ρ represents its correlation matrix. Equation (15) can then be specified as follows:

$$f(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4) = \frac{1}{|\boldsymbol{\rho}|^{0.5}} \exp(-0.5 \boldsymbol{\zeta}'(\boldsymbol{\rho}^{-1} - \mathbf{I}_4) \boldsymbol{\zeta}) \times \prod_{j=1}^4 f_j(\varepsilon_j), \quad (16)$$

where $\zeta' = (\Phi^{-1}(F(\varepsilon_1)), \Phi^{-1}(F(\varepsilon_2)), \Phi^{-1}(F(\varepsilon_3)), \Phi^{-1}(F(\varepsilon_4)))$, $\Phi(\cdot)$ denotes a standard normal cumulative distribution function (CDF), and I_4 represents a 4×4 identity matrix. The correlation matrix ρ contains six unknown parameters:

$$\rho = \begin{bmatrix} 1 & & & \\ \rho_{21} & 1 & & \\ \rho_{31} & \rho_{32} & 1 & \\ \rho_{41} & \rho_{42} & \rho_{43} & 1 \end{bmatrix}, \quad (17)$$

The log-likelihood function with respect to equation (16) can be written as follows:

$$\begin{aligned} \ln L(\theta) &= \sum_{i=1}^N \ln f(\varepsilon_1, \varepsilon_2, \varepsilon_3, \varepsilon_4; \rho) \\ &= \frac{-N}{2} \ln |\rho| - \frac{1}{2} \sum_{i=1}^N \zeta'(\rho^{-1} - I_4) \zeta + \sum_{j=1}^4 \sum_{i=1}^N \ln f_j(\varepsilon_{ji}) \end{aligned}, \quad (18)$$

A difficulty that researchers face when estimating equation (18) by ML is that the two error components of the output distance function and cost function exhibit skewed normal distributions without a close form. Specifically, their respective PDFs have the following forms.

$$f_1(\varepsilon_{1i}) = \frac{2}{\sigma_1} \phi\left(\frac{\varepsilon_{1i}}{\sigma_1}\right) \Phi\left(\frac{\varepsilon_{1i}\lambda_1}{\sigma_1}\right), \text{ where } \sigma_1 = \sqrt{\sigma_{v1}^2 + \sigma_{u1}^2} \text{ and } \lambda_1 = \frac{\sigma_{u1}}{\sigma_{v1}}.$$

and

$$f_2(\varepsilon_{2i}) = \frac{1}{\sigma_2} \phi\left(\frac{\varepsilon_{2i}}{\sigma_2}\right) \frac{\Phi(-B)}{\Phi\left(\frac{\gamma D}{\sigma_2}\right)}, \text{ where } \sigma_2 = \sqrt{\sigma_{v2}^2 + \sigma_{u2}^2} \text{ and } -B = \frac{\gamma' D \sigma_2^2 + \varepsilon_{2i} \sigma_{v2}^2}{\sigma_{u2} \sigma_{v2} \sigma_2},$$

where D represents the environmental variable vectors. These two PDFs contain the CDF of the standard normal distribution, which has no closed form, so the corresponding CDFs $F(\varepsilon_1)$ and $F(\varepsilon_2)$ in equation (18) also have no closed forms. This deters us from performing the estimation procedure with respect to equation (18). At least two methods to solve this problem exist. One is the simulated ML proposed by Greene (2003). The other attempts to determine an approximation function for $F(\varepsilon_1)$ and $F(\varepsilon_2)$, as supported by Tsay, Huang, Fu, and Ho (2013) and Huang et al. (2018). Both of these methods lead to approximated functions of $F(\varepsilon_1)$ and $F(\varepsilon_2)$, rather than their true functions. We extend on Tsay et al. (2013) and Huang et al. (2018) to associate the inefficiency term u_2 with several environmental variables. A caveat of this approach is that the resulting derived approximation functions of $F(\varepsilon_1)$ and $F(\varepsilon_2)$ are usually very complicated, which increases the difficulty of the estimation, especially when the model contains environmental variables.

The advantage of the method proposed by Huang et al. (2017) is that researchers only require the overall cost information instead of the respective cost data of the two production processes. In reality, researchers have few opportunities to obtain such detailed information.

4. Data

In the context of the network production process, banks are assumed to utilize a portion of their labor (X_1) and physical capital (X_2) to acquire deposits (X_3) in the first stage of production. In the second stage, banks are presumed to employ their remaining labor and capital together with the intermediate output yielded in the previous stage (i.e., deposits) to produce final outputs such as loans (Y_1), investments (Y_2), and noninterest income (Y_3). During the entire production process, banks must engage in certain activities to support their profit-making operations, such as legal compliance, risk management, and employee education. These supportive functions can be considered as bank CSR activities.

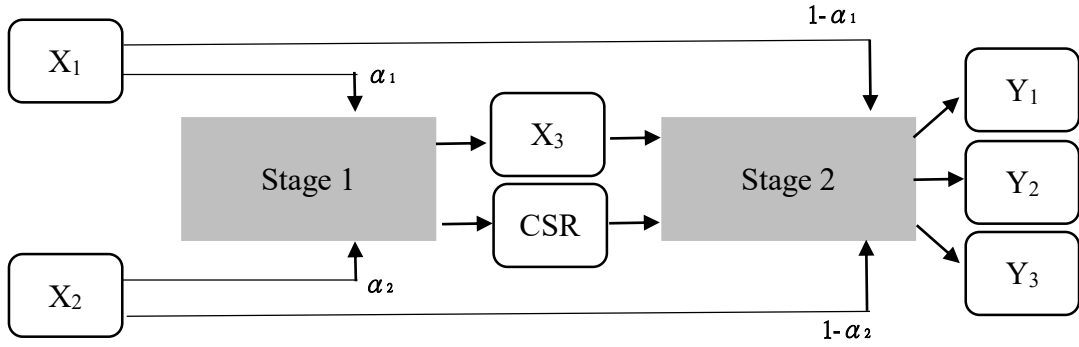


Figure 1 Production process of banks

In contrast to the method followed by Holod and Lewis (2011) and Huang et al. (2017, 2018), in the present paper, we consider that two intermediate outputs (i.e., deposits and CSR activities) are produced by banks in the first stage of production because the production of these two intermediate outputs requires consuming some portion of labor and capital. Therefore, we assume that banks use a portion of labor ($\alpha_1 X_1$) and capital ($\alpha_2 X_2$) to produce deposits and CSR activities in the first stage, where $0 \leq \alpha_1 \leq 1$ and $0 \leq \alpha_2 \leq 1$ are two unknown parameters to be estimated. Those parameters represent the proportion of labor and capital utilized in the first stage. The emergence of these parameters is crucial because they link the two production sectors and can be estimated using an econometric model without requiring individual sectoral data on the inputs of labor and capital. Huang et al. (2018) analyzed U.S. commercial banks using the network SFA, and they determined the coefficient estimates of α_1 and α_2 to be 0.2618 and 0.6761, respectively; these estimates are used as the initial values in our estimation, as described in Section 5.

In the subsequent stage, banks also use the two intermediate goods and their remaining labor and capital to extend loans (Y_1), invest in other earning assets (Y_2), and earn noninterest income (Y_3). Stage 1 can be considered to play a supportive function for banks, in which banks bear input costs without receiving revenue in return, whereas Stage 2 provides the major function of banks and can be viewed as the profit-making stage.

4.1 Input-Output data of banks

We compile all the input and output variables from the *Bureau van Dijk* database, except for CSR scores, which are extracted from the EIRIS database. The BvD Bankscope database provides banks' data until 2016; Orbit Bank Focus offers a similar database for subsequent periods. Because the data vender delivers the latest 3-year or 5-year data in some cases and our sample period spans 2003–2014, we obtain the required variables, including CAMEL indices, from the three versions of BankScope (i.e., the versions of 2007, 2011, and 2013) and from the Bank Focus 2018 version downloaded from the Wharton Research Data Service (WRDS). After excluding noncommercial banks and deleting observations with missing values, the final sample has 187 banks and 1,361 bank-year observations. Most of our sample banks are in located developed countries or regions, such as the United States, Europe, Japan, and Hong Kong.

Table 2 exhibits the relevant sample statistics. We assume that banks employ a portion of their labor and capital in the first stage of production. The mean of labor (X_1) is approximately 31.32 thousand people, which reflects the tendency of EIRIS to survey large-scale commercial banks such as Citigroup and JP Morgan Chase. Spending on labor corresponds to personnel expenses. We then define the price of labor as the ratio of personnel expenses to X_1 , and the average price of labor (W_1) is equal to 90,000 US dollars per year per worker, with the base year of 2010. The other input in the first stage is physical capital (X_2), which is measured by fixed assets. The average physical capital of the sample banks is approximately 2.25 billion constant US dollars. Its price is calculated as the ratio of other operating expenses to X_2 . The average price of X_2 (W_2) is equal to 1.30.

The inputs in the second stage are assumed to comprise the remaining portion of labor and capital, together with deposits (X_3) and CSR. The average value of deposits is approximately 208.29 billion constant US dollars with the base year of 2010 and its average price (W_3) equals 0.02, which is identified as the ratio of interest expenditure to deposits. The average CSR index is 19.79. Unfortunately, the price of CSR is unavailable. This forces us to classify CSR as a quasi-fixed input in such a manner to avoid using its price information when conducting the estimation. The TC is equal to the sum of personnel expenses (C_1), other operating expenses

(C_2), and interest expenses (C_3), and the average TC is approximately 10.63 billion constant US dollars.

Table 2 Descriptive statistics of IO variables (N = 1,361)

Variable	Definition	Mean	S.D.	Min	Max
Input variables					
X_1^b	Labor	31,319.87	53,449.18	373.00	409,720.00
X_2^a	Fixed assets	2,245.21	3,674.02	17.90	28,959.67
X_3^a	Deposits and short-term funding	208,285.71	318,016.38	1,746.41	2,089,566.12
CSR	CSR index	19.79	6.43	7.60	33.34
Input cost and Price data					
C_1^a	Personnel expenses	2,925.51	5,160.80	26.91	36,081.62
C_2^a	Other operating expenses	2,611.62	4,774.77	29.93	36,641.01
C_3^a	Interest expenses	5,089.07	9,625.82	10.88	93,639.01
W_1	C_1 / X_1	0.09	0.04	0.02	0.51
W_2	C_2 / X_2	1.30	1.47	0.05	29.99
W_3	C_3 / X_3	0.02	0.02	0.00	0.19
TC^a	$C_1+C_2+C_3$	10,626.20	17,893.91	94.17	144,869.17
Output variables					
Y_1^a	Loans	155,904.19	216,432.97	23.16	1,219,856.85
Y_2^a	Investments	146,528.48	301,518.47	134.24	2,362,991.75
Y_3^a	Non-interest income	4,135.82	7,776.50	0.41	52,537.64

Note: Superscript “a” measured by constant million US dollar, which are deflated by the consumer price index with the base year of 2010. Superscript “b” means the unit is person.

4.2 Environment variables

Although the aforementioned variables enable the analysis of our sample banks’ production efficiency scores by using the network SFA in the context of the two production stages, they do not address the determinants of bank efficiency. These determinants are typically called environmental variables in the field of efficiency and productivity analysis. Huang and Liu (1994) and Battese and Coelli (1995) have proposed a “one-step” procedure to link the one-sided inefficiency error term in a stochastic production frontier with a set of firm characteristics or environmental variables.

We categorize three groups of environmental variables that explain a bank’s operating efficiency. The first group contains a single variable: the CSR index. Whether engagement in CSR activities benefits a bank is an interesting question. Engagement in CSR can be attributable to three motivations of a firm, as proposed by the relevant literature: altruism, strategic choices, and greenwashing. The EIRIS database collects the CSR-related information from seven aspects. In addition to the CSR index, the second group consists of five CAMEL indices, and the third group is based on country-specific cultural indices.

(1) CSR index

How to measure corporate CSR performance is a critical issue for researchers in order to understand how CSR affects managerial performance. Most previous studies that have investigated developing countries have undertaken questionnaire surveys to evaluate each respondent firm's CSR index. A few studies have used proxy variables such as donations or undesirable outputs such as carbon dioxide emissions to replace the role of CSR in the analyses.

Recent studies have increasingly depended on CSR scores measured by reliable databases to analyze a variety of CSR issues. Each country may have its own dominant CSR database providers. For example, examinations of U.S. firms' CSR scores have typically employed the KLD database developed by Kinder, Lydenberg, Domini & Co., Inc. By contrast, studies of Canadian companies have typically opted for the Canadian Social Investment Database (CSID) as more appropriate. This dissertation explores the relationship between global banks' CSR scores and managerial performance. For this reason, we collect the relevant CSR data on banks from the EIRIS database.

These databases collect relevant information from questionnaire surveys, financial reports, news articles, and government evaluations to measure each firm's CSR from different dimensions. The KLD database divides CSR into several classifications: community, employee, environment, product, women and minors, military contracts, and South Africa dimensions. The CSID database separates CSR into community, diversity, employee relations, environment, international, product, business practices, and other dimensions. This reveals that community, employee, environment, and product classifications are four critical dimensions of both the KLD and CSID databases.

Brammer and Pavelin (2006) classified a portion of EIRIS CSR questions into three dimensions: employee, environment, and community categories. Because of the different rating scales of the relevant questionnaire answers, they selected particular questions that fell within certain dimensions that had the same ratings scales. Nevertheless, the scales of the three dimensions remained different, so they rescaled them to between 1 and 4; the resulting overall CSR score thus ranged from 3 (the lowest) to 12 (the highest). This study reserves the three dimension scores proposed by Brammer and Pavelin (2006), and it also includes another four dimensions: governance, stakeholders, bribery, and ESG delivery. Table 3 exhibits that the average values of the seven standardized CSR scores range from 2.07 to 3.46, and their standard deviations are between 0.84 and 1.20.

(2) CAMEL indices

Taking CAMEL indices into account is pivotal for the evaluation of bank performance. We use these indices to describe the technical efficiency of the sample banks. CAMEL indices comprise five dimensions: capital adequacy, asset quality, management ability, earning ability, and liquidity.

Each CAMEL index can be measured by different financial indicators. Following the method of Angbazo (1997) and Poon, Lee, and Gup (2009), we select the indicators with the fewest missing values. Capital adequacy is represented by the equity to total assets (*ETA*) ratio, and the sample mean value of the *ETA* is 7.08%. Asset quality is measured based on nonperforming loans to gross loans (*NPLgl*), which is an index of asset quality that has an average value of 3.04%. Management ability is assessed based on earning assets to total assets (*EAR*), and its average value is 91.48%. Earning ability is assessed by Return on Average Equity (*RROE*), the average value of which is 9.42%. Liquidity is measured by the ratio of liquid assets to deposits and short-term funding (*LATD*), which has an average value of 21.20%. The definitions of these financial indicators are listed in Table 3.

(3) Cultural indices

Our sample banks operate in numerous countries with heterogeneous cultures, which inherently affect their willingness to engage in CSR activities and the managerial abilities of various firms. The cultural indices are extracted from the books edited by Hofstede (1991) and Hofstede, Hofstede, and Minkov (2010), who established five indicators to characterize country-specific cultures: individualism (*IDV*), long-term orientation (*LDV*), uncertainty avoidance (*UAI*), power distance (*PDI*), and masculinity. We think that masculinity is of little relevance to a bank's efficiency and hence exclude this indicator from environmental variables.

Western cultures are typically more inclined to encourage individualism than Eastern cultures are, whereas oriental cultures, especially those influenced by Confucius, tend to place greater emphasis on long-term orientation than do Western cultures. In addition, Eastern cultures tend to emphasize high respect for the existing social hierarchy and the view that each member of society must behave optimally and perform their own duties. Confucius once said that when the king is king, the minister is minister; when the father is father, the son is son. Accordingly, we expect oriental cultures to exhibit higher *PDI* than Western cultures. The index of uncertainty avoidance is used to evaluate the extent to which people require concrete regulations or commands. A higher *UAI* index reflects that people feel more anxious to deal with unexpected situations. As noted by Hofstede et al. (2010; page 196), "Anxious cultures tend to be expressive cultures." This supports the notion that Western people, who usually have

higher *UAI* than do Eastern people, are more likely to ask questions and express opinions to avoid future uncertainty than Eastern people are.

Table 3 Descriptive statistics of environmental variables (N = 1,361)

Variable	Definition	Mean	S.D.	Min	Max
CSR indexes					
CSR_EMP	Employee	2.26	0.84	1.00	4.11
CSR_COM	Community	2.87	1.22	1.00	5.00
CSR_ENV	Environment	2.07	1.17	1.00	5.00
CSR_GOV	Governance	3.46	0.84	1.30	5.00
CSR_STAK	Stakeholder	3.01	1.07	1.00	4.81
CSR_BRI	Anti-bribery and Anti-corruption	3.12	1.95	1.00	5.00
CSR_ESGD	ESG delivery	3.00	1.16	1.00	5.00
CAMEL indexes					
ETA	Equity to total asset	7.08	3.07	-3.93	32.80
NPLgl	NPL to gross loans	3.04	3.69	0.05	44.89
EAR	Earning assets to Total assets	91.48	5.92	15.16	99.32
RROE	Return On Average Equity	9.42	25.22	-266.63	670.24
LATD	Liquid assets / (Deposits and Short-Term funding)	21.20	21.35	0.53	141.35
Cultural indexes					
IDV	Individualism score	65.95	21.95	18.00	91.00
LTO	Long-term orientation score	51.17	24.04	21.00	100.00
UAI	Uncertainty avoidance score	64.00	25.35	8.00	112.00
PDI	Power distance score	45.28	13.07	11.00	74.00

Note: All individual CSR indices in this table are normalized to range between 1 and 5. The variable of CSR is equal to the sum of CSR_EMP, CSR_COM, CSR_ENV, CSR_GOV, CSR_STAK, CSR_BRI, and CSR_ESGD.

5. Empirical Results

5.1 Efficiency scores

(1) First-stage estimation results

Table 4 presents the parameter estimates of the output distance function. A total of 15 of the 20 parameters achieve statistical significance at least the 10% level. Crucially, both α_1 and α_2 attain the 1% level of significance, which implies that our network structure is potentially useful to describe the sample banks' production processes.

Table 4 Output distance function estimation results

variable	parameter	coefficient (std error)	variable	parameter	Coefficient (std error)
	b0	-2.0526*** (0.0781)	t	b10	0.1043*** (0.0042)
$\ln \frac{CSR}{X_3}$	b1	1.1546*** (0.0236)	$0.5t^2$	b11	-0.0013*** (0.0002)
$0.5(\ln \frac{CSR}{X_3})^2$	b2	0.0772*** (0.007)	$t \ln \frac{CSR}{X_3}$	b12	-0.0756*** (0.0009)
$\ln \alpha_1 X_1$	b3	0.0033 (0.0199)	$t \ln \alpha_1 X_1$	b13	-0.0738*** (0.0006)
$\ln \alpha_2 X_2$	b4	-0.0214 (0.0218)	$t \ln \alpha_2 X_2$	b14	0.0133*** (0.0006)
$0.5(\ln \alpha_1 X_1)^2$	b5	-0.0051 (0.0043)	σ_{w1}	SIG_W1	0.2325*** (0.0066)
$0.5(\ln \alpha_2 X_2)^2$	b6	0.008 (0.0057)	σ_{v1}	SIG_V1	0.1027*** (0.0088)
$\ln \alpha_1 X_1 \ln \alpha_2 X_2$	b7	0.0335*** (0.0041)	α_1	ALPHA1	0.6079*** (0.0026)
$\ln \frac{CSR}{X_3} \ln \alpha_1 X_1$	b8	0.021*** (0.0045)	α_2	ALPHA2	0.3567*** (0.0031)
$\ln \frac{CSR}{X_3} \ln \alpha_2 X_2$	b9	0.052*** (0.0049)			

Note: 1. Numbers in parentheses are standard errors. 2. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

(2) Second-stage estimation results

We use a cost function and its share equations to model the second stage production process and identify the proportions of shared inputs utilized in both stages. Table 5 exhibits the estimated coefficients of the cost function. As illustrated in Table 5, 33 out of 40 parameters

achieve statistical significance at least the 10% level, implying that the translog functional form may be suitable for our data.

Table 5 Cost function estimation results

Variable	Parameter	Coefficient (Std Error)	Variable	Parameter	Coefficient (Std Error)
	C0	6.9131*** (1.5601)	$\ln \frac{w_3}{w_1} \ln y_3$	C20	-0.0147*** (0.0004)
$\ln \frac{w_2}{w_1}$	C1	-0.1777*** (0.003)	t	C21	0.0822 (0.0483)
$\ln \frac{w_3}{w_1}$	C2	1.1129*** (0.0041)	$0.5t^2$	C22	0.0099*** (0.0029)
$0.5(\ln \frac{w_2}{w_1})^2$	C3	-0.0578*** (0.0009)	$t \ln \frac{w_2}{w_1}$	C23	0.0287*** (0.0057)
$0.5(\ln \frac{w_3}{w_1})^2$	C4	0.0677*** (0.0009)	$t \ln \frac{w_3}{w_1}$	C24	-0.0199*** (0.004)
$\ln \frac{w_2}{w_1} \ln \frac{w_3}{w_1}$	C5	-0.0231*** (0.0005)	$t \ln y_1$	C25	-0.0213*** (0.0043)
$\ln y_1$	C6	0.3654 (0.2295)	$t \ln y_2$	C26	0.0027*** (0.0001)
$\ln y_2$	C7	0.4533** (0.2197)	$t \ln y_3$	C27	0.0014*** (0.0001)
$\ln y_3$	C8	-0.7169*** (0.1792)	$\ln CSR$	C28	-4.0294*** (0.8285)
$0.5(\ln y_1)^2$	C9	0.2609*** (0.0336)	$0.5(\ln CSR)^2$	C29	2.0166*** (0.3646)
$0.5(\ln y_2)^2$	C10	0.4312*** (0.0551)	$\ln CSR \ln \frac{w_2}{w_1}$	C30	-0.0701*** (0.016)
$0.5(\ln y_3)^2$	C11	0.083*** (0.0126)	$\ln CSR \ln \frac{w_3}{w_1}$	C31	-0.1777*** (0.0109)
$\ln y_1 \ln y_2$	C12	-0.2902*** (0.0495)	$\ln CSR \ln y_1$	C32	-0.1605 (0.1002)

Note: 1. Numbers in parentheses are standard errors. 2. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

Table 5 Cost function estimation results (Cont'd)

variable	parameter	coefficient (std error)	Variable	parameter	coefficient (std error)
$\ln y_1 \ln y_3$	C13	0.2323*** (0.0307)	$\ln CSR \ln y_2$	C33	0.0355 (0.0866)
$\ln y_2 \ln y_3$	C14	-0.2339*** (0.0237)	$\ln CSR \ln y_3$	C34	-0.0139 (0.0546)
$\ln \frac{w_2}{w_1} \ln y_1$	C15	0.0001 (0.0004)	$t \ln CSR$	C35	-0.0177 (0.0205)
$\ln \frac{w_2}{w_1} \ln y_2$	C16	-0.0319*** (0.0005)	σ_{w2}	SIG_W2	0.1642** (0.0675)
$\ln \frac{w_2}{w_1} \ln y_3$	C17	0.0525*** (0.0007)	σ_{v2}	SIG_V2	0.5397*** (0.0302)
$\ln \frac{w_3}{w_1} \ln y_1$	C18	0.0246*** (0.0004)	σ_3	SIGMA3	0.1332*** (0.0011)
$\ln \frac{w_3}{w_1} \ln y_2$	C19	0.0101*** (0.0003)	σ_4	SIGMA4	0.2125*** (0.0022)

Note: 1. Numbers in parentheses are standard errors. 2. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

(3) Correlations among the four equations

Because we use the Gaussian copula to establish the log-likelihood function for the simultaneous equations, we must estimate the correlation coefficients among those equations. As illustrated by equation (17), six such parameters must be estimated. We present them in Table 6, where all six of the parameters are significantly estimated at the 1% level. This implies the necessity of the simultaneous estimation procedure to improve the efficiency of the parameter estimates. R12 represents the relationship between the technical efficiency of the first stage and that of the second stage. We discover that R12 is significantly positive, which implies that a high TE value in the first stage results in a high TE value in the second stage. Also, R34 is the estimated correlation coefficients between the share equations of capital and deposits. It is reasonable to obtain negative R34, which indicates that a relatively high spending share of certain inputs would reduce the share of other inputs.

Table 6 Estimated correlation matrix

parameter	Coefficient (std error)	parameter	coefficient (std error)
R12	0.2398*** (0.0271)	R23	0.7507*** (0.0082)
R13	0.2338*** (0.0424)	R24	-0.8345*** (0.0046)
R14	-0.3809*** (0.0462)	R34	-0.2637*** (0.0079)

Note: 1. Numbers in parentheses are standard errors. 2. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

(4) The effects of CSR on inefficiency

We estimate four equations simultaneously using the copula method, and we present the two stage results above. The log-likelihood value of these simultaneous equations is 14,124.1. In this section, we will focus the environmental regression results to understand the effects of three types of environmental variables: CSR activities, CAMEL indices, and cultural indices. These environmental factors are assumed to be associated with technical inefficiency. We undertake the one-step approach to simultaneously estimate the output distance function, the cost function, and the two share equations. The coefficient estimates of the environmental factors, as illustrated in Table 7, present several valuable policy implications.

First, different components of CSR activities are determined to have different effects on a bank's cost efficiency. *CSR_ENV* (environment), *CSR_STAK* (stakeholder), and *CSR_BRI* (anti-bribery and anti-corruption) exhibit positive effects on efficiency. Unsurprisingly, *CSR_STAK* exerts positive effects on banks' efficiency because a bank's shareholders are critical members of the group of its stakeholders. Also, bribery and corruption are a reflection of bureaucracy. Ahlin and Bose (2007) revealed that when officials are more bureaucratic, license applicants must wait longer to receive permits than they do when officials are less bureaucratic. This results in resource misallocation. Accordingly, a bank with a high *CSR_BRI* score is likely to establish effective policies to prevent bribery and corruption; this leads to less bureaucracy which, in turn, promotes bank efficiency.

Our network SFA confirms that banks conducting CSR activities in environmental affairs exhibit higher efficiency measures than those that do not conduct such activities. This implies that the effect of *CSR_ENV* on efficiency supports the strategic motivation of banks becoming involved in environmental affairs. As such, banks that engage in environmental CSR activities

can enhance their efficiency. In reality, banks conduct certain environmental CSR activities such as green investment, green lending, and green deposits. However, we are aware of only a few studies that have analyzed the potential benefits of doing so.

By *contrast*, four types of CSR activities worsen banks' efficiency: *CSR_EMP* (employee), *CSR_COM* (community), *CSR_GOV* (governance), and *CSR_ESGD* (ESG delivery). *CSR_COM* and *CSR_EMP* exhibit negative effects on efficiency, as expected. Because community CSR activities are usually altruistic for banks that provide products such as microloans to minorities at very low interest rates. Altruistic CSR activities are less beneficial for banks than other types of activities and even reduce bank efficiency. *CSR_EMP* measures banks' focus on employee welfare, such as fair opportunities, job training, and other policies, to support the relationship between banks and their employees. If banks are concerned about their relationship with employees, then they may experience difficulty in laying off unqualified labor, and they may pay relatively high personnel costs.

Governance is an extremely critical issue in the managerial field. It covers topics such as female directors, codes of ethics, and the independence of board directors. Faccio, Marchica, and Mura (2016) revealed that female CEOs are more risk-averse and less overconfident than male CEOs are. Hence, firms that are managed by female CEOs have lower leverage and smoother earnings than those that are managed by male CEOs are. In addition, Faccio et al. (2016) used Tobin's Q and value-added growth, as proposed by Wurgler (2000), to represent capital allocation efficiency. Their results revealed that companies with female CEOs have lower efficiency in terms of Tobin's Q and value-added growth than those of companies with male CEOs. They attribute their findings to the inclination of female CEOs to underinvest in promising but risky projects. However, we emphasize that the governance dimension comprises several questions such as the degree of board independence and corporate codes of ethics that might be beneficial for bank efficiency. We combine these questions into a single governance dimension, which may just capture the dominant effect of this dimension.

As for ESG delivery, we consider that a bank would be more stable if it delivers ESG commitment better. However, Barth, Lin, Ma, Seade, and Song (2013) compared 4,050 banks in 72 countries during 1999–2007. They concluded that strict restrictions on bank activities tend to reduce the banks' efficiency. Our findings are similar to theirs, as our sample banks are revealed to be reluctant to grant loans to firms that have poor reputations, such as those involved in highly polluting industries and those that are controversial. Delis, Iosifidi and Tsionas (2017) examined the two hypotheses proposed by Berger and DeYoung (1997). Their empirical results confirmed the cost skimping hypothesis, which posits that cost-focused banks engage in

relatively low spending on borrower screening, resulting in long-term financial performance instability. The cost skimping hypothesis asserts the presence of a tradeoff in the relationship between stability and efficiency.

Second, the array of CAMEL indicators has long been used to evaluate banks' operational status. Our regression results reveal that banks with higher *EAR* (management capability), *RROE* (profitability), *LATD* (liquidity/solvency), and lower *ETA* (equity-to-assets) tend to have higher cost efficiency than those with lower CAMEL indicators do. The effects of *RROE* and *EAR* on efficiency are very straightforward. Both indicators reflect how effectively banks allocate and manage their resources. Banks with relatively high *ETA* are likely to be risk averse and to utilize limited leverage, resulting in relatively low efficiency (Sun and Chang, 2011). Banks that have higher *LATD* retain higher proportions of liquid assets than those with lower *LATD* do, and because such assets can be easily and rapidly used to pay down debt, their funding costs may decrease as a result. Chen, Shen, Kao, and Yeh (2018) argued that banks with higher liquidity risk have higher funding costs than those with lower liquidity risk, which reduces such banks' profitability; as such, increased *LATD* should enhance bank efficiency.

Third, *IDV* (individualism) and *UAI* (uncertainty avoidance) positively influence efficiency, whereas *LTO* (long-term orientation) and *PDI* (power distance) negatively influence on efficiency. Banks operating in Western cultures exhibit higher *IDV* (individualism) and *UAI* (uncertainty avoidance) than banks in Eastern cultures do. By contrast, banks in Eastern cultures exhibit higher *LTO* (long-term orientation) and *PDI* (power distance) than their Western counterparts do.

Li, Griffin, Yue, and Zhao (2013) verified that individualism is positively correlated with risk-taking behavior, which implies that banks with higher *IDV* are likely to have higher efficiency than those with lower *IDV*. Gorodnichenko and Roland (2017) stated that a higher *IDV* reflects a culture that encourages personal achievements and results in greater innovation than a lower *IDV* culture, which might promote efficiency. Besides, a high *UAI* means that the bank's managers are risk averse, which might imply underinvestment and reduced efficiency, but cultures with high *UAI* are inclined to construct clear guidance and systems for management, which should foster efficiency.

Banks with high *LTO* are inclined to maintain lasting relationship with long-term customers, which might reduce their transaction costs and enhance their efficiency, but it also takes a long time to establish relationships with new customers, which is costly and might decrease efficiency. High power distancing (*PDI*) implies that a bank's decisions are mainly

made by senior managers, and their decisions might tend to benefit themselves and can easily result in overinvestment (Zhang, Zhang, and Zhang, 2016). Overinvestment does not imply that banks execute numerous investments, but rather that they misallocate resources to certain products or industries.

Table 7 regression results of Environmental variables

Variable	Parameter	Coefficient (Std Error)	Variable	Parameter	Coefficient (Std Error)
	D0	4.1343*** (0.0563)	NPLgl	D9	0.0069 (0.0055)
CSR_EMP	D1	0.1212** (0.0475)	EAR	D10	-0.0391*** (0.0018)
CSR_COM	D2	0.1818*** (0.0226)	RROE	D11	-0.0024*** (1.0114E-15)
CSR_ENV	D3	-0.1256*** (0.0272)	LATD	D12	-0.0103*** (0.0002)
CSR_GOV	D4	0.1246*** (0.0273)	IDV	D13	-0.0058*** (0.0012)
CSR_STAK	D5	-0.236*** (0.0381)	LTO	D14	0.0033*** (0.0012)
CSR_BRI	D6	-0.0455*** (0.0124)	UAI	D15	-0.006*** (0.0013)
CSR_STAB	D7	0.0381** (0.018)	PDI	D16	0.0072*** (0.0019)
ETA	D8	0.0238*** (0.0064)	Log-likelihood		14,124.1

Note: 1. Numbers in parentheses are standard errors. 2. * denotes significance at the 10% level, ** denotes significance at the 5% level, and *** denotes significance at the 1% level.

6. Conclusions

We regard CSR activities as intermediate goods produced by banks in the first stage of the production process. In this manner, high CSR scores are consistent with high efficiency measures in the first stage, given an input mix, but this relationship decreases in the second stage. This is because CSR activities are treated as inputs in the second stage, similar to deposits. We adopt the network SFA to estimate the efficiency scores of 187 banks across 27 countries during 2003–2014. Most of the sample banks are based in developed countries.

The essential question is determining which CSR activities are beneficial for banks and which are not. Previous relevant studies have attempted to quantify a bank's CSR involvement.

For example, Wu and Shen (2013) used CSR indices obtained from the EIRIS database to discuss the effects of CSR on bank performance. They suggested three hypotheses to explain the effects of CSR on bank performance (i.e., the positive (strategic), negative (altruistic), and neutral (green washing) hypotheses) and revealed that the strategic CSR motive is predominant. However, the relationship between CSR and CFP remains controversial. Most studies have revealed that CSR is positively correlated with CFP (Mahoney and Roberts, 2007; Van Beurden and Gössling, 2008; Inoue and Lee, 2011; Wu and Shen, 2013), but a few studies have discovered a negative relationship (Vance, 1975; Boyle et al. 1997), mixed effects (Lee et al., 2013) or no significant correlation (Surroca, Tribó, and Waddock, 2010). As a possible explanation for these mixed findings, we propose that different CSR activities may affect bank performance in distinct directions.

As such, we divide CSR activities into seven categories (i.e., the employee, community, environment, governance, stakeholder, bribery, and stability categories), and we regard them as environmental variables together with the five CAMEL indices and four cultural indices. The inclusion of these environmental variables in the network SFA models dramatically complicates the models. We extend on Huang et al. (2017) to allow for linking environmental variables with inefficiency.

We investigate three motives for banks to engage in CSR and investigate their effects on efficiency: the strategic, altruistic, and window dressing motives. We discover that the different CSR components affect efficiency in different directions. Among them, environmental-related CSR activities can improve banks' efficiency, which is similar to their effects on efficiency in the manufacturing and agricultural industries. Bank managers should provide more environmental products to clients with high environmental awareness to benefit from this effect. Additionally, developing an effective anti-bribery system should also increase a bank's efficiency.

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