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Incorporating Credit Quality in Bank Efficiency Measurements: A Directional Distance Function Approach

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Abstract: The objective of the study was to measure the risk-adjusted efficiency of banks in 24 emerging economies for the period of 1999–2013. A two-stage network data envelopment analysis (DEA), with separate deposit mobilization and loan financing stages was used. Efficiency was measured using directional distance functions with DEA, featuring non-performing loans as undesirable outputs. The distributions of efficiency scores were different when credit quality was taken into account. The distribution of efficiency scores varied systematically with accumulation of non-performing loans across regions. The financial crisis of 2007–2008 impacted more adversely the regions that had higher proportions of non-performing loans in banks' portfolios. The results of a follow-on non-parametric regression showed that smaller, better capitalized, and private banks were more efficient. The conditions conducive for high levels of technical efficiency by banks were found to be characterized by economic growth and low inflation.

1. Introduction

The financial system plays a vital role in the economic development of an economy. Financial intermediaries, particularly the banks, mobilize funds from a diverse set of savers to investors (Drigă and Dura 2014). Efficient intermediation contributes to growth (Saini and Sindhu 2014) and economic stability. On the other hand, crisis in the banking sector could lead to broader macroeconomic instability (Baily and Elliott 2009) and adversely impact growth (Moyo et al. 2014). Despite their crucial importance to the economy, banks are prone to agency problems that may induce some managers to take excessive risks (Acharya and Naqvi 2012), and potentially jeopardize bank solvency. According to one study, 73% of the 171 failed banks in the United States for the period of 1979–1987 engaged in aggressive risk-taking (Office of the Comptroller of the Currency 1988).

There is a voluminous body of literature on the efficiency of banks (Kumar and Gulati 2014). With a few exceptions, this literature did not take into account the excessive risk-taking, often manifested in the form of non-performing loans. Moreover, almost all previous studies employed a single-stage, black-box, conceptualization of banking operations (Färe and Grosskopf 2000).[1] From a risk-modeling perspective, this is an inadequate representation of the actual banking operations, which have two stylized stages—a deposit mobilization stage and a loan financing stage—with excessive risk-taking relevant to the latter stage only. The technologies used for converting

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[1] Most previous studies used either the production or the intermediation approach to model bank efficiency.

productive inputs into outputs may vary across different stages of bank operations; therefore, single-stage efficiency measurement approaches may lead to serious misspecification of the efficient technological frontier, and the resulting efficiency measurements may be misleading. To the best of our knowledge, there are only two studies that incorporated risk-taking or credit quality into efficiency measurements, following Chung et al. (1997), while using a sufficiently flexible representation of the banking operations (Akther et al. 2013; Fukuyama and Weber 2010). These studies, however, considered banks in single countries. There is a need for applying these more robust measurement approaches for investigating bank efficiency in a multi-country, emerging economy setting over time. This would allow the efficiency patterns to be compared across countries and regions and also make it possible to investigate the impacts on bank efficiency of macroeconomic shocks such as the 2007–2008 financial crisis.

The present study attempted to fill this gap. It used a two-stage network data envelopment analysis (DEA), with separate specification of technologies for the deposit mobilization and the loan financing stages using a directional distance function. In line with the stylized banking operations, the loan financing stage in the study was modeled with an undesirable output (non-performing loans) along with a good output. The risk-adjusted efficiency scores were found to be markedly different from scores obtained without accounting for bad loans, and these differences were more pronounced in the loan financing stage, thus underscoring the restrictive nature of the common technology assumption across banking operations that was extensively used in the extant literature. A second contribution of the study is that it investigated the determinant of bank efficiency using non-parametric regression that does not rely on ad hoc assumptions. Finally, the significant differences in measured efficiency scores across regions and countries served to highlight the importance of a studying bank efficiency in a cross-country setting in the emerging economies. The regional and cross-country comparisons are important as they help answer the question how global economic shocks, such as the Asian financial crisis of 1997 and the global financial crisis of 2007–2008, impacted bank efficiency in individual countries and regions.

2. Review of Literature

Abraham Charnes et al. (1978) invented the term data envelopment analysis and proposed an input-orientated DEA that measured efficiency in terms of radial contraction of input vectors necessary to reach the efficient frontier while assuming constant returns to scale. Banker, Charnes, and Cooper (1984) extended the DEA analysis to variable returns to scale (see (Emrouznejad and Yang 2017; Liu et al. 2013)).

Efficiency studies mostly model a single-stage decision-making process. However, many organizational operations, including banks, have multiple stages that offer possibilities for separate measurements of efficiency for each stage. The pioneering paper of A. Charnes et al. (1988) introduced the notion of network DEA structures for the measurement of efficiency in multi-stage operations.

The network DEA was used for measuring the efficiency of US banks across profitability and marketing stages (Seiford and Zhu 1999), Taiwanese banks for deposit mobilization and loan financing stages (Yang and Liu 2012), and Brazilian banks for cost efficiency and productive efficiency stages (Wanke and Barros 2014).

A separate strand of literature attempted to measure bank efficiency in the context of non-performing loans by employing single-stage directional distance functions (Chung et al. 1997), seeking to reduce inputs and undesirable outputs while increasing desirable outputs (Fukuyama and Weber 2008).

As mentioned earlier, credit risk arises in the second (loan financing) stage of banking operations. Given the considerable interest of the researchers in investigating efficiency measurements in the presence of non-performing loans, network DEA—with non-performing loans at the financing stage modeled as an undesirable output—is a natural direction for extending this literature. However, very few studies modeled bank efficiency in the presence of bad loans using the network DEA framework.

Wang et al. (2014) measured the efficiency of Chinese banks through hyperbolic Farrell-type efficiency measures proposed by Färe et al. (1989). The study divided the overall efficiency into two sub-processes, i.e., deposit producing and profit earning. Huang et al. (2014) examined the super efficiency of Chinese banks using a two-stage network model with bad outputs by extending the network slack-based measure model (NSBM) of Tone and Tsutsui (2009). The non-performing loans were modeled as a second-stage undesirable output.

Fukuyama and Weber (2010) proposed two-stage directional distance functions for measuring the efficiency of Japanese banks with non-performing loans as bad output in the second stage. Akther et al. (2013) estimated the efficiency of banks in Bangladesh through two-stage directional distance functions, which modeled bad loans as an undesirable output in the second stage. While these studies employed two-stage DEA and modeled undesirable outputs following Chung et al. (1997), they all focused on single countries. This is a serious limitation as it does not permit cross-country and regional comparisons of bank efficiency measurements, which, as noted above, could shed light on differential impacts on countries of common macroeconomic shocks such as global financial crises.

The selected countries were operated under different banking regulations and supervision. This was an important consideration investigated for cross-country comparison. Barth et al. (2013) conducted a survey to collect data and measures of bank regulatory and supervisory policies for the period of 1999–2011 in 180 countries. The authors collected the data based on several bank related questions. The study concluded that the supervision and regulation of banks differ in many dimensions across selected countries. Moreover, the study found divergence in bank regulatory regimes over the past decade despite the worst global financial crisis since the Great Depression.

Most DEA efficiency studies in the existing literature conducted a follow-on analysis to investigate the determinants of efficiency, using a Tobit model (Tobin 1958) that produced point estimates of contributions of different variables. This approach relies on ad hoc distributional assumptions. An alternative is non-parametric regression based on Kernel density estimation (Rosenblatt 1956), which does not suffer from ad hoc assumptions. For example, Illueca et al. (2009) examined the productivity of Spanish savings banks by employing kernel density estimations and non-parametric regression. However, the study did not consider non-performing loans within a multi-stage network DEA.

The present study makes the following contributions: (i) incorporation of credit risk in efficiency measurements of banks; (ii) use of a sufficiently flexible multi-stage network DEA framework, which better captures stylized banking operations where credit risk arises at the loan financing stage and manifests in the form of non-performing loans; (iii) extension of efficiency measurements to a multi-country setting making possible comparisons across countries; and application of non-parametric regression, avoiding ad hoc assumptions in estimating the impact of bank characteristics and other relevant variables on efficiency.

3. Methodology

3.1. Directional Distance Functions with Undesirable Outputs

Consider a technology T with inputs $x \in R_+^N$, desirable outputs $y \in R_+^M$, and undesirable outputs (such as bad loans) $b \in R_+^J$. The directional distance function introduced by Chung et al. (1997), which seeks to directionally increase desirable outputs, while decreasing inputs and undesirable outputs, can be defined as follows:

$$\vec{D}_T \ (x, y, b; g) = \text{Sup} \ \{\beta : (x - \beta g_x, y + \beta g_y, b - \beta g_b) \in T \}, \tag{1}$$

where the nonzero vector g = $(-g_x, g_y, -g_b)$ determines the directions in which the inputs, desirable outputs, and undesirable outputs are scaled. The reference technology set T = {$(y, b):x$ can produce (y, b)}} and is assumed to satisfy the assumptions of constant returns to scale, strong disposability of desirable outputs and inputs, and weak disposability of undesirable outputs.

Supposed there were k = 1, 2, … K decision-making units (DMUs). Then, according to Chung et al. (1997), the directional distance function can be obtained by solving the following DEA problem:

$$\text{Max}\beta = \vec{D}_T(x, y, b; g_x, g_y, g_b),$$

subject to

$$\sum_{k=1}^{K} z_k \, y_{km} \geq y_{km} + \beta y_{km}, \qquad\qquad m = 1, 2 \dots M; \qquad\qquad (2)$$

$$\sum_{k=1}^{K} z_k \, y_{kj} = y_{kj} - \beta y_{kj}, \qquad\qquad j = 1, 2 \dots J; \qquad\qquad (3)$$

$$\sum_{k=1}^{K} z_k \, x_{kn} \leq x_{kn} - \beta x_{kn}, \qquad\qquad n = 1, 2 \dots N; \qquad\qquad (4)$$

$$\sum_{k=1}^{K} z_k = 1, \qquad\qquad\qquad\qquad (5)$$

$$z_k \geq 0, \qquad\qquad\qquad k = 1, 2 \dots, K;$$

where $\sum_{k=1}^{K} z_k \, y_{km}$ is the efficient frontier formed as a linear combination of outputs of the other firms. Equation (2) states that the actual output (y_{km}) produced by the firm, plus the possible expansion (βy_{km}), should be at most as large as the output represented by the efficient frontier. Likewise, Equation (3) requires that the input use (x_{kn}), minus the possible input contraction (βx_{kn}), should be at least as large as $\sum_{k=1}^{K} z_k \, x_{kn}$, the linear combination of inputs used by the other firms. The undesirable output, i.e., the bad loans are represented by y_{kj}, while βy_{kj} is the possible reduction in the undesirable output. The weights z_k are the intensity variables for expanding or shrinking the individual observed activities of DMUs to construct convex combinations of the observed inputs and outputs.

Given the network DEA, the efficiency scores were obtained separately for the deposit mobilization stage and the loan financing stages. The overall efficiency score for the bank was obtained by multiplying the two sores.

3.2. Non-Parametric Regression

Most previous studies that measured efficiency also attempted to model the determinants of efficiency in a second-stage follow-on regression, often employing the Tobit specification (McDonald 2009), which relies on ad hoc parametric assumptions. Ashraf et al. (2017) measured bank risk-taking behavior with three alternative proxies considered as dependent variables, while taking into account the non-performing loans as measures of risk in the efficiency measurement of banks. In contrast, the present study modeled the determinant of efficiency using non-parametric regression (Hayfield and Racine 2008), which does not rely on arbitrary assumptions. Moreover, it dealt differently with continuous and discrete variables.

$$Y_{it} = m\,(Z_{it}) + \varepsilon_i, \, i = 1, 2, \dots\dots N; \qquad\qquad (6)$$

where Y_{it} is the dependent variable, i.e., the efficiency score of the bank. Since regressors may be either continuous or discrete, the study defined $Z_{it} = (Z_{it}^c, Z_{it}^d)$, where Z_{it}^c refers to the vector of continuous regressors and Z_{it}^d refers to the vector of discrete regressors, t is the time in years, I is the bank in emerging economies, and N is the total sample observations (5685).

This non-parametric regression technique yields partial derivatives that are permitted to vary over the domain for the variable in question, in contrast with parametric multivariate linear regression techniques, in which the partial derivative is typically assumed to be constant over its domain (J. Racine 1997). The np package was used to estimate non-parametric regressions that suggested more robust interpretations (Hayfield and Racine 2008). The kernel bandwidths were selected via least-squares cross-validation and calculated as $3.45\sigma \, n^{-\frac{1}{5}}$ (J. S. Racine 2008). For hypothesis testing in non-parametric regression, the study employed the bootstrapping procedures for continuous variables proposed by J. Racine (1997) and Racine et al. (2006) for categorical variables.

4. Data

This study employed annual data of the banking sector from the *BankScope* database. The sample covered the study period of 1999–2013. The study analyzed the performance of 918 banks in 24 *Emerging Economies* from six regions of the world. The study included the following regions (number of banks): East Asia (213), Southeast Asia (164), South Asia (95), Latin America (244), Emerging Europe (126), and Africa and the Middle East (76). The combination of variables in both stages to measure the efficiency of banks is listed in Table 1.

Table 1. Stage-wise inputs and outputs of banking operations. DEA—data envelopment analysis.

Process	Variables		Method
	Inputs	Outputs	
Deposit mobilization stage	• Personnel expenses • Other administrative expenses • User cost of fixed assets • Total deposits	• Total deposits	Directional distance function based on network DEA
Loan financing stage	• Personnel expenses • Other administrative expenses • User cost of fixed assets	• Total loans • Other earning assets • Non-performing loans[2]	

In addition, the determinants of efficiency were investigated using the estimated efficiency scores from the DEA model as the dependent variable in a non-parametric regression, with the following bank characteristics, financial ratios, and macro variables as independent variables:

Size = log of total assets

Capital adequacy = ratio of total equity to total assets

Liquidity = ratio of total loans to total deposit

GDP_GR = growth rate of gross domestic product (GDP)

Inflation rate = annual inflation rate

Public bank dummy = 1 if the bank ownership is public; 0 otherwise.

Crisis 2007–2008 Dummy = 1 for the year 2007–2008; 0 otherwise.

East Asia dummy = 1 for banks from East Asia; 0 otherwise.

Southeast Asia dummy = 1 for banks from South East Asia; 0 otherwise.

South Asia dummy = 1 for banks from South Asia; 0 otherwise.

Latin America dummy = 1 for banks from Latin America; 0 otherwise.

Emerging Europe dummy = 1 for banks from Emerging Europe; 0 otherwise.

5. Results

The distributions of efficiency scores for each stage, as well as that of the overall score, are negatively skewed, as shown in Table 2, indicating clustering of individual banks' scores at higher efficiency levels (see Figure 1).

Table 2. Descriptive information of efficiency scores *.

Variable	Skewness	Kurtosis	Mean	Std. Deviation
Efficiency of deposit mobilization (Stage I)	−3.11	12.51	0.93	0.1293
Efficiency of loan financings (Stage II)	−1.98	3.21	0.85	0.2311
Overall efficiency	−1.60	1.79	0.80	0.2463

Note: * The model was estimated including non-performing loans (NPLs) as an undesirable output.

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[2] It may be argued that, instead of the non-performing loans (NPLs), the loan loss provisions are an alternative representation of the undesirable output in the model. Note, however, that the loan loss provisions are also calculated on the basis of non-performing loans (Bholat et al. 2016). The previous studies employed non-performing loans as an undesirable output in measuring efficiency through directional distance functions. See, for example, (Akther et al. 2013; Barros et al. 2012; Zhu et al. 2015). We followed the same convention and used NPLs to represent undesirable outputs in this study.
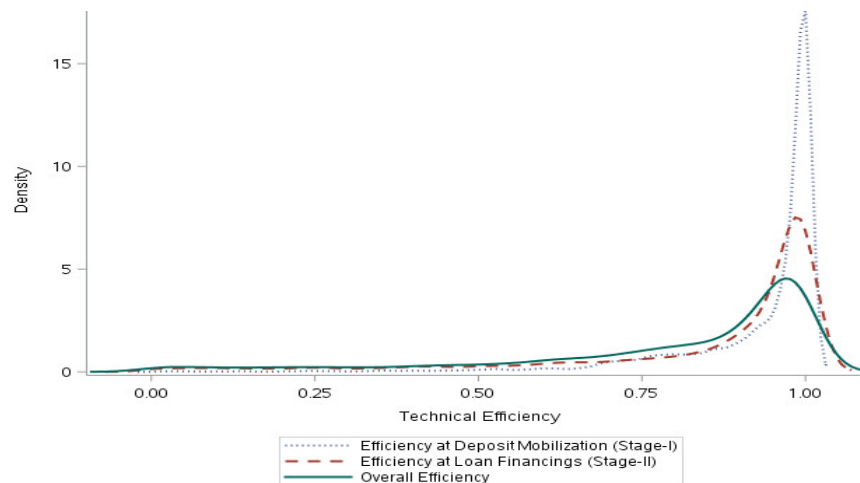
Figure 1. Distributions of measured efficiency scores.

The measured efficiency at the deposit mobilization stage was 93%, which indicates that, at this stage of operations, banks were highly efficient, possibly reflecting managerial performance metrics that reward deposit creation.

At the loan financing (second) stage, the efficiency level was 0.85 on average, and most measurements were clustered in the interval of 0.80–1.0. The banks were somewhat less efficient in the loan financing stage. This inefficiency was mainly caused by high non-performing loans because of adverse borrower selection. Our results were found to be consistent with the findings of Hamid et al. (2017); Zago and Dongili (2011).

A non-parametric Kolmogorov–Smirnov test was used to measure the equality of distributions of efficiency scores with and without the inclusion of undesirable outputs in modeling. A significant difference at the 1% level of significance was found. This implied that, once non-performing loans (NPLs) were taken into account, the technical efficiency of banks increased significantly, suggesting that an important aspect of banking production (i.e., credit quality) needs to be considered when evaluating banks' performances. Several studies employed this test to investigate the equality of distributions (Banker et al. 2010; Johnes et al. 2014; Titko et al. 2014).

By contrast, the efficiency scores calculated from the model that did not take NPLs into account had greater dispersion, and more of the mass of the distribution was concentrated in the lower efficiency range, represented by the interval of 0.25–0.75, compared to the distribution obtained upon including NPLs in the model (see Figure 2).
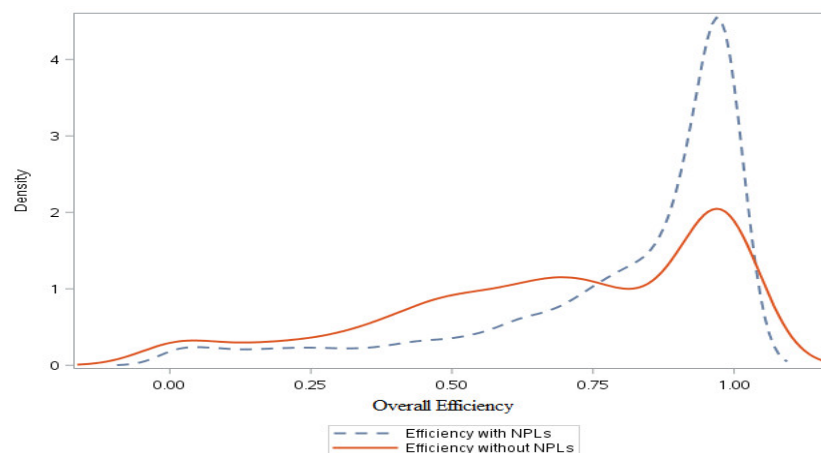

Figure 2. Comparative distribution analysis of efficiency scores with and without non-performing loans (NPLs).

The same non-parametric test was employed to measure the equality of distributions for pre-crisis and post-crisis efficiency scores (Figure 3), also finding a significant difference at the 1% level. The distribution of efficiency scores pre-crisis were more skewed to the left. In addition, the mass of the distribution was concentrated at higher efficiency levels. By contrast, the efficiency scores post-crisis were concentrated in the lower efficiency range, represented by the interval of 0.70–0.90. The overall average efficiency score pre-crisis was 0.85; however, it dropped to 0.74 post-crisis (see Table 5). This reconfirmed that the global financial crisis hit banking efficiency in emerging economies.
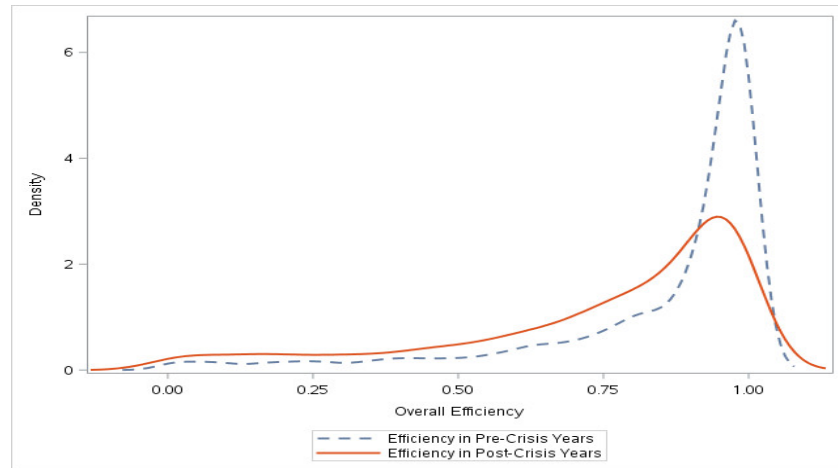

Figure 3. Comparative distribution analysis of efficiency scores pre-crisis and post-crisis.

Table 3 presents the technical efficiency scores for stage I (deposit mobilization) and stage II (loan financing), and their regional and national breakdown. The overall bank efficiency was 0.80, which resulted from a much higher average efficiency (93%) in the deposit mobilization stage than in the loan financing stage (85%). The most inefficient banks were in Africa and the Middle East where the average efficiency score was only 0.55. This was followed by South Asia and Emerging Europe, where the average efficiency scores were 0.67 and 0.68, respectively. The average overall bank efficiency scores for some countries were very low, for example, in Egypt (0.37), United Arab Emirates (UAE; 0.55), and Pakistan (0.61).

Table 3. Regional and national bank efficiency patterns. UAE—United Arab Emirates.

Region	Country Name	Number of Banks	Number of Observations	Stage I	Stage II	Overall Average Efficiency Scores	
Southeast Asia	Indonesia	80	562	1.00	0.86	0.86	
	Malaysia	46	137	0.99	0.64	0.64	0.83
	Philippines	32	191	1.00	0.94	0.94	
	Thailand	6	54	1.00	0.69	0.68	
South Asia	India	69	587	0.93	0.72	0.69	0.67
	Pakistan	26	219	0.91	0.65	0.61	
Latin America	Argentina	57	506	0.96	0.98	0.95	
	Brazil	96	640	0.96	0.97	0.93	
	Chile	30	134	0.91	0.96	0.89	0.93
	Colombia	14	93	0.95	1.00	0.95	
	Mexico	32	225	0.93	0.97	0.90	
	Peru	15	124	0.91	0.99	0.90	
Emerging Europe	Czech Republic	25	148	0.69	0.73	0.54	0.68

Region	Country Name	Number of Banks	Number of Observations	Stage I	Stage II	Overall Average Efficiency Scores	
	Greece	16	99	0.75	0.91	0.69	
	Hungary	13	94	0.80	0.93	0.74	
	Poland	33	173	0.83	0.86	0.72	
	Turkey	39	276	0.86	0.83	0.71	
	China	151	744	0.98	0.85	0.84	
East Asia	South Korea	15	61	1.00	0.91	0.91	0.85
	Taiwan	47	164	0.97	0.94	0.91	
Africa and the Middle East	Egypt	22	91	0.60	0.52	0.37	
	Morocco	12	57	0.91	0.79	0.72	0.55
	South Africa	18	91	0.85	0.70	0.65	
	UAE	24	215	0.87	0.60	0.55	
	Average	**918**	**5685**	**0.93**	**0.85**	**0.80**	**0.80**

Despite overall higher efficiency in the deposit mobilization stage, banks in some countries were very inefficient in mobilizing deposits. For example, the first-stage efficiency scores in Egypt, Czech Republic, and Greece were 0.60, 0.69, and 0.75, respectively. This suggested that there was huge potential for saving the productive input resources used by the banks, while achieving the same level of mobilization of deposits.

For the (second) loan financing stage—where the bank's risk-taking behavior may be manifested in the accumulation of non-performing loans—the average efficiency score was 85%, which is much lower than the first-stage efficiency score. In this second stage, the efficiency scores of banks in Malaysia, Thailand, Pakistan, India, Egypt, UAE, and South Africa were quite low. Again, the Egyptian banks had the lowest average efficiency score with only 52%.

Next, we discuss the regional comparisons of the overall average efficiency along with the stage-wise average efficiency. The Latin American banks were found to be the leaders in emerging economies and registered an overall average efficiency of 0.93, which was the result of an average efficiency of 0.95 at the deposit mobilization stage, and 0.97 at the loan financing stage. This was followed by East Asian and Southeast Asian banks, which registered good average efficiency scores of 0.85 and 0.83, respectively.

An important question is how taking into account bad loans as an undesirable output impacts the efficiency measurements. Zago and Dongili (2011) argued that "recognizing banks' efforts to reduce bad loans increases their efficiency". Our results (Table 4) showed that the overall efficiency scores after allowing for non-performing loans were higher at 0.80, compared to only 0.69 when NPLs were excluded. This was also true for all regions where the non-performing loans were a higher proportion of the banks' loan portfolios. However, for Latin America, where the proportion on NLPs was only about half the average proportion of NPLs across all regions, the average efficiency scores with and without the inclusion of non-performing loans were quite similar. This suggests that it is important to incorporate non-performing loans, in addition to the undesirable output DEA formulation, for measuring bank efficiency in countries and regions with higher proportions of bad loans exist in the banks' loan portfolios.

Table 4. Average overall efficiency scores with and without non-performing loans (NPLs).

Region	Share of NPLs	Efficiency Scores	
		With NPLs	**Without NPLs**
Southeast Asia	9.76	0.83	0.61
South Asia	7.29	0.67	0.51
Latin America	3.97	0.93	0.94
Emerging Europe	10.74	0.68	0.54

East Asia	4.11	0.85	0.71
Africa and the Middle East	8.98	0.55	0.41
Average	**7.48**	**0.80**	**0.69**

Table 5 shows that the overall average efficiency score during the period of 1999–2007 before the global financial crisis was 0.85. However, it dropped to 0.74 during the post-crisis period (2008–2013). A closer look at the stage-wise efficiency scores suggests that efficiency declines in the post-crisis period were more pronounced for the loan financing stage and were largely concentrated in the countries of South Asia, Africa and the Middle East, and emerging Europe—regions where the proportion of NPLs was higher. This suggests that non-performing loans had a role in the efficiency declines during the post crisis period.

Table 5. Average efficiency and NPLs pre- and post-crisis by region.

Classification	Southeast Asia	South Asia	Latin America	Emerging Europe	East Asia	Africa and the Middle East	Overall Efficiency of Banks
Efficiency pre-crisis							
Deposit mobilization stage	1.00	0.94	0.96	0.83	0.98	0.83	
Loan financing stage	0.87	0.76	0.97	0.82	0.94	0.59	**0.85**
Overall	**0.87**	**0.73**	**0.94**	**0.68**	**0.93**	**0.53**	
Efficiency post-crisis							
Deposit mobilization stage	1.00	0.91	0.92	0.78	0.98	0.81	
Loan financing stage	0.78	0.63	0.98	0.86	0.83	0.65	**0.74**
Overall	**0.78**	**0.60**	**0.90**	**0.68**	**0.81**	**0.56**	
Share of non-performing loans (%)							
Pre-crisis	12.44	8.15	4.12	9.41	5.99	7.95	
Post-crisis	6.24	6.19	3.63	11.85	2.98	9.57	

5.1. Non-Parametric Regression

The non-parametric regression estimated in the study explained efficiency scores with the help of various financial ratios and macroeconomic variables (see Table 6). A set of dummy variables representing the ownership status, financial crisis of 2007–2008, and regional banks is also included.

Note that the effects of individual independent variables were tested against the null hypothesis of no effect over the entire domain of the regression function (J. Racine 1997). The *p*-values corresponding to the derived test statistics also referred to responses across all domains. Also, note that the non-parametric regression allows the effects of individual independent variables to vary locally. Both these considerations have to be borne in the mind when interpreting the non-parametric regression results presented in Table 6 (and in Figure 4). Table 6 reports the band width and the *p*-values for individual independent variables.

Table 6. Non-parametric regression results. GDP—gross domestic product.

	Model I		Model II		Model III	
Variable	**Band Width**	***p*-Value**	**Band Width**	***p*-Value**	**Band Width**	***p*-Value**
Size	0.2853	0.07518	1.6045	0.06767	0.2852	0.41353
Capital adequacy	0.0177	0.21303	69358	< 0.0001	0.0143	0.06015
Liquidity	0.1325	0.26566	17.1520	0.38346	0.1264	0.54386
GDP growth rate	7.3452	0.84962	0.01462	0.37093	4.9081	0.06516
Inflation gate	3.1927	0.02005	0.3356	0.75188	3.6092	0.02256
Public banks	0.0746	< 0.0001	0.4999	0.02757	0.0463	<0.0001

Financial crisis of 2007–2008	0.4293	<0.00251	0.2600	0.0802	0.4474	<0.0001
East Asia	–	–	–	–	0.02753	<0.0001
Southeast Asia	–	–	–	–	0.000073	<0.0001
South Asia	–	–	–	–	0.01635	<0.0001
Latin America	–	–	–	–	0.00037	<0.0001
Emerging Europe	–	–	–	–	0.00059	<0.0001
Indonesian crisis dummy	–	–	0.5	0.48622	–	–
Malaysian crisis dummy	–	–	0.49999	0.74686	–	–
Philippines crisis dummy	–	–	0.49999	0.28070	–	–
Thailand crisis dummy	–	–	0.3107	0.08521	–	–
Brazil crisis dummy	–	–	0.49999	0.44611	–	–
Argentina crisis dummy	–	–	0.5	0.99749	–	–
Colombia crisis dummy	–	–	0.40188	0.97744	–	–
Turkey crisis dummy	–	–	0.46401	0.89724	–	–
Egypt crisis dummy	–	–	0.12138	0.01253	–	–
Morocco crisis dummy	–	–	0.49999	0.89474	–	–
Czech Republic crisis dummy	–	–	0.49999	0.58897	–	–
Greece crisis dummy	–	–	0.49999	0.59398	–	–
	$R^2 = 0.80$		$R^2 = 0.48$		$R^2 = 0.78$	
Dependent variable: overall efficiency scores						

Model I: country fixed effect; Model II: country fixed effect and country crises dummies; Model III: regional fixed effects (dummies). Note: In Model II, the details of the country crisis dummies are as follows: Indonesian crisis 1997–1999, Malaysian crisis 1997–1999, Philippines crisis 1997–2001, Thailand crisis 1997–2000, Brazil crisis 1999, Argentina crisis 1999–2002, Colombia crisis 1999, Turkey crisis 2001, Egypt crisis 2011–2013, Morocco crisis 2009, Czech Republic crisis 2009–2011, and Greece crisis 2009–2013.

The efficiency of banks may also depend on the regulatory regime, which could vary from country to country (Barth et al. 2008).[3] There are some very detailed World Bank surveys that provide a rich set of indicators of the bank regulatory environments for a large number of countries. These surveys capture the various features of the regulatory regimes as they existed at specific points in time, i.e., 1999, 2002, and 2006 (ibid. p. 5). This study used a research design based on a panel of annual bank-level data from 24 emerging economies from 1999 to 2013. The integration of both datasets for use in model estimation, where the other bank characteristics were observed annually, is not a trivial matter.[4] However, failing to control for the regulatory regime in some way may bias the results. We tried to control for the country-specific regulatory environment by introducing country fixed effects in Model I and Model II (see Table 6).

The Model I results suggest that bank size significantly affected efficiency with a *p*-value of 0.075, which was somewhat above the conventional threshold of 5%. The ownership status (public bank) was also highly significant. No other bank characteristic had a statistically significant effect. Among the two indicators of macroeconomic environment, inflation had a significant effect on bank

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[3]　We would like to thank an anonymous referee for this point.

[4]　The surveys contain a wealth of information that, when suitably combined with other sources of bank-level data, could offer rich possibilities for further research. We hope to explore some of these possibilities in our own future research. Models I and II that incorporated country fixed effects in an attempt to capture the individual country regulatory environment, while not fully capturing the dynamics of the regulatory regimes, were motivated by Barth et al. (2008).

efficiency and the GDP growth rate variable was insignificant. The impact of the 2007–2008 financial crisis on efficiency was highly significant.
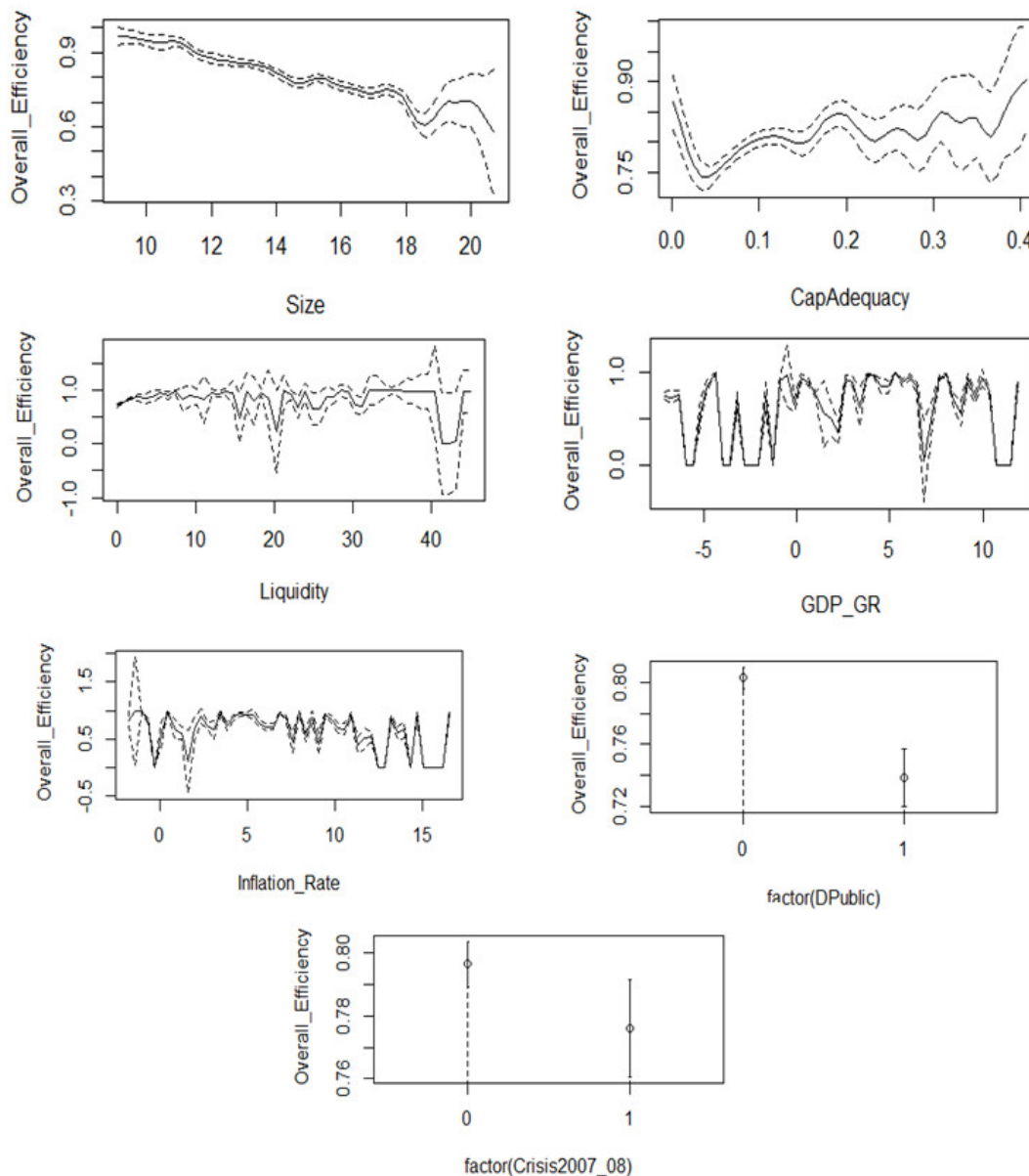

Figure 4. The relationship between technical efficiency, bank characteristics (size, capital adequacy, liquidity and public bank dummy), macroeconomic indicators (GDP growth rate and inflation rate), and the financial crisis of 2007–2008.

While the financial crisis of 2007–2008 had global effects, individual countries also had financial crises whose effects were less contagious. Model II included country financial crisis dummies. For the country in question, these dummy variables took the value of 1 during the crisis period, and 0 otherwise. Model II was also estimated with country fixed effects. The results presented in Table 6 suggest that, in addition to size and ownership status, capital adequacy was a highly significant determinant of bank efficiency. None of the macroeconomic variables had statistical significance, and the dummy variable for the 2007–2008 financial crisis had a *p*-value of 0.08, making it significant at the 10% level. Among the country financial dummies, only the dummy variables for Egypt and

Thailand were statistically significant, with the latter only marginally so. The model R^2 value was only 0.48 compared to the R^2 of 0.80 for Model I.

In contrast to Models I and II, Model III did not specify country fixed effects, and instead included dummy variables for regions to capture the regional heterogeneity of efficiency scores. All regional dummies were statistically highly significant. The model R^2 was 0.78, which was comparable to that of Model I. The bank characteristics that had statistically significant effect on efficiency were found to be capital adequacy and ownership status, with p-values of 0.06 and <0.0001, respectively. Both variables reflecting macroeconomic conditions were statistically highly significant. The dummy variable representing the impact on bank efficiency of the global financial crisis was also highly significant.

We present the partial regression plots for Model I in Figure 4. The plots for Models II and III can be found in the Appendix. The graphs from all plots show a high degree of similarity.

Increases in the capital adequacy ratio raised technical efficiency across the entire domain (top right panel of Figure 4). However, the imprecision of this effect increased, especially for capital adequacy ratios higher than 0.3. Several other studies found a positive relationship between capital adequacy and bank efficiency, for example, see (Gropp and Heider 2010; Kleff and Weber 2008).

Figure 4 also provides a graphical representation of the relationship between bank technical efficiency and the macroeconomic environment in which the banks operated. These graphs reveal interesting empirical regularities in different segments of the domain of the relationship. The banks operating in stagnant or contracting economies had poor efficiency scores (top panel), which were also highly volatile in that part of the domain.[5] As GDP growth entered positive territory, the bank efficiency score also increased. This pattern was observed to be positive at growth rates of up to about 5%. Vu and Nahm (2013) pointed out that high growth led to more savings and, hence, more deposits with the banks at a relatively low cost. For growth rates exceeding 5%, however, the technical efficiency scores became considerably more volatile and showed a somewhat declining trend.

Higher bank efficiency scores were found at low to moderate rates of inflation. Vu and Nahm (2013) also found that low inflation was associated with high levels of bank efficiency. As inflation exceeded 6%, the relationship became somewhat more volatile and declining efficiency scores were observed.[6] With inflation rates in excess of 10%, efficiency scores showed great variation and declined sharply. This finding is consistent with that of Batir et al. (2017) who pointed out that high inflation caused the efficiency of banks to decline.

The ownership status of banks indicates that public banks performed significantly poor at the 1% level of significance as compared to private banks. Several other studies pointed out the poor performance of public banks; for example, private banks were more efficient than public banks in Czech Republic and Poland (Weill 2003); public banks were less efficient compared to private banks in 15 East European transition countries (Fries and Taci 2005); joint-stock banks which were not owned by the government were found to be more efficient than state-owned banks in China (Xiaoqing Maggie and Heffernan 2007).

The results of Model III suggested that the financial crisis of 2007–2008 caused efficiency scores to decline in emerging economies. The regional banks in East Asia, Southeast Asia, and Latin America performed significantly better with p-values < 0.01. The banks in these regions had a lower proportion of non-performing loans in their portfolios. In contrast, banks in the regions of South Asia and Emerging Europe performed significantly poorly with p-values < 0.01.[7] The banks in these regions had a high proportion of non-performing loans (see Table 4). This suggests that the negative impact of the crisis on bank efficiency was associated with the accumulation of non-performing loans.

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[5] In our sample, the economies of countries such as Greece, Hungary, Czech Republic, Turkey, and UAE experienced negative growth rates and poor bank efficiency during various sub-periods.

[6] In our sample, the economies of countries such as Turkey, Argentina, Indonesia, Malaysia, and Pakistan experienced high inflation at various sub-periods and highly volatile technical efficiency scores for banks.

[7] The negative impact on efficiency of banks was due to generating higher NPLs and administrative expenses faced by banks as a result of crises in the regions of South Asia and emerging Europe.

6. Concluding Remarks

The present study modeled banking operations as consisting of two stylized stages—the deposit mobilization stage, and the loan financing stage—and separately estimated technical efficiency at each stage. An important feature of the study was the use of a cross-country panel dataset for efficiency measurement. To the best of our knowledge, no other study estimated technical efficiency for a panel or emerging economy banks using network DEA and directional distance functions featuring NPLs. This research design made it possible to perform regional comparisons of bank efficiency and also to investigate the impact of global macroeconomic shocks. Our results indicated that lower efficiency scores were concentrated in regions where the proportions of non-performing loans in banks' loan portfolios were higher.

The results obtained allowed not only profiling the efficient banks, but also a meaningful characterization of the macroeconomic environment conducive for achieving higher levels of bank efficiency. The efficient banks were smaller, better capitalized, and privately owned. The macroeconomic conditions conducive for bank efficiency were a growing economy, and low to moderate inflation rates (below ~5%). The financial crisis of 2007–2008 negatively impacted the technical efficiency of banks. The analysis of regional patterns of efficiency scores suggested that the most vulnerable banks were located in regions (South Asia and emerging Europe) where the proportion of non-performing loans was high.

Policy Implications

The study provides several policy implications. Our results indicated that banks need to be sufficiently capitalized. This may require regulations setting capital adequacy requirements that the bank could achieve by attracting capital from shareholders and investors, or acquired through mergers and acquisitions. Our results also support regulatory authorities forcing the less capitalized banks to merge.[8]

A high proportion of non-performing loans increases the risk of bank failures, macroeconomic crisis, and contagion, depending on whether the accumulation of non-performing loans took place at a single bank, within the banking system, or in countries across the region, respectively.

Finally, good macroeconomic management provides an environment in which banks can perform efficiently. Our results indicated that two dimensions of this environment were economic growth and low inflation.

Author Contributions: The research problem was identified by A.Q.; the analytical solution was pointed out by K.R.; The algorithmic implementation was performed by A.Q.; Both authors contributed to the specification of models and the interpretation of results; the paper was written by A.Q. with input from K.R. who also supervised the research.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix

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8 For example, if a small bank is merged with a large bank, then it is an empirical question whether or not the effect of the larger size on efficiency would outweigh the effect of improved capital adequacy. This study helps answer such empirical questions.
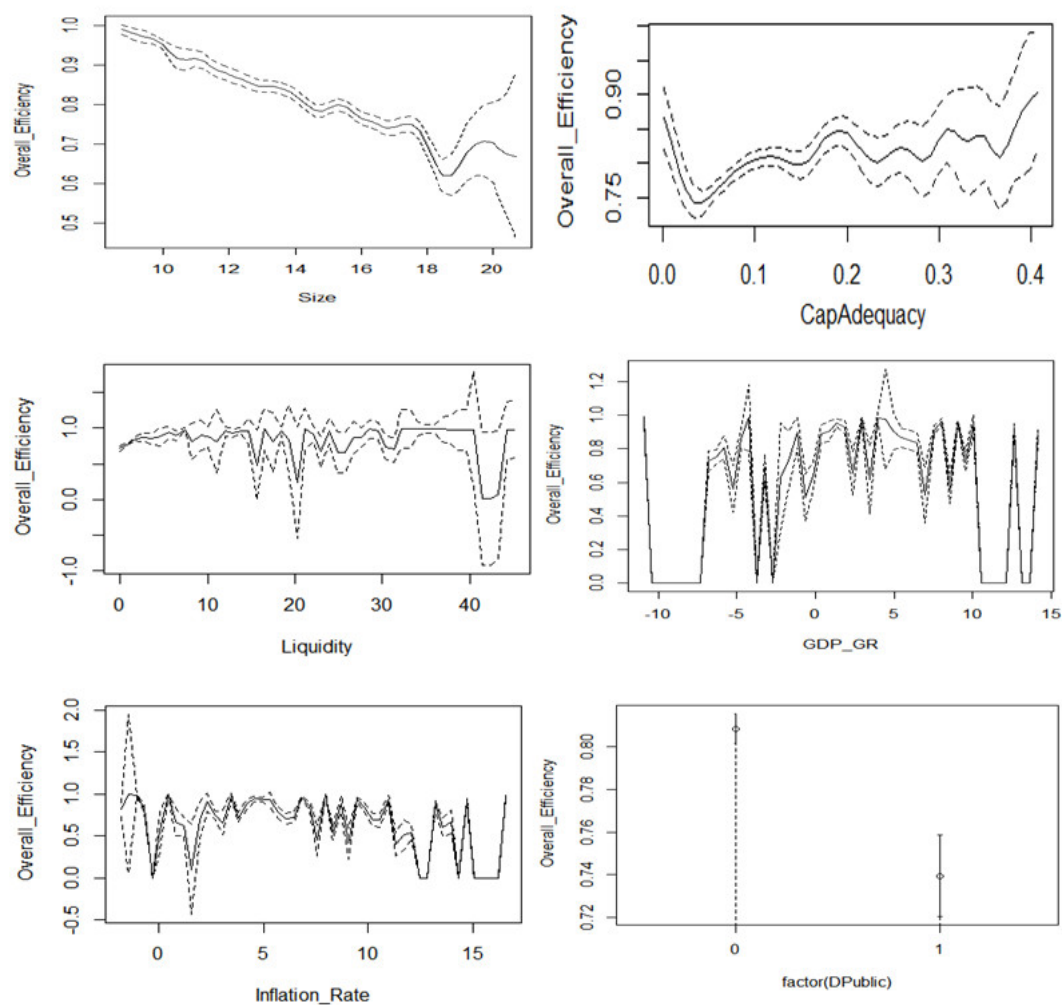
Figure A1. The relationship between technical efficiency, bank characteristics (size, capital adequacy, liquidity and public bank dummy), and macroeconomic indicators (GDP growth rate and inflation rate) (Model II).
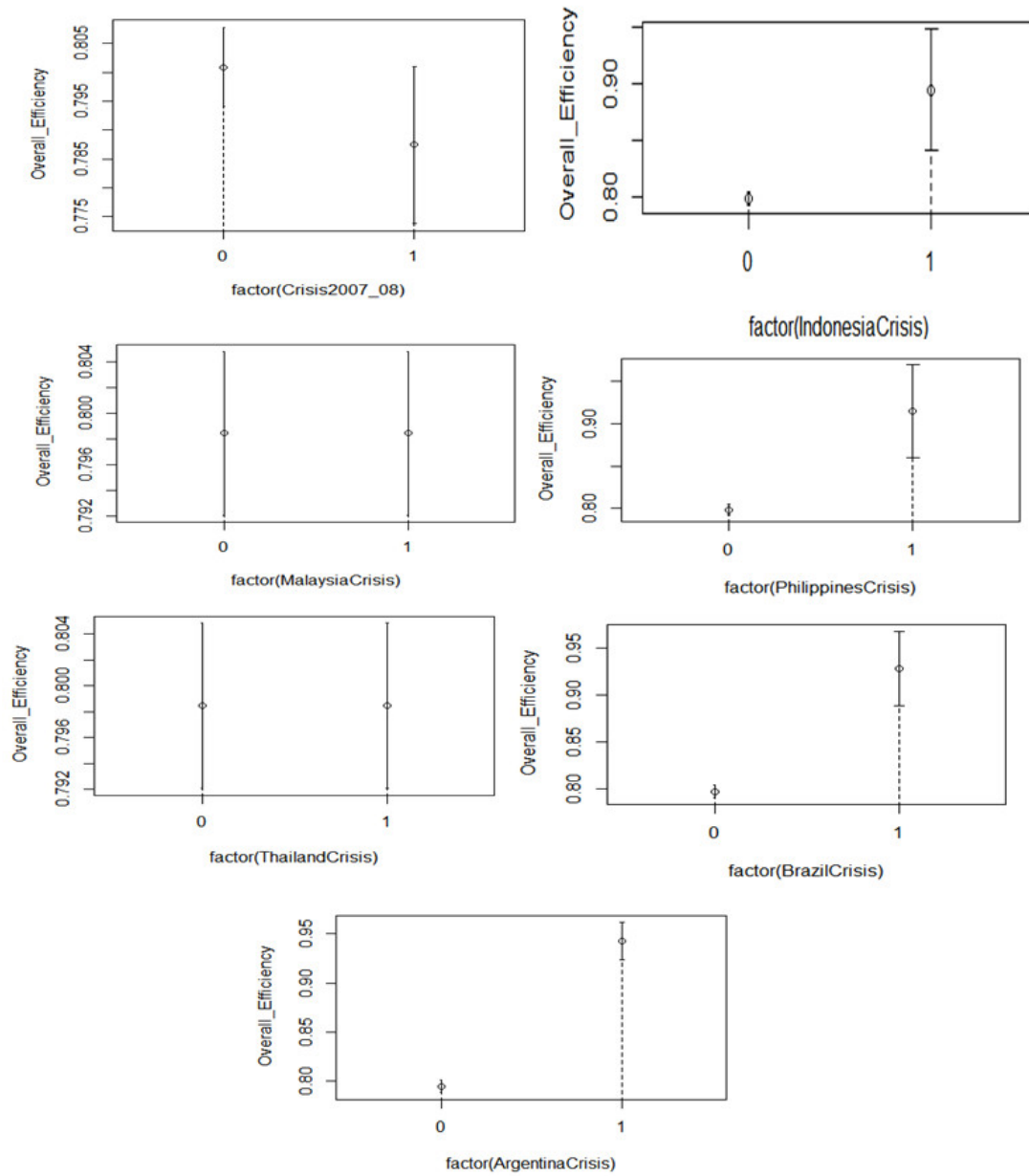
Figure A2. The relationship between technical efficiency and the financial crisis of 2007–2008, along with country crisis dummy variables (Indonesia crisis 1999 dummy, Malaysia crisis 1999 dummy, Philippines crisis 1999–2001 dummy, Thailand crisis 1999–2000 dummy, Brazil crisis 1999 dummy and Argentina crisis 1999–2002 dummy) (Model II).
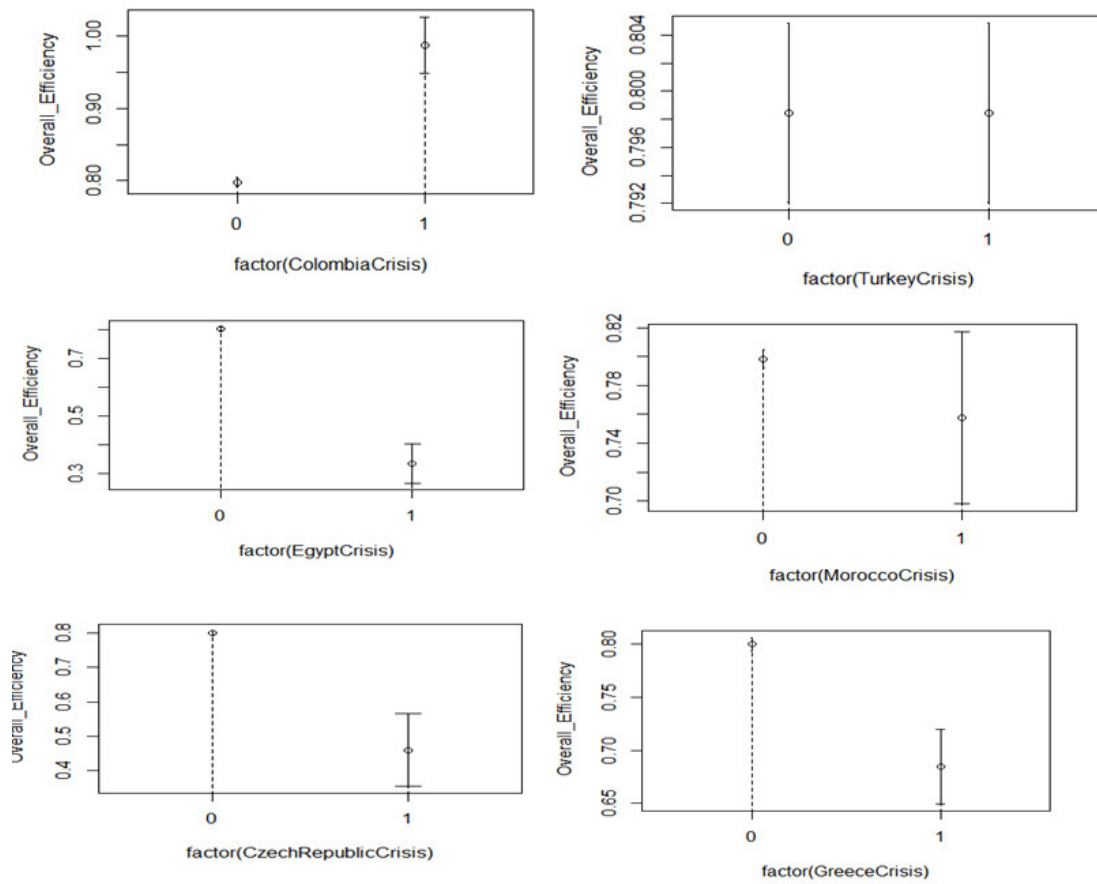
Figure A3. The relationship between technical efficiency and country crisis dummy variables (Colombia crisis 1999 dummy, Turkey crisis 2001 dummy, Egypt crisis 2011–2013 dummy, Morocco crisis 2009 dummy, Czech Republic crisis 2009–2011 dummy and Greece crisis 2009–2013 dummy) (Model II).
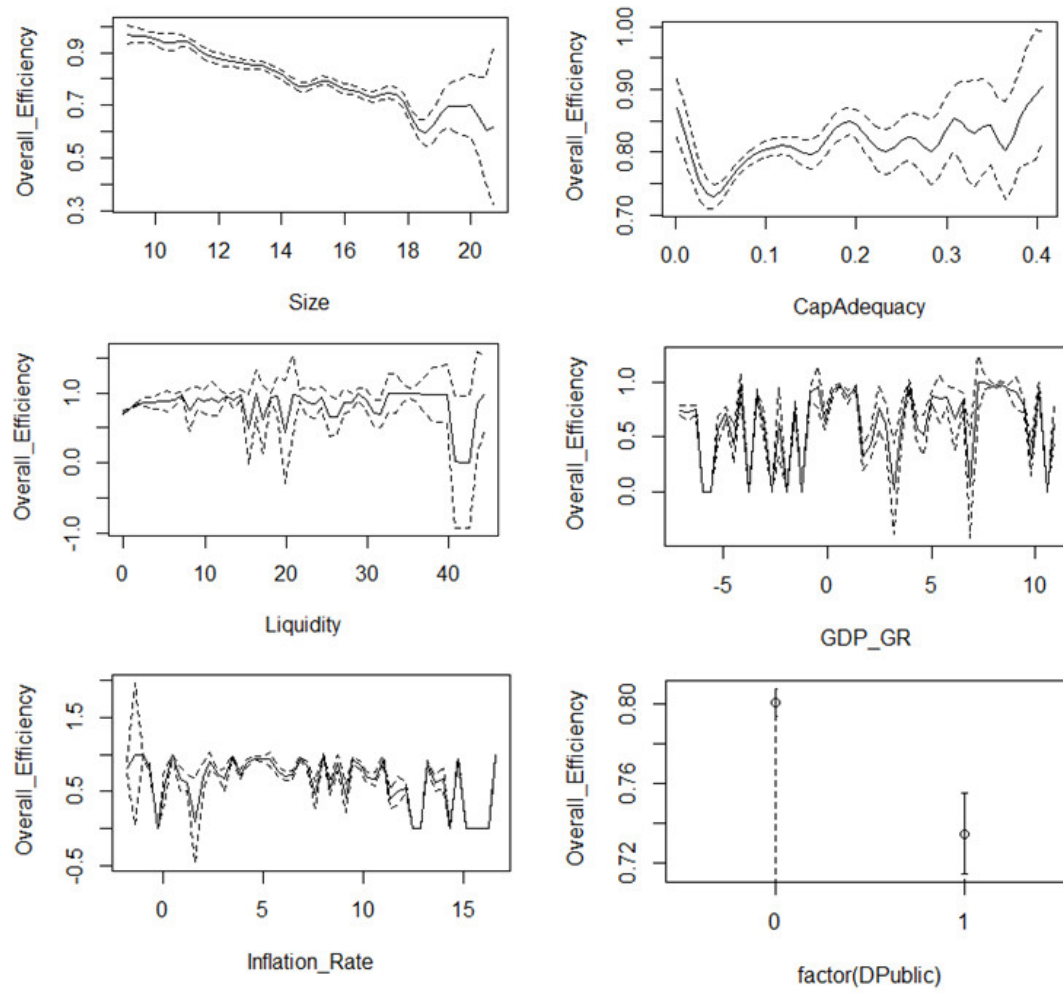
Figure A4. The relationship between technical efficiency, bank characteristics (size, capital adequacy, liquidity and public bank dummy) and macroeconomic indicators (GDP growth rate and inflation rate) (Model III).
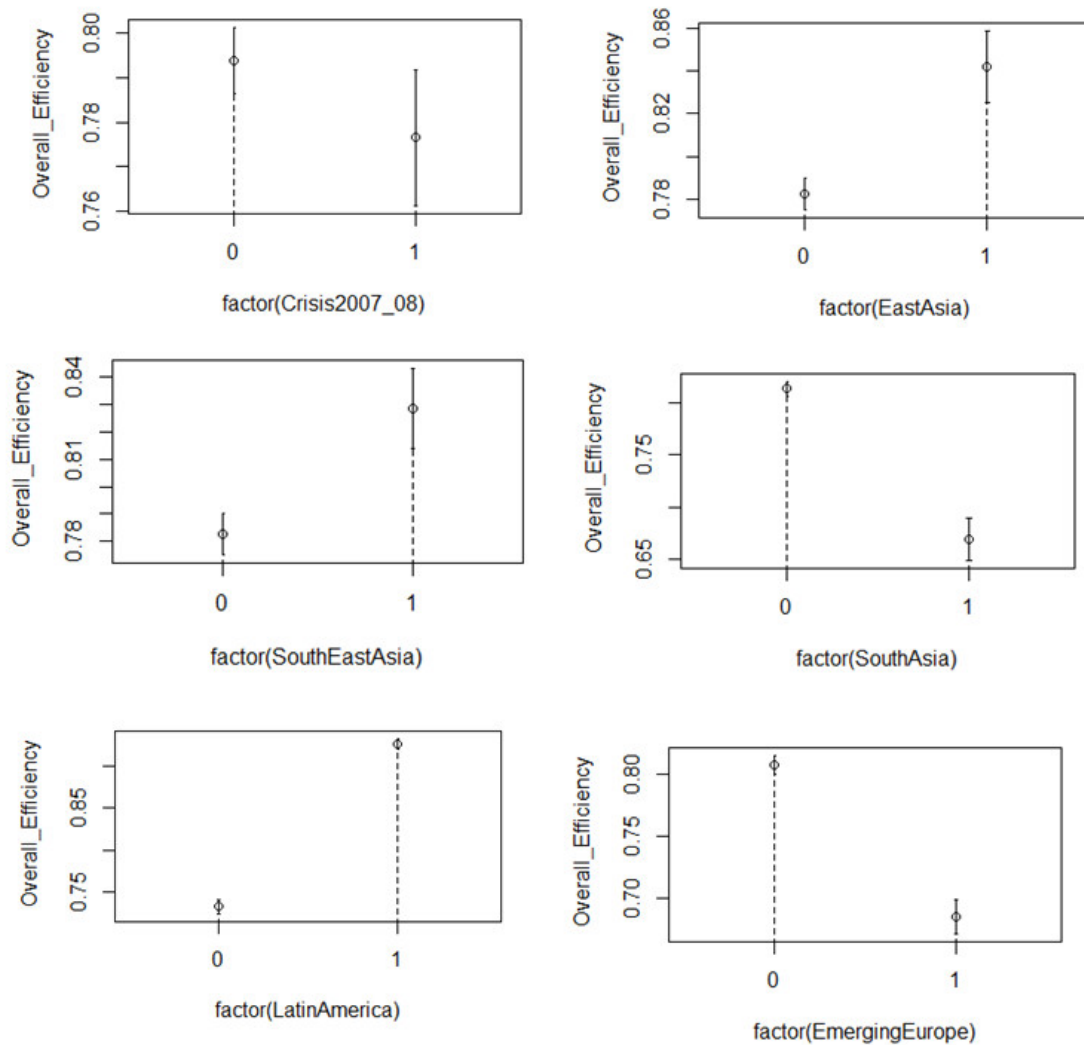
Figure A5. The relationship between technical efficiency and the financial crisis of 2007–2008, along with regional dummy variables (East Asia dummy, Southeast Asia dummy, South Asia dummy, Latin America dummy and emerging Europe dummy) (Model III).

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