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Financial distress and the Malaysian dual baking system: A dynamic slacks approach

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ABSTRACT

This paper presents an efficiency assessment of the Malaysian dual banking system using the Dynamic Slacks Based Model (DSBM) in order to assess the evolution of Malaysian Banks' potential input–saving/output–increase from 2009 to 2013. More precisely, DSBM is used first in a two-stage approach to assess the relative efficiency of Malaysian Islamic and conventional banks by emulating the CAMEL rating systems. Then, in the second stage, Monte Carlo Markov Chain (MCMC) methods applied to generalized linear mixed models (GLMM) are combined with DSBM results as part of an attempt to produce a model for banking performance assessment with effective predictive ability. Results indicate higher inefficiency levels and slacks in Islamic banks when compared to conventional ones. Furthermore, when the scope of analysis is the group of Malaysian Islamic banks, the efficiency levels of foreign banks are lower compared to their national counterparts, suggesting regulatory and cultural barriers. Policy implications are derived.

1. Introduction

Since the inception of efficiency measurement tools in banking, most studies have focused on developed economies, see, for instance, Matousek et al. (2015) and the reference therein. Paradi et al. (2011) listed the top ten countries targeted by researchers worldwide: all of them were developed economies except for India, which has been receiving increasing attention (Fujii et al., 2014). Additionally, and more specifically, Sufian et al. (2014) reported that only a limited number of papers have focused on Islamic banking, particularly in emerging economies such as Malaysia. In an earlier paper, Sufian et al. (2008) examined the performance of Islamic banks in the Middle East and North Africa (MENA), and in Asian countries. Although, their results revealed administrative inefficiencies in resource management among the banks, a deeper analysis of the Malaysian dual banking system is yet lacking.

This paper aims to fill this gap, by analyzing the efficiency of the Malaysian dual banking system with the DSBM developed by Tone and Tsutsui (2010). Differently from previous DEA (Data Envelopment Analysis) models, the DSBM uses a non-radial slack-based measure, which allows a non-proportional change of inputs and outputs. Moreover, the DSBM defines inter-temporal activities as carry-overs and allows their categorization into four types: desirable, undesirable, discretionary, and non-discretionary. These features can be particularly useful when analyzing credit risk and financial distress within the ambit of banking efficiency, as the limits of capital and equity of each institution typically vary over the course of time in different proportions and do not follow fixed limits imposed by radial measures (Wanke et al., 2015; Banker et al., 1984; Varian, 1987).

Therefore, this paper is innovative in the context not only by focusing on the Malaysian dual banking system, but also by adopting DSBM combined with General Linear Mixed Models-Monte Carlo–Markov Chain (GLMM-MCMC) method in a two-stage approach. Motivations for the present research are discussed as

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follows, both in terms of methodological and theoretical aspects. First of all, dynamic slacks models in efficiency measurement may be particularly useful to unveil the evolution of financial distress of banks over the course of time, allowing the identification of key financial inputs and outputs that are related to banking performance. On the other hand, however, the use of GLMM-MCMC may be helpful in adequately measuring the impact of contextual variables on efficiency scores, since it is possible to control for random effects, such as the common financial ratios (e.g. ROI, ROA) that may vary within the same bank type and/or origin. Second, the study adds to the existing literature particularly in regards to its practical application which emulates the CAMELS rating systems (as proposed by Wanke et al., 2015) and interprets its results linked to corporate governance characteristics (Männasoo and Mayes, 2009). As a matter of fact, the CAMELS variables are reinterpreted as inputs and outputs for the DSBM, enabling a discussion upon of which financial accounts in the balance sheet are the most relevant to apprehend good or bad banking performance over the course of time. Third, we analyze the aggregate carry-over slacks during a period of time, regressing them against different contextual variables that characterize the dual banking system in Malaysia. This is a significant contribution to the current research on efficiency in the overall bank sector. Fourth, the paper expands the existing literature with respect to the use of MCMC general linear models to predict and interpret the role of major contextual variables in the achievement of higher efficiency levels in the Malaysian dual banking system. Moreover, this segmentation is per se a contribution to the current research field on banking in terms of policy design. Fifth, our analysis covers the period from 2009 to 2013; finally, it is based on a representative sample of the Malaysian dual banking system.

The results presented here constitute a contribution to the increasing literature on Islamic banking, mainly by shedding some light on the ways through which compliance with Shariáa principles may affect financial performance. These results also expand the set of conclusions provided in recent previous studies, adding up to the body of knowledge. For example, Basov and Bhatti (2014) found beneficial impacts derived from the Shariáa-compliant limits on the set of admissible investments. Similar results were noticed by Khediri et al. (2015). These authors showed that Islamic banks are, on average, more profitable, more liquid, better capitalized, and have lower credit risk. On the other hand, Dewandaru et al. (2015) found that equal returns can be obtained with lower risks for Islamic indices.

The research content is organized as follows: Section 2 covers the literature review on financial distress, also encompassing a discussion on the Malaysian dual banking system; Section 3 contains the data and the model; Section 4 presents the empirical results, and a discussion on policy implications; while conclusions follow in Section 5.

2. Literature review

Banks play a very important role in society and have a pivotal position in the process of promoting economic growth. As a result, bank performance evaluations have received much attention over the past several years, both for theoretical and practical purposes. These studies are often grouped into two main approaches: parametric and nonparametric (Berger and Humphrey, 1997; De Borger et al., 1998; Brandouy et al., 2010; Brissimis et al., 2010; Kerstens et al., 2011; Briec and Liang, 2011; Lampe and Hilgers, 2014). The most popular parametric method is known as the stochastic frontier approach (SFA), as the nonparametric one is DEA.

Since these efficiency measurement techniques report efficiency scores, it is fundamental to establish the linkages between financial (in)efficiency or inferior/superior performance and financial distress. More precisely, these techniques should indicate how effective a financial institution is in minimizing variables related to financial distress and maximizing the ones related to financial health. In DEA, this fine-tuning between efficiency scores and decision-making is often accomplished not only by choosing the proper input and output variables set, but also by looking at their slacks.

A number of variables are thought to be associated with financial distress. Predicting failure using firm-specific characteristics together with financial structures is originally attributed to the seminal works of Altman (1968) and Altman et al. (1977), which employed discriminant analysis of financial ratios to derive the Z-score approach. More recently, Männasoo and Mayes (2009) presented a comprehensive literature review on this subject. According to these authors, although no universal set of indicators had been used across previous studies, the CAMELS factors appear to have a significant capacity to detect distress.

CAMELS is an acronym that stands for capital adequacy (C), asset quality (A), management efficiency (M), earnings (E), liquidity (L) and sensitivity to market risk (S). In recent decades, several studies reported on the use of such related-variables in risk measurement and monitoring. Examples can be found in Cole and Gunther (1995a,b), DeYoung (1998), Oshinsky and Olin (2006), Kumar and Ravi (2007), Poghosyan and Cihák (2011), and Ravisankar et al. (2010). More recently, Wanke et al. (2015) presented a practical application that emulated the CAMELS rating systems in the Brazilian banking industry using DSBM. The fundamental ideas behind this practical application are embedded in the close relationship between efficiency levels and input–reducing/output–increasing potentials: the latter may be considered as proxies for looming financial distress. In other words, consistent augments in the input–reducing/output–increasing potentials over time may constitute a leading distress indicator.

However, it should be noticed that, since the original criteria used to determine the CAMELS ratings are not disclosed to the general public (Jin et al., 2011), proxies are often selected accordingly, based both on prior studies and data availability. In Table 1 we list the major literature sub-criteria used to emulate the CAMELS rating system in different applications.

This scenario sets the stage for the main proposition of this study: efficiency levels in the Malaysian dual banking system are significantly affected by contextual variables related to the bank type (i.e., Islamic vs. conventional, and foreign vs. national). For instance, conventional banking processes in the finance sector are well known for leveraging banks' financial and operational indicators. The same basic economic principles apply to smaller national banks, which are the first to suffer the consequences of systemic financial crises. On the other hand, Islamic banking may be accountable for differences in technology production and managerial style, thus affecting efficiency levels. These issues are further explored hereafter.

2.1. On the Malaysian dual banking system and its underlying financial distress/stability

When seen from a global perspective, the growth of Islamic finance is striking. Since the inauguration of the first Islamic bank in 1975 in Dubai, Islamic finance has witnessed double-digit annual growth (Zivulovic, 2014). UKIFS (2013) reported that total Islamic financial assets will attain USD 2 trillion by year-end 2014 and, notably, 80% of these assets belong to the banking channel (EY, 2013). In this context, it becomes important to understand the role of Malaysia and its unique dual banking system experience

Malaysia has historically imposed strong supervision on its banking industry (Cook, 2008). Nowadays, the country's banking industry has 70 percent of the economy under direct supervision

Table 1
CAMELS (sub)criteria commonly used.

	Betz et al. (2014)	Maghyereh and Awartani (2014)	Wang et al. (2013)	Wang et al. (2012)	Doumpos and Zopounidis (2010)	Secme et al. (2009)	Zhao et al. (2009)	Cole and Gunther (1995a,b)	Cole and Gunther (1998)
Capital adequacy									
Total regulatory capital ratio%	√	√	√	√	√	√		√	
Equities/total assets	√	√	√	√		√	√	√	
(Equities – fixed assets)/total assets	√					√		√	
BASEL ratio	√	√			√			√	
Assets quality									
Loan loss res/gross loans					√	√	√	√	
Loan loss provision/net interest rev	√	√	√			√	√	√	
Loan loss res/impaired loans	√	√			√	√	√	√	
Impaired loans/gross loans			√	√		√	√	√	
NCO/average gross loans						√			
Impaired loans/equity					√	√	√		
Tier 1 ratio					√	√			
Management									
Net interest margin	√	√	√	√	√	√	√	√	
Net interest Revenue/average assets	√		√	√	√	√	√	√	
Other operating Income/average assets	√		√		√			√	
Non-interest Expense/average assets			√	√	√				
Earning quality									
Return on average assets (ROAA)	√	√	√	√	√	√	√	√	
Return on average equity (ROAE)	√	√		√	√		√	√	
Non-operating items/net income	√				√	√	√	√	
Cost to income ratio	√		√	√		√	√	√	
Liquidity									
Interbank ratio		√							
Net loans/total assets			√	√	√			√	
Net loans/deposits & ST funding	√			√		√		√	
Liquid assets/total Deposit & borrowings	√	√			√	√	√		
Sensitivity of market risk									
(Rate sensitive assets-rate sensitive liabilities)/average earning asset									
Rate sensitive assets/rate sensitive liabilities									
Risk weighted asset (II)/Risk weighted asset (I + II)					√				
Share of trading income	√								

of the central bank – Bank Negara Malaysia (BNM or Central Bank of Malaysia). The "dual banking" system signifies that in Malaysia the Islamic system is operating side-by-side with the conventional alternative. Over the course of the time, however, most of the other countries, particularly Muslim countries, have either tried a full-fledged Islamic banking system, or a conventional system with a few Islamic banks, or even a totally conventional banking system (Wilson, 2000).

The first Islamic bank was established in Malaysia in 1983. The timeline of the Islamic financial landscape may be characterized by three development stages (IPS, 2000). The first stage (1983–1990) was guided by the rationale of confining Islamic banking within the structure of a single Islamic bank. This would allow the bank to operate smoothly without undue competition which could hinder the progress of Islamic banking. During the second stage (1990–1994), BNM embarked on the project of disseminating Islamic banking on a nation-wide basis, with as many players as possible and the accessibility for all Malaysians. In order to achieve so, BNM allowed existing financial institutions to offer their infrastructure and branches to Islamic banking. This option was seen as the most effective way of increasing the number of institutions offering Islamic banking services at the lowest possible cost and within the shortest time frame (IPS, 2000). It enabled Islamic banking to tap into the conventional banking system infrastructure, including the existing branches and staff.

The third stage, from 1994 onwards, corresponds to the take-off years. Huang (2014) stated that Malaysian banks have grown rapidly in the last decade due to an efficient regulatory environment combined with government initiatives for the banking sector restructuration right after the 1997–1998 Asian financial crisis. In 2000, BNM introduced the Financial Sector Master-plan (FSMP), which outlined a three-phase project to restructure the Malaysian financial sector. Followed by major mergers and acquisitions among the existing banks, and liberalization to foreign banks, the l sector accomplished the transition to a fully functional and operational dual financial system. As a matter of fact, based on the Malaysian Islamic banking sector performance during 2008–2012, MIFC (2014) forecast a 19% average annual growth in total Malaysian banking assets. During the same period, conventional banks have grown at a rate of 9.3% per year. Fig. 1 depicts Malaysian Islamic banking assets as a percentage of total banking assets. An average annual increase of 14% is noticed during 2000-2013.

Even though Islamic banking operates in an interest-free environment and trades Sharia'a-compliant instruments, many of the risks associated with conventional banking, including interest-rate risks are relevant (Bacha, 2008). The author collected empirical evidence, based on Malaysian data, showing that Islamic banking profit rates/yields are highly correlated and move *in tandem* with conventional banking rates. Given that fund flow dynamics and cross-linkages are embedded within the dual banking system – Islamic and conventional – they cannot be immune to interest-rate risks. Ironical as it may be, the operations of a dual banking system may serve to bring the Islamic banking sector into closer orbit with the conventional sector.

This explains why Islamic and conventional banks are similar in terms of reaction to financial distress. This observation derives from the theoretical underpinnings upon which Islamic banks rely on: the fact that Islamic banks use the same market data as

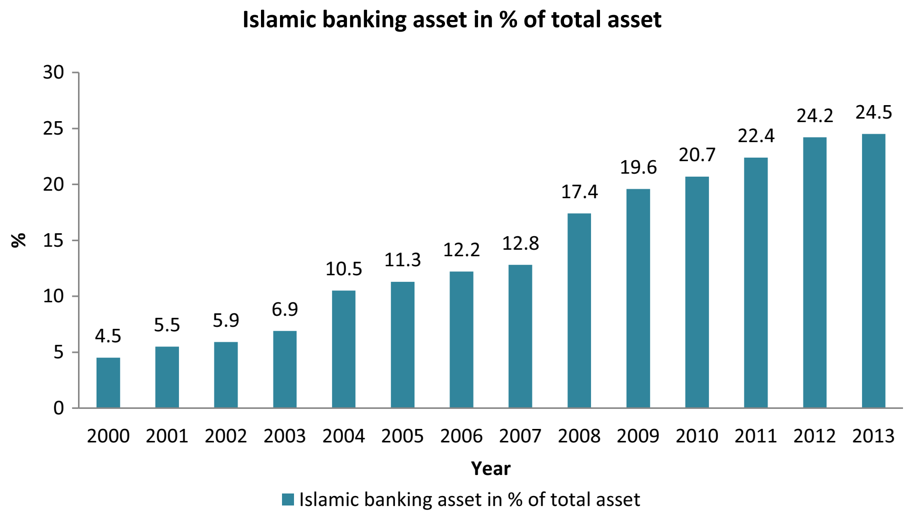
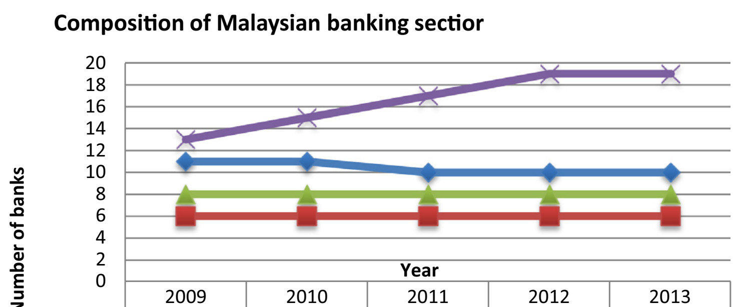


Fig. 1. Islamic banking assets as% of total banking assets in Malaysia (2000–2013) Source: Bank Negara Malaysia.



	2009	2010	2011	2012	2013
Domestic Islamic banks	11	11	10	10	10
Foreign Islamic banks	6	6	6	6	6
Domestic Conventional banks	8	8	8	8	8
Foreign conventional banks	13	15	17	19	19

Fig. 2. Makeup of Malaysian banks (2009–2013), Source: Bank Negara Malaysia.

conventional banks. Regarding such relationship, Khan (1991), and Beck et al. (2013) examined the theoretical capacity of Islamic banks for handling economic stress. Results showed that Islamic banks have better capacity of risk sharing. However, a recent study by Bourkhis and Nabi (2013) has refuted this proposition. They suggested that financial distress has an equal impact on both conventional and Islamic banks and there is no significant difference in financial stability.

Nevertheless, it is important to understand the role of financial liberalization and bank ownership with respect to financial distress and its underlying impacts on the Malaysian dual banking system. As a matter of fact, numerous studies on financial liberalization have pointed out the relevance of bank competition to financial stability (Bumann et al.,2013; Blackburn and Forgues-Puccio, 2010; Manlagñit, 2011; Park, 2012). Moreover, an inverse U-shaped relationship between foreign bank ownership and financial stability has already been modeled by means of an international comparative study using panel data (Lee and Hsieh, 2014).

In particular, Malaysia has been reported as being the one of the most restricted and unexplored financial markets (Cook, 2008). Although foreign banks had been present in Malaysia for quite a long time, until 1994 they could not enter the country with full ownership and were hampered by many restrictions, such as the requirement to be locally incorporated (Montgomery, 2003). After domestic banks consolidated their power to compete globally, Malaysia has been easing entry restrictions on foreign banks.

More recently, however, the IMF (2014) highlighted that the Malaysian financial system is now over saturated by foreign banks and financial institutions. Fig. 2 presents the composition of Malaysian dual bank participants from 2009 to 2013. By the end of 2013, Malaysian Islamic banking consisted of ten domestic and six foreign banks. In the conventional system, there were only eight domestic, but nineteen foreign banks operating side by side with Islamic banks. Over the period, the number of foreign conventional banks has risen due to the financial relaxation on entry barriers for banks with full ownership.

Table 2 presents the position of all banks currently operating in Malaysia in regards to paid-up capital, total loans and total assets. After financial restructuring and capital resizing (Basel–Tier 2), the assumption is that Malaysian banks now have adequate resilience to systemic risk (Vallascas and Keasey, 2012). It can also be seen that some of the domestic banks have continued to suffer from a shortage of paid-up capital relative to Tier 2 status. Sufian et al. (2014) pointed to foreign banks outperformance in terms of revenue generation. They argued that foreign banks have been enjoying competitive advantages and technological advances which have conveyed higher returns relative to the major domestic banks, which have higher deposit and loan volumes.

An interesting finding to be derived from Table 2 is that there is a keen eye focusing on the analysis of Malaysian dual banking efficiency and performance projections. Based on the paid-up capital issue, it is visible that foreign banks have higher paid-up capital

Table 2
Malaysian dual banks summary.

Sl No	Conventional banks					Islamic banks				
	Name	Country of ownership	Paid up capital (USD million)	Loans (USD million)	Deposits (USD million)	Name	Country of ownership	Paid up capital (USD million)	Loans (USD million)	Deposits (USD million)
1	RHB bank Bhd	Malaysia	4217.61	37072.92	47309.37	Affin Islamic bank Bhd	Malaysia	113.21	2371.67	3626.73
2	Public bank Bhd	Malaysia	6665.79	68998.68	84123.40	Alliance Islamic bank Bhd	Malaysia	94.34	2122.36	2079.81
3	Malayan banking Bhd	Malaysia	15013.4	111829.4	140654.03	AmIslamic bank Bhd	Malaysia	133.03	8766.57	8086.79
4	Hong Leong bank Bhd	Malaysia	4569.25	32257.58	44490.72	Bank Islam Malaysia Bhd	Malaysia	712.26	11823.18	12193.4
5	CIMB bank Bhd	Malaysia	7437.11	58311.51	78030.94	Bank Muamalat Malaysia Bhd	Malaysia	314.47	5724.65	5575.57
6	Alliance bank Malaysia Bhd	Malaysia	1169.97	10005.97	13311.13	CIMB Islamic bank Bhd	Malaysia	276.73	12767.2	14163.11
7	Ambank (M) Bhd	Malaysia	2322.61	19367.48	21987.14	Hong Leong Islamic bank Bhd	Malaysia	220.13	6616.92	6109.12
8	Affin bank Bhd	Malaysia	1373.46	11392.39	15811.29	Maybank Islamic Bhd	Malaysia	43.4	29954.4	36600.28
9	BNP paribas Malaysia Bhd	France	184.03	186.16	651.89	Public Islamic bank Bhd	Malaysia	62.89	8395.94	9808.21
10	Bangkok bank Bhd	Thailand	179990.25	784117.0	887597.48	RHB Islamic bank Bhd	Malaysia	243.08	7837.92	8006.82
11	Bank of America Malaysia Bhd	USA	159.62	35.44	869.87	Al-Rajhi banking & Investment Bhd	Saudi Arabia	314.47	1865.53	1881.51
12	Bank of China (Malaysia) Bhd	China	162383.33	879551.26	2603478.93	Asian finance bank Bhd	Qatar, Saudi Arabia and Bahrain	167462.26	738358.11	749609.59
13	Bank of Tokyo-Mitsubishi UFJ (Malaysia) Bhd	Japan	533.65	1670.79	2433.90	HSBC Amanah Malaysia Bhd	United Kingdom	15.72	3413.65	3965.75
14	Citibank Bhd	USA	1360.88	6446.01	9949.62	Kuwait finance house (Malaysia) Bhd	Kuwait	712.58	2319.87	2237.17
15	Deutsche bank (Malaysia) Bhd	Germany	494.25	630.35	2634.09	OCBC Al-Amin bank Bhd	China	26.73	2775.09	2902.74
16	HSBC bank Malaysia Bhd	United Kingdom	2024.87	14043.99	21450.38	Standard chartered Saadiq Bhd	United Kingdom	32.39	1621.67	2284.25
17	India international bank (Malaysia)	India	98602.20	12835.53	45685.85					
18	Industrial and commercial bank of China (Malaysia) Bhd	China	115.44	572.83	1444.75					
19	J.P. Morgan Chase bank Bhd	USA	230.53	10.03	1960.66					
20	Mizuho bank (Malaysia) Bhd	Japan	222479.25	133386.16	229439.31					
21	National bank of Abu Dhabi Malaysia Bhd	UAE	100252.52	56566.67	221567.61					
22	OCBC bank (Malaysia) Bhd	China	1780.60	17515.38	22841.19					
23	Standard Chartered bank Malaysia Bhd	United Kingdom	1239.31	10757.58	14391.64					
24	Sumitomo Mitsui banking corporation Malaysia Bhd	Japan	239.47	454.59	569.21					
25	The bank of Nova Scotia Bhd	Canada	261.26	907.92	489.34					
26	The royal bank of Scotland Bhd	United Kingdom	184333.96	111055.97	454352.83					
27	United overseas bank (Malaysia) Bhd	Singapore	1972.17	19279.34	2267.55					

Note: The exchange rate between the Malaysian currency (MYR) and the US dollar in December 2013 was 100 USD = 318 MYR, Source: http://www.xe.com/
Source: bank Negara Malaysia and bank annual reports

than domestic banks. This cluster points to government initiatives which forced restructuring (merging and acquisition) among the banks to enable them to qualify as Tier 2 capital banks. Lee and Hsieh (2013) examined panel data of 2,276 Asian banks to measure the impact of capital on bank profitability and risk. They found similar outcomes to those depicted in Table 2 – Malaysian (East Asian) banks have higher capital reserves and a positive relation with profitability. Data in Table 2 also makes it clear that in terms of loans and deposits, all of the domestic banks have performed better than the foreign banks. Having (relatively) medium paid-up capital and higher loans and deposits volumes have resulted in both profitability and inherent credit risk among domestic banks.

3. Methodology

3.1. DEA and DSBM

DEA is a non-parametric method developed by Charnes et al. (1978) as a tool for measuring the performance of a set of decision–making units (DMUs). The initial DEA models consider the constant return to scale (CRS) assumption, which ignores the fact that different DMUs could be operating at different scales. To overcome this drawback, Banker et al. (1984) introduced variable returns to scale (VRS), a model that ensures that each bank is benchmarked only against banks of similar size. This feature makes DEA particularly useful and attractive for bank regulators, especially when their focus is on identifying the best and worst practices within a group of institutions (McWilliams et al., 2005).

Over the course of several decades, these seminal models have been superseded by models that are more sophisticated, such as the DSBM slacks-based model by Tone and Tsutsui (2010). In general, under the slacks-based approach, inefficiencies are defined as non-radial excesses in inputs and non-radial shortfalls in outputs, differently from the traditional CCR and BCC. More specifically, the slacks-based approach presents some interest y_{ijt}^{fix} ing properties for decision-making (Tone, 2001): (i) the optimal solution is not affected by variables measured in different units; (ii) negative values can be handled; (iii) non-proportional input-reducing/out put-increasing potentials are handled by non-radial functions; and (iv) inputs and outputs are simultaneously, and respectively, minimized and maximized.

The DSBM is designed to measure efficiency changes over the course of time through carry-over variables that connect the production function in two consecutive periods. The underlying assumption is that these carry-overs, that is, these intermediate inputs or outputs, may potentially influence future input or output levels. More precisely, the DSBM deals with n DMUs ($j = 1,\ldots,n$) over T terms ($t = 1,\ldots,T$). At each term, DMUs have common m inputs ($i = 1, K, m$), p non-discretionary (fixed) inputs ($i = 1, K, p$), s outputs ($i = 1, K, s$) and r non–discretionary (fixed) outputs (1, K, r). Let x_{ijt} ($i = 1, K, m$), x_{ijt}^{fix} ($i = 1, K, p$), y_{ijt} ($i = 1, K, s$) and ($i = 1, K, r$) denote the observed (discretionary) input, non-discretionary input, (discretionary) input, non-discretionary input, (discretionary) output and non-discretionary output values of DMU j at term t, respectively. We symbolize the four category links as z^{good}, z^{bad}, z^{free} and z^{fix}. In order to identify them by term (t), DMU (j) and item (i), we employ the notation z_{ijt}^{good} ($i = 1, K, ngood$; $j = 1, K, n$; $t = 1, K, T$) and etc. for denoting link values where $ngood$ is the number of good links. These are all observed values up to the term T. The production possible $\{x_{it}\}$, $\{x_{it}^{fix}\}$, $\{y_{it}\}$, $\{y_{it}^{fix}\}$, $\{z_{it}^{bad}\}$, $\{z_{it}^{good}\}$, $\{z_{it}^{free}\}$ and $\{z_{it}^{fix}\}$ are defined by:

$$
\begin{aligned}
& x_{it} \geq \sum_{j=1}^{n} x_{ijt}\ \lambda_j^t\ (i = 1, K, m; t = 1, K, T) \\
& x_{it}^{fix} = \sum_{j=1}^{n} x_{ijt\,ij}^{fix}\ \lambda_j^t\ (i = 1, K, p; t = 1, K, T) \\
& y_{it}\ le \sum_{j=1}^{n} y_{ijt}\ \lambda_j^t\ (i = 1, K, s; t = 1, K, T) \\
& y_{it}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix}\ \lambda_j^t\ (i = 1, K, r; t = 1, K, T) \\
& z_{it}^{good} \leq \sum_{j=1}^{n} z_{ijt}^{good}\ \lambda_j^t\ (i = 1, K, ngood; t = 1, K, T) \\
& z_{it}^{bad} \geq \sum_{j=1}^{n} z_{ijt}^{bad}\ \lambda_j^t\ (i = 1, K, nbad; t = 1, K, T) \\
& z_{it}^{free} : free\ (i = 1, K, nfree; t = 1, K, T) \\
& z_{it}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix}\ \lambda_j^t\ (i = 1, K, nfix; t = 1, K, T) \\
& \sum_{j=1}^{n} \lambda_j^t = 1\ (t = 1, K, T)
\end{aligned}
\tag{1}
$$

where $\lambda^t \in R^n$ ($t = 1, K, T$) is the intensity vector for the term t. The last constraint corresponds to the variable returns-to-scale assumption. If we delete this constraint, we have the constant returns-to-scale model. The continuity of link flows between terms t and $t + 1$ can be ensured by the following condition:

$$
\sum_{j=1}^{n} z_{ijt}^{\alpha}\ \lambda_j^t = \geq \sum_{j=1}^{n} z_{ijt}^{\alpha} \lambda_j^{t+1}\ (\forall i; t = 1, K, T-1)
\tag{2}
$$

where the symbol α stands for *good*, *bad*, *free* or *fix*.

Using these expressions for production, we can express DMU$_o$ ($o = 1,\ldots,n$) as follows:

$$
\begin{aligned}
& x_{iot} = \sum_{j=1}^{n} x_{ijt}\ \lambda_j^t + s_{it}^-\ (i = 1, K, m; t = 1, K, T) \\
& x_{iot}^{fix} = \sum_{j=1}^{n} x_{ijt\,ij}^{fix}\ \lambda_j^t\ (i = 1, K, p; t = 1, K, T) \\
& y_{iot} = \sum_{j=1}^{n} y_{ijt}\ \lambda_j^t - s_{it}^+\ (i = 1, K, s; t = 1, K, T) \\
& y_{iot}^{fix} = \sum_{j=1}^{n} y_{ijt}^{fix}\ \lambda_j^t\ (i = 1, K, r; t = 1, K, T) \\
& z_{iot}^{good} = \sum_{j=1}^{n} z_{ijt}^{good}\ \lambda_j^t - s_{it}^{good}\ (i = 1, K, ngood; t = 1, K, T) \\
& z_{iot}^{bad} = \sum_{j=1}^{n} z_{ijt}^{bad}\ \lambda_j^t + s_{it}^{bad}\ (i = 1, K, nbad; t = 1, K, T) \\
& z_{iot}^{free} = \sum_{j=1}^{n} z_{ijt}^{free}\ \lambda_j^t + s_{it}^{free}\ (i = 1, K, nfree; t = 1, K, T) \\
& z_{iot}^{fix} = \sum_{j=1}^{n} z_{ijt}^{fix} \lambda_j^t\ (i = 1, K, nfix; t = 1, K, T) \\
& \sum_{j=1}^{n} \lambda_j^t = 1\ (t = 1, K, T)
\end{aligned}
\tag{3}
$$

$$
s_{it}^- \geq 0, \quad s_{it}^+ \geq 0, \quad s_{it}^{good} \geq 0, \quad s_{it}^{bad} \geq 0 \text{ and } s_{it}^{free} :\ free(\forall i; t)
$$

where s_{it}^-, s_{it}^+, s_{it}^{good}, s_{it}^{bad} and s_{it}^{free} are slacks denoting, respectively, input excess, output shortfall, link shortfall, link excess. and link deviation.

According to Tone and Tsutsui (2010), the overall efficiency of DMU_o $(o = 1,\ldots,n)$ is evaluated taking $(\{\lambda^t\}, \{s_{it}^-\}, \{s_t^+\}, \{s_t^{good}\}, \{s_t^{bad}\}, \{s_t^{free}\}$ and $\{s_t^{fix}\})$ variables. As regards to the non-oriented cases, built as the combination of input- and output-oriented cases, the non-oriented efficiency measure is defined by the solving program:

$$\rho_o^* = \min \frac{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m} \frac{w_i^- s_{it}^-}{x_{iot}}\right) + \sum_{i=1}^{nbad} \frac{s_{it}^{bad}}{z_{iot}^{bad}}\right]}{\frac{1}{T}\sum_{t=1}^{T} w^t \left[1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{it}^+}{y_{iot}}\right) + \sum_{i=1}^{ngood} \frac{s_{it}^{good}}{z_{iot}^{good}}\right]} \quad (4)$$

subject to (2) and (3).

This model deals with excesses in input resources and undesirable (bad) links and shortfalls in output products and desirable (good) links in a unified scheme.

Using an optimal solution $(\{\lambda_o^{t*}\}, \{s_{ot}^{-*}\}, \{s_{ot}^{+*}\}, \{s_{ot}^{good*}\}, \{s_{ot}^{bad*}\}, \{s_{ot}^{free*}\}, \{s_{ot}^{fix*}\})$ to (4), the non-oriented term efficiency is defined by:

$$\rho_{ot} = \min \frac{1 - \frac{1}{m+nbad}\left(\sum_{i=1}^{m} \frac{w_i^- s_{iot}^{-*}}{x_{iot}} + \sum_{i=1}^{nbad} \frac{s_{iot}^{bad*}}{z_{iot}^{bad}}\right)}{1 + \frac{1}{s+ngood}\left(\sum_{i=1}^{s} \frac{w_i^+ s_{iot}^{+*}}{y_{iot}} + \sum_{i=1}^{ngood} \frac{s_{iot}^{good*}}{z_{iot}^{good}}\right)} (t = 1, K, T) \quad (5)$$

A detailed presentation of the DSBM and more information can be obtained in Tone and Tsutsui (2010).

3.2. Variable selection and definition of carry-overs

Inputs and outputs selection is perhaps the most important task in employing DEA to measure the relative efficiency of the DMUs. Two approaches are widely used to identify bank inputs and outputs: the production approach and the intermediation approach (e.g. Sherman and Gold, 1985; Aly et al., 1990; Yue, 1992; Miller and Noulas, 1996; Favero and Pepi, 1995; Sealey and Lindley, 1977; Berger and Humphrey, 1992; Barros et al., 2014). Under the production approach, banks are treated as a firm geared to generate net income/profits in the long run. This firm "produces" loans, deposits, and several other kinds of assets by using labor, capital and other expenses, while keeping their losses in the production process (provisions) to a minimal amount. On the other hand, banks are considered as financial intermediaries for transforming assets, deposits, purchase funds, and labor into loans and securities under the intermediation approach. More specifically, deposits are treated as an input under the production approach, and as an output under the intermediation approach.

Fortin and Leclerc (2007), however, showed that with an incomplete list of assets and liabilities, the ratio between assets and liabilities included in the model of banking production strongly influences the efficiency score under the intermediation approach. In fact, the authors found that the average score varies significantly according to the definition of inputs and outputs, thus biasing the analysis. Fortin and Leclerc (2007) advocate either the production approach or the value-added approach. In the production approach, both credit and deposits services are included in the banking, although the high level of correlation between both types of services may lead to some specification problems. On the other hand, a value-added approach, such as that developed by Fixler and Zieschang (1999), offers an alternative that takes into account the cost of funds to measure the average interest rate spread. Therefore, taking into consideration the risk of biasing the analysis for the Malaysian banks under the intermediation approach and the detailed data requirement for the value-added approach, the production approach in banking is adopted as a starting point in this research.

Besides, as previously discussed in section 2, the selection of inputs and outputs should establish linkages between the literature review and the decision to be supported. As a matter of fact, to assist in decision making, the choice of variables in DEA models should reflect the desired perspective on efficiency analysis. Initially, the CAMELS factors are used to identify the input and output variables that should be used in this research. However, since the original factors used to determine the CAMELS ratings are not disclosed to the general public (Jin et al., 2011), proxies were selected accordingly, based both on prior studies and data availability.

On the other hand, Tone and Tsutsui (2010) classify carry-over variables, also called links, into four categories: (i) desirable links, treated as outputs and restricted to ones higher than the observed one; (ii) undesirable links, treated as inputs and whose value is restricted to be lower than the observed one; (iii) discretionary links, affecting efficiency levels indirectly and free to vary from one period to another; and (iv) non-discretionary links, also affecting efficiency levels in an indirect way, but kept fixed at a constant level from one period to another.

Putting into perspective that not only the shortage of desirable links (outputs) but also the excess of undesirable ones (inputs) is accounted as inefficiency in the DSBM, the rationale for the input/output selection is discussed next. The selection should emulate the CAMELS rating under the dynamic slacks approach. Arguments are debated in light of the production approach in banking, data availability, and the nature of the carry-over links, whether desirable or undesirable.

Capital adequacy (C) is proxied by Total Equity, a desirable output in DSBM because higher levels are likely to reduce financial distress. On the other hand, asset quality (A) is proxied by Loan Loss Provision, an undesirable carry-over (input) that should be minimized: lower levels suggest less financial distress. Similarly, management efficiency (M), proxied by the Total Expenses (operating and personnel), is treated as an undesirable input. In turn, earnings (E), is proxied by Total Net Income and treated as a desirable carry-over (output), since more is desirable. Now, with respect to liquidity (L), its proxy is given by the Total Earning Assets and it is treated as a desirable output. Lastly, sensitivity to market risk (S) is proxied by Total Assets (earnings and non-earnings), a desirable output. Total Assets are reported to be negatively related to default risk in many studies, including Abrams and Huang (1987), Wheelock and Wilson (2012), Kolari et al. (2002), Lanine and Vennet (2006), and Kato and Hagendorff (2010).

In summary, the carry-overs encompass loan loss provision (undesirable/input) and net income (desirable/output). Ordinary outputs encompass total equity, total earning assets, and total assets, while total expenses (operating and personnel) account for the single ordinary input.

3.3. The data

Data on forty-three Malaysian banks were obtained from the publicly available annual reports from 2009 to 2013. Inputs and outputs commonly found in the literature review and data availability guided the selection criteria. Adherence to the CAMELS modeling discussed previously was also a factor considered. Their descriptive statistics are presented in Table 3.

In addition, seven contextual and business-related variables were collected to explain differences in the efficiency levels. They are also presented in Table 3 and are mostly related to major elements of the banking cost structure. i.e., random effects of (i) the equity ratio, computed as the ratio between equity and total assets; (ii) the well-known return on assets ratio (ROA); (iii) the also well-known return on equity ratio (ROE); (iv) the price earnings ratio, computed as the ratio between the market value per share and the earnings per share; and (v) the cost income ratio, which equals a bank's operating expenses divided by its operating income; plus (i) fixed effects of the bank type in the Malaysian dual system (whether Islamic or conventional) and (ii) the origin of the bank (whether the bank is foreign or not). Additionally, a time variable measures the trend effect. These three last contextual variables describe the banks' national origin identifying the foreign investment in Malaysian banking and the time effect, what reflects the sector's time dynamic.

3.4. Generalized Linear Mixed Models using Markov chain Monte Carlo methods

GLMMs combine a generalized linear model with normal random effects on the linear predictor scale to provide a rich family of models that have been used in a wide variety of applications (see, for example, Diggle et al., 2002; Verbeke and Molenberghs, 2000, 2005; McCulloch et al., 2008). This flexibility comes at a price, however, in terms of analytical tractability, which has a number of implications including computational complexity, and an unknown degree to which inference is dependent on modeling assumptions (Fong et al., 2010). For instance, although likelihood-based inference may be carried out relatively easily within many software platforms, inference is dependent on asymptotic sampling distributions of estimators, with few guidelines available as to when such theory will produce accurate inference.

More precisely, GLMMs extend the generalized linear model, as proposed by Nelder and Wedderburn (1972) and comprehensively described in McCullagh and Nelder (1989), by adding normally distributed random effects to the linear predictor scale. Suppose Y_{ij} is of exponential family form: $Y_{ij}\,|\theta_{ij},\varphi_1 \sim p(\cdot)$, where $p(\cdot)$ is a member of the exponential family; that is,

$$p(y_{ij}|\theta_{ij},\phi_1) = exp[(y_{ij}\theta_{ij} - b(\theta_{ij}))/a(\phi_1) + c(y_{ij},\phi_1)], \tag{6}$$

for $i = 1,\ldots,m$ units (clusters) and $j = 1,\ldots,n_i$, measurements per unit and where θ_{ij} is the (scalar) canonical parameter. Let $\mu_{ij} = E[Y_{ij}\,|\,\beta, b_i, \varphi_1] = b^{'}(\theta_{ij})$ with

$$g(\mu_{ij}) = \eta_{ij} = x_{ij}\beta + z_{ij}b_i, \tag{7}$$

where $g(\cdot)$ is a monotonic "link" function, x_{ij} is $1 \times p$, and z_{ij} is $1 \times q$, with β a $p \times 1$ vector of fixed effects and b_i a $q \times 1$ vector of random effects, hence $\theta_{ij} = \theta_{ij}\,(\beta, b_i)$. Assume $b_i|Q \sim N(0, Q^{-1})$, where the precision matrix $Q = Q(\varphi_2)$ depends on parameters ϕ_2. It is assumed that β is assigned a normal prior distribution. Let $\gamma = (\beta, b)$ denote the $G \times 1$ vector of parameters assigned Gaussian priors. We also require priors for φ_1 (if not a constant) and for φ_2. Let $\varphi = (\varphi_1, \varphi_2)$ be the variance components for which non-Gaussian priors are assigned, with $V = \dim(\varphi)$.

Although a Bayesian approach is attractive, it requires the specification of prior distributions, which is not straightforward, in particular for variance components. Recall that we assume β is normally distributed. Often there will be sufficient information in the data for β to be well estimated with a normal prior with a large variance. The use of an improper prior for β will often lead to a proper posterior, although care is required. If we wish to use informative priors, we may specify independent normal priors with the parameters for each component being obtained via specification of 2 quantiles with associated probabilities. For logistic and log-linear models, these quantiles may be given on the exponentiated scale since these are more interpretable (as the odds ratio and rate ratio, respectively). If θ_1 and θ_2 are the quantiles on the exponentiated scale and p_1 and p_2 are the associated probabilities, then the parameters of the normal prior are given by

$$\mu = z_2 log(\theta_1) - z_1 log(\theta_2)/(z_2 - z_1), \tag{8}$$

$$\sigma = log(\theta_2) - log(\theta_1)/(z_2 - z_1), \tag{9}$$

where z_1 and z_2 are the p_1 and p_2 quantiles of a standard normal random variable.

The most prominent application in the entire arena of simulation based estimation is the current generation of Bayesian econometrics guided by Markov Chain Monte Carlo methods. In this area, heretofore intractable estimators of posterior means are routinely estimated with the assistance of simulation and the Gibbs sampler (Greene and Hill, 2010). These techniques offer stand-alone approaches to simulated likelihood estimation but can also be integrated with traditional estimators (Korsgaard et al., 2003). Computation is also an issue since the usual implementation via MCMC carries a large computational overhead. A detailed discussion on Gibbs sampler can be found in Gamerman (1996), Lange (2010), Zhu and Lee (2002) (here omitted here for the sake of simplicity).

Lastly, it is worth mentioning that limited dependent variable models can deal with censored outcomes that can arise in longitudinal settings. To enable inference in this class of models, however, one must address a central problem in multivariate discrete data analysis, namely, evaluation of the outcome probability for each observation (Korsgaard et al., 2003). Outcome probabilities are required in constructing the likelihood function and involve multivariate integration constrained to specific regions that correspond to the observed data. This latent variable framework is a general probabilistic construct in which different threshold-crossing mappings from η_{ij} to the observed responses y_{ij} can produce various censored (Tobit) outcomes. For example, the relationship $y_{ij} = 1\{0 < \eta_{ij} < 1\}y_{ij}$ leads to a Tobit model with censoring from below at 0 and from above at 1. In censored Gaussian and ordered categorical threshold models, Gibbs sampling in conjunction with data augmentation (Sorensen et al., 1998; Tanner and Wong, 1987) leads to fully conditional posterior distributions which are easy to sample from. This was demonstrated by Wei and Tanner (1990) for the Tobit model (Tobin, 1958), and in right censored and interval censored regression models.

3.5. On global separability and the adequacy of the two-stage approach

Simar and Wilson (2011) examined the wide-spread practice where efficiency estimates are regressed on some environmental variables in what is commonly known as a two-stage analysis. In a broader sense, the authors argue that this is done without specifying a statistical model in which such structures would follow from the first stage where the initial DEA are estimated. As such, these two-stage approaches are not structural, but rather *ad hoc*. The most important underlying assumption regarding two-stage analysis concerns global separability (Kourtesi et al., 2012). The next paragraphs develop this assumption.

In general lines, the vector for environmental factors or contextual variables may either affect the range of attainable values of the inputs and the outputs including the shape of the production set, or it may affect only the distribution of inefficiencies inside a set with boundaries not depending on them or both (Badin et al., 2010). Putting in other words, under separability, the environmental factors have no influence whatsoever on the support of the input-output vectors, and the only potential remaining impact of the environmental factors on the production process may be on the efficiencies' distribution. If separability assumption holds, we should expect these statistics to be "close" to zero; otherwise, we should expect them to lie "far" from zero[3].

4. Results and discussion

Initially, correlation analyses were performed on input and output variables presented in Table 4, indicating significant positive

[3] In this research, an R code was structured upon the packages np (Hayfield and Racine, 2008) and FNN (Beygelzimer et al., 2015) to compute the statistics of this test.

Table 3
Descriptive statistics of the sample.

Variable Type		Ordinary output	Undesirable carry-over input	Ordinary input	Desirable carry-over output	Ordinary outputs		Contextual						
CAMELS model		C = Capital adequacy	A = Asset quality	M = Management Efficiency	E = Earnings	L = Liquidity	S = Sensitivity to market risk	Fixed effects		Random effects				
Descriptive	Year	Total equity (1000 USD)	Loan loss provision (1000 USD)	Total expenses (1000 USD)	Total net income (1000 USD)	Total earning assets (1000 USD)	Total assets (1000 USD)	Foreign bank (1 = yes/ 0 = no)	Islamic bank (1 = yes/ 0 = no)	Equity ratio	ROA	ROE	Cost income ratio	Price earnings ratio
Mean	2009	$56,022.78	$489.55	$9,555.89	$5,357.94	$228,615.21	$323,630.70	0.56	0.37	17.34	0.47	8.44	56.48	1.05
	2010	$58,078.66	$373.49	$$10,106.82	$6,148.56	$252,467.86	$331,062.06	0.58	0.37	16.81	0.08	8.17	56.53	1.01
	2011	$64,005.54	$404.34	$11,318.30	$6,829.88	$267,649.76	$356,681.37	0.58	0.37	17.28	0.15	8.66	63.59	1.00
	2012	$69,052.75	$743.35	$11,035.55	$8,593.17	$327,318.60	$424,078.86	0.58	0.37	15.43	0.51	9.83	61.09	1.00
	2013	$76,972.09	$931.29	$9,606.89	$9,820.72	$443,429.61	$547,527.60	0.58	0.37	12.43	0.87	10.36	55.04	1.28
SD	2009	$21,594.61	$228.69	$4,990.18	$2,172.25	$91,886.48	$135,514.36	0.08	0.07	3.52	0.14	1.06	6.90	0.15
	2010	$21,718.97	$212.15	$5,256.21	$2,629.45	$101,365.71	$134,114.58	0.08	0.07	3.47	0.30	1.27	5.64	0.22
	2011	$23,911.76	$266.61	$6,001.41	$2,518.78	$108,450.44	$143,928.92	0.08	0.07	3.42	0.38	1.56	9.04	0.27
	2012	$24,283.54	$348.71	$4,807.35	$3,498.30	$134,423.44	$170,815.10	0.08	0.07	3.00	0.27	1.20	5.65	0.29
	2013	$25,937.80	$437.72	$3,292.28	$4,087.99	$210,114.02	$236,119.22	0.08	0.07	1.67	0.08	0.98	3.44	0.10
CV	2009	0.39	0.47	0.52	0.41	0.40	0.42	0.14	0.20	0.20	0.30	0.13	0.12	0.14
	2010	0.37	0.57	0.52	0.43	0.40	0.41	0.13	0.20	0.21	3.72	0.16	0.10	0.22
	2011	0.37	0.66	0.53	0.37	0.41	0.40	0.13	0.20	0.20	2.53	0.18	0.14	0.27
	2012	0.35	0.47	0.44	0.41	0.41	0.40	0.13	0.20	0.19	0.54	0.12	0.09	0.29
	2013	0.34	0.47	0.34	0.42	0.47	0.43	0.13	0.20	0.13	0.09	0.09	0.06	0.08
Max	2009	$592,052.84	$7,149.50	$202,785.20	$66,227.30	$2,755,694.80	$4,570,231.00	1.00	1.00	96.26	1.46	21.12	311.70	2.21
	2010	$548,669.05	$8,971.50	$213,709.80	$78,559.60	$2,931,542.10	$4,204,684.30	1.00	1.00	96.54	2.13	27.31	245.60	2.63
	2011	$604,578.67	$11,276.40	$245,562.00	$69,651.00	$3,193,857.00	$4,542,289.00	1.00	1.00	99.46	1.56	22.68	379.55	2.32
	2012	$580,607.98	$10,855.00	$183,136.00	$104,325.00	$4,357,643.00	$4,575,319.00	1.00	1.00	96.12	1.68	22.02	189.43	2.72
	2013	$584,122.04	$15,361.00	$90,451.00	$155,825.00	$8,287,876.00	$8,956,855.00	1.00	1.00	67.96	1.74	21.00	130.43	2.44
Min	2009	$210.20	$(4.80)	$10.60	$(6.45)	$148.90	$813.20	–	–	3.19	(2.31)	(10.20)	12.35	(3.78)
	2010	$187.10	$(28.40)	$12.00	$(193.70)	$155.80	$792.10	–	–	3.50	(9.20)	(12.36)	24.52	(5.69)
	2011	$324.91	$(1,033.00)	$32.20	$(282.30)	$266.70	$ 478.80	–	–	4.49	(12.36)	(32.44)	21.20	(5.63)
	2012	$346.97	$(161.00)	$49.30	$(9,628.00)	$65.90	$1,407.00	–	–	4.58	(10.10)	(10.51)	26.16	(9.79)
	2013	$366.47	$(153.60)	$55.20	$43.80	$168.70	$2,579.50	–	–	5.15	(0.94)	(2.03)	25.60	(0.51)

Table 4
Correlation coefficient matrix between inputs and outputs.

	Total equity	Total net income	Total earning assets	Total assets
Loan loss provision	0.639	0.482	0.534	0.545
Total expenses	0.786	0.574	0.735	0.832

Table 5
Correlation coefficient matrix within the pair of inputs and the pairs of outputs.

Outputs	Total equity	Total net income	Total earning asset
Total net income	0.71		
Total earning asset	0.70	0.69	
Total asset	0.66	0.64	0.68
Inputs	Total expenses		
Loan loss provision	0.34		

Table 6
Efficiency scores.

Year	Mean	Min	Max	SD	CV
2009	0.57	0.00	1.00	0.34	0.60
2010	0.62	0.13	1.00	0.33	0.53
2011	0.68	0.13	1.00	0.32	0.47
2012	0.45	0.02	1.00	0.44	0.98
2013	0.58	0.13	1.00	0.31	0.55

relationships between the two inputs and the four outputs variables, which are, therefore, isotonic and justified to be included in the model (Wang et al., 2011). Also, Table 5 presents the correlation coefficients within the pair of inputs and the pairs of outputs, which were also calculated from 215 observations taken in aggregate. Since their serial correlations are relatively low, putting similar DEA studies into perspective, all inputs and outputs were retained in the analysis.

Before proceeding, readers should recall that one of the frequent problems of DEA models is a lack of differentiation between DMUs, which can be caused by an excessive number of input (output) variables related to the total number of DMUs observed in the respective analysis (Adler and Berechman, 2001). According to Cooper et al. (2001), the number of DMUs is a relevant issue when using DEA as the cornerstone methodology. More precisely, following Barros et al. (2012), the combination of the measured indicators should not only ensure adherence to the literature survey, but also to the DEA convention that the minimum number of DMU observations should be three folds greater than the number of inputs plus outputs. In this research this convention is observed, since the yearly sample of 43 Malaysian banks is more than three times higher the summation of the number of inputs and outputs in this research ($43 > 18 = 3 * 6$).

Therefore, the DSBM model was then performed for the period 2009–2013 and the efficiency scores were collected separately for each year. The results for the efficiency scores are presented in Table 6, which also shows their descriptive statistics for this period. The complete set of results for each bank's annual efficiency score is shown in the Appendix A. One can easily discern that the average efficiency levels present strong oscillations from one year to another, possibly still as a consequence of the 2008–2009 world crisis. Additionally, the average efficiency level in 2013 is almost 15% lower than the peak noted in 2011. These results may suggest the beginning of a movement towards an eventual financial distress in the Malaysian banking system, since the average input reduction/output increasing potentials tend to be higher when efficiency scores are lower.

Nevertheless, a first robustness analysis based on input/output reduction was performed to assess the validity of these DSBM efficiency scores, as long as it is often deemed necessary in DEA models to use a systematic statistical method to decide which of the original correlated inputs and outputs can be omitted with the minimum loss of information, and which should be kept (Jenkins and Anderson, 2003; Bădin et al., 2012). This issue is of the utmost importance as, traditionally, highly correlated variables may cause unpredictable impacts on DEA efficiency estimates (Jenkins and Anderson, 2003; Nadimi and Jolai, 2008). In this study, PCA (Principal Component Analysis) was used to determine the most relevant inputs and outputs by extracting the factors. A single extracted factor was used to represent the original inputs and two extracted factors were used to represent the original outputs. When comparing the new set of the DSBM scores with the original ones, results indicate that discrepancies were found to be minimal. As a matter of fact, the KL divergence (Cobb, 2013; Langseth et al., 2014) between the cumulative distribution function of the original DSBM scores and the DSBM scores derived from factor extraction is 0.00273, thus suggesting a considerable overlap between both distributions. Besides, the results for the Kolmogorov-Smirnov test (Conover, 1971); for the newer nonparametric test for equality of distributions of Li et al. (2009); and for the Simar and Zelenyuk (2006) test for equality of distribution on efficiency scores – which was derived from Li (1996, 1999) – were all significant at 0.05.

Then, the efficiency scores for all years were grouped (pooled) into one vector. Fig. 3 presents the pooled Kernel densities for the efficiency scores calculated from the DSBM. It is noteworthy that the bimodal aspect of this distribution is probably also related to the intrinsic characteristic of the dual banking system that exists in Malaysia. Fig. 4 reveals that throughout the years, efficiency levels vary substantially within the 43 banks in the sample. As a matter of fact, there are substantial differences when efficiency levels are grouped by bank type or origin (cf. Fig. 5). For instance, efficiency tends to be substantially lower in Islamic banks and moderately higher in foreign banks. This suggests the eventual impact of contextual variables that may be embedded within these grouping schemes. One may consider that Islamic banks tend to present lower efficiency levels due to proportionally higher loan loss provisions and total expenses in relation to outputs (assets, net profits, and equity) when compared to conventional banks. This suggests that, in practice, Shariáa principles may imply higher parsimony and costs, and lower leveraged operations when conventional banks are closely examined. The same rationale applies when comparing domestic and foreign banks.

Then, a second robustness analysis on the efficiency scores – originally generated by the DSBM model using CAMELS variables set presented in Table 3 – was performed, taking the Malmquist Index (MI) as a cornerstone. Not only did it become possible to compare how the efficiency scores changed over the course of the years between both models (MI and DSBM), but it also revealed how different proxies for the CAMELS variables affected such results. Table 7 presents the Spearman rank correlation coefficients – and their respective 95% confidence intervals – between the original scores derived by the DSBM model and those computed for each one of the alternative proxy combination of CAMELS inputs and outputs, which were tested using MI.

A number of conclusions can be taken from Table 7. First of all, results indicate that correlations are more sensitive to the choice of the variables used to proxy the inputs when compared to those used to proxy the outputs. Second, the use of the ratio between loan loss provision and total assets to proxy the Asset Quality (A) led to non-significant results, which can be inferred by the confidence intervals that crosses zero. In all other combinations, the confidence intervals for the correlation coefficients supported the hypothesis of isotonic results between the scores derived by DSBM

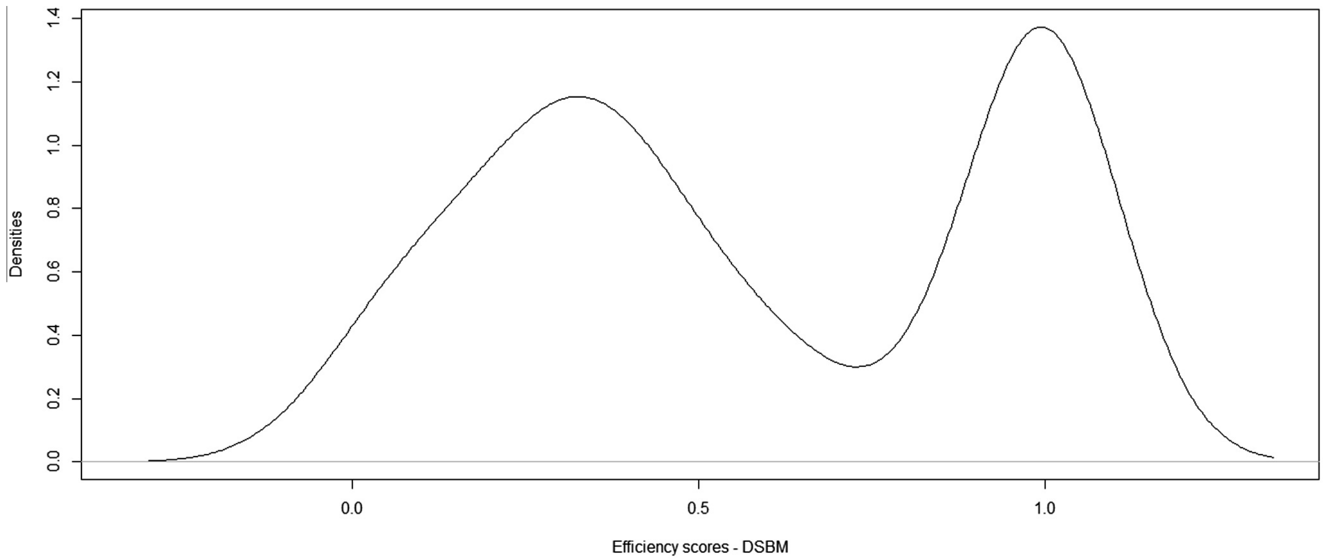


Fig. 3. Pooled Kernel density estimates.

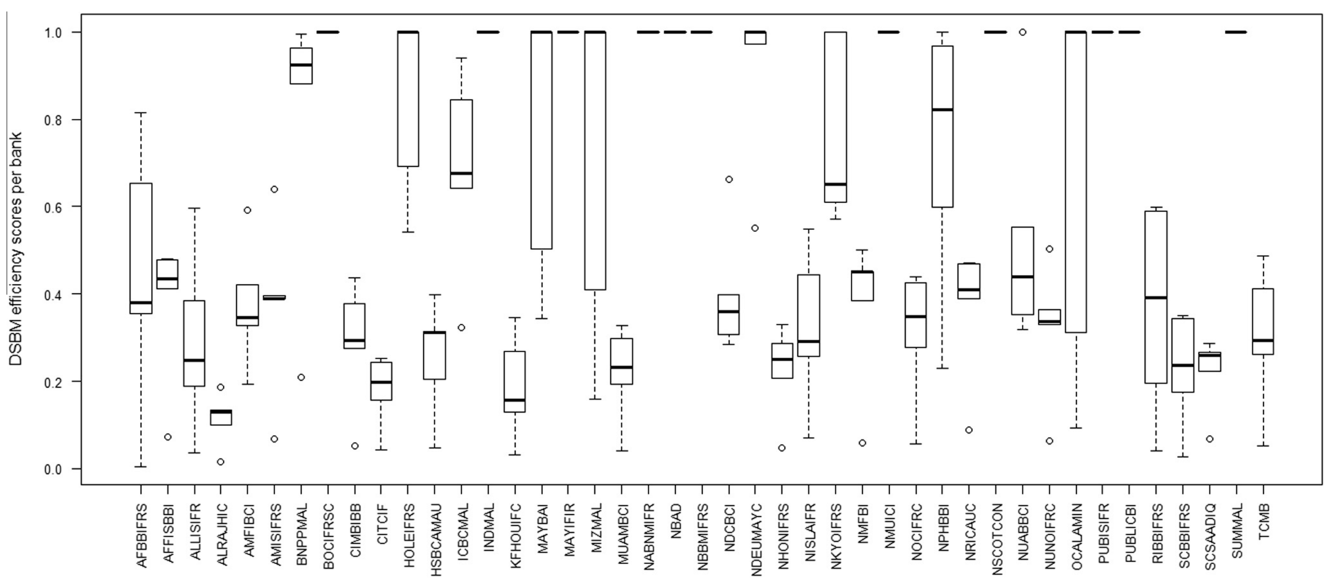


Fig. 4. Efficiency levels grouped by bank.

and MI with respect to the efficiency change over the course of the years. Third, despite the fact that correlation coefficients were maximal when Management Efficiency (M) was proxied as the ratio between total assets and total net income, one should recall the specifics of DEA models and their underlying production approach in banking with respect to the very nature of its inputs and outputs. Since inputs and outputs are required to have counterparts in physical or monetary units, the use of ratios should be avoided or used with caution. In this research, these ratios are treated as contextual variables and are considered in a subsequent step of the analysis as random effects. Therefore, the use of the original set of inputs and outputs is justified.

With regard to the contextual variables – fixed and random effects variables (cf. Table 3) – and the test for global separability (Daraio et al., 2010), the empirical value of the test statistic for the DSBM scores was found to be close to zero (0.05251433). As expected, this test value is far from zero in cases where estimates are biased towards one. Global separability, therefore, it appears to be consistent with the use of DSBM on the sample data. This suggests that the contextual variables considered here – random and fixed effects – affect only the distribution of efficiencies and not the attainable input/output combinations (or the shape of the underlying production set).

Besides, a third robustness analysis of the contextual variables was also performed before running the MCMC-GLMM model. More precisely, DSBM scores were regressed against the set of contextual variables for the fixed effects presented in Table 3 using Tobit regression. The results, presented in Table 8, indicate that efficiency levels are lower in Islamic banks. On the other hand, foreign Islamic banks appear to be even less efficient than Islamic banks or foreign banks taken in an isolated manner. This result may be explained by the cultural barriers and the historical strong regulation in Malaysia against foreign banks, as discussed in Section 2.

However, readers should also recall that the hypothesis of independence of residuals does not hold in Tobit regression when DEA is used to measure efficiency, because they are obtained from other

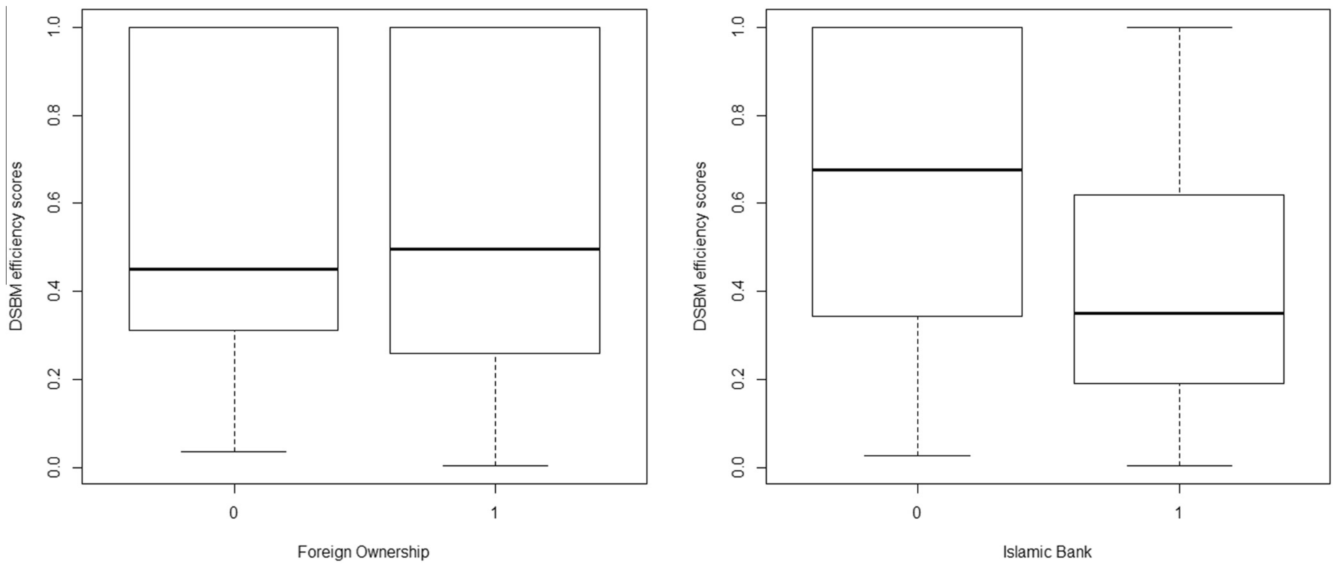


Fig. 5. Efficiency levels grouped by bank type and ownership.

Table 7
Spearman rank correlation coefficients using MI and different proxy combinations for CAMELS variables (∗).

	Original set of outputs as presented in Table 3	Capital adequacy (C) proxied as the equity ratio	Liquidity (L) proxied as the ratio between total deposits and total assets	Capital adequacy (C) proxied as the equity ratio and liquidity (L) proxied as the ratio between total deposits and total assets
Original set of inputs as presented in Table 3	0.2153150800 (0.067867246, 0.3535584)	0.1941792730 (0.04587788, 0.3341059)	0.179638385 (0.03083275, 0.3206536)	0.202653384 (0.05467699, 0.3419195)
Asset quality (A) proxied as the ratio between loan loss provision and total assets	0.1418556297 (−0.007947486, 0.2854313)	0.1165188080 (−0.03370323, 0.2615923)	0.085555014 (−0.06491039, 0.2322166)	0.067272475 (−0.08319945, 0.2147452)
Management efficiency (M) proxied as the ratio between total assets and total net income	0.4632080136 (0.336926606, 0.5731185)	0.4664050425 (0.34053677, 0.5758507)	0.423856310 (0.29279177, 0.5392872)	0.413873283 (0.28168343, 0.5306450)
Asset quality (A) proxied as the ratio between loan loss provision and total assets and management efficiency (M) proxied as the ratio between total assets and total net income	−0.0004134523 (−0.150038588, 0.1492302)	0.0005324126 (−0.14911389, 0.1501549)	−0.008125616 (−0.15756845, 0.1416811)	−0.006640666 (−0.15611995, 0.1431360)

(∗) The base case of comparison for each cell is the DSBM model using original CAMELS variables as listed in Table 3.

DMUs in the sample. This is the core argument underlying the contributions by Daraio and Simar (2005) and Simar and Wilson (2007, 2011). These authors provide evidence that Tobit estimation in the second stage may yield biased and inconsistent estimates. Therefore, a fourth robustness analysis is conducted based on the Simar and Zelenyuk (2006) test for the equality of two distributions of efficiency scores, in order to validate the significant results found in Table 8 for Islamic banks and for the interaction between Islamic and Foreign banks. Results for the bootstrap replicates obtained from these groups are depicted in Fig. 6 and reveal significant differences between their underlying distributions at 0.05, thus corroborating results presented in Table 8.

At last, as part of the second stage, a generalized linear mixed tool was used to model this set of different contextual variables, ranging from nominal to metric scales. In addition, albeit with non–Gaussian response variables (which is the case of DSBM efficiency scores) the likelihood cannot be obtained in a closed form. Markov chain Monte Carlo methods solve this problem by sampling from a series of simpler conditional distributions (Hadfield, 2010). In this paper, the response variable is assumed to follow a Gaussian distribution censored in zero (left) and one (right). The following model defines a set of simultaneous (linear) equations:

$$E(y) = X\beta + Zb, \tag{10}$$

where X and Z are design matrices for fixed and random effects, containing the predictor information depicted in Table 3, that is, the whole set of contextual variables related to the bank type in the dual banking system, the bank origin, and its cost structure, where β, b are vectors of parameters as discussed in Section 3.4. It is worth noting that the simultaneous equations defined by Eq. (10) cannot be solved directly because the expected value of y is not known *a priori*. Only the observed values, presumed to be censored Gaussian in 0 and 1, are known.[4]

Table 9 presents the MCMC-GLMM results for the DSBM scores under the censored Gaussian assumption considering the bank type and the bank origin as fixed effects and the demographic/economic variables as random effects.

Readers should recall that the first factor levels of the fixed effects were absorbed into the global intercept β_0, which is fitted by default in R. Furthermore, in Bayesian analysis, when an

[4] This system was solved using the MCMCglmm R package, which implements Markov chain Monte Carlo routines for fitting generic linear mixed models (Hadfield, 2010).

Table 8
Tobit regression results.

Coefficients:	Estimate	Std. error	*z* value	Pr(>|z|)
(Intercept)	0.81722	0.10689	7.646	2.08e−14***
Trend	−0.01919	0.02375	−0.808	0.4191
Foreign banks	0.04916	0.09404	0.523	0.6011
Islamic banks	−0.19583	0.10388	−1.885	0.0594.
Foreign_Banks * Islamic_Banks	−0.26545	0.14587	−1.820	0.0688.
Log(scale)	−0.75214	0.06491	−11.588	<2e−16***

Signif. codes:0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Scale: 0.4714.
Gaussian distribution.
Number of Newton–Raphson iterations: 3.
Log-likelihood: −161.1 on 6 Df.
Wald-statistic: 24.78 on 4 Df, *p*-value: 5.5702e−05.

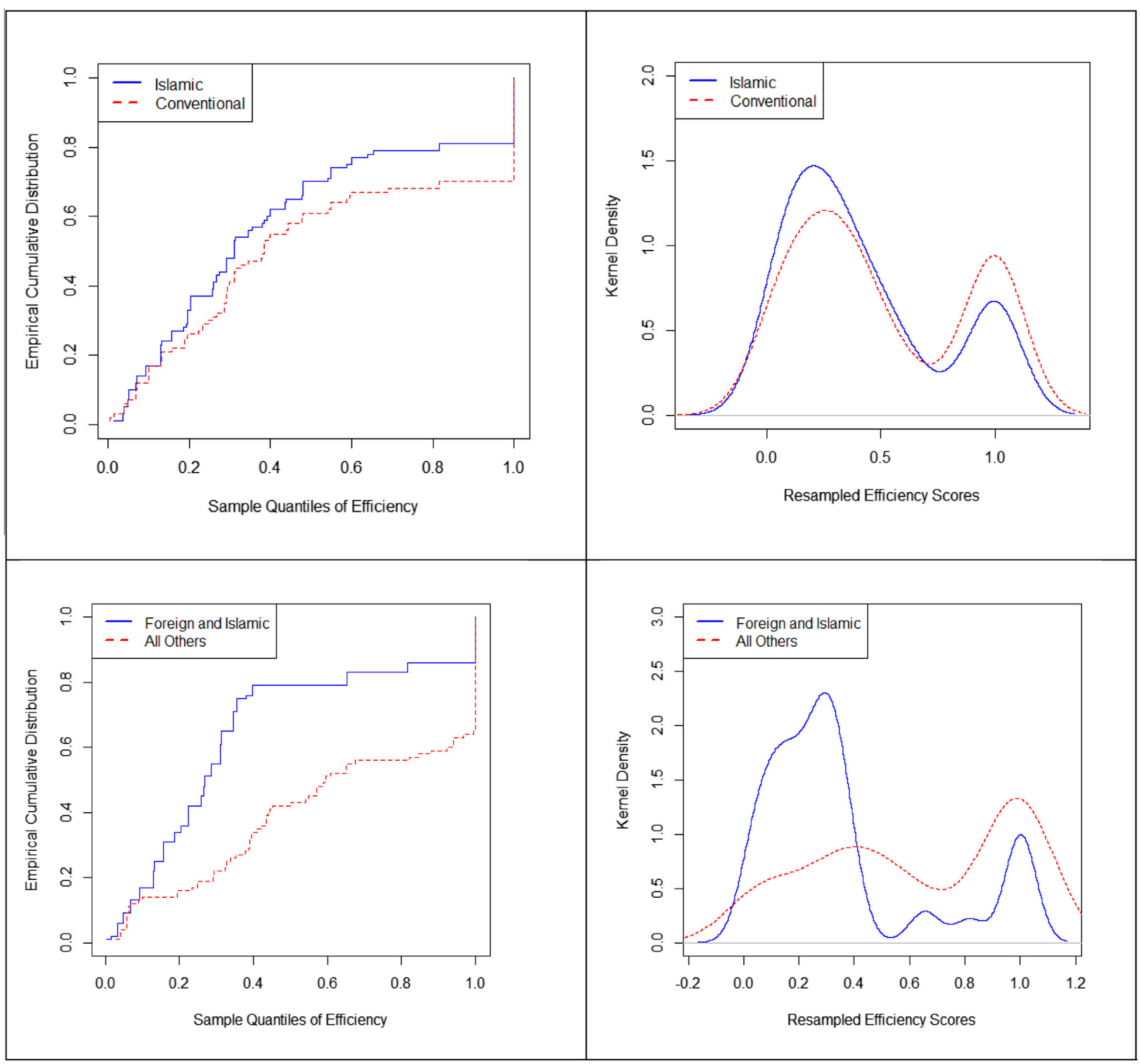


Fig. 6. Distributions for the bootstrapped efficiency scores (Test Statistic for Islamic versus Conventional: −3.710361; *p*-value: 0.04. Test Statistic for Foreign and Islamic versus All Others: −2.954183; *p*-value: 0.02).

Table 9
Results for the MCMC-GLMM on the DSBM scores.

	Post.mean	l-95% CI	u-95% CI	Eff.samp	pMCMC
(Intercept)	0.695742	0.552931	0.823951	1000.0	<0.001***
Foreign banks	0.027339	−0.106419	0.138803	911.9	0.658
Islamic banks	−0.148372	−0.275764	−0.004873	1000.0	0.036*
Trend	−0.016496	−0.047726	0.014629	1026.0	0.290
Foreign banks * Islamic banks	−0.199025	−0.398833	−0.004597	1000.0	0.052.

G-structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Equity Ratio	0.0005244	1.98e−16	0.001069	36.6
ROA	1.143e−06	1.537e−16	1.874e−07	309.9
ROE	0.0001856	1.755e−16	0.0007306	88.75
Cost Income Ratio	3.419e−06	1.495e−16	7.216e−07	95.78
Price Earnings Ratio	4.197e−06	2.152e−16	1.049e−05	164.2

R-structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Units	0.114	0.09229	0.1384	539.7

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Iterations = 25001:74951/thinning interval = 50/sample size = 1000.
DIC: 149.5033.

Table 10
Results for the MCMC-GLMM on the carry-over slacks.

Loan loss provision slack	Post.mean	l-95% CI	u-95% CI	Eff.samp	pMCMC
(Intercept)	4.01665	3.16015	4.86117	1000	<0.001***
Foreign banks	−0.65204	−1.50569	0.14975	1000	0.114
Islamic banks	−1.39900	−2.22751	−0.42404	1000	0.002**
Trend	0.03324	−0.17124	0.22755	1000	0.754
Foreign banks * Islamic_Banks	1.21229	−0.15265	2.45574	1000	0.068.

G−structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Equity ratio	2.693	0.004447	4.289	192.9
ROA	0.0002808	1.629e−16	0.0002757	292.5
ROE	0.03053	1.875e−16	0.1051	21.06
Cost income ratio	1.2e−09	1.637e−16	6.13e−09	0
Price earnings ratio	0.04064	1.916e−16	0.3039	10.84

R-structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Units	2.156	0.6922	4.6	166.3

Total Net Income Slack	Post.mean	l-95% CI	u-95% CI	Eff.samp	pMCMC
(Intercept)	7.6793	6.8299	8.6475	908.8	<0.001***
Foreign banks	−1.5543	−2.3558	−0.7184	211.5	<0.001***
Islamic banks	−1.5725	−2.4973	−0.6845	839.4	0.002**
Trend	0.3584	0.1587	0.5382	1074.9	<0.001***
Foreign banks:Islamic banks	1.4403	0.2288	2.7894	752.2	0.026*

G-structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Equity Ratio	9.776e−08	1.675e−16	5.62e−09	85.12
ROA	0.06491	2.428e−16	0.5327	20.39
ROE	0.9298	1.42e−10	3.453	11.42
Cost Income Ratio	4.965e−08	1.578e−16	1.731e−07	79.92
Price Earnings Ratio	0.04487	8.473e−10	0.2489	119

R-structure

	Post.mean	l-95% CI	u-95% CI	Eff.samp
Units	3.474	0.8504	5.299	10.27

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Iterations = 25001:74951/Thinning interval = 50/Sample size = 1000.
DIC: 840.7909.
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.
Iterations = 25001:74951/Thinning interval = 50/Sample size = 1000.
DIC: 881.1066.

effect is treated as fixed, the only information regarding its value comes from data associated with that particular level. Quite often, effects with few factor levels are candidates to be fixed effects (Hadfield, 2014). Otherwise, when an effect is treated as random, it is weighted by what other data indicate as the likely values that the effects could have. Population and individual related variables are usually considered as random (Hadfield, 2014). In addition to these comments, it should be kept in mind that in a Bayesian analysis all effects are technically random, as fixed effects are those associated with a variance component which has been set *a priori* to something large (10^8 in the MCMCglmm R package) and random effects are associated with a variance component which is not set *a priori*, but rather estimated from the data (Hadfield, 2010).

Results presented in Table 9 reveal that bank type and origin have different impact on efficiency levels. Results confirmed the signs found in Tobit regression results for the fixed effect variables (cf. Table 8), despite their significance levels and relative importance, as measured by the regression coefficients. Islamic banks tend to be less efficient than conventional ones. It is possible that a greater parsimony and smaller risk assumed in less leveraged operations, as well as higher loan loss provisions. which are typical of Islamic banking, may be negatively affecting efficiency levels. On the other hand, as regards to bank origin, it is interesting to notice a negative impact of foreign ownership on efficiency levels when Islamic banks are considered in isolation (second order interaction effect between bank type and origin). This suggests that banking operations in Malaysia may still be characterized by cultural and regulatory barriers that limit the efficiency of foreign banks, at least with respect to Islamic finance issues.

Table 10 presents the results for a similar analysis using the carry-over slacks instead, except that the censoring on the dependent variable was removed. Readers should recall one of the major propositions of this study: a movement over the course of time towards higher input increasing/output decreasing potentials may imply an eventual financial distress in the future. Although the loan loss provision slacks do not present a significant result on this trend, total net income slacks appear to be increasing significantly over the course of time for both, conventional and Islamic, domestic and foreign banks, suggesting heightened financial distress in the Malaysian banking industry. When looking at bank type and origin, a heterogeneous picture emerges: results indicate that both loan loss provision and total net income slacks are significantly higher in foreign Islamic banks, aligned with earlier findings in terms of efficiency scores. These slacks, however, tend to be higher in conventional and domestic banks, and lower in domestic Islamic banks, which at first sight appears counterintuitive, as Islamic banks presented lower efficiency levels (cf. Table 9). It seems that Islamic finance practices are interfering with the direct relationship expected to be found between efficiency scores and carry-over slacks, i.e., the higher the scores, the lower the slacks (Wanke et al., 2015). One possible explanation for this phenomenon can be found in the parsimonious practices of Islamic banking: while they promote lower levels of leveraging, and thus lead to lower aggregate efficiency levels, they also allow growth on a sustainable basis, with the most adequate dimensioning of loan loss provisions in terms of the total net income generated for the business.

5. Conclusion

This paper presents an analysis of the efficiency of the Malaysian dual banking system using DSBM and MCMC generalized linear models. It provides four major contributions to the analysis on bank efficiency. First, it focuses on the Malaysian dual banking system, shedding some light on the impacts of Islamic finance. Second, it also highlights the discriminatory power of DSBM and its carry-overs in terms of assessing potential financial distress situations, thus allowing the identification of banks' clusters where this kind of situation is more likely to happen. Third, it emulates the CAMELS risk assessment framework within the ambit of DEA models as prescribed by Wanke et al. (2015). And fourth, it offers additional insights into the literature as a whole with respect to the contextual variables analyzed, especially with respect to Islamic banks.

When analyzing major or fixed effects controlling random effects, the negative impacts of foreign and Islamic variables on Malaysian banking system efficiency levels become apparent, consistent with previous findings. For the banking system, a possible explanation for weaker Islamic banking performance may be related to tighter purse-strings and lower risks assumed in less leveraged operations, which is in accordance with the earlier findings of Khediri et al. (2015), Basov and Bhatti (2014); and Dewandaru et al. (2015). Under such circumstances, it is possible that, in Malaysia Islamic banks, outputs are produced less than proportionally – considering the same input base – in comparison to conventional banks. As regards to origin, it is interesting to notice a negative impact of foreign ownership on efficiency levels in Malaysia. This suggests that Malaysian banking operations are still affected by cultural and regulatory barriers that limited the efficiency of foreign banks until 1994. Besides, it is worth noting that efficiency levels increase rate was not found to be significant, suggesting a stagnant learning curve in Malaysian banks.

Nevertheless, this parsimony verified in Islamic banks has beneficial effects, when one analyzes the productive slacks related to total net income. These slacks are lower in Islamic banks when compared to domestic and conventional banks, thus suggesting a more sustainable path towards profitability in the long run. The results presented here can be used as a preliminary off-site screening tool by Malaysian regulators, managers, and investors to ascertain the standing of a given financial institution among the banking industry. For example, an increased focus should be placed on yearly monitoring of the net income and the loan loss provision of the banks, which represent, respectively the desirable and undesirable carry over slacks that affect efficiency levels. This being the case, attention by regulators can be further directed at potentially distressed banks, as some of them would be candidates for closer monitoring or even intervention by central bank authorities. Besides, based on the MCMC-GLMM results, it is possible to assess the causes of inefficiency within the ambit of Islamic banking regulation. This may be explained by the smaller leverage assumed within the context of Islamic finances. Additionally, bank origin also explains efficiency, implying that cultural traditions and the strong regulatory mark that existed until 1994 are a cause of efficiency. Malaysian regulators should also pay attention to this issue, tailoring compensatory policies to foreign banks that operate within the Islamic system. The MCMC-GLMM also predicts considerable impacts from a trend towards total net income slacks, suggesting that situation-specific financial distress looms ahead for Malaysians. Future research, however, is still necessary to assess the role of carry-over slacks in discriminating and predicting financial distress.

Appendix A

Appendix – Results for the efficiency scores per company and per year.

DMU	Rank	Overall score (2009–2013)	2009	2010	2011	2012	2013
Al Rajhi banking & investment corporation (Malaysia) Berhad	42	0.042	0.099	0.130	0.186	0.015	0.133
Affin Islamic bank Berhad	28	0.193	0.411	0.435	0.480	0.072	0.477
Alliance Islamic bank Berhad	36	0.143	0.384	0.188	0.596	0.036	0.248
AmIslamic bank Berhad	26	0.230	0.388	0.396	0.640	0.068	0.390
CIMB Islamic bank Berhad	34	0.156	0.294	0.377	0.438	0.052	0.275
Bank muamalat Malaysia Berhad	39	0.106	0.193	0.327	0.233	0.040	0.298
Bank Islam Malaysia Berhad	25	0.231	0.258	0.292	0.444	0.070	0.548
Asian finance bank Berhad	43	0.024	0.004	0.355	0.379	0.653	0.816
Hong Leong Islamic bank Berhad	13	0.794	0.691	0.541	1.000	1.000	1.000
HSBC Amanah Malaysia Berhad	32	0.166	0.314	0.398	0.204	0.048	0.311
Kuwait finance house (Malaysia) Berhad	41	0.082	0.346	0.157	0.130	0.032	0.268
Maybank Islamic Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
OCBC Al-amin bank Berhad	21	0.390	1.000	1.000	1.000	0.092	0.311
Public Islamic bank Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
RHB Islamic bank Berhad	35	0.156	0.195	0.589	0.599	0.040	0.391
Standard chartered Saadiq Berhad	31	0.168	0.286	0.259	0.223	0.068	0.267
RHB bank Berhad	22	0.365	0.307	0.360	0.662	0.285	0.399
Public bank Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
Malayan banking Berhad	15	0.664	1.000	1.000	1.000	0.343	0.502
Hong Leong bank Berhad	11	1.000	1.000	1.000	1.000	1.000	1.000
CIMB bank Berhad	20	0.483	0.352	0.318	0.552	1.000	0.439
Alliance bank Malaysia Berhad	30	0.178	0.501	0.384	0.451	0.059	0.451
AmBank (M) Berhad	23	0.323	0.345	0.420	0.327	0.194	0.592
Affin bank Berhad	18	0.536	0.822	0.968	1.000	0.229	0.598
BNP Paribas Malaysia Berhad	16	0.626	0.994	0.964	0.881	0.924	0.209
Bangkok bank Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
Bank of America Malaysia Berhad	24	0.239	0.409	0.390	0.469	0.089	0.472
Bank of China (Malaysia) Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
Bank of Tokyo-Mitsubishi UFJ (Malaysia) Berhad	14	0.742	0.609	0.999	0.999	0.572	0.651
Citibank Berhad	38	0.113	0.198	0.244	0.252	0.042	0.156
Deutsche bank (Malaysia) Berhad	12	0.856	0.551	0.972	1.000	1.000	1.000
HSBC bank Malaysia Berhad	37	0.140	0.251	0.286	0.329	0.047	0.207
India international bank (Malaysia) Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
Industrial and commercial bank of China (Malaysia) Berhad	17	0.595	0.322	0.675	0.941	0.845	0.641
J.P. Morgan Chase bank Berhad	33	0.159	0.261	0.294	0.412	0.053	0.486
Mizuho bank (Malaysia) Berhad	19	0.523	1.000	1.000	1.000	0.158	0.409
National bank of Abu Dhabi Malaysia Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
OCBC bank (Malaysia) Berhad	29	0.184	0.349	0.425	0.439	0.057	0.277
Standard chartered bank Malaysia Berhad	40	0.094	0.236	0.351	0.344	0.027	0.174
Sumitomo mitsui banking Corporation Malaysia Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
The bank of Nova Scotia Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
The royal bank of Scotland Berhad	1	1.000	1.000	1.000	1.000	1.000	1.000
United overseas bank (Malaysia) Bhd.	27	0.201	0.329	0.363	0.504	0.063	0.337

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