International Journal of Business and Society, Vol. 18 S1, 2017, 129-150

ISLAMIC BANKING AND PERFORMANCE IN THE ASEAN BANKING INDUSTRY: A TOPSIS APPROACH WITH PROBABILISTIC WEIGHTS

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ABSTRACT

This paper uses an integrated two-stage approach to assess the performance of 88 ASEAN (Association of Southeast Asian Nations) banks from 2010-2013. The relative importance of different financial ratios that emulate the CAMELS rating is collected using the expert opinions of 88 ASEAN bank managers with the help of a structured questionnaire. The computation of empirical joint probabilities is used first to derive weights for a number of criteria related to Capital adequacy, Asset quality, Management quality, Earnings, Liquidity, and Sensitivity to market risk. In the second stage, these weights are used as TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) inputs to assess the relative efficiency of ASEAN banks. The results reveal the prominent role of Islamic principles in banking efficiency. More specifically, these beneficial results are found when banks are private. We then use our results to develop policy recommendations.

Keywords**:** Islamic Banking; Probabilistic Weights; TOPSIS; CAMELS; Performance Evaluation.

1. INTRODUCTION

Accurately predicting financial performance and providing proper guidelines builds investors' confidence. Measuring the performance of the banking sector has remained significantly important for decades due to its unparalleled contribution in economic development and sustainability (Liu, Lu, Lu, & Lin, 2013a, 2013b). Thus, policy implications often rely on the proper measurement of bank performance. Thus far, bank performance measurement techniques are normally categorized into two main groups: parametric and non-parametric (Berger & Humphrey, 1997; Lampe & Hilgers, 2015; Sengupta, 1993). The Stochastic Frontier Approach (SFA) is the most popular parametric test (Sengupta, 1993). Among the non-parametric tests, Data Envelopment Analysis (DEA) is the most popular (Liu et al., 2013b; Paradi & Zhu, 2013). Due to some major advantages in ease of use and interpretation of benchmarking, non-parametric methods

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are now commonly used performance measurement techniques (LaPlante & Paradi, 2015; Liu et al., 2013a).

Most ASEAN economies are emerging. A growing trend identified within the recent studies on banking is related to specific performance measurements and benchmarking in emerging countries (Ebrahim, Girma, Shah, & Williams, 2014). This particular study focuses on ASEAN banks, since bank performance may react differently in different emerging economies. Besides, the impact of Islamic banking and compliance with the principles of Sharia - which is profound in this region - on banking performance is of particular interest. More precisely, Sharia prohibits acceptance of specific interest or fees for loans of money (known as “riba”, or usury), whether the payment is fixed or floating. Investment in businesses that provide goods or services considered contrary to Islamic principles (e.g. pork or alcohol) is also “haraam” (sinful and prohibited).

Therefore, this paper fills the literature gap by analyzing and exploring the sources of efficiency in the banking industry of ASEAN economies, placing a special focus on the differences between Islamic and conventional banks. This research innovates first by focusing on Islamic versus conventional banking in a dynamic region of the world and second by adopting a joint probabilities approach to derive weights criteria together with TOPSIS for performance ranking.

The contributions of the present research to the current body of knowledge are the following. First, this research evaluates the relative efficiency between Islamic and conventional banks within the ambit of ASEAN countries, adding to the scarce literature on this subject. Second, this research proposes a joint probabilities approach to compute the criteria weights of a CAMELS rating system. The scores on CAMELS criteria were obtained by interviewing 88 experts who work in different ASEAN banks. These probabilistic weights are also used as inputs for computing the TOPSIS scores based on different CAMELS rating criteria. In this research, however, the contextual variables are used to explain differences in performance of different types of banks. For policy purposes, such segmentation is, *per se,* a contribution to the current research on the banking sector. Finally, our analysis covers the period from 2010 to 2013 and is based on a representative sample of ASEAN banks.

The results presented in this study add to the growing literature on Islamic banking, corroborating previous findings and unveiling new relationships between Islamic and conventional banks. Precisely, the results of this research are consistent with and extend the findings of recently conducted studies (Wanke, Azad, Barros, & Hadi-Vencheh, 2015) that use different weighting approaches based on fuzzy logic. As regards the findings presented in this research, the prominent role of Islamic principles was also confirmed in banking efficiency.

This paper is organized in the following sections: section 2 presents the contextual setting of ASEAN countries and banking sector information. Next, section 3 covers the related literature on bank performance in model selection, followed by detailed methodology in section 4. Section 5 presents empirical results and discusses the obtained results in terms of policy implications. Section 6 presents conclusions and policy implications.

2. ISLAMIC BANKING IN ASEAN COUNTRIES

The ASEAN countries are heterogeneous (Chia & Plummer, 2015). Gross domestic product (GDP), gross national income (GNI), purchasing power parity (PPP), bank capital to assets ratio (%), nonperforming loans to total gross loans (%), and domestic credit (% of GDP) are often used as proxy variables for representing economic diversity. Considering GNI, for instance, Singapore and Brunei are equivalent to high-income nations, whereas Cambodia, Laos, and Myanmar remain in the least developed group. In contrast to these countries, Indonesia is the largest economy within the ambit of ASEAN group, followed by Thailand and Malaysia. Regulatory restrictions for entering the banking market may also vary between ASEAN countries. According to the services trade restrictions index (STRI)[1], diversity in entry restrictions is considerable. The higher the STRI score, the higher the restriction a county imposes on foreign entry and operation in the host country. According to the ASEAN Secretariat and the World Bank (2013), Indonesia and Vietnam seem to be relatively open regimes, scoring only 21 and 23 respectively out of 100. In Indonesia for instance, foreign investors can own 99 percent of a bank subject to operation as a joint venture with local partners. In contrast, Malaysia, Philippines, and Thailand are highly monitored and restricted, scoring 44, 46, and 37 respectively. Regarding Malaysia in particular, foreign owners may only own up to 49 percent of a bank.

Despite such regulatory restrictions, the Islamic banking sector in the ASEAN region is now attracting foreign investors worldwide (Venardos, 2011). The potential of the ASEAN market[2] is now one of the most attractive topics among academics, practitioners, policy makers, and investors. Among ASEAN countries, Malaysia initiated Islamic banking (Wanke, Azad, & Barros, 2016a, 2016b). Islamic Bank Berhad, the first Islamic bank in Malaysia, started its operations in 1983. Some 30 years on, the assets of Malaysia's 16 Islamic banks account for 24.2% of total banking assets (Sufian, Kamarudin, & Noor, 2014). Despite having an 87% Muslim majority, Indonesia introduced Islamic banking relatively late compared to Malaysia. According to Venardos (2011), Indonesians have waited to confirm that this new banking system is fully in accordance with Islamic principles (Shariah); additionally, Islamic banking assets in Indonesia are only 0.27% of total banking assets. However, according to Sufian and Kamarudin (2015) and Shaban, Duygun, Anwar, and Akbar (2014), such a huge unexposed market may work in favor of further Islamization of the banking sector in the ASEAN region. On the other hand, with a small population compared to other ASEAN nations, considerable wealth remains untapped among Islamic banks in Brunei. Based on the above facts, knowing the present financial performance of the ASEAN banking sectors is critical. Moreover, an analysis of the relative performance of Islamic and conventional

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[1] For the methodology of the services data collection see the paper "Guide to the Services Trade Restrictions Database" (Borchert, Gootiiz and Mattoo, 2013) and in supplementary material available at http://iresearch.worldbank.org/servicetrade

[2] Muslim Population Worldwide (www.islamicpopulation.com). ASEAN countries have roughly 17% of total Muslim population worldwide. Indonesia, Malaysia, and Brunei are Muslim majority countries representing roughly 240 million people all together. A sizable Muslim community is also found in Thailand and Philippines.

banks adds additional robustness to the results and their utility for future policy developments.

2.1. Background on Islamic Banking

The role of banks are imperative for any economy (whether secular or Islamic) due to the following four reasons (Iqbal & Molyneux, 2005): i) intermediation services, ii) creation of a wide range of assets and liabilities, iii) offering financial services, and iv) creation of incentives. The most cited rationale for offering an alternative banking system (Islamic banks) is the involvement of interest as a means of performing the above mentioned roles by traditional banks. According to Islamic regulations (Shariah), the prohibition of interest is justified for two reasons (Iqbal & Molyneux, 2005, p. 10). First, any contract based on interest does not share risk among parties. Rather than accumulate risk from all involved parties, the burden unfairly accrues to a single party. This unjust practice has an adverse effect on incumbent parties. Second, the application of interest in an economy has proven to be inefficient in resource allocation. Since banks prefer to lend money only to the most profitable projects to ensure returns on their investments, investors with low credit worthiness remain undervalued. This creates a deviation between high income and low income groups in that society.

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 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.

3. LITERATURE REVIEW

The banking sector plays an important role in promoting economic growth in society. As a result, performance evaluation of the banking sector has received a high level of attention over the past several years in both theoretical and practical areas.

Considering the fact that different efficiency measurement methods – like those presented in the Introduction – may impact the discriminatory power of efficiency scores, the choice these is of utmost importance in establishing linkages between banking efficiency (or superior performance) and financial distress (Wanke, Azad, et al., 2016a). In fact, although TOPSIS and DEA may have some similarities and specific advantages – which are more clearly depicted in Section 4.3 - different studies have shown that the first method presents superior discriminatory power over the second (Wanke, Azad, et al., 2015; Wanke, Barros, & Macanda, 2015; Wanke, Barros, & Chen, 2015) in the sense that efficiency scores are not upwards biased towards one. This kind of result is extremely useful when modelling numerous variables, such as in the case of the CAMELS rating system, to overcome what is known as the curse of dimensionality, one of the major DEA limitations.

Table 1: CAMELS (sub) criteria proposed by Wanke, Azad, et al. (2015)

	Betz, Oprică, Peltonen, and Sarlin (2014)	Maghyereh and Awartani (2014)	Wang, Lu, and Wang (2013)	Wang, Lu, and Lin (2012)	Doumpos and Zopounidis (2010)	Secme, Bayrakdaroglu, and Kahraman (2009)	Zhao, Sinha, and Ge (2009)	Cole and Gunther (1995)
Capital Adequacy								
Total Regulatory Capital Ratio%	√	√	√	√	√	√		√
Equities/total assets	√	√	√	√		√	√	√
Assets Quality								
Loan Loss Res / Gross Loans					√	√	√	√
Loan Loss Provision / Net Interest Rev	√	√	√			√	√	√
Loan Loss Res / Impaired Loans	√	√			√	√	√	√
Management								
Net Interest Margin	√	√	√	√	√	√	√	√
Net Interest Revenue / Average Assets	√		√	√	√	√	√	√
Earning Quality								
Return on Average Assets (ROAA)	√	√	√	√	√	√	√	√
Return on Average Equity (ROAE)	√	√		√	√		√	√
Liquidity								
Net Loans / Total Assets			√	√	√			√
Liquid Assets / Total Deposit & Borrowings	√	√			√	√	√	
Sensitivity of Market Risk								
Risk weighted asset (II)/ Risk weighted asset (I + II)					√			

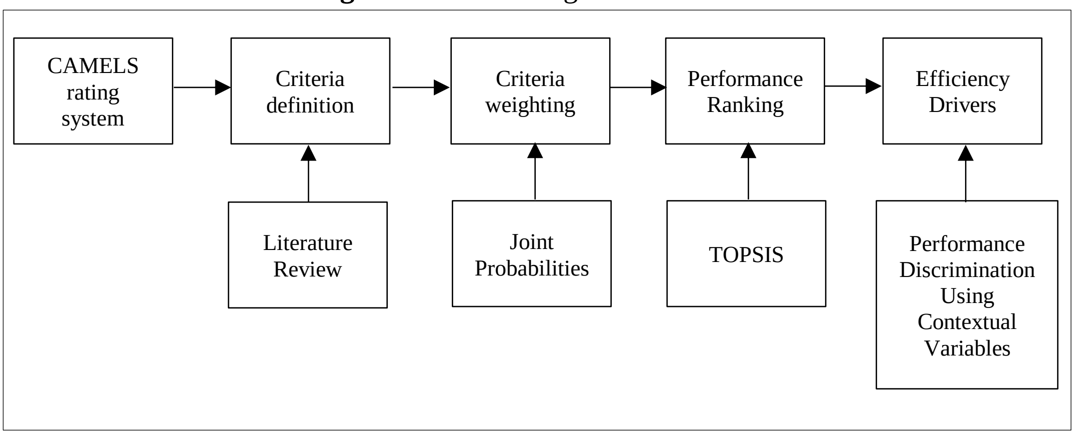
In fact, there are a number of variables that are thought to be associated with financial distress. Predicting failure using firm-specific characteristics together with financial structures is originally attributed to the seminal works of Altman (1968) and Altman, Haldeman, and Narayanan (1977) which employed discriminant analysis on financial ratios to derive the Z-score approach. More recently, Männasoo and Mayes (2009) present a comprehensive literature review on this subject. According to these authors, although there is no universal set of indicators used across previous studies, the CAMELS factors appear to have a significant role in detecting distress. The major sub-criteria used most in the literature, by which the CAMELS rating system is emulated as proposed by Wanke, Azad, et al. (2015), is shown in Table 1.

In recent times, an increasing trend in two-stage bank performance analysis can be observed. In a broader sense, the authors argue that this was done without specifying a statistical model in which such structures would follow from the first stage where the initial benchmarks were estimated. As such, these two-stage approaches were not structural, but rather *ad hoc*. The most important underlying assumption regarding two-stage analysis concerns global reparability (Kourtesi, Fousekis, & Polymeros, 2012).

4. METHODOLOGY

In this paper, TOPSIS is used with a joint probability approach in a two-stage fashion, as depicted in Figure 1.

Figure 1: Methodological framework



4.1. The Data

For each one of the CAMELS criteria, several different financial ratios are used as proxies as presented in Table 2. Contextual variables are also shown in Table 2: bank ownership (public or private); bank origin (local or foreign); bank type (commercial or investment); and bank system (Islamic or conventional). These contextual variables are considered to be exogenous. That is, the underlying assumption on contextual variables is that they affect efficiency levels without being affected by them (Assaf, Barros, and Matousek (2011). A major proposition of this study is that efficiency levels among ASEAN banks are significantly affected by contextual variables. For instance, leveraging the financial and operational indicators of banks are assumed to be the key to conventional banking operations. On the other hand, national banks are relatively small in size and may be not scale efficient. In contrast, Islamic banks may be held responsible for differences in production technology.

Table 2: Descriptive statistics on the CAMELS criteria

		Sub-criteria	Impact	Min	Max	Mean	SD
TOPSIS Criteria	C	Total Regulatory Capital Ratio (%)	+	3.25	380.68	28.226	39.949
		Growth to Total Asset Ratio (%)	+	-85.55	295.2	16.468	33.324
		Total Capital Ratio (%)	+	1.98	894.66	33.61	71.378
		Equity to Total Assets Ratio (%)	+	1	99.46	16.013	17.189
		Equity to Short Term Funding Ratio (%)	+	1.07	801.2	33.374	86.563
		Equity to Total Liabilities Ratio (%)	+	1.01	621.11	25.796	60.639
	A	Loan Loss Reserve to Gross Loans Ratio (%)	-	0.01	39.4	2.617	4.076
		Loan Loss Provision to Net Interest Revenue Ratio (%)	-	-165.41	423.15	7.789	33.516
		Loan Loss Reserve to Impaired Loans Ratio (%)	-	1.34	947.06	95.109	79.025
		Impaired Loans to Gross Loans Ratio (%)	-	-6.37	106	3.645	8.102
		NCO to Average Gross Loans Ratio (%)	-	-74	23.15	1.056	5.335
		Impaired Loans to Equity Ratio (%)	-	-5.15	102.72	9.016	11.004
		Tier 1 Ratio (%)	-	4.5	380.68	31.368	45.643
	M	Net Interest Margin (%)	+	0.01	16.24	2.365	1.786
		Net Interest Revenue to Average Assets Ratio (%)	+	0.01	10.86	1.738	1.178
		Other Operational Income to Average Assets Ratio (%)	+	-5.84	39.35	1.708	3.67
		Non-Interest Expenses to Average Assets Ratio (%)	-	-1.23	42.82	2.391	3.456
	E	Return on Average Assets (ROAA) (%)	+	-43.75	15.66	0.619	3.906
		Return on Average Equity (ROAE) (%)	+	-56.2	98.56	8.834	12.277
		Non-operating Items to Net Income (%)	-	-265.98	400	4.424	44.402
		Cost to Income Ratio (%)	-	0.66	379.55	55.41	35.074
	L	Interbank Ratio (%)	+	-0.54	974.07	67.356	127.507
		Net Loans to Deposits & Short term Funding Ratio (%)	+	0.01	346.13	47.963	40.89
		Liquid Assets to Deposit & Short term Funding Ratio (%)	+	0.39	766.22	47.083	75.238
	S	Net income to Risk Weighted Assets Ratio (%)	+	-135.75	15.51	0.462	9.634
Contextual Variables	Year			1	4	2.496	1.118
	$Year^2$			1	16	7.476	5.677
	Public Bank			0	1	0.011	0.106
	Private Bank			0	1	0.989	0.106
	Commercial Bank			0	1	0.863	0.344
	Investment Bank			0	1	0.137	0.344
	Local Bank			0	1	0.399	0.49
	Foreign Bank			0	1	0.601	0.49
	Conventional Bank			0	1	0.786	0.41
	Islamic Bank			0	1	0.214	0.41

Notes: Legend: C = Capital Adequacy; A = Asset Quality; M = Management Quality; E = Earnings; L = Liquidity; S = Sensitivity to market risk.

4.2. The Joint Probabilities Approach to Weighting

Weights in MCDM reflect the decision maker's preferences on one criterion over the others (Saaty and Vargas, 2012). Criteria weights are usually described by probabilities. If each criterion preference is set in terms of a probability distribution, then it is possible to compute the joint probability of each criterion receiving the highest preference. This score reflects the relevance of each criterion. In fact, this joint probabilities approach underlies the logic behind any traditional weighting technique, except by the use of distributions instead of crisp probabilities.

The context also recommends the probabilistic approach against other traditional weighting methods. The criteria preference set has more than 2,200 evaluations of 26 indices under six dimensional criteria. The AHP method, for instance, would require a different dataset, describing pairwise comparisons in reciprocal matrices, followed by an aggregation technique (Saaty, 1990). On the other hand, these preferences can be associated with random variables, allowing the use of probability distributions. The assignment of probability distributions to the expert preferences describes the imprecision and subjectivity related to their choices.

The joint probabilities approach has two stages: first, each criterion preference is fitted to a probability distribution; second, the probability of each criterion receiving the best preference regarding all others is chosen as its criterion weight. The software 'R' was used to compute the results of both stages; the package 'fitdistrplus' was used in the first stage and the embedded function 'integrate' helped in the second stage.

In the first stage, the observed sample values of each criterion were employed in Maximum Likelihood Estimation (MLE). This stage consists of examining the empirical likelihood function of the sample values (Konishi and Kitagawa, 2008). The best probability distribution for each criterion was selected by applying Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). These indices have the advantage of testing the significance of the difference between the outcomes of different model specifications (Wang and Liu, 2006).

In the second stage, the theory of joint probabilities is applied to compute the criteria weights. The probability of being the best criterion among all others requires the computation of multiple integrals. For instance, the joint probability of two continuous random variables '*X*' and '*Y*' describes their joint behavior by a function *f (x, y),* called the joint probability density function of X and Y, defined for all real *x* and *y* pertaining to a set *C* of pairs of real numbers, as described in Eq. (1) (Ross, 2014).

$$P\left\{\left(X,Y\right)\in C\right\}=\iint\limits_{(x,y)\in C} f(x,y)dxdy \tag{1}$$

A simplification should be considered in order to deal with independent densities f(x) and f(y) in the first stage. Readers should recall, however, that in probability theory, two random variables being linearly uncorrelated does not imply their independence. In some contexts, linear uncorrelatedness implies at least pairwise independence (as when the random variables involved have Bernoulli distributions).Keeping this is mind, a bivariate function f(x,y) should be available, derived from the context or estimated from the database. Then, the joint probability is simplified by Eq. (2).

$$P\left\{X \in A, Y \in B\right\} = \int_B \int_A f(x).f(y)dxdy \qquad (2)$$

The joint probability of criterion 'C' receiving higher preferences than criteria 'A', M', 'E', 'L', and 'S', simultaneously, is described by equation (3), where '*f*' indicates the probability density functions of each criterion, represented by their initials.

$$P\left\{C > A, M, E, L, S\right\} = \int f(c)\int_A^C f(a)\int_M^C f(m)\int_E^C f(e)\int_L^C f(l)\int_S^C f(s).dc.da.dm.de.dl.ds \qquad (3)$$

To apply the joint probabilities approach, the ranking and comparison data are processed and calculate the weights of different criteria. Table 3 presents the scale used to interview ASEAN bank managers with respect to their importance.

Table 3: Membership function of linguistic scales for pairwise comparison

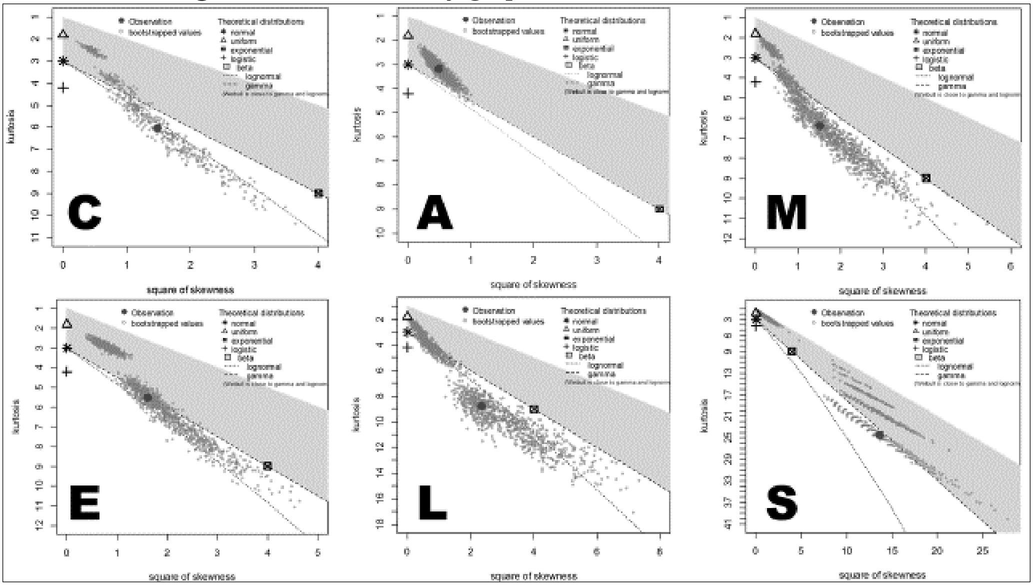
Intensity of importance of each criterion	Linguistic scale or verbal judgment of preference in pair wise comparison
1	Equal importance
2	Intermediate values between adjacent scale values
3	Moderate importance
4	Intermediate values between adjacent scale values
5	Strong importance
6	Intermediate values between adjacent scale values
7	Extreme importance
8	Intermediate values between adjacent scale values
9	Extremely high importance

The CAMELS criteria preferences were first submitted to the joint probabilities approach to compute their weights at the highest hierarchical level. The same procedure was then applied at the second hierarchical level, to compute the weights for 'C1', C2' and all the other criteria. Table 4 summarizes the outcomes of both stages, showing the best fitted distributions and their respective parameters and the weights computed from Eq. (3).

The goodness of fit procedure follows two steps within the same 'fitdistrplus' package: first, an indicative approach to the best fit by the Cullen & Frey graph, shown in Figure 2 for each criterion, using the 'descdist' function. Second, a Maximum Likelihood Estimation (MLE) to derive the parameters of the chosen distributions in the first step, using the 'fitdist' function (Delignette-Muller and Dutang, 2015).

The Cullen & Frey graph is used to present a skewness-kurtosis plot proposed by Cullen and Frey (1999). In this plot, values for common distributions are displayed. This plot

Figure 2: Cullen & Frey graphs for each CAMELS criteria



helps to choose the distributions to fit to the data. For some distributions (i.e. normal, uniform, logistic, exponential), a single point on the plot represents the distribution because the skewness and the kurtosis have only one possible value. For other distributions, the lines present the possible values (i.e. gamma and lognormal), or larger areas (i.e. beta). Delignette-Muller and Dutang (2015) caution that skewness and kurtosis are known not to be robust due to high variance and suggest a nonparametric bootstrap procedure in order to take into account the uncertainty of the estimated values of kurtosis and skewness from the data (Efron and Tibshirani, 1994).

Once selected, one or more parametric distributions may be fitted to the data set, one at a time, using the ‘fitdist’ function. The distribution parameters were estimated by maximizing the likelihood function, considering the observations of each criterion and the density function of the parametric distribution. Table 4 summarizes the best fitted probability distributions and estimated parameters (Delignette-Muller and Dutang, 2015).

4.3. TOPSIS

The TOPSIS method is designed for the linear ordering methods of multidimensional objects (Hwang and Yoon (2012); Dymova et al., 2013). Broadly speaking, the task of linear ordering involves the ordering of objects from the best to the worst, based on a latent measure – such as efficiency or performance - that is not subject to a direct observation or measurement (Jefmański & Dudek, 2015). A characteristic feature of TOPSIS is to take into consideration how far an evaluated object is from its negative- and positive-ideal solutions (Tavana et al., 2013; Roszkowska and Kacprazak, 2016). Barros and Wanke (2015) and Wanke, Barros, and Emrouznejad (2015) are examples of applications

Table 4: Outcomes for the joint probability weighting

Criterion	Best fitted probability distribution	Weights
C - Capital	**LN (meanlog=2.053276, sdlog=0.1783665)**	**0.1648107**
C1	LN (meanlog=2.053276, sdlog=0.1783665)	0.1562851
C2	G (shape= 21.502312, rate= 2.699347)	0.2478239
C3	G (shape= 21.502312, rate= 2.699347)	0.1814049
C4	G (shape= 101.07002, rate= 12.11167)	0.2290948
C5	Log (location= 7.3193585, scale= 0.7586448)	0.1289169
C6	U (min=6, max=9)	0.05647367
A - Asset	**N (mean=7.742816, sd=1.082093)**	**0.09343504**
A1	G (shape= 39.817517, rate= 5.224835)	0.1388046
A2	U (min= 5, max= 9)	0.04600713
A3	N (mean= 7.678161, sd= 1.149655)	0.1390184
A4	U (min= 5, max= 9)	0.04600713
A5	N (mean= 7.885057, sd= 1.044144)	0.1637287
A6	LN (meanlog= 2.0406334, sdlog= 0.1682568)	0.1881353
A7	N (mean= 7.655172, sd= 1.201795)	0.1439257
A8	N (mean= 8.0229885, sd= 0.7267786)	0.1343728
M - Management	**LN (meanlog=2.0617989, sdlog=0.1544432)**	**0.1470653**
M1	G (shape= 45.820345, rate= 5.719261)	0.3086786
M2	N (mean= 7.9770115, sd= 0.9343633)	0.2749578
M3	U (min= 5, max= 9)	0.09543608
M4	LN (meanlog= 2.0601423, sdlog= 0.1859627)	0.3055277
E - Earning	**G (shape=71.288987, rate=8.677221)**	**0.1628223**
E1	G (shape= 54.355851, rate= 6.595536)	0.2846531
E2	N (mean= 8.241379, sd= 0.816011)	0.238076
E3	N (mean= 8.2183908, sd= 0.8765828)	0.2410419
E4	N (mean= 8.1609195, sd= 0.9574099)	0.2362291
L - Liquidity	**LN (meanlog=2.0722295, sdlog=0.1462649)**	**0.1524037**
L1	G (shape= 58.122893, rate= 7.132115)	0.3739722
L2	LN (meanlog= 2.0476771, sdlog= 0.1731996)	0.2957365
L3	N (mean= 8.0574713, sd= 0.9142087)	0.3302914
S - Sensitivity	**G (shape=26.80075, rate=3.20284)**	**0.2794629**

Notes: Legend: U (Uniform), N (Normal), G (Gamma), LN (Log-normal).

of TOPSIS method in efficiency measurement. The fuzzy TOPSIS method was first developed by Chen (2000) and subsequent applications can be found on Chang and Tseng (2008), Uyun and Riadi (2011), Madi and Tap (2011), Yayla, Yildiz, and Ozbek (2012), and Kia, Danaei, and Oroei (2014).

In this paper, TOPSIS is used for examining efficiency among the ASEAN banks utilizing seven steps, as described next. Steps 1 and 2 are focused on criteria normalization. Step 3, on the normalization of weights obtained from the joint probability approach. Steps 4 to 6, on the computation of the ideal and non-ideal solutions. And last, Step 7 is focused on ranking the alternatives.

Step 1: An evaluation matrix $(x_{ij})_{mxn}$ is obtained where *m* presents alternatives and *n* stands for criteria. The criteria consist of inputs or outputs used in this study and the alternatives are the number of banks.

Step 2: Now, using the vector normalization method, the matrix $(x_{ij})_{mxn}$ is normalized to a regulated matrix $R^* = (r_{ij})$, as presented in Eq. (4):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}},\ i = 1,2,\dots m \ and\ j = 1,2,\dots,n \tag{4}$$

Step 3: The weighted normalized decision matrix is calculated for efficiency assessment using Eq. (5):

$$\begin{aligned} W &= (w_{ij})_{mxn} \\ &= (w_j r_{ij})_{mxn} \end{aligned} \tag{5}$$

Here $\mathrm{w_j}$ is the weight given to the j criteria, and $\sum_{\mathrm{j=1}}^{\mathrm{n}} \mathrm{w_j} = 1$. For this study, an electronic structured questionnaire using the CAMELS and their sub criteria was sent. A total of 88 managers of different ASEAN banks have responded. Weights of different criteria and sub criteria were obtained from joint probability weighting.

Step 4: Determine the worst alternative (the negative ideal) A_a and the best alternative (the positive ideal) A_b utilizing Eq. (6) and Eq. (7):

$$\begin{aligned} A_a &= \{\langle \min(w_{ij} |\ i = 1,2,\dots,m) |\ j \in J_+\rangle, \langle \max(w_{ij} |\ i = 1,2,\dots,m) |\ j \in J_-\rangle\} \\ &= \{\alpha_{aj} | j = 1,2,\dots,n\} \end{aligned} \tag{6}$$

$$\begin{aligned} A_b &= \{\langle max(w_{ij} | i = 1,2,\dots,m | j \in J_+\rangle, \langle \min(w_{ij} | i = 1,2,\dots,m) | j \in J_-\rangle\} \\ &= \{\alpha_{bj} | j = 1,2,\dots n\} \end{aligned} \tag{7}$$

Here, $J_+ = \{j | j \in positive\}$ and $J_- = \{ j |\ j\ \in negative\}$, which are a set of positive (benefit) and negative (cost) attributes, respectively.

Step 5: Using the distance d_{ia} function in Eq. (8) the distance between the target alternative *i*, and the worst condition A_a was calculated:

$$d_{ia} = \sqrt{\sum_{j=1}^{n} \left(w_{ij} - \alpha_{aj}\right)^2}\ , i = 1,2,\dots,m \tag{8}$$

and the distance d_{ib} between the alternative *i* , and the best condition A_b, by Eq. (9).

$$d_{ib} = \sqrt{\sum_{j=1}^{n}\left(w_{ij} - \alpha_{bj}\right)^2}, i = 1,2, \dots, m \tag{9}$$

Here, d_{ia} and d_{ib} are the Euclidean distance from the target alternative i to the worst and the best conditions, respectively.

Step 6: Calculate the similarity of alternatives i to the worst condition (the inefficient best conditions), respectively:

$$S_i = d_{ia} | (d_{ia} + d_{ib}) \tag{10}$$

where $0 \leq S_i \leq 1$, $i = 1,2, \dots, m$.
$S_i = 0$, (if and only if the alternative solution has the worst condition)
$S_i = 1$, (if and only if the alternative solution has the best condition)

Step 7: Finally, rank the alternatives according to S_i within the ambit of 88 ASEAN banks for assessment of the impact of contextual variables.

5. RESULTS AND DISCUSSION

In this research, the theory of joint probabilities was used among CAMELS related variables to determine the weights of the performance evaluation based on hierarchy (cf. Table 3). A group of 88 managers of different ASEAN banks were asked to provide their perceptions on the relative importance of CAMELS related variables through a structured questionnaire (c.f. Table 2). The questionnaire was sent to each selected bank's head office addressing the Human Resource Manager. Only "Senior Managers" with five years of experience among the respective banks have participated in the survey through "google form" link. Bank managers have articulated their experiences using a five likert scale where 1 stands for unimportant to 5 stands for very important. Software package R codes were used to perform all joint probabilistic computations. The normalized weight vector was calculated taking account of CAMELS variables, as given in Table 5.

It should be noted that among the variables that emulate the CAMELS rating system, sensitivity to market risk (0.2794629), capital adequacy (0.1648107), and earning quality (0.1628223) were considered the most relevant criteria for assessing financial distress. These results are in line with the findings of the earlier study of Wanke, Azad, et al. (2015), except for earning quality. These weights are also used for efficiency calculations. The major weight is carried by sensitivity to market risk, which has only one sub-criterion—net income to risk weighted asset ratio. Again, the current study is in line with earlier findings of (Wanke, Azad, et al., 2015). The fact that the sensitivity to market risk criteria carries most of the total weight reveals that ASEAN banks are severely affected by market interest rates. Linked to this, a number of previous studies has also revealed that market sensitivity to risk is associated to bank failure (Cook, 2008; Soedarmono, Machrouh, & Tarazi, 2011, 2013; Wanke, Azad, et al., 2016a). Liquidity and management quality, however, also merit attention since their weights are close to the weights of sensitivity to market risk. Among all variables, asset quality is found to be bearing the least weight and is therefore the least important criterion. The use of probabilistic weights

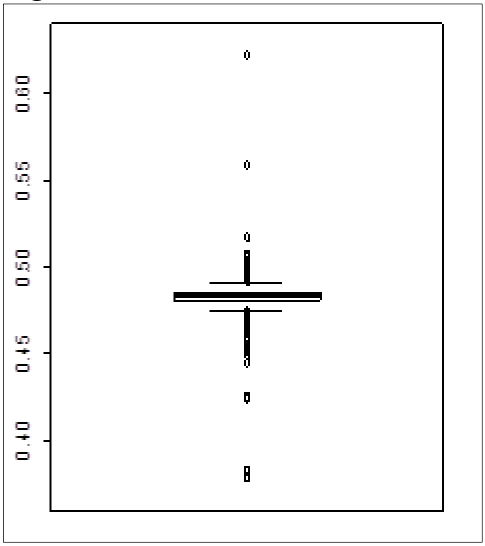
Table 5: Probabilistic weights for the variables that emulate the CAMELS rating system

Criteria	Prob. weights for each criteria (1)	Sub-criteria	Prob. weights for sub-criteria (2)	Final Prob. Weights (1) x (2)
C	0.1648107	Total Regulatory Capital Ratio	0.1562851	0.025757457
		Growth to Total Asset	0.2478239	0.04084403
		Total Capital Ratio	0.1814049	0.029897469
		Equity to Total Assets	0.2290948	0.037757274
		Equity to Short Term Funding	0.1289169	0.021246885
		Equity to Total Liabilities	0.05647367	0.009307465
A	0.09343504	Loan Loss Reserve to Gross Loans	0.1388046	0.012969213
		Loan Loss Provision to Net Interest Revenue	0.04600713	0.004298678
		Loan Loss Reserve to Impaired Loans	0.1390184	0.01298919
		Impaired Loans to Gross Loans	0.04600713	0.004298678
		NCO to Average Gross Loans	0.1637287	0.015297998
		NCO to Net Inc. before Lone Loss Provisions	0.1881353	0.017578429
		Impaired Loans to Equity	0.1439257	0.013447704
		Tier 1 Ratio	0.1343728	0.012555128
M	0.1470653	Net Interest Margin	0.3086786	0.045395911
		Net Interest Revenue to Average Assets	0.2749578	0.040436751
		Other Operational Income to Average Assets	0.09543608	0.014035336
		Non-Interest Expenses to Average Assets	0.3055277	0.044932523
E	0.1628223	Return on Average Assets (ROAA)	0.2846531	0.046347872
		Return on Average Equity (ROAE)	0.238076	0.038764082
		Non-operating Items to Net Income	0.2410419	0.039246997
		Cost to Income Ratio	0.2362291	0.038463365
L	0.1524037	Interbank Ratio	0.3739722	0.056994747
		Net Loans to Deposits & Short term Funding	0.2957365	0.045071337
		Liquid Assets to Deposit & Short term Funding	0.3302914	0.050337631
S	0.2794629	Net income to Risk Weighted Assets	1	0.2794629

Notes: Columns (1) and (2) reproduces the weights presented in Table 4. The last column is the product of the first two columns.

for the variables that emulate the CAMELS rating system reveals, therefore, significant adherence to previous studies.

Figure 3: Distribution of TOPSIS scores



Then, for ranking bank performance, TOPSIS calculations were based on the criteria that emulate the CAMELS rating system. Referring to Table 2, these criteria can present either a positive or a negative impact on efficiency levels. The probabilistic results on these weights, presented in Table 5, were also considered in the TOPSIS calculations. Figure 3 depicts the distribution of the TOPSIS efficiency scores, which presents good discriminatory power since they are concentrated around 0.50 and away from 1.0, one of the major shortcomings of efficiency models, thus corroborating previous studies such as Wanke, Barros, and Chen (2015); Wanke, Barros, and Macanda (2015) and Barros and Wanke (2015). Observing the results obtained, PT JP Morgan securities ranked first in 2013 with a score of 0.623. The least efficient bank is Hong Leong Investment Bank Berhad with a score of 0.378 in 2010. The best practice score is equal to 1, which signifies 100% efficiency. This means that PT JP Morgan's inefficiency is 1-0.623 = 0.377. Broadly speaking, an initial comparison with U.S. and European banks' efficiencies based on previous studies suggests that ASEAN banks' efficiencies are relatively low. As a result, the contextual variables may cause these results and may help in explaining these differences.

Next, TOPSIS scores are regressed using a Tobit regression against contextual variables (Wanke, Azad, et al., 2016a) and cross-checked with a Beta regression, as described in Wanke, Barros, and Figueiredo (2016). Main effects and secondary effects are considered and results for both sets of regressions are presented in Table 6. Readers should recall that the Tobit regression is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable. Similarly, the class of Beta Regression models is commonly used by practitioners to model variables that assume values in the standard unit interval (0, 1) and is based on the assumption that the dependent

Table 6: Results for the Beta and Tobit Regression Analyses

	Estimate	Std. Error	z value	Pr(>|z|)
Beta Regression Results				
Intercept	-0.0616217	0.0109103	-5.648	1.62e-08 ***
year	-0.0033671	0.0060963	-0.552	0.580723
sqyear	0.0004559	0.0012	0.38	0.704008
priv	-0.0116002	0.0095498	-1.215	0.224481
comm	0.0010035	0.009151	0.11	0.912681
foreign	0.0683483	0.0239032	2.859	0.004245 **
islam	-0.0218321	0.013588	-1.607	0.108118
priv:comm	0.0097915	0.0100574	0.974	0.330273
priv:foreign	-0.04381	0.0222079	-1.973	0.048527 *
priv:islam	0.0431938	0.0127422	3.39	0.000699 ***
comm:foreign	-0.0247615	0.0088817	-2.788	0.005305 **
comm:islam	-0.0228271	0.01468	-1.555	0.119952
foreign:islam	-0.0122008	0.0087711	-1.391	0.164217
Phi coefficients (precision model with identity link):				
phi	2756.1	122.7	22.46	<2e-16 ***
Type of estimator: ML (maximum likelihood)				
Log-likelihood: 3265 on 14 Df				
Pseudo R-squared: 0.02691				
Number of iterations: 30 (BFGS) + 2 (Fisher scoring)				
Tobit Regression Results				
Intercept	0.484566	0.0027052	179.122	< 2e-16 ***
year	-0.0008261	0.0015116	-0.547	0.584714
sqyear	0.0001119	0.0002975	0.376	0.706767
priv	-0.0028335	0.0023678	-1.197	0.231435
comm	0.0002559	0.002269	0.113	0.910189
foreign	0.0169084	0.0059251	2.854	0.004321 **
islam	-0.0054298	0.0033684	-1.612	0.106963
priv:comm	0.0023834	0.0024937	0.956	0.339187
priv:foreign	-0.0108341	0.0055046	-1.968	0.049047 *
priv:islam	0.010686	0.0031576	3.384	0.000714 ***
comm:foreign	-0.0061355	0.0022025	-2.786	0.005340 **
comm:islam	-0.0056219	0.0036393	-1.545	0.122401
foreign:islam	-0.0030369	0.0021745	-1.397	0.162534
logSigma	-4.6617628	0.0222607	-209.416	< 2e-16 ***
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1				
Newton-Raphson maximisation, 13 iterations				
Return code 2: successive function values within tolerance limit				
Log-likelihood: 3272.01 on 14 Df				

variable is beta-distributed and that its mean is related to a set of regressors through a linear predictor with unknown coefficients and a link function. Additionally, regressions involving data from the unit interval, such as rates and proportions, are typically heteroskedastic, because they display more variation around the mean and less variation as we approach the lower and upper limits of the standard unit interval. Finally, the distributions of rates and proportions are typically asymmetric, and thus Gaussian-based approximations for interval estimation and hypothesis testing can be quite inaccurate in small samples. The chief motivation for the Beta Regression model lies in the flexibility delivered by the assumed Beta law. The Beta density can assume a number of different shapes depending on the combination of parameter values, including left- and right-skewed or the flat shape of the uniform density (which is a special case of the more general beta density). The evident flexibility makes the beta distribution an attractive candidate for data-driven statistical modeling. The idea underlying beta regression models dates back to earlier approaches such as Williams (1982) or Prentice (1986) . Our interest in what follows will be more closely related to the recent literature, i.e., modeling continuous random variables that assume values in (0,1), such as rates, proportions, and concentration or inequality indices (e.g., Gini).

As regards the results of the paper, both regressions agree in the sign and significance of their variables. Efficiency levels tend to be higher in foreign banks, even when they are commercial and private. Foreign banks appear to suffer from cultural and regulatory barriers, which is suggested by the negative sign, especially when they are private owned (Wanke, Azad, et al., 2016a). The same effect is verified within the ambit of commercial banks. In addition, Islamic banking presents a very strong and significant impact in efficiency levels, especially with respect to private institutions. These results are in accordance with (Sufian & Kamarudin, 2015; Sufian, Mohamad, & Muhamed-Zulkhibri, 2008; Venardos, 2011; Wanke, Azad, et al., 2016b). The cross check of both Beta and Tobit regressions for examining the sources of efficiency of ASEAN banks reveal that bank ownership (foreign banks) and bank nature (Islamic banks) have significant influence on bank efficiency. Thus, the robustness of these results are checked. These findings signify that both social and cultural influences are prevailing in the ASEAN bank industry. Nevertheless, policy-makers must consider developing appropriate policies for handling such bias and nurturing true market competition for the utmost development of the banking industry in the long-run.

6. CONCLUSION

In this paper, the banking efficiency of ASEAN countries was analyzed by using probabilistic weighting and TOPSIS. A special emphasis was placed on the impact of Islamic banking, although different types of banks were also assessed. To the best of our knowledge, the major contributions of this paper are threefold. Firstly, this paper, for the first time, combines the variables that emulate the CAMELS rating system for measuring bank performance with joint probabilistic weighting of these same variables. This paper, therefore, departs from previous studies where AHP was used for weight estimation. Secondly, this paper employs TOPSIS for calculating efficiency scores, with superior discriminatory power since efficiencies are concentrated around 0.50 and away from 1.0. Finally, bank type, ownership, and origin are utilized in a robust regression procedure, where results are cross-checked based on Tobit and Beta regressions.

By using bank type, ownership, and origin in the regression analysis, it is possible to explain the causes of inefficiency within the environment of the ASEAN banking system. In other words, based on the Beta and Tobit regression results, it is possible to measure the impact of different contextual variables that may act as efficiency drivers. In this sense, cultural and regulatory barriers may help in explaining the low efficiency of foreign private banks, although foreign origin, when considered in an isolated fashion, presented a positive impact. Decision-makers can benefit from these results by establishing an action plan over time to help foreign private banks increase efficiency based on their distinct characteristics. For example, they can consider different governance mechanisms with private stakeholders to allow foreign private banks to close their efficiency gaps vis-à-vis Islamic private banks. Future research should address the impact of mergers and acquisitions on banking performance in light of these contextual variables.

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