Predicting performance in ASEAN banks: an integrated fuzzy MCDM–neural network approach

Peter Wanke,1 Md. Abul Kalam Azad,2 C.P. Barros3 and Abdollah Hadi-Vencheh4

(1) COPPEAD Graduate Business School, Federal University of Rio de Janeiro, Rua Paschoal Lemme, 355 21949–900, Rio de Janeiro, Brazil
E-mail: peter@coppead.ufrj.br
(2) Department of Applied Statistics, Faculty of Economics and Administration, University of Malaya, 50603, Kuala Lumpur, Malaysia
(3) ULisboa and CEsA - Research Centre on African, Asian and Latin American Studies, ISEG – Lisbon School of Economics and Management, Rua Miguel Lupi, 20 1249–078, Lisbon, Portugal
(4) Department of Mathematics, Isfahan (Khorasgan) Branch, Islamic Azad University, Isfahan, Iran

Abstract: This paper presents a performance assessment of 88 Association of Southeast Asian Nations banks from 2010 to 2013, using an integrated three-stage approach on financial criteria that emulates the CAMELS rating system. More precisely, fuzzy analytic hierarchy process is used first to assess the relative weights of a number of criteria related to capital adequacy (C), asset quality (A), management quality (M), earnings (E), liquidity (L), and sensitivity to market risk (S) based on the opinion of 88 Association of Southeast Asian Nations experts. Then, these weights are used as technique for order of preference by similarity to ideal solution inputs to assess their relative efficiency. Lastly, neural networks are combined with technique for order of preference by similarity to ideal solution results to produce a model for banking performance with effective predictive ability. The results reveal that contextual variables have a prominent impact on efficiency. Specifically, parsimony in equity leveraging derived from Islamic finance principles may be the underlying cause in explaining higher efficiency levels.

Keywords: Islamic banking, conventional banking, FAHP, TOPSIS, ANN, performance

1. Introduction

There is a growing number of studies conducted with different methods to assess performance in banking. These studies are often grouped into two main approaches, that is, parametric and non-parametric (Berger & Humphrey, 1997; De Borger et al., 1998; Brandouy et al., 2010; Brissimis et al., 2010; Kerstens et al., 2011; Briec & Liang, 2011; Lampe & Hilgers, 2014). The most popular parametric method is known as the stochastic frontier approach, whereas the most popular non-parametric methods are ratio analysis and data envelopment analysis (DEA; Gunay, 2012; Yang, 2009; Chen, 2002; Tözüm, 2002; Li et al., 2001; Deliktas & Baieclar, 2005; Paradi & Zhu, 2013). When put into perspective, however, non-parametric methods are widely used in different banking industries in various countries and regions around the globe (LaPlante & Paradi, 2015).

With respect to ratio analysis, Tözüm (2002), for example, measured banking performance emphasizing that single ratios were not sufficient to address its complexity. In turn, Li et al. (2001) compared Chinese banks in terms of their performances by using nine financial ratios. As regards DEA, there are numerous studies focusing on US (Berger et al., 1987; Bauer et al., 1993; Berger & Humphrey, 1997), European (Barros et al., 2007; Barros & Peypoch, 2009; Kontolaimou & Tsekouras, 2010), Asian (Berger et al., 2009; Chen et al., 2005; Kumbhakar & Wang, 2005; Assaf et al., 2010; Barros et al., 2010; Barros et al., 2012), South American (Staub et al., 2010; Wanke & Barros, 2014), and African banking (O’Donnell & Westhizen, 2002; Azam et al., 2004; Figueira et al., 2006; Kirkpatrick et al., 2008; Okeahalam, 2008; Ikhide, 2008; Kiyota, 2009; Assaf et al., 2010; Kebede & Wassie, 2013).

An emerging trend in banking performance measurement is related to the use of multi-criteria decision-making (MCDM) methods such as analytic hierarchy process (AHP) and technique for order of preference by similarity to ideal solution (TOPSIS) for criteria weighting and efficiency ranking, respectively (Hemmati et al., 2013). Although there are many AHP and TOPSIS-based studies on performance evaluation in different areas, their application in banking or general business is still less numerous than parametric and non-parametric methods (Bilbao-Terol et al., 2014; Seçme et al., 2009; Shaverdi et al., 2011; Hemmati et al., 2013;
Tseng et al., 2009). Frei and Harker (1999), for example, used the AHP method as an alternative to DEA in the measurement of bank performance, examining the relation between financial and operational criteria to achieve higher efficiency levels. Yurdakul and Ic (2004) assessed banking efficiency using AHP altogether with financial and non-financial performance criteria in credit risk assessment. Albayrak and Erensal (2005) analysed the financial and non-financial performance criteria for the evaluation of Turkish banks using fuzzy AHP (FAHP). Recently, Shaverdi et al. (2011) used TOPSIS to rank the performance of banks based on criteria weights obtained using FAHP.

Another emerging trend verified within the studies on banking industry is related to specific issues relevant to understand their performance in emerging markets (Sturm & Stefanović, 2010; Ebrahim et al., 2014). In this regard, Islamic banking is of particular interest. Sufian, Kamarudin and Noor (2014) reported that only limited studies have focused on Islamic banking, particularly in developing economies such as Malaysia. In an earlier paper, Sufian, Mohamad and Muhamed-Zulkhibri (2008) examined performance of Islamic banks in Middle East and North Africa and Asian countries. Their findings exposed managerial inefficiencies in resource management among the banks.

This paper, therefore, fills a literature gap by analysing and exploring the sources of efficiency between Islamic and conventional banks listed in the Association of Southeast Asian Nations (ASEAN) database. It innovates in this context first by focusing on Islamic versus conventional banks – in addition to other contextual variables – and second by adopting an integrated three-stage approach involving FAHP, TOPSIS, and artificial neural networks (ANN). Results presented in this research constitute a contribution to the growing literature on Islamic banking, especially as regards shedding light on how adherence to Sharia principles may affect financial performance. These results are consistent with and extend the findings of recently conducted studies, thus adding to the body of knowledge. As regards the findings presented here, although the variables related to a greater parsimony in loans and smaller risk assumed in less leveraged operations led to higher efficiency levels in Islamic banks, it is worth noting these conclusions were derived considering a CAMELS rating system weighted by expert opinions.

The remainder of the paper is organized as follows: Section 2 presents the contextual setting; Section 3 covers the literature review; and Section 4 presents the methodology. The empirical results are presented and discussed in terms of policy implications in Section 5. Conclusions follow in Section 6.

2. Contextual setting

The ASEAN economy has been receiving significant attention from a global perspective (Emrouznejad & Anouze, 2010; Asian Development Bank, 2014; Sufian & Kamarudin, 2015). More specifically, Islamic banking (i.e. banks guided by Islamic Shariah) has experiences increasing popularity in major ASEAN countries (Nguyen, Skully, & Perera, 2012). With this regard, a number of studies have been conducted to examine bank performance in individual ASEAN countries (Chu & Lim, 1998; Ng et al., Khezrimotlagh, 2014; Shaban et al., Akbar, 2014; Sufian & Chong, 2008). However, an absolute empirical study of bank performance in total ASEAN economy has, thus far, not been undertaken (Sufian & Kamarudin, 2015). This study fills the gap by examining ASEAN banks' performance with special attention to Islamic versus conventional banking.

In this paper, we examine bank performance of ASEAN countries by considering the following issues: first, over the last three and half decades, a significant upward trend is observed in the rate of bank merger, foreign bank entry, and foreign direct investment in ASEAN countries (Moshirian, 2008). Second, in recent years, Islamic banking has witnessed increasing popularity in the ASEAN region, and hence, the number of Islamic banks and market share of Islamic products have significantly increased (Soedarmono et al., 2011; Williams & Nguyen, 2005). Next, by establishing ASEAN Economic Community (AEC), ASEAN countries are preparing to present as a single market, thereby allowing free flow of capital across the region.

The ASEAN economy has often been cited as the most diversified in terms of economic integration (Chia & Plummer, 2015). The proxy variables of economic and financial diversity are gross domestic product (GDP), gross national income (GNI), PPP (current international dollar), bank capital to assets ratio (%), bank non-performing loans to total gross loans (%), and domestic credit to private sector by the banks (% of GDP). Referring to GDP value in 2014 alone, Figure 1 clearly shows that six major nations account for more than 95% of the ASEAN economy. Despite the broad diversity of ASEAN, this paper identified a huge opportunity for achieving synergic benefits by offering banks’ ability to generate profit through AEC.

Unlike the Middle East, the Islamic banking sector in the ASEAN region is relatively young and underdeveloped (Venardos, 2011). However, competing with the traditional interest-based banking system, the Islamic banking sector is enjoying a rapid expansion (Ariss, 2010; Ernst & Young, 2013). Imam and Kpodar (2013) investigated the determinants of the pattern of Islamic bank expansion around the world using country-level data for 1992–2006. The analysis illustrates that income per capita, proportion of Muslims in the population, and economic integration with Middle Eastern countries are linked to the development of Islamic banking. Interest rates have a negative impact, while the quality of institutions is not found to be significant. The 11 September 2001 attacks were not a major factor in the expansion. The potential of this huge untapped market is now the most attractive topic.
among the academics, practitioners, policymakers, and investors. Among the ASEAN countries, Malaysia successfully developed the wave of Islamic banking and now functions as the Islamic financial hub among the Asian countries (ElGindi et al., 2009; Sufian et al., 2014).

3. Literature Review

Putting into perspective the fact that the different efficiency measurement methods or approaches – presented in Section 1 – return efficiency scores, it is fundamental to establish the linkages between banking efficiency or bank superior performance and financial distress (Wanke et al., 2015). More precisely, these methods or approaches should be capable of indicating how effective a financial institution is in minimizing variables related to increasing financial distress and maximizing others related to increasing financial health (Tsai and Chang, 2010). Within the ambit of MCDM techniques, this fine-tuning between efficiency scores and decision-making is often accomplished by choosing the proper set of criteria and their impacts – positive or negative – in terms of financial distress.

Several criteria 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 that presented a comprehensive literature review on this subject. According to several authors (Altman, 1968; Altman et al., 1977; Männasoo & Mayes, 2009), although there is no universal set of indicators used across previous studies, the CAMELS criteria appear to have a significant power to detect distress. CAMELS 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 these variables in risk measurement and monitoring. Examples can be found in Cole and Gunther (1995), 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 DEA dynamic slacks. The fundamental ideas behind this practical application are embedded in the close relationship between efficiency levels and distance to the frontier of best practices: the latter may be considered as proxies of looming financial distress. In other words, a consistent movement towards lower efficiency levels over the course of time may constitute a leading distress indicator.

However, it should be noted that, because the original criteria used to determine the CAMELS ratings are not disclosed to the general public (Jin, Kanagaretnam, & Lobo, 2011), proxies are often selected accordingly, based both on prior studies and availability of data. Table 1 lists the major sub-criteria found in the literature, which are used to emulate the CAMELS rating system in different applications.

4. Methodology

There is a tradition for using MCDM methods (Peng et al., 2011), namely, the AHP (Saaty, 1980; Ramanathan, 2013); Promethee (Brans & Vincke, 1985; Corrente et al., 2013); Electre (Hatami-Marbini & Tavana, 2011; Corrente et al., 2013); Dematel (Tsay et al., 2009); Vikor (Opricovic, 1998; Opricovic & Tzeng, 2007); TOPSIS (Lai et al., 1994); and Uta (Siskos et al., 2014). TOPSIS has been used in research on energy (Wang et al., 2014) and information and communications technology companies (Li & Chou, 2014) and in the assessment of government bond funds (Bilbao-Terol, et al., 2014).

As regards the methodology used in this research, which builds upon AHP and TOPSIS, these two methods are superior to other multi-attribute methods, such as additive weighting and weighted product methods, because a hierarchy among goal, attributes, and alternatives is not considered. Those methods evaluate the alternatives with respect to only attributes with a single level. Moreover, while TOPSIS uses positive and negative ideal solutions, AHP formalizes our intuitive understanding of a complex problem using a hierarchical structure. These characteristics provide
superiority to AHP and TOPSIS against many other multi-attribute decision-making methods (Kahraman, 2006).

Therefore, in this paper, a model for assessing banking performance based on the criteria of the CAMELS rating system is presented. The model is based on the premise that banking performance should be viewed as a product of capital adequacy, assets quality, management, earning quality, liquidity, and sensitivity to market risk. While FAHP is used to assess the weights of these criteria, TOPSIS is used to rank bank performance in light of them. The methodological framework of this research is depicted in Figure 2.

Financial ratios have been grouped observing the major CAMELS criteria, as presented in Table 2, which also gives their major descriptive statistics. The data source also provided information on contextual variables for each bank, such as ownership (public or private), origin (local or foreign), type (commercial or investment), and system (Islamic or conventional). All of these variables were coded as dummies.

It is noteworthy that these contextual variables are neither inputs nor outputs, but are thought to affect the production process. Because these variables identify the sources of efficiency variations, they are also directly linked

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Total regulatory capital ratio%</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Equities/total assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>(Equities – fixed assets)/total assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>BASEL ratio</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Assets quality</td>
<td>Loan loss res/gross loans</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Loan loss provision/net interest rev</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Loan loss res/impaired loans</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Impaired loans/gross loans</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>NCO/average gross loans</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Impaired loans/equity</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Tier 1 ratio</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Management</td>
<td>Net interest margin</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Net interest revenue/average assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Other operating income/average assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Non-interest expense/average assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Earning quality</td>
<td>Return on average assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Return on average equity</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Non-operating items/net income</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Cost-to-income ratio</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Liquidity</td>
<td>Interbank ratio</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Net loans/total assets</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Net loans/deposits and st funding</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Liquid assets/total deposit and borrowings</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Sensitivity of market risk</td>
<td>Rate sensitive assets-rate sensitive liabilities/average earning asset</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Risk-weighted asset (II)/risk-weighted asset (I + II)</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
<tr>
<td>Share of trading income</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
<td>√</td>
</tr>
</tbody>
</table>
to policy formulation. Past studies in banking have introduced these contextual variables as exogenous (Assaf et al., 2011; Assaf et al., 2012; Assaf et al., 2013). Put differently, an important underlying assumption on contextual variables considered by all these banking authors is that these contextual variables are exogenous, that is, they affect efficiency levels without being affected by them. Here, these contextual variables represent, therefore, decision variables based on the banking discretion rather than endogenous variables generated within the ambit of an efficiency model or a production process.

This scenario leads us to the major proposition of this study. Efficiency levels in ASEAN banks are significantly affected by contextual variables related to the bank ownership, origin, type, and system (i.e. Islamic versus conventional or foreign versus local, etc.). For instance, conventional banking processes in the finance sector are well known for leveraging the financial and operational indicators of banks. The same basic economic principles apply to national banks, which tend to be small and are the first to suffer the consequences of systemic financial crises. On the other hand, Islamic banking may be

---

**Table 2: Descriptive statistics on the CAMELS criteria**

<table>
<thead>
<tr>
<th>Sub-criteria</th>
<th>Impact</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td>C Total regulatory capital ratio (%)</td>
<td>+</td>
<td>3.25</td>
<td>380.68</td>
<td>28.226</td>
<td>39.949</td>
</tr>
<tr>
<td>Growth to total asset ratio (%)</td>
<td>+</td>
<td>-85.55</td>
<td>295.2</td>
<td>16.468</td>
<td>33.324</td>
</tr>
<tr>
<td>Total capital ratio (%)</td>
<td>+</td>
<td>1.98</td>
<td>894.66</td>
<td>33.61</td>
<td>71.378</td>
</tr>
<tr>
<td>Equity to total assets ratio (%)</td>
<td>+</td>
<td>1</td>
<td>99.46</td>
<td>16.013</td>
<td>17.189</td>
</tr>
<tr>
<td>Equity to short-term funding ratio (%)</td>
<td>+</td>
<td>1.07</td>
<td>801.2</td>
<td>33.374</td>
<td>86.563</td>
</tr>
<tr>
<td>Equity to total liabilities ratio (%)</td>
<td>+</td>
<td>1.01</td>
<td>621.11</td>
<td>25.796</td>
<td>60.639</td>
</tr>
<tr>
<td>A Loan loss reserve to gross loans ratio (%)</td>
<td>-</td>
<td>0.01</td>
<td>39.4</td>
<td>2.617</td>
<td>4.076</td>
</tr>
<tr>
<td>Loan loss provision to net interest revenue ratio (%)</td>
<td>-</td>
<td>-165.41</td>
<td>423.15</td>
<td>7.789</td>
<td>33.516</td>
</tr>
<tr>
<td>Loan loss reserve to impaired loans ratio (%)</td>
<td>-</td>
<td>1.34</td>
<td>947.06</td>
<td>95.109</td>
<td>79.025</td>
</tr>
<tr>
<td>Impaired loans to gross loans ratio (%)</td>
<td>-</td>
<td>-6.37</td>
<td>106</td>
<td>3.645</td>
<td>8.102</td>
</tr>
<tr>
<td>Impaired loans to equity ratio (%)</td>
<td>-</td>
<td>-74</td>
<td>23.15</td>
<td>1.056</td>
<td>5.335</td>
</tr>
<tr>
<td>Impaired loans to equity ratio (%)</td>
<td>-</td>
<td>-5.15</td>
<td>102.72</td>
<td>9.016</td>
<td>11.004</td>
</tr>
<tr>
<td>Tier 1 ratio (%)</td>
<td>-</td>
<td>4.5</td>
<td>380.68</td>
<td>31.368</td>
<td>45.643</td>
</tr>
<tr>
<td>M Net interest margin (%)</td>
<td>+</td>
<td>0.01</td>
<td>16.24</td>
<td>2.365</td>
<td>1.786</td>
</tr>
<tr>
<td>Net interest revenue to average assets ratio (%)</td>
<td>+</td>
<td>0.01</td>
<td>10.86</td>
<td>1.738</td>
<td>1.178</td>
</tr>
<tr>
<td>Other operational income to average assets ratio (%)</td>
<td>+</td>
<td>-5.84</td>
<td>39.35</td>
<td>1.708</td>
<td>3.67</td>
</tr>
<tr>
<td>Non-interest expenses to average assets ratio (%)</td>
<td>-</td>
<td>-1.23</td>
<td>42.82</td>
<td>2.391</td>
<td>3.456</td>
</tr>
<tr>
<td>E Return on average assets (%)</td>
<td>+</td>
<td>-43.75</td>
<td>15.66</td>
<td>0.619</td>
<td>3.906</td>
</tr>
<tr>
<td>Return on average equity (%)</td>
<td>+</td>
<td>-56.2</td>
<td>98.56</td>
<td>8.834</td>
<td>12.277</td>
</tr>
<tr>
<td>Non-operating items to net income (%)</td>
<td>-</td>
<td>-265.98</td>
<td>400</td>
<td>4.424</td>
<td>44.402</td>
</tr>
<tr>
<td>Cost-to-income ratio (%)</td>
<td>-</td>
<td>0.66</td>
<td>379.55</td>
<td>55.41</td>
<td>35.074</td>
</tr>
<tr>
<td>L Interbank ratio (%)</td>
<td>+</td>
<td>-0.54</td>
<td>974.07</td>
<td>67.356</td>
<td>127.507</td>
</tr>
<tr>
<td>Net loans to deposits and short-term funding ratio (%)</td>
<td>+</td>
<td>0.01</td>
<td>346.13</td>
<td>47.963</td>
<td>40.89</td>
</tr>
<tr>
<td>Liquid assets to deposit and short-term funding ratio (%)</td>
<td>+</td>
<td>0.39</td>
<td>766.22</td>
<td>47.083</td>
<td>75.238</td>
</tr>
<tr>
<td>S Net income to risk-weighted assets ratio (%)</td>
<td>+</td>
<td>-135.75</td>
<td>15.51</td>
<td>0.462</td>
<td>9.634</td>
</tr>
</tbody>
</table>

Contextual variables

- Year
- Year²
- Public bank
- Private bank
- Commercial bank
- Investment bank
- Local bank
- Foreign bank
- Conventional bank
- Islamic bank

© 2015 Wiley Publishing Ltd

Expert Systems, xxxx 2015, Vol. 00, No. 00
4.2. Fuzzy analytic hierarchy process

4.2.1. Background on triangular fuzzy numbers and triangular fuzzy matrices

Before proceeding directly with the explanation of the major computational steps of FAHP, readers should be aware that the use of fuzzy numbers in FAHP should observe their underlying addition and multiplication properties when operating with matrices. Triangular fuzzy numbers (TFNs) are commonly found in FAHP uses (Lu et al., 2007; Shaverdi et al., 2011). On the other hand, it is well known that the matrix formulation of FAHP uses triangular fuzzy matrices (TFMs) to be expressed such as \( M = (m_{ij})_{m \times n} \), where \( m_{ij} \) represents, respectively, the spreads to the left and to the right from \( a_{ij} \). If \( M \) is a TFN expressed as \( M = (a, a, \beta) \), its membership function is given by

\[
\mu_M(x) = \begin{cases} 
0 & \text{for } x \leq m - \alpha \\
\frac{1 - m - x}{\alpha} & \text{for } m - \alpha < x < m \\
1 & \text{for } x = m \\
\frac{1 - x - m}{\beta} & \text{for } m < x < m + \beta \\
0 & \text{for } x \geq m + \beta 
\end{cases}
\]

The membership function equals 1 when \( x \) reaches the mean value, \( m \). Besides, considering \( a \) and \( \beta \) to be, respectively, the spreads to the left and to the right of the TFN \( M \), it is possible to affirm that this number is symmetrical around the mean if both spreads assume the same value, that is, if \( a = \beta \).

Several researches have attempted to define the arithmetic operations of TFNs over the course of time. They were pioneered by Dubois and Prade (1980), who introduced the definitions of their arithmetic operations. Consider \( M = (m, a, \beta) \) and \( N = (n, \gamma, \delta) \) to be two TFNs. Their arithmetic operations are defined as it follows (Shyamal & Pal, 2007):

- Addition: \( M + N = (m + n, a + \gamma, \beta + \delta) \)
- Scalar multiplication: If \( \lambda \) is scalar, \( \lambda M = (\lambda m, \lambda a, \lambda \beta) \) when \( \lambda \geq 0 \). Otherwise \( \lambda M = (\lambda m, -\lambda \beta, -\lambda a) \) when \( \lambda \leq 0 \). Particularly, \( -M = (-m, \beta, a) \)

Subtraction: \( M - N = (m - n, a + \gamma, \beta + \delta) \).

Given two TFNs, \( M \) and \( N \), their addition, subtraction, and scalar multiplication, that is, \( M + N, M - N, \) and \( \lambda M \) are TFNs.

Multiplication: One may show that the membership function shape of \( M \cdot N \) is not necessarily triangular. However, if the spreads of \( M \) and \( N \) are sufficiently small compared with their mean values \( m \) and \( n \), then this shape follows a triangle form.

A robust decision rule is given next (Shyamal & Pal, 2007):

(a) When \( M \geq 0 \) and \( N \geq 0 \) (\( M \geq 0 \), if \( m \geq 0 \))

\[ M \cdot N = (m, a, \beta) \cdot (n, \gamma, \delta) \approx (m n, m \gamma + n a, m \delta + n \beta) \]

(b) When \( M \leq 0 \) and \( N \leq 0 \)

\[ M \cdot N = (m, a, \beta) \cdot (n, \gamma, \delta) \approx (m n, n a - m \delta, n \beta - m \gamma) \]

(c) When \( M \leq 0 \) and \( N \geq 0 \)

\[ M \cdot N = (m, a, \beta) \cdot (n, \gamma, \delta) \approx (m n, n a - m \delta, n \beta - m \gamma) \]

Where spreads are not small compared with mean values, a better approximation is given next:

\[ (m, a, \beta) \cdot (n, \gamma, \delta) \approx (m n, m \gamma + n a - a \gamma, m \beta + n \beta + \beta \delta) \]

for \( M > 0, N > 0 \).

On the other hand, a TFN of order \( m \times n \) can be given as \( A = (a_{ij})_{m \times n} \), where \( a_{ij} = (m_{ij}, a_{ij}, b_{ij}) \) is the \( ij \)th elements of \( A \), \( m_{ij} \) is the mean value of \( a_{ij} \), and \( a_{ij}, b_{ij} \) are, respectively, the left and right spreads of \( a_{ij} \). Likewise classical matrix algebra, let us consider the following operations involving TFMs, given that \( A = (a_{ij}) \) and \( B = (b_{ij}) \) are two TFMs of the same order. In such cases, the following relationships are observed (Shyamal & Pal, 2007):

(i) \( A + B = (a_{ij} + b_{ij}) \)
(ii) \( A - B = (a_{ij} - b_{ij}) \)
(iii) For \( A = (a_{ij})_{m \times n} \) and \( B = (b_{ij})_{n \times p} \), \( A \cdot B = (c_{ij})_{m \times p} \)

\[ c_{ij} = \sum_{k=1}^{n} a_{ik} \cdot b_{kj}, \ i = 1, 2, ..., m \text{ and } j = 1, 2, ..., p \]

(iv) \( A^T = (a_{ij}) \) (the transpose of \( A \))
(v) \( kA = (ka_{ij}) \), where \( k \) is a scalar.

4.2.2. Background on multi-criteria decision-making and fuzzy analytic hierarchy process computation

Multi-criteria decision-making for structuring decision problem and evaluating alternatives provides a rich collection of methods (Malczewski, 2006). In most management and decision-making problems, the management team already has a well-defined goal that must be achieved (Kordi, 2008). In order to reach that aim, it is always necessary to choose from a number of criteria, which, in the field of the multi-criteria decision making analysis, are referred to as alternatives.
For applying MCDM, a tool is needed that takes the ranking and comparison data, processes them, and calculates the weights of different alternatives or criteria. The AHP, a powerful tool in applying MCDM, was introduced and developed by Saaty in 1980. In the AHP method, obtaining the weights or priority vector of the alternatives or the criteria is required. The decision-making process starts with dividing the problem into a hierarchy of issues to be considered in the work (Kordi, 2008). These hierarchical orders help to simplify the illustration of the problem and render it more easily understood. In each hierarchical level, the weights of elements are calculated. Figure 3 illustrates the criteria hierarchy considered in this research. The decision on the final goal is made considering the weights of criteria and alternatives.

The FAHP is a direct extension of Saaty’s AHP method (1980). Analogously to the original AHP, in FAHP, the elements in the reciprocal matrices are represented by fuzzy numbers instead of crisp ones (Chiou et al., 2005; Huang et al., 2008). Many papers have been published in the literature on both the theory and application of FAHP (Ahlaticogl & Tiryaki, 2007; Stefanović et al., 2015). A vast literature review of the relevant techniques can be found in Kahraman, Cebeci and Ruan (2004). Operational scales for FAHP can be found, for example, in Abdel-Kader and Dugdale (2001) and Wang and Chen (2007). The first one is adopted here because of its widespread use and is presented in Table 3 in light of the intensity importance scale for each criterion (Amiri, 2010; Ozcan et al., 2010; Kordi, 2008).

Therefore, in general lines, FAHP should observe the following steps (Lu et al., 2007; Shaverdi et al., 2011), as described next.

**Step 1:** Determine the relative importance of the decision criteria. By a pairwise comparison departing from Table 3, the matrix $R$, containing fuzzy estimates for the relative significance of each pair of factors, is constructed.

![Figure 3: Methodological framework of this research.](image)

### Table 3: Membership function of linguistic scales for pairwise comparison of banking performance criteria

<table>
<thead>
<tr>
<th>Intensity of importance of each criterion</th>
<th>Linguistic scale or verbal judgement of preference in pairwise comparison</th>
<th>TFN scale</th>
<th>Reciprocal TFN scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Equal importance</td>
<td>(1, 1, 1)</td>
<td>(1, 1, 1)</td>
</tr>
<tr>
<td>2</td>
<td>Intermediate values between adjacent scale values</td>
<td>(1/2, 3/4, 1)</td>
<td>(1, 4/3, 2)</td>
</tr>
<tr>
<td>3</td>
<td>Moderate importance</td>
<td>(2/3, 1, 3/2)</td>
<td>(2/3, 1, 3/2)</td>
</tr>
<tr>
<td>4</td>
<td>Intermediate values between adjacent scale values</td>
<td>(1, 3/2, 2)</td>
<td>(1/2, 2/3, 1)</td>
</tr>
<tr>
<td>5</td>
<td>Strong importance</td>
<td>(3/2, 2, 5/2)</td>
<td>(2/5, 1/2, 2/3)</td>
</tr>
<tr>
<td>6</td>
<td>Intermediate values between adjacent scale values</td>
<td>(2, 5/2, 3)</td>
<td>(1/3, 2/5, 1/2)</td>
</tr>
<tr>
<td>7</td>
<td>Extreme importance</td>
<td>(5/2, 3, 7/2)</td>
<td>(2/7, 1/3, 2/5)</td>
</tr>
<tr>
<td>8</td>
<td>Intermediate values between adjacent scale values</td>
<td>(3, 7/2, 4)</td>
<td>(1/4, 2/7, 1/3)</td>
</tr>
<tr>
<td>9</td>
<td>Extremely high importance</td>
<td>(7/2, 4, 9/2)</td>
<td>(2/9, 1/4, 2/7)</td>
</tr>
</tbody>
</table>

TFN, triangular fuzzy numbers.
More precisely, pairwise comparison matrices of all the criteria in the dimensions of the hierarchy system were constructed through an expert questionnaire sent to 88 interviewees. Linguistic terms by TFN were assigned to these pairwise comparisons by eliciting from each expert their viewpoint criteria, according to the display in Table 3, such as

$$
\tilde{R} = \begin{bmatrix}
\tilde{r}_{11} & \tilde{r}_{12} & \ldots & \tilde{r}_{1n} \\
\tilde{r}_{21} & \tilde{r}_{22} & \ldots & \tilde{r}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{r}_{n1} & \tilde{r}_{n2} & \ldots & \tilde{r}_{nn}
\end{bmatrix}
$$

(2)

Step 2: Calculate fuzzy estimates for the weights of the decision criteria based on the matrix \( R \) by TFM multiplication, as described in Section 4.2.1, squaring the TFM several times until convergence of the weights.

Step 3: Make pairwise comparisons of alternatives under each of the criteria separately. Then, \( n \) matrices \( (R^1, R^2, \ldots, R^n) \), each of which contains fuzzy estimates for the relative significance of each pair of alternatives, are constructed.

$$
\tilde{R} = \begin{bmatrix}
\tilde{r}_{11} & \tilde{r}_{12} & \ldots & \tilde{r}_{1n} \\
\tilde{r}_{11} & \tilde{r}_{22} & \ldots & \tilde{r}_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\tilde{r}_{n1} & \tilde{r}_{n2} & \ldots & \tilde{r}_{nn}
\end{bmatrix}
$$

(3)

Step 4: Calculate fuzzy estimates for the weight of each alternative under each criterion separately, based on the matrices \( (\tilde{R}^1, \tilde{R}^2, \ldots, \tilde{R}^n) \). More precisely, compute the fuzzy weights of each criterion by TFM multiplication, as described in Section 4.2.1, squaring the TFM several times and using Buckley (1985) normalization at each iteration, which is described as follows:

$$
\tilde{r} = (\tilde{a}_{11} \otimes \tilde{a}_{12} \otimes \ldots \otimes \tilde{a}_{nn})^{1/n}
$$

(5)

$$
\tilde{w}_i = \tilde{r}_i (\tilde{r}_1 \otimes \ldots \otimes \tilde{r}_n)^{-1}
$$

(6)

where \( \tilde{a}_{im} \) is a fuzzy comparison value of criterion \( i \) to criterion \( n \); thus, \( \tilde{r}_i \) is a geometric mean of fuzzy comparison value of criterion \( i \) to each criterion. \( \tilde{w}_i \) is the fuzzy weight of the \( i \) th criterion, which can be indicated by a TFN, \( \tilde{w}_i = (L_{wi}, M_{wi}, U_{wi}) \). Here, \( L_{wi}, M_{wi} \), and \( U_{wi} \), stand for the lower, middle, and upper values of the fuzzy weight of the \( i \) th criterion. As discussed in Thomason (1977), Hashimoto (1983), Kandel (1996), and Kolodziejczyn (1988), these three values converge to the same crisp number as a resultant of the convergence of the power sequence of TFM for a large number of iterations, where TFM are squared each time. With respect to this result, this research differs from previous studies insofar as an exact solution is found for each criterion weight (Felix & Chan, 2007).

Step 5: Obtain a final score for each alternative by adding the weights per alternative (obtained in Step 4) multiplied by the weights of the corresponding criteria (obtained in Step 2).

4.3. Technique for order of preference by similarity to ideal solution

The TOPSIS method, which was first developed by Hwang and Yoon (1981), is a widely accepted MCDM technique based on the concept that the positive ideal alternative has the best level for all considered attributes, whereas the negative ideal is the one with the worst attributed values (Chen & Lu, 2014). More precisely, the ideal solution is the one that maximizes benefit and minimizes total costs. On the contrary, the negative-ideal solution is the one that minimizes benefit and maximizes cost (Seçme et al., 2009). Figure 4 shows the analytical framework for the TOPSIS method.

In our research, the TOPSIS technique for the efficiency analysis of ASEAN banks is carried out as follows:

Step 1: An evaluation matrix consisting of \( m \) alternatives and \( n \) criteria is developed, with the intersection of each alternative and criteria given as \( x_{ij} \), from which a matrix \( (x_{ij})_{mxn} \) is obtained. In this study, the criteria represent the inputs or outputs that the authors choose for efficiency analysis, and the alternatives are the number of samples.
Step 2: The matrix \((x_{ij})_{m \times n}\) is then normalized to a regulated matrix \(R^* = (r_{ij})\). In this study, the authors use the vector normalization method, as demonstrated in equation (7):

\[
r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad i = 1, 2, \ldots, m \text{ and } j = 1, 2, \ldots, n
\]

Step 3: Calculate the weighted normalized decision matrix for efficiency assessment by equation (8):

\[
W = (w_{ij})_{m \times n} = (w_{ij}r_{ij})_{m \times n}
\]

where \(w_i\) is the weighting given to the \(j\) criteria and \(\sum_{j=1}^{n} w_j = 1\).

In our study, an electronic questionnaire containing the sub-criteria of the CAMELS main criteria was sent to 88 of the managers of different ASEAN banks. The weights were obtained from FAHP, discussed in the previous section.

Step 4: Determine the worst alternative (the negative ideal assessment unit) \(A_b\) and the best alternative (the positive ideal assessment unit) \(A_p\) by using equations (9) and (10):

\[
A_p = \{ \min(w_{ij}| i = 1, 2, \ldots, m) | j \in J_+ \},
\]

\[
A_b = \{ \max(w_{ij}| i = 1, 2, \ldots, m) | j \in J_- \} = \{ a_{ij} | j = 1, 2, \ldots, n \}
\]

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

Step 5: Calculate the distance \(d_{ia}\) between the target alternative, \(i\), and the worst condition, \(A_a\), by equation (11):

\[
d_{ia} = \sqrt{\sum_{j=1}^{n} (w_{ij} - a_{ij})^2}, \quad i = 1, 2, \ldots, m
\]

and the distance \(d_{ib}\) between the alternative, \(i\), and the best condition, \(A_b\), by equation (12).

\[
d_{ib} = \sqrt{\sum_{j=1}^{n} (w_{ij} - b_{ij})^2}, \quad i = 1, 2, \ldots, m
\]

where \(d_{ia}\) 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 alternative \(i\) to the worst condition (the inefficient best conditions), respectively:

\[
S_i = d_{ia}/(d_{ia} + d_{ib})
\]

where \(0 \leq S_i \leq 1, \quad i = 1, 2, \ldots, m\).

\(S_i = 0\), 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: Rank the alternatives according to \(S_i\), where a higher value of \(S_i\) indicates a better solution with respect to higher efficiency levels within the ambit of 88 ASEAN banks, allowing the subsequent assessment of the impact of contextual variables.

4.4. Neural networks

Readers should note that most of the studies previously presented on banking tried to explain the drivers affecting efficiency, yet no predictive analysis was carried out. Nonetheless, it is extremely important to predict the performance of banks: bad performance may result in insolvency (Wu et al., 2006). Thus, devising a model for predicting the performance of banks would be useful to clients in terms of limiting or obviating such insolvency (Charitou et al., 2004; Neves & Vieira, 2006; Gutiérrez et al., 2010). In this sense, this research also proposes the use of contextual variables to predict the performance of banks. Specifically, neural networks are trained to assess how these variables could be used as predictors of efficiency in ASEAN banks.

There is an emerging literature on the application of ANNs on efficiency scores derived from non-parametric methods, such as DEA (Misiunas et al., 2015) and TOPSIS (Barros & Wanke, 2015), for predictive or classificatory purposes.

Neural networks are defined by important parameters that cannot be estimated from the data in a direct fashion (Palomares-Salas et al., 2014). These parameters are usually referred to as tuning parameters as there is no analytical formula to determine appropriate values for them (Kuhn & Johnson, 2013). Cross-validation may be used to control the choice of the tuning parameters, thereby avoiding what is commonly referred to as overfitting. In such cases, it is very common to find that accuracy rapidly increases with the tuning parameter and then, after peaking, decreases at a slower rate as overfitting begins to occur. The best model is then chosen based on the numerically optimal value of the tuning parameter, that is, the one that yields the highest accuracy. The number of hidden layers and the decay rate (weights) are the tuning parameters frequently used in neural networks (Torgo, 2011).

As regards the selection of contextual variables for predicting efficiency scores, we observed the prescription in Moro, Cortez and Rita (2014). As long as we are working with a relatively small number of contextual variables, we performed a manual selection by using problem domain knowledge, that is, by having a clear understanding of what the attributes actually mean. Manual inclusion/exclusion of these variables led to minimal variations in the results that are now presented.

5. Results and discussion

Before proceeding, it is worth commenting that the results presented in this section were obtained using several R packages: topsis (for TOPSIS computations), caret (for training neural networks and extracting relative importance...
of contextual variables), and nnet (for neural network computations). The remainder R codes were developed by the authors.

The FAHP was used in this research to determine the weights of the main criteria of the performance evaluation hierarchy based on the collected variables that emulate the CAMELS rating system (cf. Table 3). A questionnaire including these criteria was sent to 88 managers of different ASEAN banks to collect their perceptions on the relative importance of these criteria. Pairwise comparison scores were carried out in accordance with the discussion presented in Section 4.2, and R codes were used to perform all FAHP computations and the squaring of TFM at each iteration until convergence of the weights. After the normalization, the normalized weight vector was calculated with respect to the main CAMELS criteria, as given in Table 4.

Readers should note that sensitivity to market risk, capital adequacy, and liquidity were considered as the most relevant CAMELS criteria for assessing financial distress and therefore efficiency levels. Asset quality, management quality, and earning quality, however, also merit attention because they present weights close to the previously mentioned criteria. Sensitivity to market risk has only one sub-criterion (net income to risk-weighted asset ratio), which carries most of the total weight. On the other hand, as regards capital adequacy, equity-based ratios appear to be the most relevant sub-criterion, while within liquidity sub-criterion, liquid assets to deposit and short-term funding ratio receives the most importance.

Then, the TOPSIS method was used for ranking banks in terms of the criteria that emulate the CAMELS rating system. Readers should refer to Table 2 to ascertain whether these criteria present a positive or a negative impact on efficiency levels. FAHP results on these weights were considered as the inputs.

Next, a neural network analysis was performed on the TOPSIS efficiency scores using the contextual variables presented in Section 4 as their predictors. All steps taken followed those presented in Faraway (2006) and in Kuhn and Johnson (2013). When different cross-validation measures are applied and different numbers of hidden layers are considered, a clear picture emerges with respect to the response bias or the overfitting within each predictive technique. Figure 5 illustrates the apparent root mean-squared error (RMSE), which tends to decrease with the number of hidden layers of the neural network. This result clearly suggests a response bias towards a larger number of hidden layers.

Additionally, Figure 6 illustrates that a common pattern within the cross-validation methods is seen where RMSE is smaller for lower hidden layer values and peaks at higher values in the context of this particular neural network. The most accurate neural network obtained (RMSE = 0.0248) used the bootstrap technique for 19 hidden layers and a decay rate of 0.1. This signifies a mean error rate of 2.48% points if we consider the efficiency scale ranging from 0 to 100%. The number of folds used in all cross-validation methods was 25, except for the 10-fold cross-validation and the repeated 10-fold cross-validation.

**Table 4: FAHP weights for the CAMELS rating system**

<table>
<thead>
<tr>
<th>Criteria</th>
<th>FAHP weights for criteria</th>
<th>Sub-criteria</th>
<th>FAHP weights for sub-criteria</th>
<th>Final FAHP weights</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.171</td>
<td>Total regulatory capital ratio</td>
<td>0.174</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Growth to total asset</td>
<td>0.151</td>
<td>0.026</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Total capital ratio</td>
<td>0.166</td>
<td>0.028</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equity to total assets</td>
<td>0.137</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equity to short-term funding</td>
<td>0.191</td>
<td>0.033</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Equity to total liabilities</td>
<td>0.182</td>
<td>0.031</td>
</tr>
<tr>
<td>A</td>
<td>0.163</td>
<td>Loan loss reserve to gross loans</td>
<td>0.142</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Loan loss provision to net interest revenue</td>
<td>0.142</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Loan loss reserve to impaired loans</td>
<td>0.175</td>
<td>0.029</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Impaired loans to gross loans</td>
<td>0.142</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td></td>
<td>NCO to average gross loans</td>
<td>0.122</td>
<td>0.020</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Impaired loans to equity</td>
<td>0.136</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Tier 1 ratio</td>
<td>0.142</td>
<td>0.023</td>
</tr>
<tr>
<td>M</td>
<td>0.160</td>
<td>Net interest margin</td>
<td>0.267</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Net interest revenue to average assets</td>
<td>0.216</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Other operational income to average assets</td>
<td>0.249</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-interest expenses to average assets</td>
<td>0.267</td>
<td>0.043</td>
</tr>
<tr>
<td>E</td>
<td>0.157</td>
<td>ROAA</td>
<td>0.250</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td></td>
<td>ROAE</td>
<td>0.250</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Non-operating items to net income</td>
<td>0.250</td>
<td>0.039</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Cost-to-income ratio</td>
<td>0.250</td>
<td>0.039</td>
</tr>
<tr>
<td>L</td>
<td>0.164</td>
<td>Interbank ratio</td>
<td>0.300</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Net loans to deposits and short-term funding</td>
<td>0.300</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Liquid assets to deposit and short-term funding</td>
<td>0.400</td>
<td>0.066</td>
</tr>
<tr>
<td>S</td>
<td>0.185</td>
<td>Net income to risk-weighted assets</td>
<td>1.000</td>
<td>0.185</td>
</tr>
</tbody>
</table>

FAHP, fuzzy analytic hierarchy process; NCO, Net Charge-Offs; ROAE, return on average equity; ROAA, return on average assets.

---

Expert Systems, xxxx 2015, Vol. 00, No. 00 © 2015 Wiley Publishing Ltd
The relative importance of each contextual variable is given in Figure 7. As regards TOPSIS efficiency scores, the top predictors for the neural networks of ASEAN banks are variables related to the combinations – found within the data collected – among bank type (commercial), origin (foreign), ownership (private), and system (Islamic), besides a quadratic trend component. Note that as regards the banking system, Islamic banking tends to present a smaller impact on efficiency levels when compared with those related to bank type, origin, and ownership. The linear trend component presented a negligible effect.

Figure 7: Relative importance of contextual variables.

Figure 8 presents the one-dimensional sensitivity analysis on the TOPSIS efficiency estimates for the best neural network model, as described in Cortez and Embrechts (2013). Contextual variables were standardized before performing this marginal analysis, as suggested in Faraway (2006). When analysing the major effects, one perceives a positive impact of foreign, private, commercial, and Islamic banks on efficiency levels, which is consistent with previous findings. As regards the banking system, a possible explanation for a higher performance of Islamic banking may be related to the greater parsimony and smaller risk.
assumed in less leveraged operations, in accordance with the earlier findings of Ben Khediri, Charfeddine and Youssef (2015); Basov and Bhatti (2014); and Dewandaru, Bacha, Masih and Masih (2015). As regards origin, it is interesting to note a positive impact of foreign ownership in efficiency levels. This suggests that ASEAN banking operations may not be affected by cultural and regulatory barriers that limit the efficiency of foreign banks. Nevertheless, it is worth noting that the rate of increase of efficiency levels seems to be diminishing over the course of time, which is indicated for the quadratic component, possibly suggesting that certain limits have been reached in the learning curve of ASEAN banks.

As regards the secondary effects related to the combinations of different kinds of banks found within the data, one perceives the positive impact exerted by Islamic banking on efficiency when investment banks are local and privately owned, when compared with conventional ones.
On the other hand, however, private ownership seems to increase efficiency within foreign commercial banks that comply with Islamic banking rules. These results indicate that the impact of a given contextual variable may depend on the specific combinations of other variables, thus implying that policies designed to increase the efficiency levels in ASEAN banks should first consider the cluster a given bank belongs to.

6. Conclusion

This paper presents an analysis of the efficiency of ASEAN banks using FAHP, TOPSIS, and neural networks. TOPSIS enables a ranking to be made of the efficiency of the banks analysed, and based on this ranking, a large variation in bank efficiency is verified. Maybank Investment Bank Berhad ranked first with a score in 2013 of 0.784, which, relatively to the frontier of best practices – a value equal to 1 signifies 100% efficiency – presents an inefficiency level of 1–0.784 = 0.216. The least efficient bank is Hong Leong Investment Bank Berhad, which in 2010 scored 0.206. Therefore, the efficiency of the ASEAN banking system is low when compared with the efficiency analyses of US and European banks. Causes for this result may reside in the operational procedures of the banks analysed or in the model adopted. Therefore, no definitive conclusion may be derived. Assuming the results are due solely to the banks’ procedures, they should reformulate them and benchmark their practices against US and European banks in order to increase efficiency.

Based on the results of the neural network analysis, it is possible to explain the causes of inefficiency within the environment of the banking system, besides type, ownership, or origin of the bank. Islamic banks tend to be more efficient than conventional ones. This may be explained by the lower leveraging assumed within the context of Islamic finances. Nor does bank origin explain inefficiency, suggesting that cultural traditions are not a cause of inefficiency for foreign banks. The neural networks also predict a limited impact of trend on efficiency levels over the course of time, suggesting that, although ASEAN banks do learn from their operational procedures, such learning has decelerated in recent years. Further research is necessary to confirm these results.

Acknowledgement

Research was made with the support of Calouste Gulbenkian Foundation.

References


Ernst&Young (2013) World Islamic Banking Competitiveness Report 2013–14: The Transition Begins (pp. 1–81), Ernst & Young, UK.


**The authors**

**Peter Wanke**

Peter Wanke is an associate professor of logistics, supply chain management, operations research, and soft computing at COPPEAD Graduate Business School (Federal University of Rio de Janeiro). He publishes systematically on these subjects in international peer-reviewed journals.

**Md. Abul Kalam Azad**

Md. Abul Kalam Azad received his MSc from University of Bedfordshire, UK, and his MBA and BBA from International Islamic University Chittagong, Bangladesh. His research fields are finance, corporate governance, and bank performance.

**C.P. Barros**

C. P. Barros is an associate professor of Economics at ISEG-school of Economics and Management, University of Lisbon. His research is undertaken in the CESA research centre and is supported by Gulbenkian Foundation.

**Abdollah Hadi-Vencheh**

Abdollah Hadi-Vencheh is a professor of Operations Research and Decision Sciences. His research interests lie in the broad area of performance management, data envelopment analysis, multi-criteria decision-making, fuzzy logic, and fuzzy decision-making.