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A dynamic network DEA model for accounting and financial indicators: A case of efficiency in MENA banking

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ABSTRACT

Middle East and North Africa (MENA) countries present a banking industry that is well-known for regulatory and cultural heterogeneity, besides ownership, origin, and type diversity. This paper explores these issues by developing a Dynamic Network DEA model in order to handle the underlying relationships among major accounting and financial indicators. Firstly, a relational model encompassing major profit sheet, balance sheet, and financial health indicators is presented under a dynamic network structure. Subsequently, the dynamic effect of carry-over indicators is incorporated into it so that efficiency scores can be properly computed for these three substructures. The impact of contextual variables related to bank ownership, its type, and whether or not it has undergone a previous merger and acquisition process is tested by means of a stochastic non-linear model solved by differential evolution, which combines bootstrapped Simplex, Tobit, Beta, and Simar and Wilson truncated regression results. The results reveal that bank type, origin, and ownership impact efficiency levels differently in terms of profit sheet, balance sheet, and financial health indicators, although the impact of culture and regulatory barriers seem to prevail at the country level.

1. Introduction

As the banking industry plays a pivotal role in economic system, there has been an increasing interest among policy-makers, practitioners, and academics to identify its best practices. This interest has specifically intensified over the past few years as a direct consequence of the global financial crisis in 2008 and its impact on major accounting and financial indicators in the banking industry worldwide (Howland & Rowse, 2006; Kosmidou & Zopounidis, 2004; Raunig, Scharler, & Sindermann, 2014). Accounting and financial indicators, whenever taken individually or in aggregate, are key elements for monitoring corporate performance, although the specific impact of their underlying relationships on banking performance is yet to be further explored (Wanke, Azad, et al., 2015).

From that time on, most banking performance studies focused, however, on the US and other developed countries with little attention paid to emerging markets and other developing economies (Apergis & Polemis, 2016; Mokni & Rachdi, 2014; Thi, Daly, & Akhter, 2016). Therefore, this research fills a literature gap by focusing on the banking industry of Middle East and North Africa (MENA) countries. A Dynamic Network Data Envelopment Analysis (DEA) model that makes it possible to account for the underlying relationships between major profit sheet, balance sheet, and financial health indicators over the course of time is proposed here.

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In this context, the MENA banking industry differs from other economic blocks and regions around the world not only due to the cultural and regulatory heterogeneity of its countries, but also due to the ownership and type diversity of its banks. MENA presents itself as a challenging field of study filled with contrasting situations (Apergis & Polemis, 2016; Mokni & Rachdi, 2014). In fact, the banking sector in MENA countries has visible diversity considering their inherent characteristics (Hassan, Mohamad, & Khaled I. Bader, 2009; Rosman, Wahab, & Zainol, 2014). In recent years for instance, bank performance has been mostly categorized based on their market regulation (Mostafa, 2007), ownership, and bank type comparison - i.e. Islamic vs. Conventional banks or public vs. private banks, or foreign vs. local banks - (Hassan, Mohamad, Khaled, & Bader, 2009; Mokni & Rachdi, 2014; Sufian & Noor, 2009).

Earlier empirical studies have presented some evidence regarding bank ownership and efficiency, yet they are inconclusive. Berger and Bonaccorsi di Patti (2006) proposed that the difference between foreign and local bank performance was a function of their respective global and home field advantages. The actual position is dependent in part on national differences and so require single country studies to identify which is most applicable, as long as specific cultural and regulatory barriers could act as strong endogenous variables in banking efficiency. There are also some arguments in respect to local banks as to whether the type of ownership—state or private—may have an impact, although private banks are often expected to be more efficient. Fewer exceptions are related to incipient markets or underdeveloped countries (Wanke, Azad, Barros, & Hadi-Vencheh, 2015; Wanke, Barros, Azad, & Constantino, 2016; Wanke, Barros, & Emrouznejad, 2016; Wanke, Barros, & Macanda, 2015).

Putting it more specifically, the major objective of this research is to investigate the impact of exogenous variables such as the bank type (Islamic vs. conventional), origin (local vs. foreign), and ownership (public vs. private) on different accounting and financial indicators in light of the underlying cultural and regulatory barriers found in MENA countries, which are the endogenous variables. Efficiency scores for (i) profit sheet, (ii) balance sheet, and (iii) financial health indicators over the course of the time frame analyzed (2006–2014) are computed by means of a Dynamic Network DEA model that arranges these three types of indicators within the ambit of a 3-stage process structure. The impacts of such endogenous and exogenous contextual variables on these three efficiency substructures are further computed by stochastic programming and solved by differential evolution where bootstrapped Simplex, Tobit, Beta, and Simar and Wilson (2007, denominated SW hereafter) truncated regressions results are combined in an optimal fashion.

Therefore, this research extends the literature on banking efficiency in several ways. First, the proposed model takes into account intertemporal dynamic effects measured in the form of carry-overs along with the major accounting and financial indicators used to assess banking efficiency. Previous research suggests that capturing the effect of carry-over activities on bank efficiency variations is very important, particularly to assess financial distress in banking by using a proper set of inputs and outputs that is chosen among traditional accounting and financial statements (Wanke, Azad, & Barros, 2016a). Second, most DEA approaches ignore the network structure of the internal relationships that may underlie the decision-making unit (DMU) (Kaffash & Marra, 2016). Finally, this research considers a representative sample from MENA banks and uses stochastic programming on alternative bootstrapped regression estimates to capture the association between efficiency scores and the endogenous/exogenous contextual variable set.

The paper is organized as follows. Section 2 provides a brief contextual setting on the MENA banking industry in light of how accounting and financial statements are structured and how they affect each other over the course of time. The literature review on network and dynamic DEA models and their applications are then presented in Section 3 followed by the methodology in Section 4 in which the proposed Dynamic Network DEA model is further discussed together with the stochastic programming model for combining bootstrapped Simplex, Tobit, Beta, and SW truncated regressions based on differential evolution. Section 5 presents the dataset used as well as the analysis of the results. The discussion and conclusion are given respectively in Sections 6 and 7.

2. Contextual setting

The MENA region includes 28 countries. In short, the importance of MENA in world economy may be drawn from two major characteristics: economic importance and regional connectivity. Firstly, the economic importance of MENA comes from its vast reserve of petroleum and natural gas: 8 of the 12 OPEC countries belong to MENA (O'Sullivan, Rey, & Mendez, 2011, pp. 42–67). More specifically, MENA holds ownership of a total of 60% of the world's oil reserve and 40% of its natural gas reserve (Griffiths, 2017). Moreover, the richest Islamic banks belong to MENA. Secondly, MENA connects Asia with Europe with a number of important trading canals (Bitar, Saad, & Benlemlih, 2016). This character attracts foreign investors with more monetary value and higher competition.

The banking sector in the MENA region has often been branded with diversified characteristics (Vergos & Elfeituri, 2016). Over the last few decades, banks in MENA countries have seen rapid growth in credit, deregulation, and a higher growth in bank ownership by foreign countries. A number of studies have examined various issues of banking studying both individual countries (Al Shamsi, Aly, & El-Bassiouni, 2009; Assaf, Barros, & Matousek, 2011; Omran, 2007) and groups of them (Apergis & Polemis, 2016; Bitar et al., 2016; Mokni & Rachdi, 2014). Highlighting the importance and recent performance of the banking sector in the MENA region, Neaime and Gaysset revealed the fact that financial stability is negatively related to financial inclusion among the MENA countries. Moreover, financial inclusion is not found to be related to poverty. Notably, financial integration in MENA countries is negatively contributing to financial stability. In particular, during the crisis in 2008, Egypt experienced a huge outflow of cash deposit that further widen the gap between rich and poor. Concisely, modeling bank efficiency among the MENA region may significantly contribute to financial stability and economic integration while reducing poverty and unemployment. Thus, studying profit sheet, balance sheet, and financial health indicators along with bank contextual variables to examine bank efficiency among MENA countries is worthy.

Recent studies on bank efficiency in the MENA region mostly focus on comparative studies in terms of ownership and bank nature. Omran (2007) examined 12 banks in Egypt during 1996–1999 in respect of changes in ownership and bank performance. His findings reveal that state-owned banks performed better when their ownerships changed to private. However, Mohieldin and Nasr (2007) examined banks in Egypt during 1995–2005 and found that privatization of banks owned by the state can adversely affect bank performance due to both social and political barriers in successful implementation of bank privatization. Recent studies such as Srairi (2013) and Haque and Brown (2017) examined MENA as a whole and reveal that bank efficiency increases with ownership concentration and restricted supervision by the government. Their study also suggests that government ownership on banks have a positive impact of their cost efficiency.

Additionally, Vergos and Elfeituri (2016) examined the effect of deregulation and foreign ownership in bank efficiency. They examined 11 countries during 2000 until 2012 and broke down the bank efficiency results into technological, technical, and scale efficiency. Thus, their findings reveal that neither foreign nor state ownership has an impact on bank efficiency improvements, but rather a mix of regulation policies based on the changing characteristics of different countries should be proposed individually for a country to be able to enhance its bank efficiency. Likewise, there is no concrete finding on bank deregulation that can be positive for bank efficiency in general.

A growing literature on bank efficiency in the MENA region is also debating on bank nature: conventional banks vs. Islamic banks (Mokni & Rachdi, 2014; Mongid, 2016; Srairi, 2013; Sufian & Noor, 2009). Srairi (2013) examined the relation between bank ownership and risk for 10 MENA countries over the period 2005–2009. His findings reveal that both conventional and Islamic banks perform indifferently when their ownership is private. Overall, Islamic banks have found low exposer to risk compared with their counter parts.

The interrelations between profit sheet and balance sheet with financial health indicators are significant. These relationships have often been ignored in previous research (Casu, Girardone, & Molyneux, 2006). For instance, the profit sheet, the balance sheet, and the cash flow statement are the three financial statements issued every quarter or year by all listed companies. The profit sheet however, similarly to the cash flow statement, indicates modifications in accounts that occur over a given timeframe. The balance sheet, differently, is an instantaneous image of a very different nature, showing what is owned and owed at a single moment.

Profit sheets should be compared from distinct accounting periods so that the changes in operating costs, revenues, and net income can be properly compared, revealing the company's dynamics. For instance, although the income of a company might be growing, its expenses could be increasing at a faster pace, signaling financial distress in the future. In other words, a profit sheet is an accounting statement that synthesizes the revenues, income, and costs verified over a given timeframe. It gives information about a company's dynamic capability of generating profit by either increasing revenues or reducing costs.

Profit sheet items are mostly linked with the bank performance over a period. In fact, the long-term influence of profit items can be seen in the balance sheet. Besides this relationship between profit sheet and balance sheet, financial health ratios of a bank provide relative movements of a bank's performance (profit items) in relation to its balance sheet items (assets, equities, and liabilities). A way to measure the overall financial health of a bank includes the amount of assets it owns and how much income it must generate to cover regular costs and other expenses. Thus, this research for the first time examines comparative bank efficiency of MENA countries based on these three sources of data to define the best alternative variables in describing relative bank performance (efficiency).

3. Background on network and dynamic DEA models

DEA is a non-parametric linear programming technique proposed by Charnes, Cooper, and Rhodes (1978) to evaluate the relative efficiency of DMUs with multiple inputs and outputs. Unlike the parametric methods, a specific functional form does not determine the DEA efficient frontier. Instead, it involves constructing a production frontier based on the actual input–output observations in the sample. Thus, a DEA efficiency score for a specific DMU is measured by the empirically constructed efficient frontier defined by the best-performing DMUs(Paradi, Rouatt, & Zhu, 2011)(Paradi et al., 2011)(Paradi et al., 2011). Most of the studies have focused on the efficiency of a DMU as a "black-box" and very few studies have attempted to study the impact of DMU internal activities on the cost efficiency measurement. In fact, a DMU may consist of several sub-structures that may affect overall efficiency levels differently. Therefore, efficiency cannot be measured within the ambit of any specific sub-structure of a DMU. Network DEA models were proposed to overcome this limitation. Modeling such network structures has been critically debated (Cook, Zhu, Bi, & Yang, 2010; Färe & Grosskopf, 1996; Golany, Hackman, & Passy, 2006; Chiang Kao, 2009; C. Kao, 2009; Chiang Kao, 2014; Lewis & Sexton, 2004; Paradi et al., 2011; Sexton & Lewis, 2003; Kaoru Tone & Tsutsui, 2010).

One of the earliest and simplest network structures is the two-stage DEA model in which two serially connected productive processes or sub-structures are assumed to work together in the main DMU. In other words, DMUs are formed by two consecutive stages where the first stage outputs become the second stage inputs (Golany et al., 2006). This consists of a particular case of the multi-stage network structure (Färe (1991); (Färe & Grosskopf, 1996, 1997; Färe & Whittaker, 1995; Kaoru Tone & Tsutsui, 2010, 2014). To be more precise in the taxonomy of DEA models, Castelli, Pesenti, and Ukovich (2010) suggested a classificatory framework based on the type of the productive process of the DMU: shared flow, multi-stage, and network models. This being the case, a comprehensive definition of network DEA may include more than two stages that are connected in series or in parallel.

The above literature on network DEA and on structures that are connected in parallel also sheds some light on the very nature of dynamic systems, where the operation of a DMU continuously occurs over different periods and where two consecutive periods are connected by carry-overs, a concept originally proposed by Färe and Grosskopf (1996). Such systems have received considerable attention due to their resemblance to real life systems (Nemoto & Goto, 1999, 2003; K. Tone & Tsutsui, 2009; Tone & Tsutsui, 2014). For instance, in real world business, each bank at each term t has its respective inputs and outputs along with the carry-over to the consecutive term t+1. Failure to capture this dynamic nature in bank performance assessment in prior studies can end up with biased efficiency estimates, which in turn can badly affect a bank's long term strategic decisions. This issue is addressed by the dynamic DEA model developed by several studies (Bogetoft, Färe, Grosskopf, Hayes, & Taylor, 2008; Ch; Kao, 2008; Park & Park, 2009) based on the network DEA models of Färe and Grosskopf (1997). The rationale is that current inputs or outputs may potentially influence the future input or output levels and consider the connecting production functions between two consecutive time periods. Recently, Kaoru Tone and Tsutsui (2010) extended the slack-based measure (SBM) framework of Pastor, Ruiz, and Sirvent (1999) and Kaoru Tone (2001) to dynamic productive networks. Unlike the radial measures that overestimate the efficiency estimates when there are non-zero slacks in the constraints defining the technology (Fukuyama & Weber, 2010), the non-radial Dynamic Network SBM deals with non-proportionate change of inputs, outputs, and carry-overs.

Applications of Dynamic Network SBM in the banking industry can be found in (Avkiran, 2015; Fukuyama & Weber, 2013, 2015; Wanke, Azad, et al., 2016a). Dynamic studies are most meaningful since banks are engaged in a complex business structure and outcome in banking can be achieved over a period (Wanke, Azad, et al., 2016a). Avkiran (2015) examined banks in China using an SBM-based dynamic network DEA. His results revealed that the carry-over effect of efficiency estimation in the following years has a significant impact on overall efficiency. Discrimination in efficiency estimates, dimensionality, stability of estimates, and sensitivity of results to divisional weights are found in satisfactory level when testing robustness. Applications of Dynamic Network DEA models can be found also in other areas of optimization studies (Chen, 2009; de Mateo, Coelli, & O'Donnell, 2006; Nemoto & Goto, 1999; von Geymueller, 2009; Wanke & Barros, 2016).

4. Methodology

This section is divided into two subsections. The first one is focused on the Dynamic Network DEA model and its application to modeling the relationships between major financial and accounting indicators in MENA banks. The underlying logic between "profit sheet", "balance sheet", and "financial health ratio" efficiency levels is discussed. The second one is focused on the non-linear stochastic program used to combine bootstrapped Tobit, Simplex, Beta, and truncated (SW) regressions. Not only are the motivations for combining forecasts presented, but also the technique used to solve this problem (differential evolution).

4.1. Proposed dynamic network DEA model

In traditional DEA, DMUs are considered to be a black-box and efficiency scores are computed without considering the interrelationship among sub-structures within the system. Therefore, this section presents the relational models to compute efficiency scores in dynamic network structures, as generically depicted in Fig. 1.

Let's consider n DMUs $(j = 1, \ldots, n)$ consisting of K sub-structures $(k = 1,\ldots,K)$. Let m_k, r_k, and L_{kh} also be the number of inputs and outputs in sub-structure k and the set of links leading from k to sub-structure h, respectively. The term $x_{ikj} \in R^+(i = 1, \ldots, m_k; k = 1, \ldots, K; j = 1, \ldots, n)$ is used for denoting the input i in DMU_j to produce the output $y_{rkj} \in R^+(r = 1,\ldots,r_k; k = 1,\ldots,K; j = 1,\ldots,n)$, that is, to produce the output r from DMU_j. Further, the term $z_{l(kh)j} \in R^+(j = 1, \ldots, n; l = 1, \ldots, L_{kh})$ is used as an intermediate link from sub-structure k to sub-structure h.

The input-oriented dynamic network DEA model is estimated by solving the following linear programming problem given as shown in model (1).

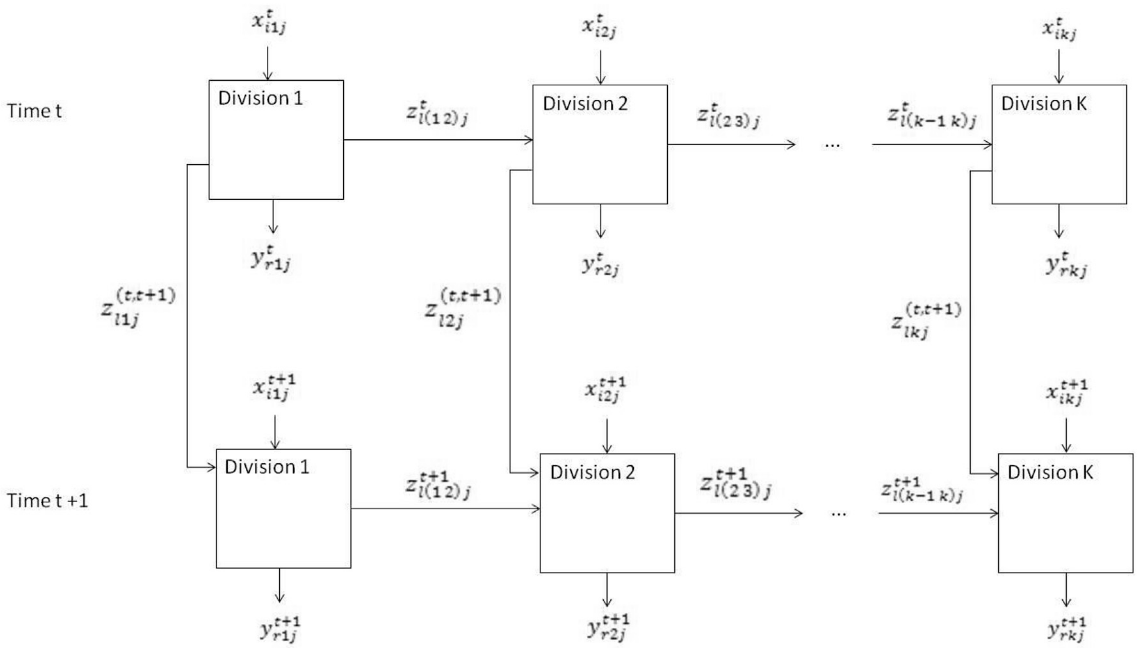

Fig. 1. General Dynamic Network DEA model.

$$\begin{aligned}
&\min \sum_{i=1}^{m_k} \overline{x}_{iko}^t \\
&S.T. \\
&\sum_{i=1}^{n} \lambda_{kj}^t x_{ikj}^t \leq \overline{x}_{iko}^t \qquad i=1,\ldots m_k \\
&\sum_{i=1}^{n} \lambda_{kj}^t y_{rkj}^t \geq y_{rko}^t \qquad r=1,\ldots r_k \\
&\sum_{i=1}^{n} \lambda_{hj}^t z_{l(kh)j}^t \geq z_{l(kh)o}^t \qquad l=1,\ldots L_{kh} \\
&\sum_{i=1}^{n} \lambda_{kj}^t z_{l(hk)j}^t \leq z_{l(kh)o}^t \qquad l=1,\ldots L_{hk} \\
&\sum_{i=1}^{n} \lambda_{kj}^t z_{lkj}^{(t,t+1)} \geq z_{lko}^{(t,t+1)} \qquad l=1,\ldots L_k \\
&\sum_{i=1}^{n} \lambda_{kj}^{t+1} z_{lkj}^{(t,t+1)} \leq z_{lko}^{(t,t+1)} \qquad l=1,\ldots L_k \\
&\lambda_{kj}^{t+1}, \lambda_{kj}^t, \overline{x}_{iko}^t \geq 0
\end{aligned}$$

Model (1) yields a CRS (constant returns to scale) specification. If one wants to assess efficiency scores under a VRS technology assumption, additional constraints assuring that lambdas sum up to one should be implemented.

First, the linear programming presented in model (1) is solved for $t = 1,\ldots,T$, where a minimal virtual input vector is found for each period. Then, each sub-structure efficiency is calculated as follows in eq. (2) and the overall structure efficiency (network efficiency – NE) is defined observing a weighted mean where each w_k is set as the respective sub-structure weight, as presented in eq. (3):

$$NE_{ko}^t = \frac{\sum_{i=1}^{m_k} \overline{x}_{iko}^{t^*}}{\sum_{i=1}^{m_k} x_{iko}^t} \tag{2}$$

$$NE_o^t = \sum_{k=1}^{K} w_k NE_{ko}^t \tag{3}$$

where. $\sum_{k=1}^{K} w_k = 1$.

It is worth mentioning that when modeling network DEA, either additive or multiplicative efficiency decomposition can be considered depending on the specifics of the two-stage structure in question and on the returns-to-scale (CRS or VRS) premises taken. In fact, Kao. (2008) suggested that the overall efficiency can be broken down into the product of efficiency of each stage when CRS are assumed and there are no exogenous inputs and outputs in the two-stage structure. The problem is that network DEA models that consider multiplicative efficiency decomposition cannot be turned into linear ones under the VRS premise or when the input/output set presents exogenously defined variables, such as the carry-overs and links that may exist in dynamic versions of network DEA. Conversely, the additive efficiency decomposition, which is the one used here, can very often be resolved linearly (Chen, 2009). There is, however, a computational issue left as demonstrated by Guo et al.: it should be figured out how to determine the w_k weights that apply on the efficiencies of the three individual stages. Considering that the best solution that achieves maximal overall efficiency is not known unless all possible values of weights are tested, a less cumbersome approach should be adopted when setting these exogenously defined weights. In our study, there are three efficiency vectors for each network substructure— "profit sheet", "balance sheet", and "financial health indicators"—to which different exogenously defined weights should be applied so that overall efficiency levels can be computed.

In fact, within the ambit of multi-criteria decision-making literature, when referring to exogenously defined weights, some alternative approaches could be considered. The steps taken in this research to create distinct weighting schemes are depicted further. Nevertheless, it should be observed that even though the weighting approach is used to determine overall efficiency scores, the contextual variables are still used as regressors to predict efficiency scores.

The Ng weighting model is adopted here. It considers that there are I DMUs per each year and that they should be ranked in terms of J sub-structure efficiency scores. Further, let the efficiency of $i-$ th year DMU in terms of each of the $j-$ th sub-structure be denoted as y_{ij}. The purpose is to aggregate different sub-structure efficiency scores of a year DMU into a single overall score. The Ng-model uses a 0–1 scale for all items, which consists of a proper fit for DEA scores. To make the year rank observing different efficiency vectors easier, Ng sets a nonnegative weight w_{ij} , which is the weight of the individual efficiency of the $i-$ th year under the $j-$ th sub-structure of the productive process of the DMU. The sub-structure efficiency vectors are assumed to be ordered in a descending fashion, such that $w_{i1} \geq w_{i2} \geq \ldots \geq w_{iJ}$ for all year i. The Ng model for computation purposes is given next:

$$\max \quad S_i = \sum_{j=1}^{J} y_{ij} w_{ij}$$

$$s.t. \quad \sum_{j=1}^{J} w_{ij} = 1$$

$$w_{i1} \geq w_{i2} \geq \ldots \geq w_{iJ}$$

$$w_{ij} \geq 0, \; i = 1, \ldots, I \;\&\; j = 1, \ldots, J,$$

It is important to note that under Ng's approach, the weights are determined when the model is solved. Hence, it can be used complementary for other approaches such as DEA in which decision-makers can eventually exogenously specify weights in network structures. However, differently from Ng, we used combinatorial analysis using R codes to generate the universe of combinations where the three efficiency vectors for each sub-structure are placed in alternative orders of importance. Specifically, the Ng model was performed 3! = 6 times for the full set of sub-structure combinations in different orders of importance (e.g. "profit-balance-financial", "profit-financial-balance", "balance-profit- financial", etc.). In all cases, the weights for the three sub-structure efficiency vectors summed up to one. Results for the yearly averaged weights obtained in all possible combinations using the Ng weighted linear model are depicted in the Appendix.

Fig. 2 illustrates the inputs (I), outputs (O), carry-overs (C), and linking (L) of the intermediate variables within the ambit of the three sub-structures of the dynamic network designed for the MENA banks. The specific statistical details of the data are further discussed in Section 5. As shown in Fig. 2, the variables of the first stage, called "profit sheet" efficiency, are net loans (I), net interest margin (O and L), and gross loans (C). This stage represents the profitability of the banking industry due to the loan activity. It is necessary for banks to attain a certain level of gross loans over the course of time to support this activity (Casu et al., 2006). Besides, the performance of this stage impacts the subsequent sub-structure called "balance sheet" efficiency where earning and non-earning assets (I) are converted altogether with the profitability of the loan activity into equity (O and L) and total assets (C and L). Not only does the equity generation depend over the course of the time on the asset creation due to banking profitability derived from the loan activity and their inherent liabilities (Casu et al., 2006), but also both variables, total assets (L) and equity (L), are the cornerstones of the substructure called "financial health ratios" efficiency. These variables, along with cost and loan loss provisions (I), are fundamental for producing sound indicators of income (O and C), which is the numerator for important financial health ratios in banking such as ROA (income/asset ratio), ROE (income/equity ratio), income to cost ratio, loan exposure (income to loan loss provision), etc. (Casu et al., 2006). It is important to mention that common variables acting simultaneously as outputs and as links or carry-overs in a given sub-structured were attributed a fair share of 50% during the computations of the Network DEA model.

4.2. Stochastic programming model for combining bootstrapped regressions

In this research, the impacts of the contextual variables related to the ownership of the bank, its type and origin upon the "profit sheet", "balance sheet", and "financial health ratio" efficiency levels are tested by a robust regression approach. In this approach, Tobit

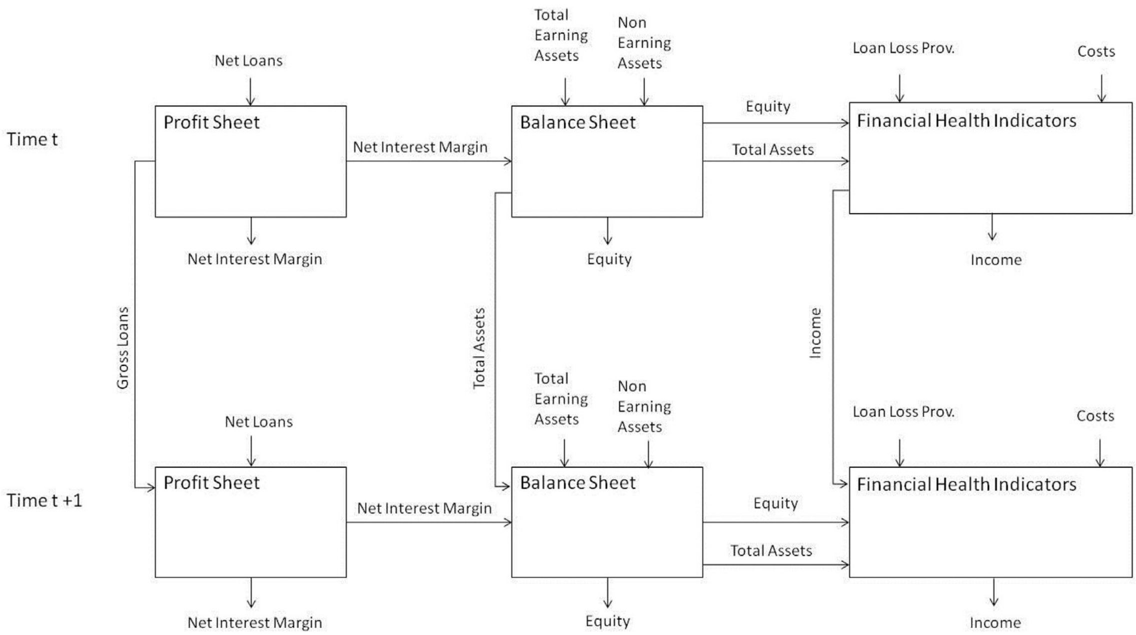

Fig. 2. Dynamic Network DEA model for MENA banks.

(Wanke, Azad, & Barros, 2016b), Simplex (Barros et al., 2017), Beta (Wanke, Barros, & Figueiredo, 2016), and SW bootstrapped truncated regressions (Simar & Wilson, 2007), individually designed to handle dependent variables bounded in 0 and 1, are combined by means of stochastic non-linear programming and bootstrapping. This is justified because most regression approaches produce biased results in two-stage DEA analysis because they do no often take into account the underlying issues caused by the lack of discriminatory power of the scores computed in the first stage (Wanke, Barros, Azad, et al., 2016). The discriminatory power is low because efficiency scores tend to be upwardly biased towards one. Therefore, a robust regression approach should reflect an adequate distributional assumption in order to handle this type of bias. This may be obtained via bootstrapping (Simar & Wilson, 2007, 2011) and combining forecasts to yield smaller variance errors (James, Witten, Hastie, & Tibshirani, 2013; Ledolter, 2013).

The non-linear stochastic optimization problem for the combination of Simplex, Beta, Tobit, and SW truncated bootstrapped regressions is presented in model (4) where w_1, w_2, w_3, and w_4 represent the weight ranging from 0 to 1 assigned to the vector of the residuals of the Tobit regression ($\boldsymbol{Rt}$), Beta regression ($\boldsymbol{Rb}$), Simplex regression ($\boldsymbol{Rs}$), and Simar and Wilson ($\boldsymbol{Rsw}$) respectively. This model optimizes the value of w so that the variance (Var) of the combined residuals is minimal. Both regressions were bootstrapped and combined 100 times so that a distributional profile of w can be collected for the “profit sheet”, “balance sheet”, and “financial health indicators” best efficiency predictions. Residual variances were collected assuming a linear model for each regression linking efficiency estimates and contextual variables.

$$\min Var(w_1\boldsymbol{Rt} + w_2\boldsymbol{Rb} + w_3\boldsymbol{Rs} + w_4\boldsymbol{Rsw})$$

$$S.T. \quad \sum_{i=1}^{4} w_i = 1$$

$$0 \le w_1 \le 1$$

$$0 \le w_2 \le 1 (5)$$

$$0 \le w_3 \le 1$$

$$0 \le w_4 \le 1$$

Model (5) was solved using the differential evolution (DE) technique. DE is a member of the family of genetic algorithms, that mimics the process of natural selection in an evolutionary manner; see Holland (1975), Thangaraj, Pant, Bouvry, and Abraham (2010), and

Table 1
Descriptive statistics.

Variables		Min	Max	Mean	SD	CV
Inputs	Net Loans	82.64	1831655.65	72234.94	144250.47	2.00
	Total Earning Assets	147.41	2329533.90	119822.82	266910.23	2.23
	Non-Earning Assets	−7933.60	599019.10	20718.66	59036.99	2.85
	Loan Loss Prov.	16.53	366331.13	14466.56	28850.09	1.99
	Costs	1050.00	1375608.73	68511.85	138488.62	2.02
Intermediate or Link Variables	Net Interest Margin	−7.17	9.77	2.86	1.30	0.45
	Equity	5.93	268361.60	13252.22	27685.97	2.09
	Total Assets	224.48	2636705.50	142678.29	324119.66	2.27
Outputs	Net Interest Margin	−7.17	9.77	2.86	1.30	0.45
	Equity	5.93	268361.60	13252.22	27685.97	2.09
	Income	−2832.72	37096.97	1942.92	4398.68	2.26
Carry-Overs	Gross Loans	82.64	1831665.60	74057.84	145112.73	1.96
	Total Assets	224.48	2636705.50	142678.29	324119.66	2.27
	Income	−2832.72	37096.97	1942.92	4398.68	2.26
Contextual variables	Trend	1	9	4.996	2.586	0.518
	Trend^2	1	81	31.648	26.528	0.838
	Bank Ownership	Public			Private	
		23.17%			76.83%	
	Bank Type	Conventional			Islamic	
		73.17%			26.83%	
	Bank Origin	Local			Foreign	
		54.88%			45.12%	
	Merge and Acquisitions	M&A			Not M&A	
		57.32%			42.68%	
	Country	Algeria	Bahrain	Dubai	Egypt	Iran
		4.88%	7.32%	2.44%	8.54%	6.10%
		Israel	Jordan	Kuwait	Lebanon	Malta
		7.32%	2.44%	7.32%	9.76%	1.22%
		Morocco	Oman	Qatar	Saudi Arabia	United Arab Emirates
		3.66%	3.66%	7.32%	14.63%	13.41%

Mullen, Ardia, Gil, Windover, and Cline (2011) for further details. The R package named DEoptim was used to solve this problem. A detailed description of this package can also be found in Ardia, Boudt, Carl, Mullen, and Peterson (2011) and Mullen et al. (2011).

5. The data

The data on MENA banks was obtained from the BankScope database for the period of 2006–2014. From a total of 20 countries (as of now in the World Bank database), 15 countries were included in this study. The remaining countries were deducted either because of their recent war situation, unstable economic condition, or data unavailability. Thus, the final sample size of 738 units involves the combination of 82 banks for a period of 9 years (Algeria-36; Bahrain-54; Egypt-63; Iran-54; Israel-54; Jordan-18; Kuwait-72; Lebanon-72; Malta-9, Morocco-27; Oman-27; Qatar-54; Saudi Arabia-108; United Arab Emirates-108 units). All monetary values are expressed in USD and adjusted by annual inflation rates. As discussed in section 4.1, inputs, outputs, linking variables, and carry-overs were chosen in accordance to what is a common sense in the banking literature on how profitability derived from the loan activity turns into total assets, equity and, ultimately into sound financial indicators (Casu et al., 2006). In addition, contextual variables related to the bank ownership, type, and origin are assessed as exogenous factors, while the country of origin represent the endogenous factors imposed by cultural and regulatory barriers. The idea is to control the computed efficiencies for these endogenous variables as differences in the slope of the Tobit, Simplex, Beta, and SW bootstrapped truncated regressions. Their descriptive statistics are also presented in Table 1.

As regards the negative values verified in some DMUs, it is important to mention that all inputs, outputs, links, and carry-overs were rescaled observing the normalization by scaling between 0 and 1 before running the proposed NDEA model, that is:

$$Normalized\ (ei) = (ei - Emin)\ /\ (Emax - Emin) \tag{6}$$

where *Emin* is the minimum value for variable *E* and *Emax* = the maximum value for variable E. If *Emax* is equal to *Emin*, then normalized value is set to 0.5. In order to handle the resulting minimal zero values, a small value of 0.01 was added into these cases.

6. Discussion of results

The distribution of the scores computed for the “profit sheet”, “balance sheet”, and “financial health ratios” sub-structures is presented in Fig. 3 (left and right). One can easily see that “profit sheet” efficiency scores in MENA banks are lower and more dispersed than the “balance sheet” and “financial health indicator” scores, while the “overall” efficiency scores for these three sub-structures present an intermediate behavior in magnitude since they are computed as a linear weighted combination from them. These results suggest that the banking industry is MENA countries is proportionally less efficient in generating profits from the loan activity than in turning this profitability into new assets and equity and into sound indicators of financial health. One possible explanation for this effect may rely on the very nature of the variables within each substructure. While “profit sheet” variables are computed cumulatively and systematically on a yearly basis, “balance sheet” variables portray an instantaneous picture of the financial accounting statements and “financial health indicators” can be understood as their derivatives at a given point of time.

Taking a closer look on how these efficiency scores are distributed throughout the MENA countries (cf. Fig. 4) and the years (cf. Fig. 5), it is possible to make some claims on endogeneity and trend effects. Although the three sub-structure efficiency levels remained quite stagnant over the period analyzed, despite the world financial crisis initiated in 2008 and its post-unfolding effects, they present a strong level of heterogeneity depending upon each country analyzed. This suggests the tremendous impact of endogenous effects such as cultural barriers and regulatory marks on banking efficiency to the detriment of an increasing or decreasing trend in banking efficiency over the course of the years. Some light is also shed when exogenous variables such as banking type, origin, and ownership are taken into consideration. In fact, there are countries where the “profit sheet” efficiency is higher than the “balance sheet” efficiency in contrast to

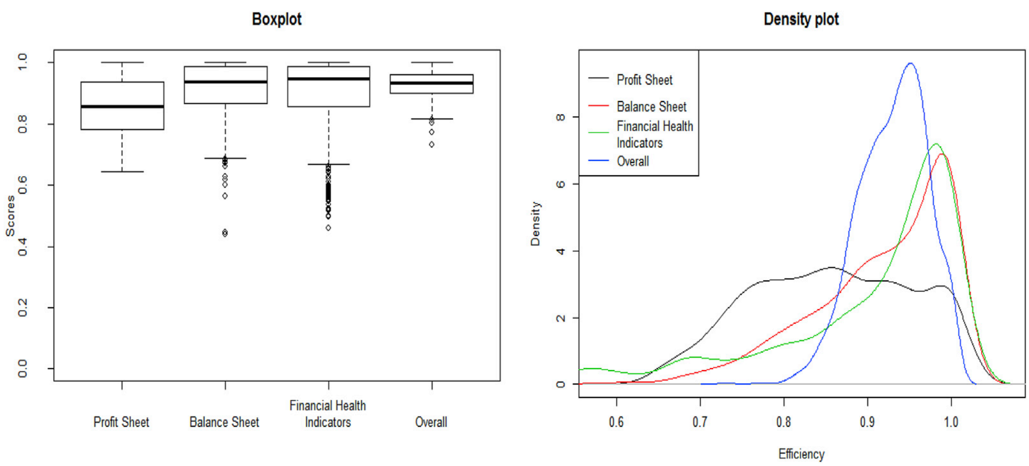

Fig. 3. Distributions for the efficiency scores.

the overall perspective depicted in Fig. 3. This also suggests an eventual impact of Islamic banking practices on loans where there are no interest rates involved, but instead, banks are much more involved in the processes of asset creation and equity generation. On the other hand, countries with a lower presence of foreign financial institutions tend to present higher efficiency levels on their “financial health indicators” sub-structure, thus suggesting some kind of negative impact due to the adoption of tighter regulatory practices against foreign institutions.

As regards the distributional fits of each one of these four efficiency scores, Fig. 6 depicts the Gaussian, Simplex, SW, and the Beta adjustments for their inverse cumulative distributions. It is not possible to affirm at first sight, however, whether a specific distribution is preferable to the other. This suggests that combining a mix of such regression results may be a sound approach. In fact, results for the Kullback-Leibler (KL) divergence presented in Table 2 indicate that differences between both adjustments are minimal for most assumptions, sometimes favoring one distributional assumption, that is, one specific regression type to the detriment of the other. However, it is worth mentioning that, as expected in Simar and Wilson (2007), the SW distributional assumption outperformed the Gaussian assumption used in Tobit regression due to bias removal in scores close to 1, although in some cases Simplex and Beta assumptions presented a better distributional fit, capturing better the different shapes depicted in Fig. 3 (b). As regards the overall scores computed as a linear weighted combination from the three main substructures, the SW assumption did not perform so well as the other assumptions possibly due to the lack of a methodological foundation for applying its resampling procedures to network DEA structures.

The results for the stochastic non-linear optimization on the 100 bootstrapped Tobit, Simplex, SW, and Beta regression residuals are presented in Fig. 7. As regards the three main substructures, the results suggest an almost even split between the weight assigned to SW and the summation of the weights assigned for Simplex, Tobit, and Beta regressions. Also interesting to note is that in these three substructures, the Simplex assumption always performed better than the Beta and the Gaussian ones. These results suggest the importance of combining different methods not only in terms of bias removal, but also in terms of capturing different distributional shapes.

The combined bootstrapped regression results for the coefficients of the contextual variables and the intercept (country effect) within each efficiency type are respectively presented in Fig. 8 and Fig. 9.

Readers should note that if the distribution of the bootstrapped coefficients and intercepts cross the solid line that marks zero in each graph from Figs. 7 and 8, it should be interpreted as a non-significant variable. Analogously to what was found in the descriptive analysis, “profit sheet” efficiency tends to be significantly higher in local, public, and Islamic banks, while no significant effect was found to be accountable from previous M&A (cf. Fig. 8). It seems that strong regulatory and cultural barriers against foreign banks together with the greater parsimony in lending money verified under the Islamic banking system are contributing positively to the profitability of the loan activity within these three groups of banks. However, this beneficial impact of local and Islamic banks is not verified in the process of asset creation and equity generation, although the positive impact of foreign banks on increasing the size of the banking

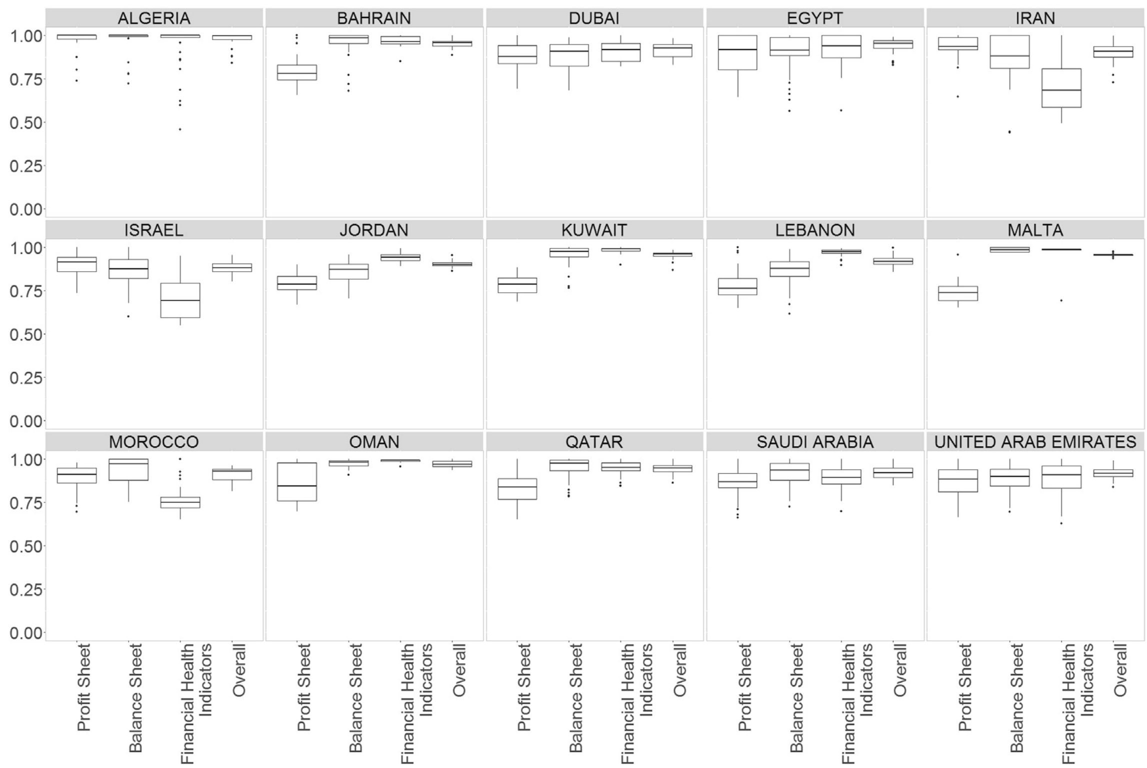

Fig. 4. Distribution of efficiency scores per country.

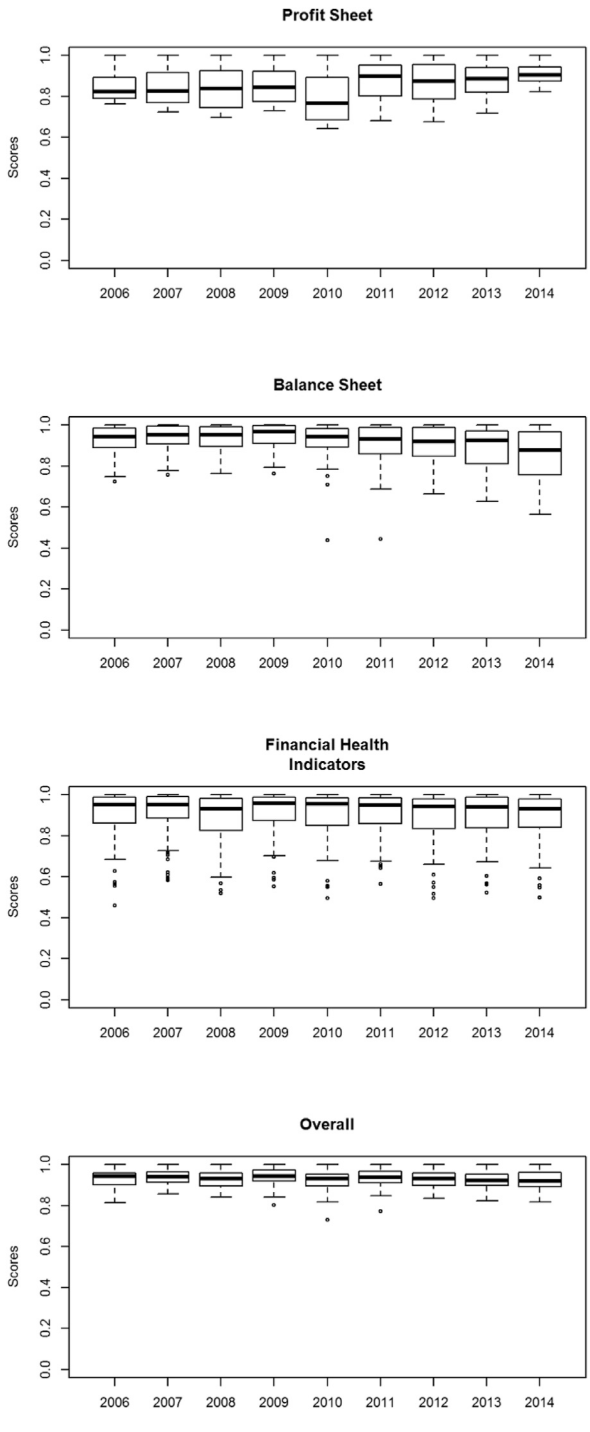

Fig. 5. Distribution of efficiency scores per year.

operation based on profit accumulation should also be noted. Again, it is not possible to make a claim on the impact of M&A on these results whatsoever for the "balance sheet efficiency". Things are different, however, with respect to the beneficial impact of mergers when "financial health indicators" efficiency is put into perspective. Altogether with local, public, and Islamic banks, banks that have undergone M&A tend to present more sound financial health indicators. This result may be geared by the less leveraged banking operations verified in Islamic banking where income tends to be tied up with the asset base. In fact, conventional banks are not obliged to purchase assets when loaning funds for customers in exchange of interest rates, which is different from Islamic banks. At last, although all these effects seem to be diluted and non-significant in terms of the "overall" efficiency, it is possible to claim for a significant role of

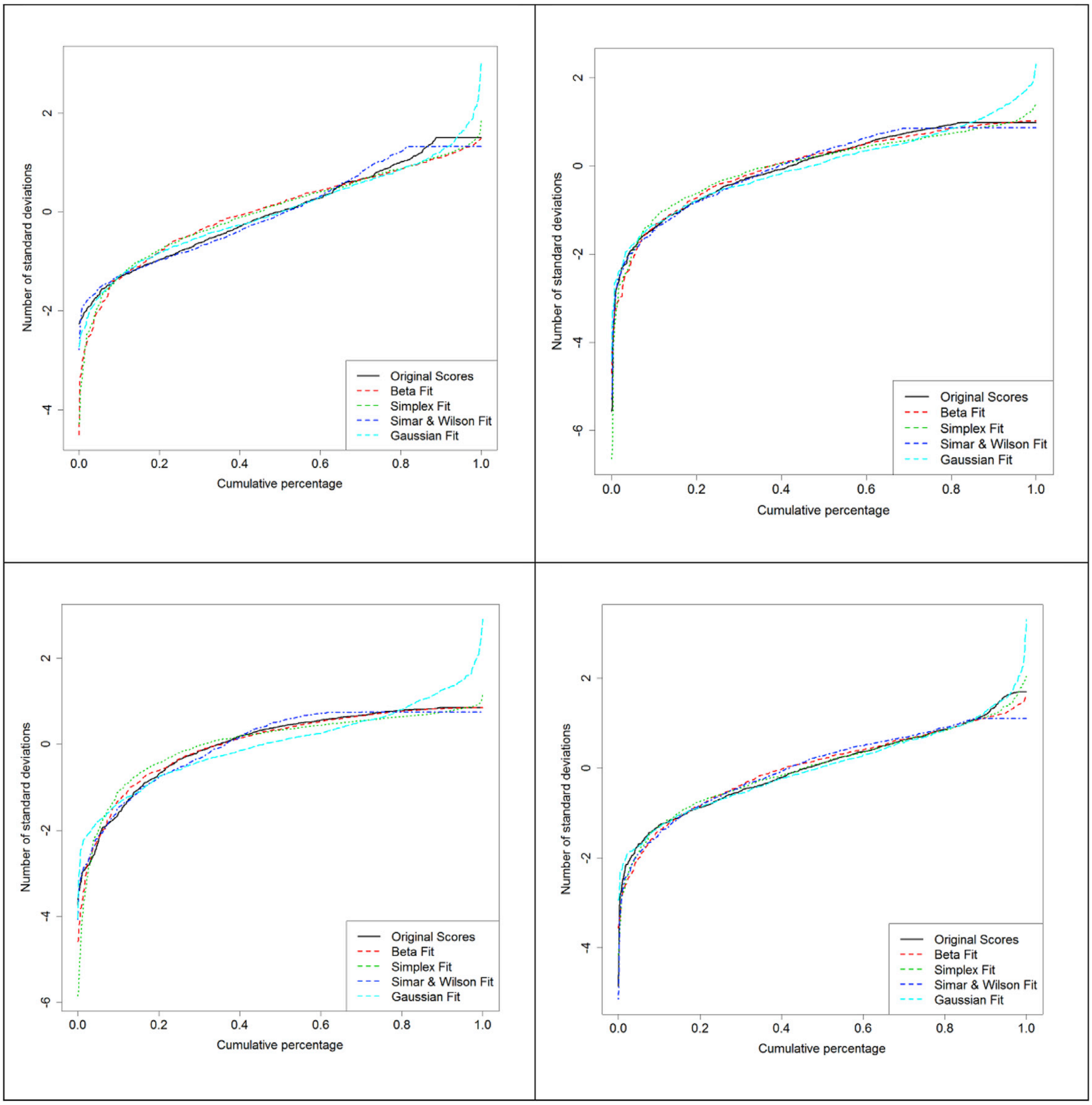

Fig. 6. Inverse cumulative distributions for the different efficiency scores: "profit sheet" (top left),"balance sheet" (top right), "financial health indicators" (bottom left), and "overall" (bottom right).

Table 2
Results for the KL divergence considering Beta, Simplex, Simar & Wilson and Gaussian assumptions.

	Beta Fit	Simplex Fit	Simar & Wilson Fit	Gaussian Fit
Profit Sheet	4.74%	3.56%	1.56%	1.87%
Balance Sheet	1.61%	2.05%	1.87%	14.50%
Financial Health Indicators	0.28%	1.49%	1.85%	53.59%
Overall	2.37%	0.31%	5.08%	3.19%

public banking in overall efficiency within the ambit of MENA banks during the period analyzed.

Fig. 9 illustrates the intercepts (country effects) for each one of the efficiency types. Algeria is the category of reference (intercept = 0) among all other intercepts it should be compared to. During the time encompassed by this research, Algeria's banking industry has historically been characterized by low intermediation and penetration rates, although both have increased dramatically in recent years primarily due to ample liquidity stimulated from oil price shocks. Islamic banking has been identified by Algerian authorities as being among the key areas to support economic growth based on abundant oil resources. Islamic finance is currently dominated almost entirely by Algeria's oldest private bank, Al Baraka Bank.

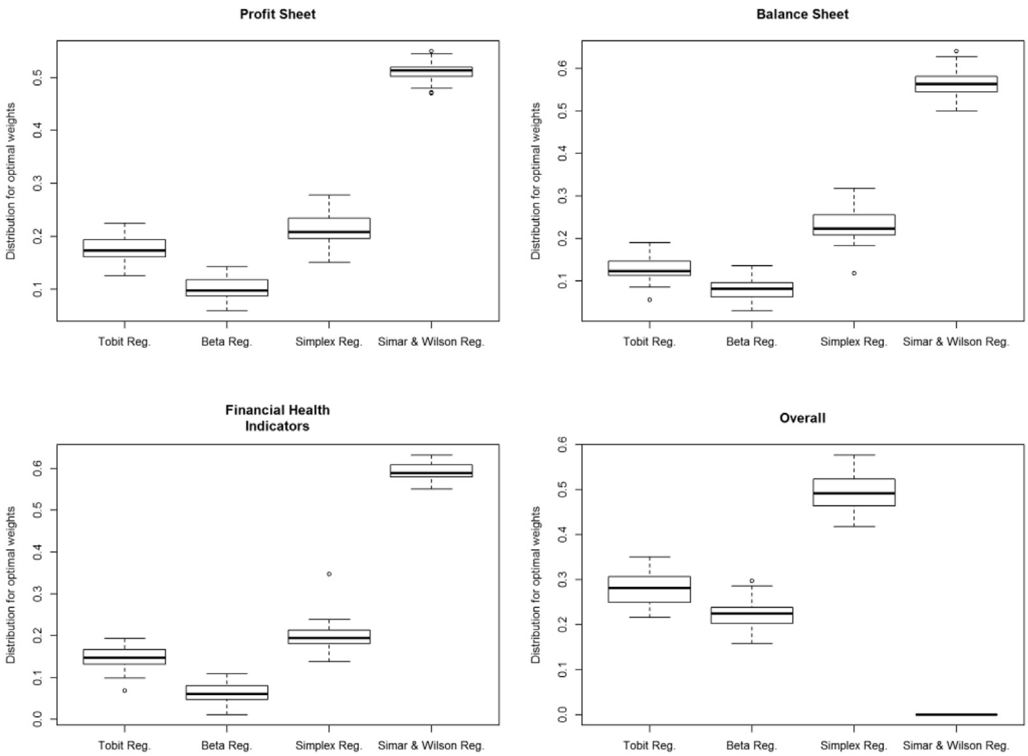

Fig. 7. Distribution on the optimal values of *w* for each efficiency distribution.

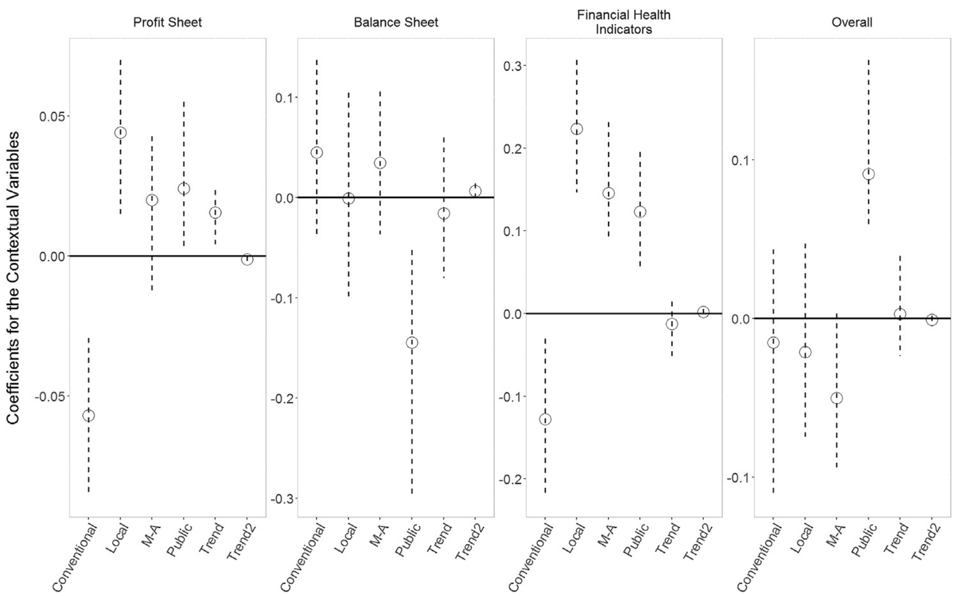

Fig. 8. Combined bootstrapped regression results for the coefficients of the contextual variables within each efficiency type.

When compared to other countries, banks in Algeria have until now been as profitable as their counterparts in other MENA countries that are not oil exporters such as Lebanon, Jordan, and Malta. In fact, the impact of excess of liquidity due to higher oil prices in profit efficiency was also verified in the banking industry of other OPEC countries that also belong to the MENA group (e.g. Kuwait, Saudi Arabia, Qatar, and United Arab Emirates). This may suggest the interference of local regulatory policies and barriers amidst particular cultural aspects of each country to the detriment of oil-geared liquidity, as long as non-oil exporters such as Egypt, Iran (under trade embargo), Israel, Morocco, and Oman presented better “profit sheet” performance.

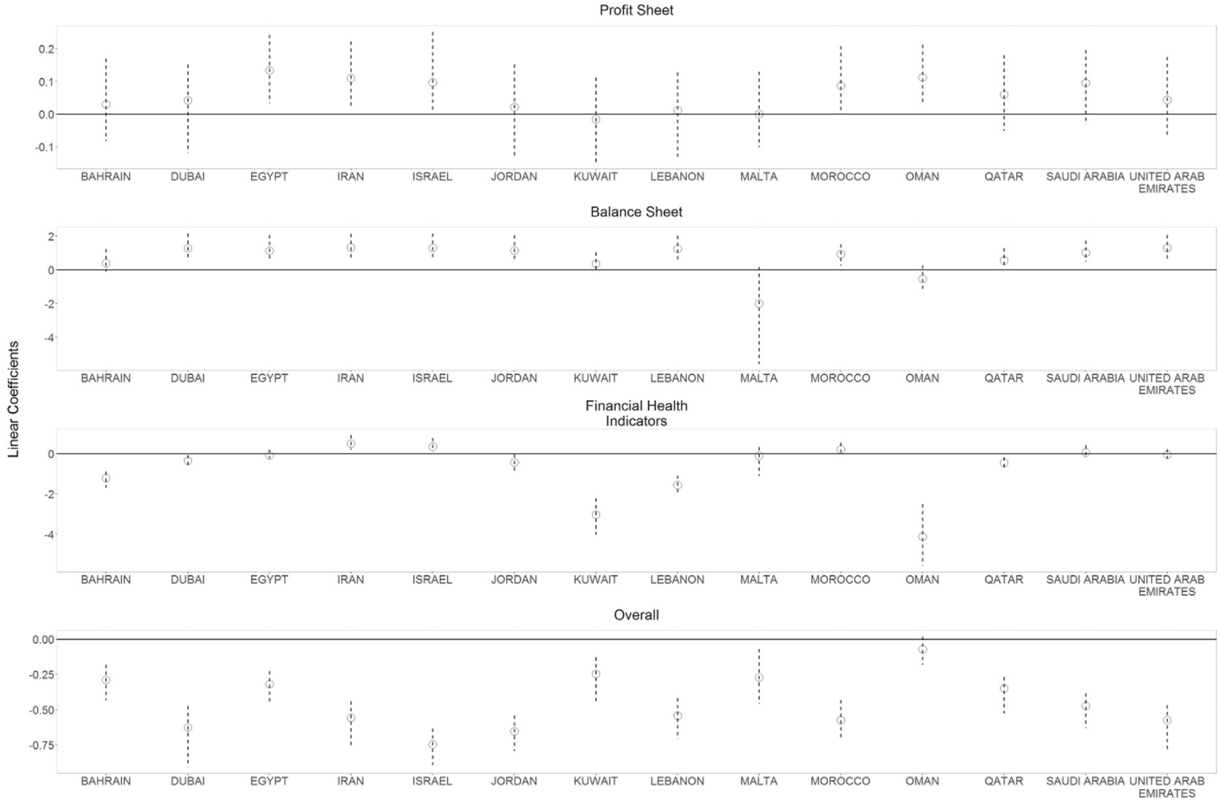

Fig. 9. Combined bootstrapped regression results for the intercepts (country effect) within each efficiency type.

Also interesting to note as regards to "balance sheet" efficiency is that the country's economy size and relative political stability seem to be a relevant underlying factor beneath the process of asset creation and equity generation, as it is mostly verified in the larger economies of Egypt, Iran, Israel, and Saudi Arabia. This picture is not so clear, however, as regards to "financial health indicators" efficiency, which seems to be negatively impacted by population size, smaller countries, and/or fewer business opportunities.

Thus, the above results reveal that a bank's character impacts bank efficiency levels differently in terms of profit sheet, balance sheet, and financial health indicators. Additionally, the impact of cultural and regulatory barriers seems to prevail at the country level. Now, if

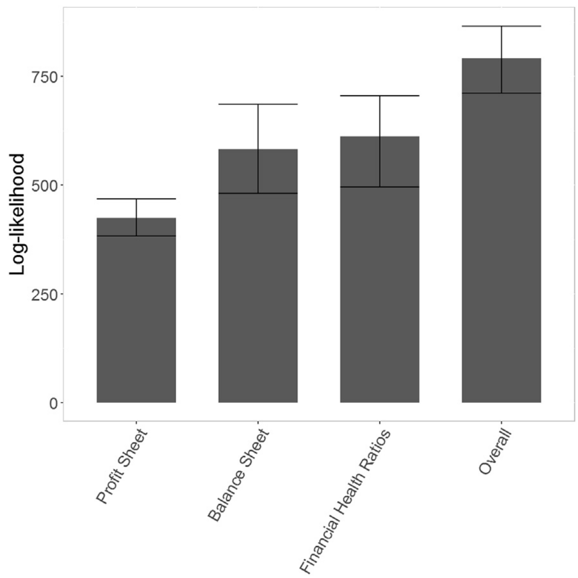

Fig. 10. Log-likelihood ratios for the Combined bootstrapped regression results.

we relate the diversification in bank efficiency results with economic progress of MENA countries, we see that examining bank efficiency may significantly vary due to either the bank level or the country level variables, other than the actual efficiency. For instance, countries with high cash inflow due to oil export (i.e. Kuwait, Saudi Arabia, and Qatar) might find their banks more efficient than other countries. Similarly, countries with high population or less business opportunities (e.g. Lebanon and Jordan) might reconsider examining bank efficiency using financial health ratio. Regardless the country level variables, in general, the results reveal that countries in the MENA region need to re-examine bank efficiency; meaning that either the banks are operating efficiently, or the selection of variables are showing them efficient.

At last, log-likelihood ratios for the combined bootstrapped regressions are presented in Fig. 10. Although this index for model adjustment is numerically higher for the "overall" and "financial health indicators" efficiency levels, they cannot be used to perform any direct comparison between these different models whatsoever, so caution is required in their interpretation. They are left as a register for the readers.

7. Conclusions

This paper explored efficiency in MENA banks using a novel Dynamic Network DEA model where overall efficiency was broken down in accordance to major accounting and financial indicators. A specific non-linear stochastic optimization model was also developed to combine bootstrapped Tobit, Simplex, Simar and Wilson, and Beta regressions in the second stage of the analysis so that fitting bias could be reduced, and overall accuracy of the model be improved in light of endogenous and exogenous contextual variables. These models constitute not only a contribution to the banking literature, but also to the overall efficiency literature since this is the first study of this kind conducted so far.

Major results suggest that MENA banks are facing a performance threshold geared by the distinctive nature of banking type, whether conventional or Islamic. As long as Islamic banks present less leveraged loan activity and therefore better "financial health ratios" efficiency, the greater parsimony of Sharia principles in Islamic banks may not be contributing to a faster pace in asset creation and equity generation ("balance sheet efficiency") when compared to foreign banks. Further research should be directed to better understand at what point of the accounting and financial statements resides the performance balance between these two alternative banking systems.

Additionally, results reinforce the existence of regulatory marks and cultural barriers that may explain why similar countries in size and geographical location may be performing differently in the banking industry. More specifically, attention should be drawn to the MENA countries that also belong to the OPEC group to better understand why the excess of liquidity caused by the oil boom price in the last years produced such timid effects in "profit efficiency". On the other hand, there is also room left to understand the idiosyncratic aspects of countries with stronger cultural bonds with the Western hemisphere such as Israel and Malta, and how they affect efficiency within the ambit of the MENA group.

The broad conclusion is that to extract exact bank efficiency scores, policymakers and bank regulators should emphasize bank specific characters (e.g. bank type, ownership) as well as bank level variables (e.g. profit sheet, balance sheet, and financial health indicators) while taking into account the structure and composition of the individual country's economic condition. A key challenge for policymakers is to find the optimum balance that can ensure selection of appropriate variables or bank efficiency calculation while relating bank efficiency with the relevant economic aspects in country level data. Above all, future economic integration and perquisite for developing a shield against a financial sector crisis requires a better understanding of current bank performance and determinants. Our results significantly shed light on the dynamics of bank efficiency modeling and selection of appropriate variables considering both bank level and industry level data.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2019.01.004.

Appendix

Table A1
Average weights for the three substructures per DMU (2006–2014) *.

DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum	DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum
Banque de Développement Local	0.293	0.284	0.423	1	Banque Libano-Francaise	0.13	0.324	0.546	1
Banque Extérieure d'Algérie	0.259	0.481	0.259	1	Byblos Bank S.A.L.	0.148	0.287	0.565	1
Banque Nationale d'Algérie	0.426	0.287	0.287	1	Crédit Libanais S.A.L.	0.139	0.306	0.556	1
Crédit Populaire d'Algérie	0.398	0.194	0.407	1	Fransabank sal	0.204	0.204	0.593	1
Ahli United Bank BSC	0.139	0.463	0.398	1		0.231	0.241	0.528	1

(continued on next page)

Table A1 (*continued*)

DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum	DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum
					Société Générale de Banque au Liban - SGBL				
Albaraka Banking Group B.S.C.	0.25	0.269	0.481	1	HSBC Bank Malta Plc	0.139	0.454	0.407	1
Arab Banking Corporation BSC-Bank ABC	0.111	0.481	0.407	1	Attijariwafa Bank	0.472	0.398	0.13	1
BBK B.S.C.	0.111	0.398	0.491	1	Attijariwafa Bank (Combined)	0.389	0.481	0.13	1
Gulf International Bank BSC	0.136	0.488	0.377	1	Banque Centrale Populaire SA	0.213	0.463	0.324	1
National Bank of Bahrain	0.157	0.463	0.38	1	Bank Dhofar SAOG	0.361	0.352	0.287	1
Dubai Islamic Bank PJSC	0.389	0.333	0.278	1	Bank Muscat SAOG	0.176	0.296	0.528	1
Emirates Islamic Bank PJSC	0.269	0.361	0.37	1	National Bank of Oman (SAOG)	0.111	0.398	0.491	1
Arab African International Bank	0.167	0.398	0.435	1	Ahli Bank QSC	0.13	0.481	0.389	1
Banque Misr SAE	0.556	0.241	0.204	1	Doha Bank	0.167	0.454	0.38	1
Commercial International Bank (Egypt) S.A.E.	0.333	0.25	0.417	1	International Bank of Qatar Q.S.C.	0.139	0.444	0.417	1
EFG-Hermes Holding Company SAE	0.204	0.296	0.5	1	Qatar Islamic Bank SAQ	0.213	0.37	0.417	1
Faisal Islamic Bank of Egypt	0.315	0.269	0.417	1	Qatar National Bank	0.167	0.417	0.417	1
HSBC Bank Egypt S A E	0.315	0.222	0.463	1	The Commercial Bank (QSC)	0.194	0.444	0.361	1
National Bank of Egypt	0.472	0.407	0.12	1	Al Rajhi Bank Public Joint Stock Company	0.395	0.247	0.358	1
Bank Keshavarzi-Agricultural Bank of Iran	0.352	0.417	0.231	1	Arab National Bank Public Joint Stock Company	0.287	0.509	0.204	1
Bank Mellat	0.454	0.324	0.222	1	Bank AlBilad	0.241	0.315	0.444	1
Bank of Industry and Mine	0.389	0.417	0.194	1	Bank AlJazira JSC	0.241	0.324	0.435	1
Bank Saderat Iran	0.509	0.333	0.157	1	Banque Saudi Fransi JSC	0.296	0.352	0.352	1
Bank Tejarat	0.5	0.306	0.194	1	Islamic Development Bank	0.25	0.426	0.324	1
Bank Hapoalim BM	0.5	0.389	0.111	1	National Commercial Bank (The)	0.37	0.491	0.139	1
Bank Leumi Le Israel BM	0.5	0.38	0.12	1	Riyad Bank	0.25	0.583	0.167	1
FIBI Bank	0.481	0.315	0.204	1	Samba Financial Group	0.343	0.278	0.38	1
Israel Discount Bank LTD	0.472	0.343	0.185	1	Saudi British Bank JSC (The)	0.352	0.269	0.38	1
Mercantile Discount Bank Ltd.	0.204	0.352	0.444	1	Saudi Hollandi Bank	0.176	0.5	0.324	1
Mizrahi Tefahot Bank Ltd.	0.398	0.435	0.167	1	Saudi Investment Bank (The)	0.185	0.519	0.296	1
Arab Bank Group (Combined)	0.185	0.287	0.528	1	Abu Dhabi Commercial Bank	0.398	0.444	0.157	1
Arab Bank Plc	0.167	0.296	0.537	1	National Bank of Abu Dhabi	0.361	0.472	0.167	1
Ahli United Bank KSC	0.111	0.417	0.472	1	Abu Dhabi Islamic Bank - Public Joint Stock Co.	0.361	0.398	0.241	1
Al Ahli Bank of Kuwait (KSC)	0.111	0.491	0.398	1	Bank of Sharjah	0.213	0.25	0.537	1
Commercial Bank of Kuwait K.P.S.C. (The)	0.111	0.398	0.491	1	Commercial Bank of Dubai P.S.C.	0.389	0.204	0.407	1
Gulf Bank KSC (The)	0.12	0.361	0.519	1	Emirates NBD PJSC	0.454	0.361	0.185	1
	0.139	0.352	0.509	1	First Gulf Bank	0.231	0.324	0.444	1

(*continued on next page*)

Table A1 (*continued*)

DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum	DMU	Profit Sheet	Balance Sheet	Financial Health Indicators	Weight Sum
National Bank of Kuwait S.A.K.									
Kuwait Finance House	0.148	0.352	0.5	1	Mashreqbank PSC	0.278	0.352	0.37	1
Bank Audi SAL	0.185	0.241	0.574	1	National Bank of Fujairah PJSC	0.231	0.231	0.537	1
Bank of Beirut S.A.L.	0.12	0.343	0.537	1	Sharjah Islamic Bank	0.13	0.444	0.426	1
Bankmed, sal	0.139	0.306	0.556	1	Union National Bank	0.157	0.444	0.398	1

*The mean average weights for profit sheet, balance sheet, and financial health indicator structures are, respectively, 0.267, 0.366, and 0.367.

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