# Merger and Acquisitions in South African Banking: A Network DEA Model

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**Abstract**: Banking in South Africa is known for its small number of companies that operate as an oligopoly. This paper presents a strategic fit assessment of mergers and acquisitions (M&A) in South African banks. A network DEA (Data Envelopment Analysis) approach is adopted to compute the impact of contextual variables on several types of efficiency scores of the resulting virtual merged banks: global (merger), technical (learning), harmony (scope), and scale (size) efficiencies. The impact of contextual variables related to the origin of the bank and its type is tested by means of a set of several robust regressions to handle dependent variables bounded in 0 and 1: Tobit, Simplex, and Beta. The results reveal that bank type and origin impact virtual efficiency levels. However, the findings also show that harmony and scale effects are negligible due to the oligopolistic structure of banking in South Africa.

**JEL Classification:** C6, G21, G34,

**Keywords:** Banks; South Africa; Merger and Acquisitions; Network; DEA; Robust Regression Analysis.

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## 1. Introduction

The term “mergers and acquisitions” (M&A) refers to the process of merging or acquiring all or part of another company’s property rights. An M&A is carried out under certain conditions in order to obtain controlling rights (Song and Chu, 2006). A merger or acquisition is an important strategic move made by a company to improve its enterprise performance management. Successful mergers can produce many gains such as cost savings, increased profits, upscaling, and freeing up abundant resources (Johnes and Yu, 2008; Fried and Lovell, 1999; Weber and Dholakia, 2000; Halkos and Tzeremes, 2013; Peyrache, 2013). Consequently, numerous studies have been performed in many developed economies that examine the potential gains from mergers. However, to decrease the high failure rate of M&A activities, one of the critical steps that should be taken by a bidder company trying to identify suitable target companies prior to an M&A is to determine whether the prospective partner can offer synergies and the necessary relevant attributes to complement those of the acquiring company. The need to predict M&A outcomes has drawn the attention of many researchers (Dietrich and Sorensen, 1984; Pasiouras and Gaganis, 2007; Powell, 2001; Gale and Shapley, 1962), including those focused on efficiency measurement (Chow and Fung, 2012).

This research focuses on a strategic fit of M&A deals involving South African banks by using a network DEA (Data Envelopment Analysis) model variant as the cornerstone method to compute several efficiency indicators of virtually merged companies. The South African banking industry is unique for several reasons. In Africa, it is one of the largest and the most sophisticated. The South African banking industry compares favorably to that of advanced economies distinguishing South Africa from many other emerging economies. The global competitiveness report (2015-2016) ranked South Africa`s financial market development at $12^{th}$ position out of 140 countries surveyed. Since the dawn of the 2008/2009 global financial crisis, South African banks have been under pressure from rising operational cost emanating from increased regulation requirements and competition with the possible entrance of foreign banks (Ncube, 2009). Recently, a poor global economic outlook, commodity price fallout, and uncertainty of the domestic macroeconomic performance have posed downside risks to the economic growth of South

Africa. However, despite this general negative economic outlook of a challenging domestic and global economic climate, South African banks remain financially sound and profitable. One way to ensure sustainable profitability into the foreseeable future is to create larger, more efficient and productive banks through the strategy of mergers and acquisitions.

Despite the numerous studies focusing on banking efficiency and productivity using DEA (Berger and Humphrey, 1992; Berger and Humphrey, 1997; Fukuyama and Weber, 2009a, 2009b, 2010; Holod and Lewis, 2011; Sufian, 2010) and other stochastic frontier analyses (Baten and Kamil, 2011), a more systematic research approach to banks in African countries is still missing (O'Donnell and Westhnizen, 2002; Azam et al., 2004; Figueira et al., 2006; Kirkpatrick et al., 2008; Okeahalam, 2008; Ikhide, 2008; Kiyota, 2009; Assaf et al., 2012; Kebede and Wassie, 2013; Olson and Zoubi, 2011), thus indicating a literature gap. This situation contrasts with the extensive research that has been carried out on American banks (Berger et al., 1987; Bauer et al. 1993; Berger and Humphrey, 1997), on European banks (Barros et al., 2007; Kontolaimou and Tsekouras, 2010), Asian banks (Berger et al., 2009; Chen et al., 2005; Kumbhakar and Wang, 2005; Barros et al., 2010; Barros et al., 2012a), and even South American banks (Staub et al., 2010; Wanke and Barros, 2014). The exception is Wanke et al. (2016a) who focused on the dynamic slacks of Mozambican banks. Therefore, this research is innovative in this context because it adopts a network DEA approach to assess M&A in an African country characterized by an oligopolistic structure, which distorts banking competition to a certain extent (Apergis, 2015).

The motivations for the present research are as follows. Firstly, and justifying the present research, South Africa is one of the African countries that has been most favored by the commodity price boom of the last ten years with clear impacts on its economy (Hawthorne et al., 2005; Mboweni, 2007). Secondly, this paper builds upon previous studies related to banking efficiency by evaluating relative efficiency among virtual South African banks and their major drivers (Ncube, 2009; Maredza and Ikhide, 2013). To the best of our knowledge, this is the first time South African banks have been analyzed in terms of potential M&A in contrast to previous studies (Marcus, 2000; Agbloyor et al., 2012). Thirdly, the present analysis includes an assessment of the impact of the origin and the type of the bank in relation to the strategic fit of both bidder and target companies.

Thus, the purpose of this study is to assess the determinants of M&A within the context of South African banks based on business-related variables commonly found in the literature: bank type and origin. In order to achieve this objective, an efficiency analysis was developed using a network DEA (NDEA) model built upon Shi et al. (Forthcoming) and Gattoufi et al. (2014) where different M&A NDEA model efficiency estimates are computed first of all. They are related to the global effects of the M&A, which can be broken down into harmony (scope), learning (technical), and scale (size) effects. Next, a set of robust regression approaches such as Tobit, Simplex, and Beta is performed to assess the impact of such contextual variables on these efficiency measures. Researchers frequently face situations where they are interested in modelling proportions, percentages or values, such as efficiency scores, within the open interval (0; 1) and according to one or several covariates within the architecture of the regression (Wanke and Barros, 2016; Wanke et al., 2016c). The normality assumption is not supported for this type of variable, thus invalidating conclusions that might otherwise be obtained from these results. Asymmetry of the response variable and multicollinearity are two of the most frequent problems that the normal model cannot accommodate. In this situation, several alternatives have been developed, such as Beta regression that leverages the advantages of the general linear model and the simplex regression that is part of a more general class of models, i.e., dispersion models (López, 2013).

This paper is structured beginning with this introduction and then presents the contextual setting, which includes a description of the South African banks. The literature survey is then presented followed by the methodology section in which the M&A NDEA model is further discussed. Section 5 presents the data followed by the discussion of the results and the conclusion in Sections 6 and 7.

## 2. Contextual Setting

In the past decade, the South African banking industry has attracted a lot of interest from abroad with a significant number of bank branches and offices of foreign banks establishing their presence in the country (see Table 1). To date, the South African banking sector has a composition of 17 registered domestic banks, 15 branches of foreign banks, 40 representative offices of foreign banks, and 16 controlling companies (SARB, 2015). However, the banking industry is highly concentrated and dominated by the big five banks that together contributed to 89.2 percent to the total banking assets as at 31 December 2015 (SARB Supervision Report, 2015). The rest of the banks represented 3.5 percent while local branches of foreign banks accounted for 7.3 percent. Over the years, the number of banks have been declining, particularly domestic banks, mainly due to liquidation, mergers, or acquisitions. Table 2 shows the number of approval of local and foreign expansions by South African banking groups. The SARB supervision report (2015) noted that the most applications received in 2015 were from the five largest banking groups in South Africa.

Insert Table 1 Here

Insert Table 2 Here

## 3. Literature Review

There is a tradition of evaluating the efficiency of banks in the US and Europe (Berger and Humphrey, 1997; De Borger et al., 1998; Brandouy et al., 2010; Brissimis et al., 2010; Kerstens et al., 2011). A focus on African banking, however, is more restricted (Chen, 2005; Erasmus and Makina, 2014). Ikhide (2008) analyzed the efficiency of commercial banks in Namibia using the standard econometric frontier approach. Barros et al. (2014) analyzed the efficiency of Angola banks with a DEA B convexity model. Wanke et al. (2015) analyzed the efficiency of Angola banks with a DEA model using the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS). Wanke et al. (2016a) analyzed for the first time Mozambique banks with a DEA model. Barros et al. (2010) analyzed the efficiency of Angola banks with a Bayesian Stochastic frontier. Therefore, African banks have recently attracted more research. Following this approach, Poshakwale and Qian (2011) analyzed the competitiveness and efficiency of Egyptian banks. Zhao and Murinde (2011) analyzed bank deregulation in Nigeria. Mwega (2011) analyze the competitiveness of banking in Kenya. Mlambo and Ncube (2011) analyzed competition and efficiency in South Africa banks.

In South Africa, Okeahalam (2006) employed the Bayesian stochastic frontier approach to assess the production efficiency of 61 bank branches of one large South African bank in 9 provinces of the country. The author found productive efficiency of banks to be 83.1% suggesting that on average banks could reduce their costs by 16.9% without altering their output levels. Van der Westhuizen (2008) employed the Malmquist DEA approach to evaluate the scale, technical efficiency, and productivity changes of the top four South African banks. The results for scale and technical efficiency under both the input and output orientation were above 90%. The findings also showed that three banks operated on the increasing returns to scale region while one bank exhibited decreasing returns to scale. Ncube (2009) employed the parametric stochastic frontier approach to determine both cost and profit efficiency of four large and four small South African banks. The study concluded that South African banks were relatively better at controlling cost than generating profit as indicated by the lower profit efficiency score and a higher cost efficiency score. Maredza and Ikhide (2013) used a two-stage methodology framework to investigate the impact of the sub-prime financial crisis on efficiency and productivity of the big four South African commercial banks. The DEA based Hicks-Moorsteen total factor productivity (HMTFP) index approach was utilized. The censored Tobit model was applied in the second stage to examine the impact of environmental factors on generated bank efficiency scores. Other bank efficiency studies in South Africa include Okeahalam (2008), Okeahalam (2006), Oberholzer et al. (2010), Greenberg and Simbanegavi (2009), and Mlambo and Ncube (2011).

Therefore, as can be inferred from the literature review, this paper is innovative in this context by using an updated dataset of South African banks by adopting an NDEA approach to assess the different impacts of M&A. As a matter of fact, banks are looking for an optimal positioning of their activities on the market for converging to an optimal size. This explains their recourse to M&A to converge to that size. Thus, it seems that M&A is a form of alliances to raise the market share of banks subject to an M&A. In this context, Chaffai and Dietsch (1999) noted that an M&A enables banks to reduce their costs and improve their efficiencies at the allocative and productive levels. Indeed, according to the industrial economy theory, it is often assumed that the size is strongly linked to economies of scale. Actually, the size increase involves a lower unit cost due to the decrease in the mean fixed cost. In fact, according to Dietsch (1992), Chaffai (1998), Chaffai and Dietsch (1999), Chaffai and Dietsch (2000), and Sassenou (1992), only a critical size can minimize the unit production costs.

On the other hand, it is important to note that the voluntary nature of the M&A makes them more acceptable to the employed staff. Employee support for the M&A operations allow enhancing the labor productivity and overall efficiency. The aim of our empirical study is to detect the effect of the M&A on the performance of South African banks as well as on their sizes. Besides, and broadly speaking, we will try to find out to what extent the M&A could change the nature of banks, which includes their returns to scale. The NDEA model adopted here is based mainly on the conceptual framework for efficiency decomposition depicted by Bogetoft and Otto (2010).

Indeed, most of the benchmarking literature is concerned with evaluating the performance of individual firms, making the unit of analysis the firms. It is, however, also possible to evaluate the efficiency of a collection of firms and thus to evaluate whether or not there is the best possible industry structure or whether it would be better to merge some of the firms or split up others. The next paragraphs illustrate how such analyses can be done.

First, consider the possible impact of merging firms 1 and 2, which have used similar inputs to produce similar outputs (i.e., a horizontal merger). Let their present production be $(x^1, y^1)$ and $(x^2, y^2)$, respectively. It is not necessary that they use exactly the same input and output types because some of the dimensions of the $x$ and $y$ vectors can always be set to 0. If the two units become integrated but continue to operate as two independent entities, they will transform the vector of inputs $x^1 + x^2$ into the vector of outputs $y^1 + y^2$. To evaluate the potential efficiency gains from the merger, we can use the Farrell approach to measure the potential gains from merging firms 1 and 2:

$$E^{1+2} = \min\{E \in \mathbb{R}_+ | \ (E(x^1 + x^2), y^1 + y^2) \in T\}. \tag{1}$$

Here $E^{1+2}$ is the maximal proportional reduction in the aggregated inputs $x^1 + x^2$ that allows the production of the aggregated outputs $y^1 + y^2$. If $E^{1+2} < 1$, there are attainable savings via M&A. If $E^{1+2} > 1$, the merger is costly. A score of $E^{1+2} = 0.8$ would suggest that 20% of all inputs could be saved by integrating firms 1 and 2. Likewise, a score of $E^{1+2} = 1.3$ would suggest that integration would necessitate 30% more of all resources. We can use the same logic in evaluating merged entities as in evaluating individual entities. The larger the distance to the frontier, the more inefficient the merged firm is. Being inefficient represents a loss. On the other hand, being inefficient also suggests possibilities for improvement. Corporate synergy occurs when corporations, through their interactions, are able to produce more services with a given set of resources, or to produce a given set of services with less resources (Bogetoft and Otto, 2010). The synergies from a merger can be captured by the increase in improvement potential when operations are moved from independent to joint ones. Formally, a radial Farrell like input based measure of the potential overall gains from merging the H-firms is calculated as follows:

$$E^H = \min\{E \in \mathbb{R}_+ | (E \textstyle\sum_{k \in H} x^k, \sum_{k \in H} y^k) \in T\} \tag{2}$$

Such that $E^H$ is the maximal proportional reduction in the aggregated inputs $\sum_{k \in H} x^k$ that allows the production of the aggregated output profile $\sum_{k \in H} y^k$. This measure of the potential overall merger gain from a merger encompasses several effects. They can be broken down into technical or learning efficiency, scale or size efficiency, and harmony or scope efficiency. These underlying concepts are briefly presented in the next paragraphs before introducing the NDEA model presented in this research in the next Section. The first efficiency source is related to technical or learning effects, which is often associated with the ability to adjust to best practices. Consider a horizontal merger of A and B as illustrated in 1.

Insert Figure 1 Here

If the organizations merge but operate as they have done in the past, one can see that there are considerable saving potentials, as represented by the distance of A + B to the production possibility set. One can argue, however, that a considerable share of these potential gains were also available on an individual basis if the individual entities had optimized their businesses as represented by the A* and B*. If businesses A* and B* integrate, this would lead to the aggregate A*+B*, where the potential savings are considerably less than in A + B. This is often referred to as a learning or technical efficiency effect.

Another source of potential savings, called the scope or harmony effect, is associated with the mix of resources used and the mix of services provided. To illustrate this, consider two firms with the same levels of output and input requirements corresponding to the $L(x)$ curve as illustrated in Fig. 2.

Insert Figure 2 Here

One can see that A is quite Input 1 intensive while B is Input 2 intensive. It is clear, however, that neither of the factor mixes may be optimal—at least they cannot be optimal simultaneously. As a matter of fact, the rate of substitution between Input 1 and Input 2 is different in the two firms. In A, a large amount of Input 1 is required to compensate for the loss of extra Input 2, while in B many Input 2 units are required to compensate the loss of one Input 1. This means that there are possibilities to improve by moving some Input 2 from B to A and some Input 1 from A to B. If we move the factors as indicated with the dashed lines, both firms end up at (A+B)/2. There are different possibilities for each of the firms to save. Of course, similar possibilities exist on the output side, such as by moving some obligations from A to B and other obligations from B to A, different service combinations could be achieved that require less resources to produce or that match the existing factor combinations in a better way.

In addition to these effects, a merger will also have an impact on the scale of the operations. This leads to the so-called scale or size effect. The three effects above, the learning, harmony, and size effects, determine the combined effect of a merger. Using the above notions of learning LE, harmony HA, and size SI effects, it follows that the merger efficiency E can be estimated as:

$$E^H = LE^H \cdot HA^H \cdot SI^H. \quad (3)$$

It is important to observe that, if the technology is convex, the harmony effect is always weakly positive with $HA \leq 1$, while the size effect may or may not favor a merger in a convex technology. In a convex technology that also satisfies the assumption of constant or increasing returns to scale, the size effect is always positive (Bogetoft and Otto, 2010).

## 4. Background on DEA models applied to M&A

DEA is a non-parametric model first introduced by Charnes et al. (1978). Based on linear programming (LP), it is used to address the problem of calculating relative efficiency for a group of DMUs by using a weighted measure of multiples inputs and outputs (Hou et al., 2014; Wanke, 2012; Kruger et al., 2002). Consider a set of $n$ observations on the DMUs (Decision Making Units). Each observation, $DMU_j$ ( $j = 1,..., n$ ) uses $m$ inputs $x_{ij}$ ( $i = 1,..., m$ ) to produce $s$ outputs $y_{rj}$ ( $r = 1,..., s$ ). $DMU_o$ represents one of the $n$ DMUs under evaluation, and $x_{io}$ and $y_{ro}$ are the $i^{th}$ input and $r^{th}$ output for $DMU_o$, respectively. Model (1) presents the envelopment modelling for the variable return-to-scale frontier types where $\varepsilon$ is a non-Archimedean element and $s_i^-$ and $s_r^+$ account, respectively, for the input and output slack variables (Zhu, 2003; Bazargan and Vasigh, 2003).

$$
\begin{aligned}
&\max \phi - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
&s.t. \\
&\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{io}, \forall i \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \phi y_{ro}, \forall r \\
&\lambda_j \geq 0, \forall j \\
&\sum_{j=1}^{n} \lambda_j = 1
\end{aligned}
\qquad (4)
$$

Recently, DEA has frequently been applied to M&A. Numerous studies aimed at analyzing the efficiency of an M&A's gains have been conducted. For example, Bogetoft and Wang (2005) built economic production models using a DEA approach to estimate the potential efficiency gains from mergers. Lozano and Villa (2011) also proposed a DEA-based approach to estimate the efficiency gains resulting from a merger. In addition, some studies (Halkos and Tzeremes, 2013; Peyrache, 2013; Lo et al., 2001; Liu et al., 2007) also applied DEA in an M&A context. DEA is also a useful tool when judging a firm's size in an M&A context. Researchers such as Wu et al. (2011) established a greedy algorithm based on a DEA approach. The aim was to choose the proper candidate target company for a bidding company from the perspective of the firm's size when considering a merger and acquisition. Lin et al. (2008) proposed a framework consisting of both efficiency and risk analyses. The framework allows the simulation of virtual mergers and hence the determination of the optimal number of firms in the industry by using a DEA approach. However, an empirical study (Chapin and Schmidt, 1999; Harris et al., 2000) found that efficiency gains do not coincide with a return to scale in most cases. Therefore, the fit of an M&A should not only focus on efficiency gains, but also prevent the M&A from producing an oversized organization.

It is worth mentioning, however, that all above approaches treat each DMU as a "black box" in M&As, but ignore the internal structure of the production process. In many real applications, DMUs may contain several production processes before achieving final outputs (Kao and Hwang, 2008; Zha and Liang, 2010; Zhou et al., 2013). Recently, Lozano and Villa (2010) estimated the potential merger gains of two DMUs with parallel structures and found that a hypothetically merged DMU combined by two DMUs could have potential cost savings. Wu et al. (2011) estimated the potential gains of banks in the dynamic network from the revenue perspective. This approach is extended by Wu and Birge (2012) to measure the potential merger gains of banks in serial-chain structures. The two approaches extended the pure merger efficiency decomposition to a two-stage production system after individual technical inefficiency is eliminated, but they didn't evaluate the overall merger efficiency. Because the two approaches are from the output perspective, they avoid the problem of the hypothetical DMU's outputs surpassing the production possibility set (Shi et al., Forthcoming; Gattoufi et al., 2014).

On the other hand, in many real mergers, the performance goal is set to minimize the total cost while keeping outputs at current levels. For example, Chase Manhattan Bank and Hurray Bank merged in 1995 with the purpose of cutting operational cost as the two banks were near in geography and similar in operating business. After merger, the merged bank has saved the expense of US$ 1.5 billion including shutting down overlapped branches and laying off staff. Afterwards, the Chase Manhattan Bank acquired Hambrecht & Quist in 1999 and Robert Fleming and Beacom in 2000 for the same input-saving purpose. Therefore, it is necessary to evaluate the potential merger gains from the input perspective. But a problem arises that the merged DMU may surpass the frontier containing original DMUs. This might be one reason that not many studies considered evaluating potential merger gains from the input perspective (Shi et al., forthcoming; Gattoufi et al., 2014).

In this paper we develop a two-stage input-oriented efficiency model by minimizing the inputs of this new hypothetical DMU while maintaining its outputs at sum of the pre-merger level of potential mergers. The model developed here departs from the researches of Shi et al. (Forthcoming) and Gattoufi et al. (2014), although in the analysis performed in this research, unit costs and prices are not considered in the input and output vectors. In the approach developed here, differently from previous papers, the constant returns to scale (CRS) were considered as the underlying assumption, assuring, therefore, that the hypothetical merged DMU does not surpass the original production possibility set. Besides, an initial approach for selecting target and bidder companies based on efficient and non-efficient companies was adopted here. Then, similarly to previous researches that apply the efficiency decomposition principles found in Bogetoft and Otto (2010), we extend this to a two-stage structure to estimate the merger efficiency of a hypothetical DMU for the overall system and both sub-systems, and decompose the merger efficiency into technical, harmony, and scale efficiencies for the entire system and both sub-systems.

Suppose there are $n$ companies in the market, which can be treated as $n$ DMUs to be evaluated. The $n$ DMUs are divided into two groups according to the value of their efficiency, which is determined by model (4). If efficiency is equal to 1, the $DMU_j$ falls into the bidder group, thus E={$DMU_1$, $DMU_2$, …, $DMU_t$}; otherwise, it falls into the target group, thus S={$DMU_1$, $DMU_2$, …, $DMU_h$}. In addition, t+h=N, $E \cap S = \emptyset$. The combination between an arbitrary bidding company, say, $DMU_d$, $d \in \{1, \dots, t\}$, and an arbitrary target company, say, $\text{DMU}_\text{k}$, $k \in \{1, \ldots, h\}$, is regarded as an M&A fit scheme or a virtual company resultant from a possible M&A, say, $\text{DMU}_{\text{d\&k}}$, which belongs to $\Phi_K$. Once these two groups are assigned, the proper formulations for the M&A NDEA model can be presented next.

In order to measure the potential gains from mergers in the input perspective, the input-oriented efficiencies for each original DMU and hypothetical DMU should be computed. The minimal input vector of each original DMU while maintaining the output vector at the current level can be calculated by $I(Y) = \min\{X' | (X', Y) \in T\}$ (see more details in Cooper et al. 2007). Similarly, the minimum input vector for each hypothetical DMU can be calculated by:

$$I_J(Y_J) = \min\{X'_J | (X'_J, Y_J) \in M^K\}, J \in \Phi_K \tag{5}$$

Based on the estimated input vector, the efficiencies of original DMUs and hypothetical DMUs can be computed. The input-oriented efficiency of $DMU_{j0}$ producing $y_{j0}$ is calculated by:

$$E_{j0} = I(y_{j0})/x_o \tag{6}$$

Where $x_{jo}$ is the actual input vector of $DMU_{j0}$ and $I(y_{j0})$ is calculated by $I(y_{j0}) = \min\{x|(x_{j0}, y_{j0}) \in T\}$. Similarly, the merger efficiency of hypothetical $DMU_J$ from the input-oriented perspective is defined as a ratio between the minimum input vector and the actual input vector of producing the output $Y_J$ as follows:

$$E^J = I(Y_J)/X_J \tag{7}$$

As proposed by Bogetoft and Wang (2005), the merger efficiency $E^J$ can be decomposed into technical or learning efficiency ($LE^J$), harmony or scope efficiency ($HA^J$), and scale efficiency ($SI^J$) such that:

$$E^J = LE^J * HA^J * SI^J \tag{8}$$

The calculation of technical or learning efficiency and pure merger efficiency can be summarized (see details in Bogetoft and Otto, 2010) as follows:

$$LE^J = \sum_{j \in \Psi_K^J} I(Y_j)/X_J , J \in \Phi_K \tag{9}$$

$$E^{J*} = \frac{I(Y_J)}{\sum_{j \in \Psi_K^J} C(Y_j)} , J \in \Phi_K \tag{10}$$

Where $E^{J*}$ is the maximal reduction in the aggregated inputs of technically efficient DMUs in $j \in \Psi_K^J$ that allows the production of the output $Y_J$. Hence we can reduce inputs by merger if $E^{J*} < 1$. The harmony and scale efficiencies could be calculated as follows:

$$HA^J = \frac{I(Y_J/N)}{\sum_{j \in J} I(Y_j)/N} , J \in \Phi_K \tag{11}$$

$$SI^J = \frac{I(Y_J)}{K * I(Y_J/N)} , J \in \Phi_K \tag{12}$$

As these expressions show, the technical effect (learning effect) $LE^J$ measures the reduction in inputs if each DMU learns best practices but remains an independent entity. The harmony effect $HA^J$ measures the minimal input vector necessary for the average output vector compared to the average input vector corrected for individual learning. The scale effect $SI^J$ measures the effect of operating at the full (integrated) scale compared to the average scale of candidate DMUs. If $HA^J < 1 (SI^J < 1)$, the harmony effect (scale effect) favors the merger. If $HA^J > 1 (SI^J > 1)$, the harmony effect (scale effect) works against the merger. Decomposing the potential gains is important because a full-scale merger is typically not the only option available for DMUs, and alternative organizational changes may be easier to implement. The above approaches could be extended to systems composed of two processes connected in series, which are further discussed next.

Consider a generic two-stage process as shown in Fig. 3 for each set of n DMUs. We assume each $DMU_j (j = 1, \dots, n)$ has $m$ inputs $x_{ij} (i = 1, \dots, m)$ to sub-system 1 and $D$ outputs $z_{dj} (1, \dots, D)$ from that sub-system. These D outputs then become inputs to sub-system 2 to generate the final outputs $y_{rj} (r = 1, \dots, s)$, hence $z_{dj} (d = 1, \dots, D)$ behaving as intermediate measures.

Insert Figure 3 Here.

Again, each hypothetical $DMU_J (J \in \Phi_K)$ is defined as the merger of a set of K candidate DMUs with a two-stage production process in set $\Psi_K^J$, $\Psi_K^J \subset \Theta$. The two-stage input-oriented efficiency model to estimate the minimum input vector of the hypothetical DMUs is presented next. Under the CRS assumption, this minimum input vector for the hypothetical $DMU_{J_o}$ with a two-stage production process can be computed as follows:

$$
\begin{aligned}
& \min \sum_{i=1}^{m} x'_{iJ_o} \\
s.t. \; & \sum_{j \in \Theta} \lambda_j x_{ij} + \sum_{J \in \Phi_K} \lambda_J x_{iJ} \le x'_{iJ_o}, \qquad i = 1, \dots m \\
& \sum_{j \in \Theta} \mu_j y_{rj} + \sum_{J \in \Phi_K} \mu_J y_{rJ} \ge y_{rJ_o}, \qquad r = 1, \dots s \\
& \sum_{j \in \Theta} \lambda_j z_{dj} + \sum_{J \in \Phi_K} \lambda_J z_{dJ} \ge \tilde{z}_{dJ_o}, \qquad d = 1, \dots D \\
& \sum_{j \in \Theta} \mu_j z_{dj} + \sum_{J \in \Phi_K} \mu_J z_{dJ} \ge \tilde{z}_{dJ_o}, \qquad d = 1, \dots D \\
& \tilde{z}_{dJ_o} \ge 0, \qquad d = 1, \dots, D \\
& \lambda_j, \mu_j \ge 0, \qquad j = 1, \dots, n \\
& \lambda_J, \mu_J \ge 0, \qquad J = 1, \dots, N
\end{aligned}
\tag{13}
$$

where $\left(x'_{iJ_o}, \tilde{z}_{dJ_o}, \lambda_j, \lambda_J, \mu_j, \mu_J\right)$ are decision variables. The objective of this model is to minimize the input vector $\sum_{i=1}^{m} x'_{iJ_o}$ of each hypothetical $DMU_{J_o}$ while maintaining the final output vector $Y_{J_o}$ in sub-system 2 at the current level. Suppose that the optimal solution to the model (13) is $\left(x'^{*}_{iJ_o} \tilde{z}^{*}_{dJ_o}, \lambda_j^*, \lambda_J^*, \mu_j^*, \mu_J^*\right)$. This being the case, the merger efficiencies of the hypothetical $DMU_J$ could be calculated in a manner as previously discussed. Hence, the merger efficiency of $DMU_{J_o}$ for the overall system and both sub-systems are defined as (Shi et al., Forthcoming; Gattoufi et al., 2014):

$$
\begin{aligned}
E^{J_o} &= \frac{\sum_{i=1}^{m} x'^{*}_{iJ_o} + \sum_{d=1}^{D} \tilde{z}^{*}_{dJ_o}}{\sum_{i=1}^{m} x_{iJ_o} + \sum_{d=1}^{D} z_{dJ_o}} \\
E_1^{J_o} &= \frac{\sum_{i=1}^{m} x'^{*}_{iJ_o}}{\sum_{i=1}^{m} x_{iJ_o}} \\
E_{\mathbf{2}}^{J_o} &= \frac{\sum_{d=1}^{D} \tilde{z}^{*}_{dJ_o}}{\sum_{d=1}^{D} z_{dJ_o}}
\end{aligned}
\tag{14}
$$

where the denominators are obtained from the optimal values of model (13). The decomposition of the overall merger efficiency for the whole system and both sub-systems into technical efficiency, harmony, and scale efficiency is addressed by the following model. The minimum input vector of $DMU_{j0}$ producing the final outputs at the current level for each DMU individually could be estimated as follows:

$$
\begin{aligned}
&\min \sum_{i=1}^{m} t_{ij0} \\
&s.t.\ \sum_{j\in\Theta} \lambda_j x_{ij} + \sum_{J\in\Phi_K} \lambda_J x_{iJ} \le t_{ij0}\,, \qquad i = 1, \dots m \\
&\sum_{j\in\Theta} \mu_j y_{rj} + \sum_{J\in\Phi_K} \mu_J y_{rJ} \ge y_{rj0}\,, \qquad r = 1, \dots s \\
&\sum_{j\in\Theta} \lambda_j z_{dj} + \sum_{J\in\Phi_K} \lambda_J z_{dJ} \ge p_{dj0}\,, \qquad d = 1, \dots D \\
&\sum_{j\in\Theta} \mu_j z_{dj} + \sum_{J\in\Phi_K} \mu_J z_{dJ} \ge p_{dj0}\,, \qquad d = 1, \dots D \\
&\lambda_j, \mu_j \ge 0, \qquad j = 1, \dots, n \\
&\lambda_J, \mu_J \ge 0, \qquad J = 1, \dots, N
\end{aligned}
\tag{15}
$$

where $\left(\lambda_j, \mu_j, \lambda_J, \mu_J, p_{dj0}, t_{dj0}\right)$ are the decision variables. Again, the objective of this model is to minimize the input vector of $DMU_{j0}$ while maintaining the final output vector $Y_{j0}$ at the current level. The CRS technical efficiencies of $DMU_{j0}$ for the overall system are determined as ratios of the minimum weighted sum of inputs for $DMU_{j0}$ to the actual weighted sum of inputs. The technical efficiency of DEA efficiency of $DMU_J$ for the overall system and both sub-systems are defined as (Shi et al., Forthcoming; Gattoufi et al., 2014):

:

$$
\begin{aligned}
TE^{J_o} &= \frac{\sum_{j\in\Psi_K^{J_0}} \sum_{i=1}^{m} t_{ij}^{*} + \sum_{d=1}^{D} \sum_{j\in\Psi_K^{J}} p_{dj}^{*}}{\sum_{i=1}^{m} x_{iJ_o} + \sum_{d=1}^{D} z_{dJ_o}} \\
TE_1^{J_o} &= \frac{\sum_{j\in\Psi_K^{J_0}} \sum_{i=1}^{m} t_{ij}^{*}}{\sum_{i=1}^{m} x_{iJ_o}} \\
TE_2^{J_o} &= \frac{\sum_{d=1}^{D} \sum_{j\in\Psi_K^{J}} p_{dj}^{*}}{\sum_{d=1}^{D} z_{dJ_o}}
\end{aligned}
\tag{16}
$$

The minimum input vector of producing the average of the $N$ individually technical efficient candidate DMUs could be estimated in the following model:

$$
\begin{aligned}
&\min \sum_{i=1}^{m} h_{iJ0} \\
&s.t.\ \sum_{j\in\Theta} \lambda_j x_{ij} + \sum_{J\in\Phi_K} \lambda_J x_{iJ} \le h_{iJ0}\,, \qquad i = 1,\dots m \\
&\sum_{j\in\Theta} \lambda_j z_{dj} + \sum_{J\in\Phi_K} \lambda_J z_{dJ} \ge f_{dj}\,, \qquad d = 1,\dots D \\
&\sum_{j\in\Theta} \mu_j z_{dj} + \sum_{J\in\Phi_K} \mu_J z_{dJ} \ge f_{dj}\,, \qquad d = 1,\dots D \\
&\sum_{j\in\Theta} \mu_j y_{rj} + \sum_{J\in\Phi_K} \mu_J y_{rJ} \ge \overline{y_{rJ0}}\,, \qquad r = 1,\dots s \\
&\lambda_j, \mu_j \ge 0, \qquad j = 1,\dots,n \\
&\lambda_J, \mu_J \ge 0, \qquad J = 1,\dots,N
\end{aligned}
\tag{17}
$$

where $h_{iJ0}$ is the potential minimum input vector while maintaining the average of the output bundle in sub-system 2 at the current level. Model (20) minimizes the weighted sum of inputs for $DMU_{J0}$. Thus, as previously discussed, the harmony efficiencies could be obtained as:

$$
\begin{aligned}
HA^{J_o} &= \frac{\sum_{i=1}^{m} h^*{}_{iJ_o} + \sum_{d=1}^{D} f^*{}_{dJ_o}}{\frac{1}{N}\sum_{j\in\Psi_K^{J_0}} \sum_{i=1}^{m} t_{ij}^* + \frac{1}{N}\sum_{d=1}^{D} \sum_{j\in\Psi_K^{J_0}} p_{dj}^*} \\
HA_1^{J_o} &= \frac{\sum_{i=1}^{m} h^*{}_{iJ_o}}{\frac{1}{N}\sum_{j\in\Psi_K^{J_0}} \sum_{i=1}^{m} t_{ij}^*} \\
HA_{\mathbf{2}}^{J_o} &= \frac{\sum_{d=1}^{D} f^*{}_{dJ_o}}{\frac{1}{N}\sum_{d=1}^{D} \sum_{j\in\Psi_K^{J_0}} p_{dj}^*}
\end{aligned}
\tag{18}
$$

where the denominator is the optimal solutions of model (15) and the numerator is the optimal solutions of model (17). Lastly, the potential gains from scale effects can be obtained by calculating $SI^{J0}$ that measures the inputs for operating at the full (integrated) scale compared to the average scale of the original entities in a two-stage production process. Hence, the scale efficiency can be defined as follows (Shi et al., Forthcoming; Gattoufi et al., 2014):

$$SI^{J_o} = \frac{E^{*J0}}{HA^{J0}} = \frac{\sum_{i=1}^{m} x'^{*}_{iJ_o} + \sum_{d=1}^{D} \tilde{z}^{*}_{dJ_o}}{N\sum_{i=1}^{m} h^{*}{}_{iJ_o} + N\sum_{d=1}^{D} f^{*}{}_{dJ_o}}$$

$$SI_1^{J_o} = \frac{E_1^{*J0}}{HA_1^{J0}} = \frac{\sum_{i=1}^{m} x'^{*}_{iJ_o}}{N\sum_{i=1}^{m} h^{*}{}_{iJ_o}} \tag{19}$$

$$SI_2^{J_o} = \frac{E_2^{*J0}}{HA_2^{J0}} = \frac{\sum_{d=1}^{D} w_d \tilde{z}^{*}_{dJ_o}}{N\sum_{d=1}^{D} f^{*}{}_{dJ_o}}$$

Equation (19) presents the decomposition of the overall merger efficiency into overall technical efficiency, overall harmony efficiency, and overall scale efficiency. It is also very important to decompose these efficiencies to both sub-systems.

## 5. Data and efficiency assessment

The data on South African banks was obtained from Bankscope for the period 2003 to 2012. Thus, the final sample size of 90 units involves the combination of 9 banks for a period of 10 years. The choice of inputs and outputs is perhaps the most important task in employing DEA to measure the relative efficiency of the DMUs. Two approaches are widely used to identify a bank's inputs and outputs: the production approach and the intermediation approach (e.g. Sherman and Gold, 1985; Aly et al., 1990; Yue, 1992; Miller and Noulas, 1996; Favero and Pepi, 1995; Sealey and Lindley, 1977; Berger and Humphrey, 1992; Barros et al., 2014). Under the production approach, banks are treated as a firm to produce loans, deposits, and other assets by employing labor and capital. However, under the intermediation approach, banks are considered financial intermediaries that transform deposits, purchase funds, and labor into loans and other assets. More specifically, deposits are treated as an output under the production approach and an input under the intermediation approach. In this research, both approaches are used in a complimentary fashion in the network productive structure of South African baking, as is further detailed.

The inputs and the outputs considered were chosen not only because they were commonly found in the literature review, but also in accordance with the availability of data regarding physical and monetary productive resources. They also reflect the nature of the two-stage productive structure for banking under the production and the intermediation approaches, analogously as what was depicted in Wanke and Barros (2014). In stage 1, called “Production Approach”, employees, fixed assets, and operational expenses are minimized to attain a certain level of deposits and loans. Simultaneously, in stage 2, called “Intermediation Approach”, loans and deposits are also minimized to attain a certain level of productive outputs such as interest and non-interest income. Monetary inputs and outputs used in this research are expressed in current millions of South African Rand adjusted by its annual inflation. Their descriptive statistics of the inputs, outputs, and the intermediate variables used in the M&A NDEA model are presented in Table 3. In addition to these inputs and outputs, it should be noted that contextual, business-related variables such as the linear and the squared trend components and whether the bank is commercial (1 = yes / 0 = no) and local (1 = yes / 0 = no) were also collected. The idea is to control the computed efficiencies for these exogenous variables. Their descriptive statistics are also presented in Table 3.

Insert Table 3 Here

**6. Results and Discussion**

Initially, traditional DEA CCR estimates revealed the existence of 22 efficient companies from 2003 to 2012, which were classified as bidders. Furthermore, 67 companies from 2003 to 2012, with efficiency levels lower than one, were classified as targets. Therefore, the total number of possible M&A fit schemes (virtual companies) found in this research is 1474 (22*67). Readers should note that M&As were considered valid only if they would have occurred in the same year for both target and bidder companies. Their efficiency estimates are given in Fig. 4 using the model presented in Section 4. A number of conclusions can be drawn from a quick inspection on this figure with respect to the South African banking industry. First of all, due to the oligopolistic nature of this sector, harmony (scope) and scale (size) effects tend to be neutral in the overall and in both productive stages, that is, concentrated in 1. However, a resulting merger led to an oversized virtual company (Investec & ABSA in 2012). One possible explanation for this effect is the fact that ABSA and Investec banks are among the five largest banks in South

Africa in terms of their balance sheet asset size. It is therefore highly expected that the resultant merged bank would exceed the minimum efficient scale resulting in diseconomies of scale. On the other hand, the harmony effects for the overall and the two productive stages are not upwards biased like those found in the size effect. As a matter of fact, they are distributed around 1 despite the strong concentration in this neutral efficiency. This may suggest that the contextual variables related to bank type or origin may affect the productive scope. More precisely, ABSA & FNB (1.12), ABSA & Nedbank (0.95), ABSA & Standard (1.12), ABSA & Capitec (1.29), Sasfin Bank & Investec (0.99), Sasfin Bank & TEBA/UBANK (0.77), Investec & FNB (1.11), Investec & Nedbank (0.85), Investec & Standard (1.03), Investec & TEBA/UBANK (0.98), Investec & Capitec (0.97), Investec & ABSA (1.05), Investec & African Bank (0.86), TEBA/UBANK & Capitec (0.96), TEBA/UBANK & African Bank (0.83) are the resulting virtual companies with gains (efficiencies lower than one) or diseconomies (efficiencies higher than one) in harmony or scope efficiency. The majority of mergers involving larger banks appear to be associated with diseconomies of scale while mergers involving smaller banks exhibited economies of scale (Mertens and Urga, 2001). This is also consistent with Athanasoglou and Brissimis (2004) who found evidence of post-merger diseconomies of scale in larger banks and economies of scale for medium banks.

Insert Fig. 4 Here

Second, it is possible to affirm that the vast majority of the M&As analyzed in the South African banking industry are beneficial not only in terms of the overall merger effect, but also with respect to the technical efficiency effects. Potential gains derived from M&A are higher in stage 1 (production approach) and lower in stage 2 (intermediation approach), thus suggesting that it is possible to reduce employees, fixed assets, and operational expenses proportionally more than the expected reduction in the loans and deposits, considering a given level of interest and the non-interest income. This is in line with the synergistic effect of M&A, as expected in the banking industry, because it is common for banks to lay off personnel and fixed assets while increasing the base of loans and deposits.

Overall and network efficiency scores were regressed against contextual variables using Tobit regression (Wanke et al., 2016a) and cross-checked with Beta and Simplex regression such as described in Wanke et al. (2016b). Contextual variables were adjusted to reflect similarities and dissimilarities in merged companies. All regressions agree in sign when significant results below 0.05 occur, which are identified in bold. Results indicate that merger gains tend to be higher when both banks are local and lower when both banks are commercial. These results suggest that local banks are more attuned to South African banking regulation than their foreign counterparts are. Besides, these savings derived from mergers appear to be decreasing over the course of the years, thus indicating that the opportunity from learning from M&A is getting smaller, possibly due to similar managerial practices and widespread diffusion of similar information technologies that close the productive gap between different institutions. These results are in accordance with Marcus (2000) who states that the gains of a merger may deteriorate even if there are no significant operational problems. She argues that the complexity of unifying cultures, working methods, and systems may cause some inconvenience even to customers. Perhaps, on the other hand, this decrease in post-merger gains over the years may not have any significant relation to the banks under study, but merely reflect the catastrophic effect of the global financial crisis of 2007/2008 and the global economic recession that followed. Significant gains in size efficiency appear to be marginal and are related to both commercial and local banks. On the other hand, significant gains in harmony (scope) tend to be substantial when both banks are local and to be smaller when both banks are commercial. Moreover, a merger between a commercial bank and investment bank would present a corporate customer with the convenience of a one-stop shop offering both commercial and investment products (Berger and Humphrey, 1992). Once again, these results reflect the oligopolistic nature of the market where it is very difficult to capture scale economies from merged operations with foreign institutions. Besides, as regards the scope of operations, not only the protective nature of the market favors the merger of local institutions to the detriment of foreign ones, but also when investment and commercial banks are merged due to strong market regulations with regards to their respective niches. Higher gains of scope efficiency for mergers between local banks is in line with the home field advantage hypothesis as proposed by Berger and Humphrey (1992) and Liao (2010). The authors argue that in comparison with foreign banks, local banks have an advantage in terms of asset size, market share, language, culture, and regulations.

The implications of these results are related to the fact that efficient M&A emerges when different types of banks from local origin structures take part in this process simultaneously, although the possibility of learning from such mergers are decreasing over the course of time. Gains are expected to be concentrated proportionally more in the production approach or in the first stage, rather than on the intermediation approach or the second stage.

Insert Table 4 Here.

## 7. Conclusion

This paper presents an analysis of the efficiency of South African banks using an M&A NDEA model and a robust regression approach to handle efficiency scores bounded within 0 and 1. M&A NDEA enables the efficiency of a virtual bank to be assessed, not only in overall terms, but also with respect to the two productive stages that reflect the production and the intermediation approaches in banking, structured in a complimentary fashion. It thus makes it possible to identify the optimal strategic fit between two possible merger candidates. Based on the set of Tobit, Beta, and Simplex regression results, the drivers of virtual efficiency are bank type, bank origin, and trend. However, given the oligopolistic nature of its banking industry, M&A involving South African banks can easily lead to situations where the new virtual company will face limited opportunities for learning. This being the case, a greater emphasis should be given to merging commercial banks with investment ones and vice-versa, focusing on their local origin. Further research is necessary to confirm these results, especially those related to the origin of the bank. Other regions around the globe should also be the object of future studies. However, we also underscore the fact that a merger should not only be evaluated based on the benefits to the bidder and target bank, but should also promote the soundness and stability of the banking sector as a whole (Marcus, 2000). This is especially important given the concentrated nature of South African banking and for that reason regulation in South Africa maintains a tough stance on mergers involving two or more large banks.

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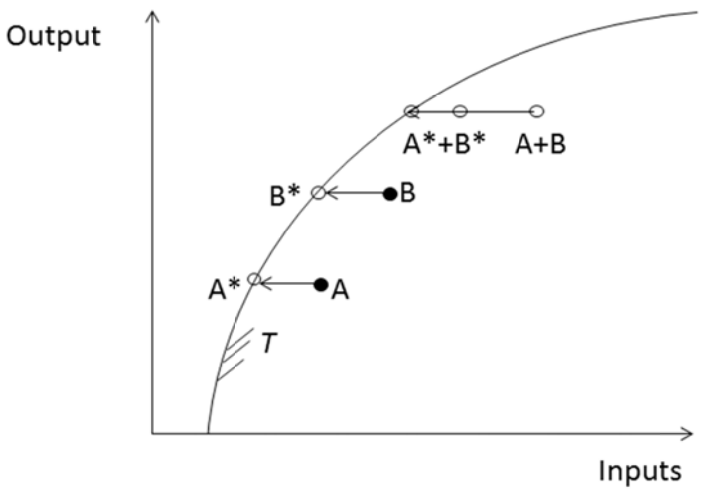


**Fig. 1**. Learning or technical efficiency effect

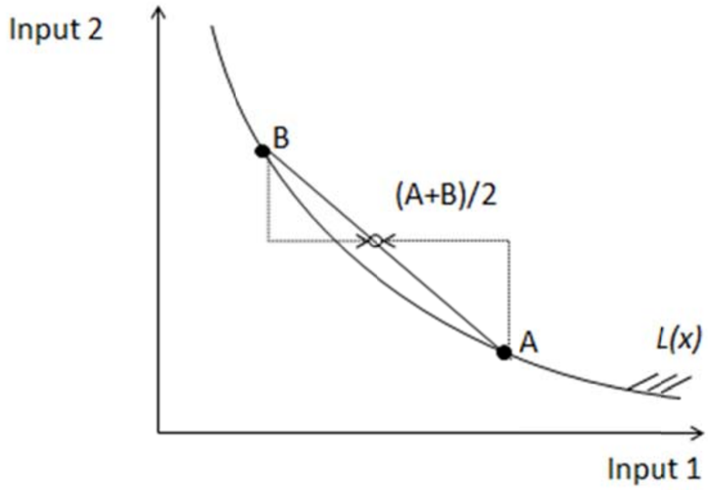


**Fig. 2**. Harmony or scope effect

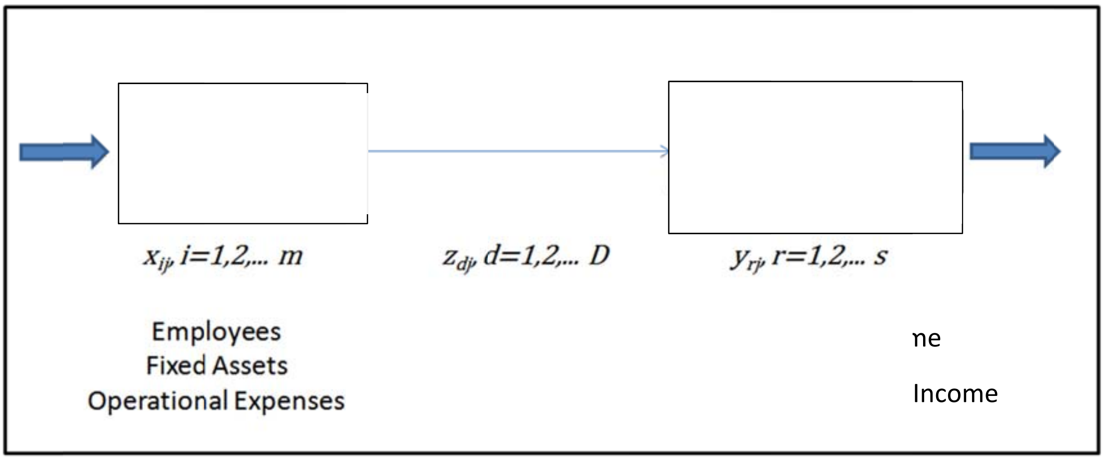


**Fig. 3.** Two-stage production process for South African banking industry

**Table 1.** South African Banking Sector: Number of Banks Registered (2006 – 2015)

| | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Domestic Banks** | 19 | 19 | 19 | 18 | 17 | 17 | 17 | 17 | 17 | 17 |
| **Local Branches of Foreign banks** | 14 | 14 | 14 | 13 | 13 | 12 | 14 | 14 | 14 | 15 |
| **Representative offices** | 43 | 46 | 43 | 42 | 41 | 43 | 41 | 43 | 40 | 40 |
| **Controlling Companies** | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 | 16 |

*Source: SARB Annual Report (2015).*

**Table 2.** Local & Foreign expansions by South African Banking Groups (2006 – 2015)

| | **2006** | **2007** | **2008** | **2009** | **2010** | **2011** | **2012** | **2013** | **2014** | **2015** |
|---|---|---|---|---|---|---|---|---|---|---|
| **Local** | 16 | 12 | 15 | 10 | 16 | 19 | 12 | 19 | 13 | 40 |
| **Foreign** | 8 | 25 | 19 | 26 | 22 | 27 | 14 | 21 | 25 | 19 |
| **Total** | **24** | **37** | **34** | **36** | **38** | **46** | **26** | **40** | **38** | **59** |

*Source: SARB Annual Report (2015).*

**Table 3**: Descriptive statistics for inputs, outputs, and contextual variables

| Variables | | | Min | Max | Mean | SD | CV |
|---|---|---|---|---|---|---|---|
| Inputs & Outputs | X | Employees | 1174.000 | 75756 | 29958.447 | 20106.398 | 0.671 |
| | | Fixed Assets | 88.100 | 21711 | 5048.577 | 4709.184 | 0.933 |
| | | Operational Expenses | 585.100 | 137220 | 46934.192 | 31914.863 | 0.680 |
| | Y | Interest Income | 330.800 | 140783 | 45333.383 | 31881.386 | 0.703 |
| | | Non-Interest Income | 144.000 | 49484 | 16146.478 | 11317.315 | 0.701 |
| | Z | Deposits | 317.400 | 1164323 | 386833.717 | 282822.271 | 0.731 |
| | | Loans | 370.600 | 1136922 | 404637.968 | 288347.592 | 0.713 |
| Contextual and Business-related characteristics | | Trend | 1 | 10 | 5.273 | 2.831 | 0.537 |
| | | Trend^2 | 1 | 100 | 35.758 | 33.048 | 0.924 |
| | | Commercial | 66/132 - (50%) | | | | |
| | | Local | 98/132 - (74.24%) | | | | |

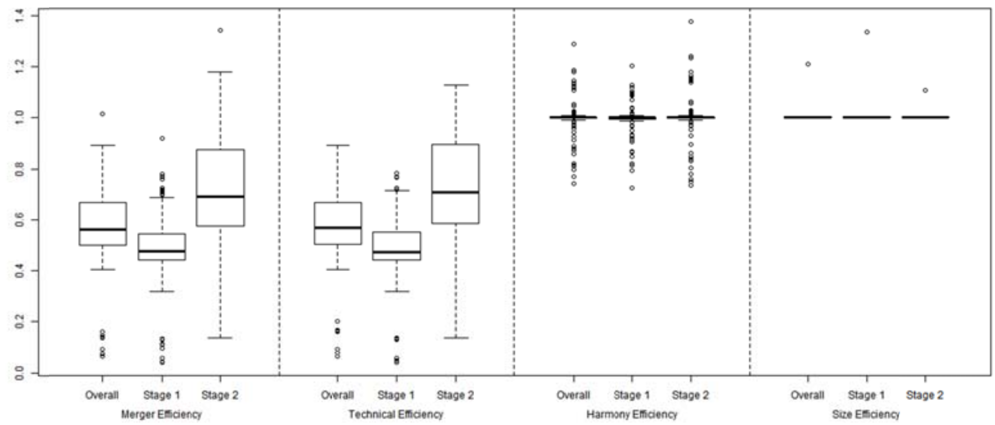


**Fig. 4.** Efficiency estimates distribution for the M&A NDEA.

**Table 4.** Results for the Beta, Simplex, and Tobit Regression Analyses

| Contextual | Merger Efficiency | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Overall | | | | | | Stage1 | | | | | | Stage2 | | | | | |
| | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | |
| | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) |
| (Intercept) | 0.39957 | **2.61E-12** | -0.77003 | **1.18E-02** | -0.87016 | **3.64E-02** | 0.282226 | **7.85E-11** | -1.15678 | **5.06E-05** | -1.00913 | **1.86E-02** | 0.631617 | **8.87E-15** | -0.51528 | 1.14E-01 | 0.124033 | 7.71E-01 |
| Both Commercial | 0.056333 | **0.02907** | 0.105809 | 0.440064 | -0.23455 | 0.210929 | 0.008655 | 0.659045 | -0.06571 | 0.600979 | -0.24832 | 0.19649 | 0.127584 | **0.000529** | 0.332609 | **0.022903** | 0.101887 | 0.593632 |
| Both Local | -0.03513 | 0.235149 | -0.35101 | **0.025804** | -0.70306 | **0.00101** | -0.02017 | 0.369679 | -0.30791 | **0.031916** | -0.59266 | **0.007053** | -0.07579 | 0.072503 | -0.4353 | **0.009408** | -1.40143 | **2.13E-10** |
| Trend | 0.02256 | 0.219132 | 0.191854 | 0.05094 | 0.297279 | **0.026459** | 0.041142 | **0.003189** | 0.307319 | **0.000797** | 0.29228 | **0.033135** | -0.01848 | 0.480439 | 0.06043 | 0.564417 | 0.137213 | 0.316041 |
| Trend 2 | 0.00159 | 0.31393 | 0.001821 | 0.830224 | -0.00116 | 0.919454 | -0.00017 | 0.887562 | -0.00744 | 0.341521 | -0.00165 | 0.888747 | 0.004843 | **0.031497** | 0.006731 | 0.455377 | -0.00027 | 0.981797 |
| Contextual | Technical Efficiency | | | | | | | | | | | | | | | | | |
| | Overall | | | | | | Stage1 | | | | | | Stage2 | | | | | |
| | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | |
| | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) |
| (Intercept) | 0.378105 | **7.73E-13** | -0.78594 | **1.80E-02** | -1.56623 | **4.63E-04** | 0.262914 | **7.55E-11** | -1.07451 | **3.79E-04** | -1.16653 | **6.65E-03** | 0.60553 | **2.90E-16** | -0.36093 | 3.01E-01 | -1.04627 | **1.49E-02** |
| Both Commercial | 0.048948 | **0.04013** | 0.158682 | 0.294262 | -0.0299 | 0.881339 | 0.006702 | 0.71353 | -0.07448 | 0.585008 | -0.24594 | 0.202059 | 0.111557 | **0.000859** | 0.350963 | **0.026759** | 0.12879 | 0.506003 |
| Both Local | -0.0112 | 0.682019 | -0.09636 | 0.578557 | -0.11702 | 0.607906 | -0.00053 | 0.979963 | -0.11152 | 0.474494 | -0.1642 | 0.455355 | -0.04348 | 0.257126 | -0.2131 | 0.242153 | -0.29142 | 0.187016 |
| Trend | 0.026882 | 0.113029 | 0.203154 | 0.05739 | 0.429882 | **0.002825** | 0.045051 | **0.000522** | 0.329929 | **0.000706** | 0.319202 | **0.020926** | -0.01368 | 0.565643 | 0.032994 | 0.768461 | 0.257278 | 0.062595 |
| Trend 2 | 0.00112 | 0.442592 | 0.004327 | 0.643848 | -0.00507 | 0.681593 | -0.0006 | 0.590415 | -0.0063 | 0.456705 | 0.000263 | 0.982279 | 0.00433 | **0.034398** | 0.0128 | 0.189387 | 0.003515 | 0.767735 |
| Contextual | Harmony Efficiency | | | | | | | | | | | | | | | | | |
| | Overall | | | | | | Stage1 | | | | | | Stage2 | | | | | |
| | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | | Tobit | | Beta | | Simplex | |
| | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) |
| (Intercept) | 0.983388 | **4.96E-239** | -0.26205 | 3.34E-01 | -0.3467 | 3.88E-01 | 0.973624 | **0.00E+00** | 0.047693 | 8.50E-01 | -0.43804 | 2.72E-01 | 0.992441 | **6.85E-171** | -0.35505 | 2.14E-01 | 0.169071 | 6.74E-01 |
| Both Commercial | 0.029977 | **0.025972** | 0.28624 | **0.019193** | 0.699309 | **0.00011** | 0.028049 | **0.009448** | 0.291968 | **0.010301** | 0.793609 | **9.59E-06** | 0.031662 | **0.049195** | 0.27409 | **0.033733** | 0.533797 | **0.003334** |
| Both Local | -0.02435 | 0.114563 | -0.27282 | 0.05093 | -0.87926 | **2.29E-05** | -0.01819 | 0.142022 | -0.25571 | 0.052299 | -0.73035 | **0.000416** | -0.03006 | 0.103262 | -0.27716 | 0.058879 | -0.85188 | **4.3E-05** |

| | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Trend | 0.004679 | 0.625136 | 0.067217 | 0.440782 | 0.195545 | 0.130701 | 0.006645 | 0.387323 | 0.082888 | 0.305548 | 0.259713 | **0.04262** | 0.002879 | 0.801497 | 0.052275 | 0.569656 | 0.08199 | 0.526484 |
| Trend 2 | -0.00027 | 0.7404 | -0.00508 | 0.497342 | -0.01594 | 0.151485 | -0.00045 | 0.493719 | -0.00579 | 0.406 | -0.01862 | 0.090916 | -0.00011 | 0.912693 | -0.0056 | 0.47875 | -0.01502 | 0.177822 |

| Contextual | Size Efficiency | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Overall | | | | Stage1 | | | | Stage2 | | | |
| | Tobit | | Beta | | Tobit | | Beta | | Tobit | | Beta | |
| | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) | Estimate | Pr(>\|z\|) |
| (Intercept) | 1.016607 | **0.00E+00** | -2.84961 | **2.57E-11** | 1.026373 | **0.00E+00** | -2.84961 | **2.57E-11** | 1.008357 | **0.00E+00** | -2.84961 | **2.57E-11** |
| Both Commercial | -0.00713 | **0.02876** | -0.13912 | 0.454967 | -0.01133 | **0.02876** | -0.13912 | 0.454967 | -0.00359 | **0.02876** | -0.13912 | 0.454967 |
| Both Local | -0.01001 | **0.007429** | -0.19079 | 0.370245 | -0.0159 | **0.007429** | -0.19079 | 0.370245 | -0.00504 | **0.007429** | -0.19079 | 0.370245 |
| Trend | -0.00345 | 0.136777 | -0.06564 | 0.620121 | -0.00548 | 0.136777 | -0.06564 | 0.620121 | -0.00174 | 0.136777 | -0.06564 | 0.620121 |
| Trend 2 | 0.000397 | **0.046672** | 0.007518 | 0.508779 | 0.00063 | **0.046672** | 0.007518 | 0.508779 | 0.0002 | **0.046672** | 0.007518 | 0.508779 |