UNVEILING THE ENDOGENOUS RELATIONSHIP BETWEEN TECHNICAL EFFICIENCY AND VALUE CREATION IN Mergers AND ACQUISITIONS IN NIGERIA

MFON AKPAN1, PETER WANKE3, ZHONGFEI CHEN4* and JORGE MOREIRA ANTUNES2

Abstract
There is a growing literature on how the beneficial impacts of horizontal mergers and acquisitions (M&A) should be measured. Thus far, however, there have been few studies addressing endogeneity between technical efficiency and value creation: they tend to present a bidirectional and simultaneous relationship. This research contributes to the debate by investigating the impact of voluntary horizontal M&A on these metrics in Nigeria between 1995 and 2012, in light of the individual performance of bidders, targets, and the resulting corporate companies. First, technical efficiency, technology gap ratio, and returns-to-scale estimates were computed based on a meta-frontier DEA approach, together with a set of contextual variables that encompass performance indicators which reflect the value creation process. Then, robust regressions were used to discriminate these efficiency estimates in terms of such business-related variables, correcting for endogeneity and controlling for industry and trend effects. The results reveal that these contextual variables significantly impact virtual efficiency and returns-to-scale levels, and that there is a trade-off between efficiency and value creation at some point in the merging process. Managerial implications are derived.

JEL Classification: O16, O55, C14
Keywords: Mergers and acquisitions, Nigeria, technical efficiency, value-creation, endogeneity

1. INTRODUCTION

Every firm’s prime objective is to grow profitably, which can possibly be obtained in domestic and foreign markets (Gupta, 2012). The internal growth can be a result of developing new products, by increasing the capacity of existing products, or through sustained improvement in sales (Mallikarjunappa and Nayak, 2007). External growth can be realised by acquiring existing firms (Ghosh and Das, 2003). Mergers and acquisitions (M&As) are significant forms of external growth (Mallikarjunappa and Nayak, 2007). Hence, the business world is characterised by increasing M&A with a number of strategic business motives. M&A has become an extensive global phenomenon as a possible path for business restructuring.

* Corresponding author: School of Economics, Jinan University, Huangpu West Road No. 601, Guangzhou, Guangdong 510632, China. E-mail: hongyeczf@163.com.
† Faculty of Accountancy & Management, Universiti Tunu Abdul Rahman (UTAR).
‡ COPPEAD Graduate Business School, Federal University of Rio de Janeiro.
§ School of Economics, Institute of Resource, Environment and Sustainable Development Research, Jinan University.

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doi: 10.1111/saje.12233
Broadly speaking, the term M&A refers to the process of merging two companies’ property rights or the acquisition of all or part of one company’s property rights by another. An M&A is conducted under certain conditions to obtain controlling rights (Theron, 2001; Song and Chu, 2006; Kiesel et al., 2017). A merger or acquisition is an important strategic move made by a company to improve the management performance of its enterprise. Successful mergers can produce many gains as verified in different economic sectors such as cost savings, increased profits, upscaling and abundant resources (Fried et al., 1999; Weber and Dholakia, 2000; Johnes and Yu, 2008; Halkos and Tzeremes, 2013; Grimbeek et al., 2013; Peyrache, 2013; Kiesel et al., 2017; Chen et al., 2018).

Consequently, there have been numerous studies in many developed economies examining the potential gains to be made from mergers (Bogetoft and Wang, 2005; Bogetoft and Otto, 2010; Gattoufi et al., 2014; Shi et al., 2017; Chen et al., 2018). However, to decrease the high failure rate of M&A activities, one of the critical steps that should be taken by a bidding company trying to identify suitable target companies prior to an M&A is to determine whether the prospective partner can offer synergies and the relevant attributes needed to complement those of the takeover company. The need to make such M&A predictions has drawn the attention of many researchers in many industries around the world (Gale and Shapley, 1962; Dietrich and Sorensen, 1984; Powell, 2001; Pasiouras and Gaganis, 2007) including those focused on efficiency measurement (Chow and Fung, 2012) and value creation (Meglio and Risberg, 2011).

In fact, within the ambit of M&A, the synergistic gains expected in terms of technical efficiency and value creation can come from increased operational performance, greater economies of scale, efficient management and the removal of overlapping facilities (Zollo and Meier, 2008; Sudarsanam, 2010a,b; Grimbeek et al., 2013; Chen et al., 2018). Additionally, internal investment brings about the growth of the enterprise globally by relocating funds or operational capacity to serve new markets abroad.

Thus far, however, previous studies have neglected the endogenous relationship between technical efficiency and value creation. Not only do they present a bidirectional relationship, but there is also a simultaneous one when exploring synergy gains. Very often predictions with respect to the likelihood of success of an M&A and its drivers are based exclusively on one perspective to the neglect of the other. Precisely, technical efficiency is the effectiveness with which a given set of inputs is used to produce an output. A firm is said to be technically efficient if it is producing the maximum output from the minimum quantity of inputs, such as labour, capital and technology. On the other hand, value creation is the ultimate result of corporate actions that increase the worth of goods, services or even a business. Companies focus on value creation both in the context of creating better value for customers purchasing its products and services, as well as for shareholders in the business who want to see their share value increasing. This study innovates in this context by collecting from different sources and time spans comprehensive primary datasets that allow not only the computational of technical efficiency and value creation effects of M&A in Nigeria, but also their endogenous relationship. Broadly speaking, it is hypothesised in this research that there is not a direct causation of one to another, but rather a feedback process over the course of time between technical efficiency and value creation that explain the synergistic gains from amalgamation.

When studying this phenomenon in Nigeria, it is worth mentioning that in this country horizontal M&As can increase market concentration. Economic sectors are not only
small but are also controlled by a limited number of competitors. The impacts upon
customers of unregulated M&A in countries such as Nigeria can be very serious, leading
to frequent and unnecessary price increases of goods and services. The M&A literature
on Nigeria has reported mostly on the short-term impacts of M&A in the financial sec-
tor, which is focused on services, rather than on customer goods (Umoren and Olokoyo,
2007; Onikoyi and Awolusi, 2014). Although the results of the operating performance of
the financial sector after M&A suggest an improvement (Onikoyi and Awolusi, 2014),
there is no documented evidence on long-term horizontal voluntary M&A in this and
other economic sectors in Nigeria. The issues mentioned previously suggest a literature
gap to be filled. Not only should endogeneity between technical efficiency and value cre-
ation within the M&A ambit be addressed, but this relationship should also be explored
in the context of a concentrated, small-sized economy, such as the one in Nigeria.

Precisely, this paper fills the gap by examining the performance of voluntary horizontal
M&A on a long-term basis (from 1995 to 2012) among firms listed on the Nigerian stock
exchange market. A novel two-stage data envelopment analysis (DEA) bootstrapped-ro-
416 bust-regression approach was developed in this study to enable this. First, the impact of
the M&A was compared in terms of how the bidder companies, the target companies
and the corporate resulting companies actually performed using a meta-frontier where
technical efficiency, technology gap ratios and returns-to-scale were computed. Then,
different bootstrapped robust regressions were performed on these efficiency estimates
(as on the dependent variables) to assess the impact of two important value creation
indicators – residual income valuation (RIV) and economic value-added (EVA) – as
the explanatory variables. The results were not only corrected for endogeneity (lagged
efficiency scores were used as instruments), but they were also controlled for industry
and trend effects.

While RIV and EVA are oriented to capture how M&A affects the value creation pro-
cess within the ambit of the firm, DEA is oriented towards the impact of M&A upon the
frontier of best practices, thus allowing the computation of efficiency scores. Hence, this
research innovates using well-known methods employed by M&A researchers not only
to assess the technical efficiency, but also the financial performance of the firms merged
(Krishnakumar and Sethi, 2012). DEA, RIV and EVA, as argued by Krishnakumar
and Sethi (2012), should be considered whenever possible to enrich the M&A literature
as findings on its eventual countervailing forces show whether technical efficiency im-
proves to the detriment of value generation or vice versa. Furthermore, the timeframe of
the dataset used in this research allowed the examination of such relationships from a
long-term perspective.

The organisation of this paper is as follows: section 2 presents the literature review and
the research hypotheses. Section 3 depicts the data and provides the theoretical back-
ground on the methodology adopted. The results are discussed and analysed in section 4,
while policy implications and conclusions are given in section 5.

2. LITERATURE REVIEW

There is long debate in the literature on how M&A performance should be measured
and what indicators or metrics should be used, but there is a consensus that financial
performance assessments of the resulting companies alone may not be the only and
acceptable yardstick (Ramakrishnan, 2008; Rao-Nicholson et al., 2016). In fact, apart from improved financial performance, long-term improvements in technical efficiency are also a reflection of the economies of scale and scope that emerge during the amalgamation. Therefore, short-term studies of stock price performance are unable to determine whether amalgamation leads to long-term economic benefits at the industry level (Ramakrishnan, 2008), thus suggesting a research gap.

Financial indicators tend to be mostly used such as profits, short-term share prices or those showing the achievement of expected synergy in operating performance (Meglio and Risberg, 2011). For example, Rani et al. (2015) studied the performance of 305 M&As in India from 2003 to 2008 using 14 major indicators related to operating efficiency, profitability, efficiency, leverage and liquidity. The results suggest that profitability and operating efficiency showed a significant improvement due to the better utilisation of fixed assets and that expenses and liquidity indicators showed a long-term improvement after M&A. In addition, results for the well-known DuPont model also showed a long-run improvement in the operating profit margins. The DuPont model, which is also called DuPont analysis and DuPont equation, was created in the early 1900s and became a well-established method of performing financial statement analysis (Soliman, 2008). It decomposes return on net operating assets into profit margin and asset turnover that provide insights into the underlying drivers of operating profitability (Bauman, 2014). The authors justify these findings by arguing that higher profits are ultimately generated by higher unit net sales, which are a direct consequence of better operating margins and higher prices and are not due to the efficient utilisation of the fixed assets in generating higher sales. It is noteworthy that, in accordance with Kohers et al. (2000), although accounting indicators may be useful for assessing performance, they may not properly reflect the technical improvement of the resulting company in the long term. In fact, Aureli (2015), in analysing the performance of targeted firms over an eight-year period in Italy, argues that foreign bidders may search for know-how and technical expertise (reflected in operating efficiency levels) to the detriment of financial performance indicators.

So in terms of the improvement of technical efficiency at the industry level, Scippaccercola and Sepe (2014) present DEA as a valuable methodological approach. This has helped with identifying the efficient frontier by using mathematical programming and by not imposing functional forms. Not only is DEA quite operational regarding the input/output selection of the firms or DMUs (decision-making units) involved in the M&A, but also DEA brings out possible efficiency improvements for inefficient DMUs. In other words, it shows how the inefficient DMUs can be upgraded towards the efficient frontier by using reference sets (peers) of the related DMUs. The envelopment model helps in finding the reference sets for each individual company (Karaduman, 2006). Indeed, most of the benchmarking literature is concerned with evaluating the performance of individual firms (Alba et al., 2009; Silva et al., 2015; Deshpande et al., 2016). It is, however, also possible to evaluate the efficiency of a collection of bidder and target firms and thus to evaluate whether this would be the best possible industry structure or whether it would be better to merge some of the firms and even to split others up.

For example, consider the possible impact of merging Firms 1 and 2 that 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. Besides, if the two units become integrated but continue to operate as two independent entities, they will transform the inputs $x^1 + x^2$ into the outputs $y^1 + y^2$, subject to some kind of synergy. In fact, Cameron and Green (2009) argue that the main purpose of most mergers is to attain market power whereby the bidder firm gets access to brands, new customers, technologies, new facilities or employees. When two firms merge, as a by-product, the resultant synergy may entail the merged company being more successful than the two separate firms.

Synergies can come from cost reduction or from the economies of scale that the bidder took advantage of (Cameron and Green, 2009). These economies of scale can be achieved at various levels such as at the organisational level where rationalisation is applied with redundancy being eliminated and personnel management being centralised. Logistics and transportation represent one of the major operating areas where higher technical efficiency levels can be achieved through joint operations. For instance, M&A yields a more direct or unique distribution route representing a geographic area that was not used before the M&A. There are also financial synergies reflected in the cost of capital for the firm.

Therefore, it could be said that when the benefit exceeds the cost that is incurred in creating synergy, synergy value is created in a real sense by more efficiently producing and delivering products that are perceived as more valuable by customers. That is where the joint effect of technical efficiency and value creation come together in synergy creation due to amalgamation. However, assessing the synergy level expected is not easily performed a priori, and the challenge becomes enormous when it comes to long-term evaluations of value creation. In the literature (Lipworth and Strebel, 1976; Khan et al., 2011), they are frequently found to be negative. Evidence from the US by Moeller et al. (2005) shows that bidder firms’ shareholders experience a numerically significant wealth loss of 10% over five years after an M&A transaction, despite improvements in productivity and efficiency levels. Many reasons have been advanced for this negative outcome such as the self-interest of agency motive and the self-confidence of the hubris hypothesis.

In order to overcome such measurement bias or difficulties, Guest et al. (2010) proposed an alternative method to capture the synergies that arise from M&A from the perspective of value creation: the residual income valuation (RIV). This method focuses on comparing the fundamental value of bidders before and after the merger. If the difference between before and after is positive, it means that there has been a realisation of the synergy resulting from the merger. Conversely, a negative value implies the non-realisation of the synergy and that it also destroyed consolidated equity. Improper stock pricing and unrealistic market expectations are the main reasons that may obfuscate the conclusions derived from an RIV. In short, the authors argue that for effective value to be created, the marginal profit rate of return must be larger than the marginal cost of capital (Guest et al., 2010).

Besides, most of the examples of M&As found in the literature are from developed countries with only a few being from other emerging countries or economies (Meglio and Risberg, 2011). As for the Nigerian case, the literature on M&As is rather focused on the financial sector to the detriment of the customer goods industries where operating synergies may arise (Umoren and Olokoyo, 2007; Onikoyi and Awolusi, 2014; Matousek and Solomon, 2018). This research contributes to the literature not only by measuring underlying value creation or destruction after horizontal M&As in Nigeria, but also by

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using them as predictors of technical efficiency while correcting for endogeneity and controlling for the industry. The main goal was to assess whether there is a trade-off over time between value creation and gains in technical efficiency in the resulting companies through the eventual shift of the efficiency frontier as consequence of the merger process between targets and bidders.

Hence, the seven research hypotheses of this study are as follows:

H1: M&As in Nigeria yield higher technical efficiency levels in resulting companies due to synergistic gains created by a feedback process between technical efficiency and value creation due to the amalgamation.

Devos et al., (2009) and Takeuchi, (2013) argue that resulting companies may improve their technical efficiency by increasing their turnover, by getting bidders to work together to achieve targets and by engaging in research and development (R&D) thereby gaining from asset complementarities and improved operations. It is expected that the shareholders of both target and bidder firms will benefit from the technical efficiency gains (Aik et al., 2015a, 2015b; Masoumi et al., 2017), suggesting endogeneity between anticipated and actual technical efficiency improvements in terms of the firms’ market value and earnings per share (Fee and Thomas, 2004; Gupta, 2012).

H2: M&As in Nigeria yield higher value creation in resulting companies due to synergistic gains created by a feedback process between technical efficiency and value creation due to the amalgamation.

Cameron and Green (2009) argue that one of the main purposes of most M&As is growth and creating synergies by acquiring brands, new customers, technologies, new facilities and employees. When two firms merge, their combined synergies may result in higher value creation. First, there could be growth in sales brought about by new products or services offered to the market. Synergies could also come from reduced operating costs and from potential economies of scale and scope, which the bidder could exploit. According to Heldenberg, economies of scale can be achieved by rationalising physical and human resources and increasing sales, while economies of scope, on the other hand, could result from increased technical expertise and a better mix of products and services (Rachida and Eglantine, 2012). Both factors provide a favourable scenario, reducing borrowing costs from financial institutions. Economies of scale and scope also bring about productive gains, which justify the endogeneity between technical efficiency and value creation.

H3: There is a trade-off between value creation and technical efficiency in bidder firms in Nigeria in the long run due to the concentrated structure of its industries with few players.

Moeller et al. (2005) and Chen et al. (2011) show that financial returns for bidder firms are low – close to zero and mostly negative. Silva Rosa et al. (2004) argue that most M&A transactions involve non-listed target firms. In fact, those who acquired unlisted target firms obtained significant positive and abnormal returns, unlike the bidders for listed target firms, who got negative returns. O’Sullivan and Tuch (2007) found that long-term performance results were overwhelmingly non-positive. Nevertheless, synergistic gains and maximised shareholder earnings have largely been used as reasons for M&A transactions or deals; however, existing studies do not provide sufficient evidence that expected economies of scale and scope among M&A transactions will be achieved, creating value for shareholders. One reason why M&A may not result in synergistic

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gains could be the bidder firm overpaying for the target company due to overestimating it (Emott, 2011), which is particularly true in small-scale, quasi-monopolistic economies. Therefore, synergistic returns do not meet expectations in terms of debt repayment, dividend returns and the market growth valuation despite some gains in technical efficiency as a result of reducing costs and eliminating operational redundancies.

H4: M&As in Nigeria yield oversized companies (i.e. decreasing returns-to-scale) due to the concentrated structure of its industries with few players.

This is a direct consequence of H3. Resulting companies in Nigeria could be oversized in terms of the scale of the market they are supposed to serve. Decreasing or increasing efficiency based on size is what returns to scale imply (Karimzadeh, 2012). If the resulting company’s average output (output per unit) increases as its inputs do, it shows increasing returns to scale. Conversely, if the resulting company’s average output decreases with an increase in its inputs, this exhibits decreasing returns to scale. Finally, if the average outputs remain the same with increasing inputs, constant returns to scale are exhibited (Tsai and Chou, 2015).

H5: The effects hypothesised in H1 and H2 are time-dependent.

In addition to the impacts imposed by the limited size of the Nigerian economy (H3), the choice of the time horizon matters when evaluating the resulting company’s performance either in terms of gains in technical efficiency or in terms of creating value. A long time period is often needed to allow an evaluation of the impact of technical efficiency following an M&A transaction because improvements in efficiency require a long time horizon to be realised (Manson et al., 2000; Ghosh, 2001; Rahman and Limmack, 2004). On the other hand, regarding value creation, evaluating the impact of technical efficiency after an M&A over a longer time horizon creates other problems as other operating and financial policies may also affect the firm’s valuation (Sudarsanam, 2010a,b).

H6: M&As in Nigeria yield lower technology gap ratios in companies that result from the amalgamation.

Bruhn et al. (2017) found a positive correlation between technological change and M&A among Brazilian companies. In fact, Gorg and Greenaway (2004) and Buckley et al. (2010a, 2010b) argue that reductions in the technology gap ratio are often due to the presence of firms with different technological skills and expertise. Hence, there is a belief that technology gap ratios, or technical efficiency differentials, are the basis for assuming that M&A operations positively affect the performance of resulting companies. It is important to mention that very often these differentials are found when a domestic company is acquired by a multinational one.

H7: The impacts of M&As in Nigeria vary according to the type of industry due to the technological constraints and specifics of the production process in each case.

According to Godbole (2009), synergies can be achieved by putting together manufacturing facilities and the sales momentum. Synergies can also be achieved by putting assets to more profitable use and by leveraging market power. Although these new growth opportunities create new capabilities and resources along with new products and markets (Sudarsanam, 2010a,b), Gachino (2010) suggests that heterogeneity in creating synergy
may arise because of higher level diversity among industries in terms of learning capabilities and productive technologies. Furthermore, different national policies have different effects across industries. Hence, some industries such as oil and gas in Nigeria offer better transformation or innovations and new knowledge absorption situations, making target companies more aggressive or competitive.

These hypotheses were tested using the novel two-stage DEA approach, which is discussed further in Section 3.

3. METHODOLOGY: DATE AND METHODS

3.1. The Data

The total number of M&As collected in this research encompassed 30 pairs of bidding and target companies between 1995 and 2012 in Nigeria. Considering that these 30 M&As occurred at different stages within this 17-year time span and that eventually not all years were available for the triplet bidders–targets–resulting companies, the final sample yielded 883 observations. The data were collected as classified by the Nigerian Stock Exchange (NSE) observing the criteria described below.

(i) The bidder firms must have been listed on the Nigerian Stock Exchange and acquired more than 60% voting rights of target firms, assuming that 60% was sufficient to grant control, as identified in section 313(1) of the Security and Exchange Commission Act of 2011.

(ii) The target firms may have been listed on the NSE or they may not have been listed firms.

(iii) Mergers were restricted to the horizontal type M&As, which take place in the same industry among companies with the same or similar products, markets and technologies.

(iv) Both bidder and target firms were domiciled in Nigeria.

(v) Acquisitions of subsidiaries where bidders had already acquired a stake of more than 60% were not considered in accordance with Song et al. (2005). In fact, these transactions do not reflect a firm’s intention to seek external growth, so to include them would have introduced bias into the analysis.

(vi) Mergers involving insurance firms, investment trusts and other financial institutions such as banks, which are mostly involuntary due to government interventions, were excluded. Besides, their peculiar accounting requirements would also have implied a particular treatment.

(vii) A cut-off criterion of 3 years of pre-merger and post-merger financial data was deemed necessary for both bidder and target firms, besides the year of the M&A event.

The descriptive statistics for the inputs, outputs, and contextual variables used in this research are presented in Table 1. All monetary values refer to the Nigerian currency, the Naira, and have been corrected for inflationary effects over time. The subsequent sections fully describe the methods involved in the analysis and the respective variables used. In short, the following steps encompass how the methods and variables used complement each other in order to test the seven hypotheses previously presented.
Table 1. Descriptive statistics for the inputs, outputs and contextual variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>SD</th>
<th>CV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Invested capital (IC)</td>
<td>19,593.00</td>
<td>951,930,000.00</td>
<td>30,733,562.62</td>
<td>77,944,328.61</td>
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<tr>
<td>Total assets (TA)</td>
<td>9,227.00</td>
<td>1,269,754,495.60</td>
<td>28,560,976.14</td>
<td>109,360,817.00</td>
<td>3.83</td>
</tr>
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<td>Labour cost (LC)</td>
<td>11,223.00</td>
<td>38,047,404.00</td>
<td>3,024,488.39</td>
<td>5,167,401.80</td>
<td>1.71</td>
</tr>
<tr>
<td>Asset replacement cost (ARC)</td>
<td>4,054.00</td>
<td>54,626,000.00</td>
<td>1,971,857.62</td>
<td>4,657,026.59</td>
<td>2.36</td>
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<tr>
<td>Outputs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Margin of contribution (MC)</td>
<td>32,024.13</td>
<td>3,731,700,846.92</td>
<td>66,897,828.57</td>
<td>254,132,810.01</td>
<td>3.80</td>
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<tr>
<td>Net operating profit after taxes (NOPAT)</td>
<td>-183,893,186.00</td>
<td>181,323,000.00</td>
<td>3,185,969.24</td>
<td>14,924,449.84</td>
<td>4.68</td>
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<tr>
<td>Turnover (TO)</td>
<td>34,692.00</td>
<td>673,181,997.00</td>
<td>44,558,530.33</td>
<td>81,619,649.05</td>
<td>1.83</td>
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<tr>
<td>Earnings before interest and taxes (EBIT)</td>
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<td>188,294,000.00</td>
<td>4,380,061.93</td>
<td>16,560,140.83</td>
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<tr>
<td>Contextual</td>
<td></td>
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<td></td>
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<td></td>
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<tr>
<td>Cost of capital (COC)</td>
<td>-1.29</td>
<td>3.20</td>
<td>0.34</td>
<td>0.45</td>
<td>1.33</td>
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<tr>
<td>Dividend per share (EDPS)</td>
<td>0.00</td>
<td>12.93</td>
<td>1.20</td>
<td>2.35</td>
<td>1.96</td>
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<tr>
<td>Book value per share (BVPS)</td>
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<td>11.71</td>
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<td>Cost of equity (Re)</td>
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<td>Price of total assets (PTA)</td>
<td>0.13</td>
<td>3,839,289.00</td>
<td>10,171.89</td>
<td>143,893.02</td>
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<td>Price of labour (PL)</td>
<td>58.90</td>
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<td>12,223.74</td>
<td>137,857.02</td>
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<td>Price for cost of capital (PC)</td>
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<td>167.07</td>
<td>1.84</td>
<td>9.34</td>
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<tr>
<td>Return on invested capital (ROIC)</td>
<td>-1.88</td>
<td>3.18</td>
<td>0.13</td>
<td>0.32</td>
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<tr>
<td>Return on equity (ROE)</td>
<td>-12.15</td>
<td>4.67</td>
<td>0.15</td>
<td>0.84</td>
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<td>Economic value added (EVA)</td>
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<tr>
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<td>Bidder</td>
<td>Target</td>
<td>Control</td>
<td>39.64%</td>
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<td>Industry type</td>
<td>Consumer group</td>
<td>Healthcare</td>
<td>Industrial</td>
<td>Oil and gas</td>
<td>Services</td>
</tr>
<tr>
<td></td>
<td>43.26%</td>
<td>4.19%</td>
<td>27.07%</td>
<td>11.89%</td>
<td>13.59%</td>
</tr>
</tbody>
</table>

- Inputs and outputs were used in the DEA model to compute technical efficiency scores (H1, H3, H5, H7), technology gap ratios (H6) and returns-to-scale (H4) for targets, bidders and resulting companies based on the meta-frontier concept.
- Financial performance indicators such as cost of capital (COC), dividend per share (EDPS), book value per share (BVPS), cost of equity (Re), price of total assets (PTA), price of labour (PL), price for cost of capital (PC), return on invested capital (ROIC) and return on equity (ROE) were used to compute RIV and EVA indicators of value creation. Once the result of RIV showed to be positive/negative and, therefore, confirmed value creation/destruction in a given M&A, EVA was used to proxy the positive value creation in the subsequent analysis due to its robustness as long as it was based on fundamental profit and balance sheet indicators (H2).
- Contextual variables were used in the respective robust regression methods to assess not only how value creation is related to technical efficiency (robust regression approach for technical efficiency with endogeneity correction – H1, H2, H3, H5, H7), returns-to-scale (robust multinomial logistic regression – H4) and technology gap ratios (robust Cauchy regression – H6), but also to control these results for industry and trend effects besides different relevant financial indicators.

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At last, readers should note that while financial performance indicators are completely endogenous to technical efficiency and therefore an endogeneity correction can be proposed, the same does not occur with technology gap ratios and returns-to-scale since a simultaneous and bidirectional relationship cannot be established. Besides, industry type and trend effect can be considered as exogenous to these three efficiency indicators and help to control the financial performance impacts.

3.2. The Methods
3.2.1. Efficiency Indicators for the First Stage: Data Envelopment Analysis (DEA) DEA is a non-parametric method first introduced by Charnes et al. (1978). It is based on linear programming and is used to address the problem of calculating the relative efficiency of a group of decision-making units (DMUs) by using multiple measures of inputs and outputs. Given a set of DMU inputs and outputs, DEA determines for each DMU a measure of efficiency obtained as a ratio of weighted outputs to weighted inputs. There are several variations of the technique (Cooper et al., 2007). They differ not only with regard to the type of returns to scale and how the distance to the frontier is calculated for inefficient DMUs, but also with respect to changes in efficiency over time, undesirable outputs, resource congestion and the disposability of outputs and inputs, to mention just some of the possible variations.

Besides, DEA neither imposes a specific functional relationship between production outputs and inputs, nor any assumptions of the specific statistical distribution of the error terms (Cullinane et al., 2006). An efficient frontier is on the boundary of a convex polytope created in the space of inputs and outputs where each vertex is an efficient DMU (Duša and Helgason, 1996). Another feature of DEA is that the relative weights (\( \lambda \)) of the inputs and outputs do not need to be known a priori, implying that these weights are determined as part of the solution of the linear problem (Zhu, 2003).

Assume \( s = 1 \ldots S \) production units with inputs \( x_s^T = (x_{s1}, \ldots, x_{sn}) \) and outputs \( y_s^T = (y_{s1}, \ldots, y_{sm}) \). Column vectors \( x_s \) and \( y_s \) form the \( s \)th columns of matrices \( X \) and \( Y \). Assume further that \( \lambda^T = (\lambda_1, \ldots, \lambda_s) \) is a non-negative vector and \( e^T = (1, \ldots, 1) \in R^S \) is a vector of unit values. The DEA-CCR (Charnes et al., 1978) and the DEA-BCC (Banker et al., 1984) are shown in equations (1) to (3):

\[
\begin{align*}
\text{DEA-CCR} & \quad \text{Input-oriented} \\
\text{Constant returns to scale} & \quad \text{DEA-BCC} \quad \text{Input-oriented} \\
\min_{\theta, \lambda} & \quad \text{DEA-BCC} \quad \text{Output-oriented} \\
\theta & \quad \text{Variable returns to scale} \\
\text{s.t.} \theta x_s - X \lambda & \geq 0 \\
Y \lambda & \geq y_s \quad (1) \\
\lambda & \geq 0
\end{align*}
\]

\[
\begin{align*}
\text{max}_{\eta, \lambda} & \quad \text{s.t.} \quad ny_s - Y \lambda & \leq 0 \\
\text{s.t.} & \quad \lambda & \leq x_s \\
\lambda & = 1 \\
(3)
\end{align*}
\]

In this research, the input–output set was considered by observing a variable returns-to-scale assumption. An input orientation was also observed suggesting that inputs are minimised so that current output levels can be attained after the M&A and therefore the synergistic effects could be captured. While \( \theta \) computed from equation (2) provides
the technical efficiency scores for the bidders, targets and resulting companies within the ambit of the meta-frontier, the summation of $\hat{\lambda}$ obtained from equation (1) yields the return to scale for each company. When the sum of $\hat{\lambda}$ is equal to 1, constant returns to scale are observed and the company is said to be operating at the most productive scale and size. A value higher (lower) than 1 signifies that the company is experiencing increasing (decreasing) returns to scale.

Gradually developed from the basic concept of a DEA model, the concept of a meta-frontier function was proposed by Rao et al. (2003). The purpose of the DEA meta-frontier is to assess the efficiencies of firms that operate in different regions using distinct technologies. Notably, the main characteristic of this model is the way in which it measures inter-regional efficiency (Wongchai et al., 2012). The leading function of a certain set of data for the elements of any production function mirrors the meaning of the meta-frontier function of firms/units (Bartese et al., 2004). Several studies use meta-frontier data as their main research method with an emphasis on measuring the technical efficiency ratio and the technology gap ratio. To the best of our knowledge, this is the first time this concept has been used to analyse how performance changed in bidders, targets, and resulting companies before and after M&As took place.

The DEA meta-frontier is based on the overall data obtained from all firms/units operating with distinct technologies in all regions. By using the meta-frontier function, the minimal input shown in equation (2) can give a technical efficiency score for a given firm provided the data obtained covers all regions and time periods.

An input–output combination $(a, b)$ is technically efficient with respect to the meta-frontier function when $D(a, b) = 1$, where $D(.)$ is the distance function to the meta-frontier. In general, an output-oriented measurement of the technical efficiency of an observed pair $(a, b)$ with respect to the meta-technology function of region $k$ is determined as in equation (4):

$$TE_k(a, b) = D_k(a, b)$$

where $D_k(.)$ is the distance function to the meta-frontier considering a given $k$ group of firms or regions or any other subset encompassed by the meta-frontier. For instance, if $D_k(a, b) = 0.7$, this indicates that the average technical efficiency of subset $k$ is 0.7 (Wongchai et al., 2012).

The input-oriented technology gap ratios (TGRs) can be determined by the input distance functions from meta-technology, $D^*$, and subset technologies, $D_k$, as in equation (5):

$$TGR_k(a, b) = D^*(a, b) / D_k(a, b)$$

The technology gap ratio is defined by the concept of input-oriented technical efficiency (TE) as presented in equation (6), where $^*$ denotes the computation for the overall meta-frontier and $k$ denotes the computation for the respective meta-frontier subset:

$$TGR_k(a, b) = TE^*(a, b) / TE_k(a, b)$$

For instance, as illustrated in equation (6), if the technical efficiency of the input/output vector related to its own region is 0.5 and 0.7 considering the meta-technology, then the technology gap ratio is equivalent to 0.714 (0.5/0.7). This number explains that, in
view of the input vector, the potential output for region $k$ and its technology is 71% of the meta-frontier function.

3.2.2. Financial Performance at the Second Stage: RIV and EVA Indicators

3.2.2.1. Residual Income Valuation The residual income valuation (RIV), previously applied by Guest et al. (2010), Feltham and Ohlson (1995) and Sirower and O’Byrne (1998) to investigate the value creation process in M&As, departs from the cost of capital, the interest discount rate and the investment risk. The basic RIV formulation is equivalent to the future value of the dividends expected:

$$FV_t = \sum_{i=1}^{\infty} \frac{E_i [D_i + 1]}{(1 + r)^i}$$

(7)

where $FV_t$ is the stock’s fundamental valuation at period $t$, $E_i [\cdot]$ is the expectation from the data available at period $t$, $D_i$ is the dividend for the period $t + 1$, and $r$ is the cost of equity. Another assumption is the clean surplus accounting relationship, which states that all the modifications in the equity book value have to pass through the income statement:

$$BV_t = B_{t-1} + NeI_t - D_t$$

(8)

where $BV_t$ is the equity book value at time $t$ and $NeI_t$ is the net income for the time $t$. The basis of this assumption is that it allows dividends expressed in terms of future returns and book values. Inserting equation (8) into equation (7) results in the following equation, equation (9):

$$FV_t = BV_t + \sum_{i=1}^{\infty} \frac{E_i [NeI_{i+1} - r_e B_{i+1-1}]}{(1 + i)^i} - \frac{E_i [B_{i+\infty}]}{(1 + r_e)^\infty}$$

(9)

The last term in equation (9) is assumed to be zero as the value tends to infinity, while the second term is the present value of future residual income. Therefore, the present value sum of the future residual income plus the equity book value $(BV)$ become equal to the fundamental value:

$$FV_t = BV_t + \sum_{i=1}^{\infty} \frac{E_i [NeI_{i+1} - r_e B_{i+1-1}]}{(1 + i)^i}$$

(10)

Hence, equation (10) represents the sum of the book value and the present value of the future residual earnings. The difference between the values computed using equation (10) before and after the M&A gives the fundamental value created or lost by the acquisition. A positive difference indicates that value has been created. Bild et al. (2002) argue from the financial theory perspective that if the marginal return from a merger is not greater than the marginal cost, no fundamental value has been created. Readers should refer to these authors for additional derivations.

3.2.2.2. Economic Value Added (EVA) The economic value added (EVA) is calculated using the approach presented by Leepsa and Mishra (2013). Consider that EVA is equal
to the net operating profit after tax (NOPAT) minus the weighted average capital cost (WACC) times the invested capital (IC). Also, consider the following financial ratio measures proposed by Aruna and Nirmala (2013) to capture profitability:

(i) Operating profit margin (OPM) computed as the ratio between gross profit and sales
(ii) Return on invested capital (ROIC) computed as the ratio between net profit and invested capital
(iii) Net profit margin (NPM) computed as the ratio between net profit and sales

3.2.3. Robust Regression Approach for Technical Efficiency Scores In this research, the impacts of the contextual variables on the bidders, targets and resulting companies’ technical efficiency are tested by a robust regression approach. In this approach, Tobit (Wanke et al., 2016a), Simplex (Barros et al., 2017), Beta (Wanke et al., 2016b) and SW-bootstrapped-truncated regressions (Simar and Wilson, 2007) are individually designed to handle dependent variables bounded in 0 and 1 combined by means of stochastic non-linear programming and bootstrapping. This is justified because most regression approaches produce biased results in two-stage DEA analyses because often they do not take into account the underlying issues caused by the lack of discriminatory power of the scores computed in the first stage (Wanke et al., 2016c). The discriminatory power is low because efficiency scores tend to be upward-biased towards one. Therefore, a robust regression approach should reflect an adequate distributional assumption to handle this type of bias. This may be obtained via bootstrapping (Simar and Wilson, 2007, 2011) and combining forecasts to yield smaller variance errors (James et al., 2013; Ledolter, 2013).

The non-linear stochastic optimisation problem for combining 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 following regressions, respectively: Tobit \( (Rt) \), Beta \( (Rb) \), Simplex \( (R) \) and Simar & Wilson \( (Rs + Rw) \). This model optimises 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 \( w \) could be collected for the bidder, target and resulting companies’ best efficiency predictions. Residual variances were collected assuming a linear model for each regression linking efficiency estimates and contextual variables.

\[
\begin{align*}
\min & \ Var \left( w_1 Rt + w_2 Rb + w_3 R + w_4 Rs + Rw \right) \\
\text{S.T.} & \sum_{i=1}^{4} w_i = 1 \\
& 0 \leq w_i \leq 1 \quad (11)
\end{align*}
\]
Model (11) was solved using the differential evolution (DE) technique. DE is a member of the family of genetic algorithms that mimic the process of natural selection in an evolutionary manner, see Holland (1975). The R package named DEoptim, which implements the DE algorithm, was first published in CRAN in 2005. Interested readers should refer to Ardia et al. (2011) and Mullen et al. (2011) for a detailed description of the package.

3.2.3.1. Endogeneity Correction The conflicting results in prior studies for the M&A impacts on levels of technical efficiency and value generated may also be explained by not properly controlling for endogeneity. An important issue in studying the relation between levels of efficiency and financial indicators is the direction of causation. This is not clear ex ante; in other words, it is not clear what comes up first. A common technique for tackling the endogeneity problem is to use instruments (Renders and Gaeremynck, 2006). In particular, a set of instruments that are assumed to be exogenous is selected and then the robust regression is performed in two phases. The endogenous variable is first regressed on the instruments and then the estimated value of the endogenous variable is included in the second-phase equation instead of the endogenous variable itself. A good instrument has a strong correlation with the endogenous variable but is not correlated with the error term of the equation, meaning that it is exogenous. However, in practice it is extremely difficult to find such an instrument (Maddala, 1997). Therefore, most empirical studies work with “imperfect” instruments. The imperfect instruments are either exogenous but have a low correlation with the endogenous variable (“weak-instruments”) or are not exogenous but have a high correlation with the endogenous variables (“semi-exogenous” or “quasi-instrumental” variables) (Mroz, 1987). As we have panel data, technical efficiency scores lagged one year were used as a “quasi-instrument,” similar to that in Renders and Gaeremynck (2006). This instrument should be highly correlated with the endogenous variable because it is difficult to reverse technical efficiency scores in the short term. Furthermore, this instrument is less endogenous than the current levels of technical efficiency as financial performance in year \( t \) could not have influenced technical efficiency scores in year \( t-1 \). However, technical efficiency scores in \( t-1 \) can be correlated with those computed in year \( t \). The degree of exogeneity of this instrument depends on how current performance is related to past performance.

Therefore, in this research the robust regression presented in section 3.2.3 was performed in two phases. In phase 1:

\[
\theta_{t-1} = r_t + e_t + \epsilon
\]  

(12)

where \( \theta_{t-1} \) is the lagged technical efficiency scores vector for the meta-frontier, \( r_t \) and \( e_t \) are, respectively, the matrix of financial indicators computed using the RIV and EVA techniques and \( \epsilon \) is the error term. In phase 2:

\[
\theta_t = \theta_{t-1} + i_t + \epsilon
\]  

(13)

where \( \theta_t \) is the technical efficiency scores vector for the meta-frontier and \( i_t \) is the matrix of dummy variables that represents each industry type. Again, \( \epsilon \) is the error term. Linear and squared trend components are also considered in phase two. Fig. 1 presents the
aggregate correlation matrix between efficiency scores and the set of endogenous contextual variables used in equation (12). Apart from the linear and squared trend components and the dummies created to control the industry type, multicollinearity is low within the ambit of the EVA and RIV indicators with the exception of the pairs formed by the cost of capital and the cost of equity and by the labour and total asset prices. Besides, the efficiency scores appear to be moderately correlated to some of the contextual variables and the trend component, thus complying with the prerequisite of using lagged efficiency scores as an instrument. Results for the Arellano–Bond test confirmed the presence of a first-order correlation in the differenced residuals, which does not imply that the estimates were inconsistent.

3.2.4. Robust Regression Approach for Return-to-Scale Indicators Logistic regression is a generalisation of linear regression used for predicting dichotomous or multi-class dependent variables (Hosmer and Lemeshow, 2000). It assumes that the response variable is linear in the coefficients of the predictor variables. Its main advantage is a simple probabilistic formula for classification. In this research, in order to explain the three different returns-to-scale (RTS) groupings (increasing, constant and decreasing) after evaluating the meta-frontier for all bidders, targets, and resulting companies, multinomial logistic regression analyses were performed considering the contextual variables as the predictor variables. As in section 3.2.3, bootstrapping was also performed on the multinomial logistic regression. A resample size of 200 was considered.

3.2.5. Robust Regression Approach for Technology Gap Ratios The TGR ratio expressed in equation (6) can be approximated by a Cauchy distribution (Ferguson, 1962). The Cauchy distribution is a symmetric, bell-shaped distribution on $(-\infty, \infty)$. A random
vector $X = (X_1, \ldots, X_k)'$ is said to have the multivariate Cauchy distribution if every linear combination of its components $Y = a_1 X_1 + \ldots + a_k X_k$ has a Cauchy distribution (Molenberghs and Lesaffre, 1997). That is, for any constant vector $a \in \mathbb{R}^k$, the TGR random variable should have a univariate Cauchy distribution.

As regards the Cauchy regression (Mizera and Müller 2002), readers should note that for a Cauchy RV, we have that $(e_i | \sigma^2, \omega_j) \sim N \left( 0, \sigma^2 \omega_j^{-1} \right)$ and $\omega_j \sim \chi^2 (1)$ imply $(e_i | \sigma^2) \sim \text{Cauchy} \left( 0, \sigma^2 \right)$. The derivative of the log-likelihood function is given next:

$$\hat{\omega}_i = \frac{2\sigma^2}{\sigma^2 + \hat{e}_i^2}$$  \hspace{1cm} (14)

where $\hat{e}_i = y_i - x_i' \hat{\beta}$ is the current residual. It is relevant to note that the second derivative of the log-likelihood function is given as:

$$\frac{2}{\sigma^2 + e_i^2} - \frac{4e_i^2}{(\sigma^2 + e_i^2)^2}$$  \hspace{1cm} (15)

which means that the optimal solution for the maximal value of the log-likelihood function is not convex, so there are multiple modes. The approach proposed by Mizera and Müller (2002) finds one of them, but there is the need to restart the optimisation at different values to make sure the actual maximum likelihood is found.

4. ANALYSIS AND DISCUSSION OF THE RESULTS

4.1. Robust Regression Approach for Technical Efficiency Scores

The distribution of the aggregate efficiency scores per year and industry type computed for the bidder, target and corporate resulting companies is presented in Fig. 2 (left and right). One can easily see that median efficiency scores are slightly larger in target firms in comparison with bidder and corporate ones, although the dispersion of efficiency in the corporate companies appears to be considerably larger. This is possibly a result of the amalgamation process and a consequence of the higher levels of heterogeneity of target firms in comparison with bidder ones, as suggested by the interquartile range. Besides, it is worth noting that the distribution of efficiency scores of bidder companies is bimodal, which may suggest the impacts of industry type and trend effects. In fact, Figs 3 and 4 depict that the M&A effect on bidder, target and resulting companies’ efficiency levels is quite heterogeneous depending not only on the industry type, but also on the temporal perspective. Broadly speaking, it is possible to affirm that the technical efficiency levels of resulting companies tend to lie in between those of the original target and bidder companies with the exception of the industrial sector where the drop is more accentuated. It also seems that the median efficiency gap between target and bidder companies diminishes over the course of time, although the score dispersion has substantially increased for each company type, thus reflecting increased diversification and heterogeneity of the Nigerian economy in terms of its firms and respective market segments.

As regards the distributional fit of the aggregate efficiency scores per year and industry type, Fig. 5 depicts the Gaussian, Simplex, SW and Beta conditional inverse cumulative
distributions. They were computed conditionally to the set of contextual variables presented in Table 1. It is possible to affirm at first sight the superiority of the SW adjustment in comparison with the three other assumptions. Although this is coherent with the literature since the bootstrapped-truncated regression is a bias-free procedure (Simar and Wilson, 2007, 2011), the combination of a mix of regression results may still be a sound approach as long as the distributional shapes depicted in Fig. 2 lie far away from the truncated normal assumption. In fact, the results for the Kullback–Leibler (KL) divergence presented in Table 2 suggest that differences in predictive power between these assumptions are not sufficiently overwhelming to make a case in favour of one specific regression type to the detriment of the other. However, it is worth mentioning that, as expected in Simar and Wilson (2007, 2011), the SW distributional assumption outperformed the Gaussian, Simplex and Beta assumptions due to the bias removal in scores close to 1, although for lower scores the Gaussian, Simplex and Beta assumptions presented a better distributional fit, better capturing the different shapes depicted in Fig. 2 (right).

The results for the stochastic non-linear optimisation on the 100 bootstrapped Tobit, Simplex, SW and Beta regression residuals are presented in Fig. 6 observing the two steps performed for endogeneity correction described in section 3.2.3.1. The results suggest a strong dominance of the weights assigned to the SW approach (almost 100%) to the detriment of the marginal weights assigned for the Simplex, Tobit and Beta regressions in both steps. These results indicate the importance of combining different methods not only in terms of bias removal, which was practically achieved by the SW approach, but also in terms of capturing different distributional shapes, mainly for lower efficiency scores.

The combined bootstrapped regression results for the coefficients of the contextual variables obtained in both steps for endogeneity correction are presented in Fig. 7.

Readers should note that if the distribution of the bootstrapped coefficients and intercepts crosses the solid line, which marks zero in each graph of Figs 7 and 8, it shall be interpreted as a non-significant variable. The results indicate that the efficiency scores of bidder and target companies are, respectively, significantly lower and significantly higher than the efficiency scores of the resulting companies (category of reference). In

Figure 2. Distribution of efficiency scores per bidder, target and resulting company (Left: boxplot. Right: density plot) [Colour figure can be viewed at wileyonlinelibrary.com]
Figure 3. Boxplot of the distribution of efficiency scores per industry type
Figure 4. Boxplot of the distribution of efficiency scores per year
accordance with what was previously discussed, it seems that the levels of technical efficiency of resulting companies lie in between the efficiency levels of the bidders and targets, thus partially corroborating H1 since only bidders appear to benefit from the technical efficiency gains that may be derived from amalgamation.

As regards industry type and putting the health care sector as the category of reference into perspective, it seems that M&A does not produce significant efficiency gains for the industrial and services sectors, while levels of technical efficiency appear to diminish in the oil, gas and consumer goods industries. These results corroborate H7 since the impact of M&A on levels of efficiency may vary according to the industry type. The levels of efficiency appear to be higher in industries where a job shop on demand production technology prevails such as for health care and services. Job shops are typically small productive systems that handle customised orders characterised by small predictability. Higher efficiency levels are also verified where barriers to entrance are higher such as in

\[
\text{Figure 5. Inverse cumulative distributions for the efficiency scores [Colour figure can be viewed at wileyonlinelibrary.com]}
\]

\[
\text{Table 2. Results for the KL divergence}
\]

<table>
<thead>
<tr>
<th>Beta fit</th>
<th>Simplex fit</th>
<th>Simar &amp; Wilson fit</th>
<th>Gaussian fit</th>
</tr>
</thead>
<tbody>
<tr>
<td>11.11%</td>
<td>12.06%</td>
<td>9.24%</td>
<td>12.57%</td>
</tr>
</tbody>
</table>

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the industrial sector. On the other hand, efficiency levels appear to be low in strongly regulated sectors such as oil and gas and where the competition is high, such as in the consumer goods industry.

With respect to the dynamics of the M&A effects on efficiency levels over the course of time, the linear and squared trend components presented significant results, negative and positive, respectively. These results suggest that efficiency levels tend to drop in the initial years and then rise in the subsequent years. It is interesting to triangulate these results with the significant negative coefficients obtained for the expected dividend per share (EDPS), the book value per share (BVPS) including both RIV and EVA indicators. Hence, H3 and H5 are corroborated as long as there is a trade-off over time with respect to technical efficiency and value creation: efficiency increases over time as a long-term movement, while value creation on the other hand is high at the beginning, possibly due to the overestimation of EDPS and BVPS. Besides, the concentrated structure of the Nigerian market may in turn make it difficult to realise synergistic gains in terms of M&A in the long term and therefore H2 is not corroborated.

It is interesting to note that the impact of M&A on levels of efficiency is higher in capital-intensive operations to the detriment of labour intensive ones. This is denoted by the positive and significant signs of cost of capital (COC), price of total assets (PTA), price for cost of capital (COC) and return on invested capital (ROIC). On the other hand, the price of labour (PL) showed a negative and significant relationship with efficiency scores. Again, evidence is provided for accepting H7 with respect to the impact of the type of industry, as well as for the partial acceptance of H1, as long as in the Nigerian economy capital intensity appears to be a prerequisite for exploiting synergistic gains from amalgamation. This is clear when it concerns gains related to facility and logistics consolidation. Maybe capital intensity is also a prerequisite for transferring knowledge between bidders and targets within the frame of resulting companies.

4.2. Robust Regression Approach for Return-to-Scale Indicators

With respect to RTS classification and prediction, results for the multinomial logistic regression are presented in Figs 8 and 9, respectively. The results indicate that the majority
Figure 7. Results for the bootstrapped robust regression approach
of observations fall within the DRS group (Fig. 8 upper). Bidder and resulting corporate companies tend to be too big for the tasks they have to perform. On the other hand, target companies tend to be too small for the markets they serve, being concentrated in the IRS group (Fig. 8 lower). These results corroborate H4 showing that very often M&A in Nigeria results in oversized companies.

The results for the RTS drivers are depicted in Fig. 9 where DRS is the category of reference confirming that target companies are more likely to present CRS or IRS. Besides, IRS companies tend to present larger EVA and smaller EDPS and BVPS. This discrepancy may justify the fact that very often business analysts overvalue target firms to make the M&A economically attractive. Target companies also present lower values for the price of capital and for the return on invested capital, suggesting that they are less capital-intensive. This may explain the intrinsic difficulties involved for bidders trying to exploit synergistic gains in targets in accordance to the results presented in the previous section. Again, the trade-off between technical efficiency and value generated from
Figure 9. M&A RTS prediction by bootstrapped-multinomial-logistics regression
M&A is present here: target companies are efficient labour-intensive operations and it may be difficult to exploit synergistic gains in a country where the workforce is highly illiterate. Lastly, as regards industry type, oil and gas and consumer goods companies tend to present DRS, which may be justified because of the relevance of these sectors for the Nigerian economy. Nigeria is the most populated African country with a heavy dependence on oil production and exports. These features may justify the oversized companies that are a result of M&A in these sectors. Trend components were found to be insignificant.

4.3. Robust Regression Approach for Technology Gap Ratios

Results for the TGR are depicted in Figs 10 and 11. One can easily note the fat tails in Fig. 8, which is a common distributional fit that can be observed when the ratio of two quantities is taken. Readers should be aware that the higher the score, the lower the gap between the meta-frontier and the respective frontier yielded by each company type. A TGR score equal to 1 means that there is no technological gap. M&A in Nigeria are surprisingly increasing the TGR. As long as bidders and targets present smaller levels of TGR, the resulting controlling companies will be too big in relation to the markets they serve. They will also be unable to coordinate a transfer of knowledge and to exploit synergistic gains between capital-intensive (bidder) and labour-intensive (target) operations. Therefore, H6 is partially rejected. In fact, the TGR is lower in the oil and gas sector that benefits from a transfer of knowledge and technology from abroad and whenever BVPS and EDPS are decoupled in terms of book value and market value, respectively. There is a number of factors that may explain this decoupling in favour of EDPS: growth perspective, management style, branding, R&D, marketing and goodwill. It is interesting to note that these factors may be linked to unique or differentiated less capital intensive operations as denoted by the negative signs of COC and PC. This decoupling could not only be used as a sign for anticipating the impact of M&A in terms of the TGR of the resulting corporate company, but also deserves to have its roots investigated by business analysts when performing due diligences within the M&A ambit.

![Figure 10. Density plot for the TGR (Colour figure can be viewed at wileyonlinelibrary.com)](image-url)

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Figure 11. Results for the bootstrapped Cauchy regression
5. CONCLUSIONS AND MANAGERIAL IMPLICATIONS

This paper has unveiled the trade-off between value generation and technical efficiency in horizontal M&As in Nigeria, correcting the results for endogeneity and controlling for industry type. Several methods were used in a complementary fashion to allow a precise diagnostic on the 30 M&As that have occurred over the last 20 years in this country. The results indicate that conducting an M&A in Nigeria is a very challenging process that can easily lead to oversized companies compared to market size. Besides, barriers imposed by labour-intensive operations create additional difficulties in the process of transferring knowledge and exploiting synergistic gains. This being the case, levels of technical efficiency tend to drop after amalgamation and to recover slowly over the course of time in an antagonist movement with value creation. In fact, it appears that companies that are acquisition targets tend to be overestimated by the business analysts of the interested bidder companies during the due diligence process in terms of their potential for creating value. Not only is M&A in Nigeria challenging, but it is also heterogeneous across economic sectors and industry types. Different regulations for the various sectors, different types of production process and difficulties in transferring know-how from abroad all play a significant role.

Managerial implications call for practitioners and investment bankers to re-evaluate the M&A process and with competent hands in the target firms to appropriately fill gaps in terms of the needs of bidder firms after these transactions. Prompt and proper analysis of the target firm’s true financial and operational position is required before making a selection. Further, key technical staff from target firms should be utilised to properly blend and maximise the expected synergistic gains in the amalgamated business. Implementing these recommendations will minimise, if not eliminate, the likelihood of overestimating the target firms. The implication for the management of both the target and bidder firms is that a proper study and understanding of the sectors’ regulations, the types of production processes and the skills involved in transferring know-how are required. These will enable both technical efficiency and synergy improvements to be achieved by the new organisation.

REFERENCES


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