

THE RELATIVE SUCCESS OF IFRS ADOPTED AFRICAN COUNTRIES TO ATTRACT FOREIGN INVESTMENT

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Abstract: Within the context that the adoption of International Financial Reporting Standards (IFRS) can be linked to institutional isomorphism, the purpose of the study was to determine how successful IFRS-adopted African countries are to convert governance and economic factors into foreign direct investment (FDI) and foreign portfolio investment (FPI). Data envelopment analysis (DEA) was used to develop two models to calculate the technical efficiency (TE) for 16 African countries that adopted IFRS (2014-2019). The first model considered how multiple economic factors as input variables are converted into FDI and FPI, while similarly, the second model considered governance factors as input variables.

JEL Classification: C61; F18; M41

Keywords: International Financial Reporting Standards (IFRS), foreign direct investment (FDI), foreign portfolio investment (FPI), data envelopment analysis (DEA), institutional isomorphism

1. Introduction

Financial reporting is an essential and relevant source of information for various users, including foreign investors (Deegan, 2013). The reality of accounting diversity, however, is that it often prevents investors from getting reliable financial information for strategic investment decisions (Vidal-Garcia et al., 2016). The move

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towards the adoption of a single set of global accounting standards became a reality in 2001 with the advent of the International Accounting Standards Board's (IASB) International Financial Reporting Standards (IFRS) (Ball, 2016). Prockazka (2012) emphasises that such standardised financial reporting is expected to enhance the quality of financial information and improve the inflow of foreign investments, which lends support for the adoption of IFRS in many countries.

The literature suggests that accounting information prepared in accordance with a standardised global accounting framework, often becomes part of the specifc country's institutional structures (Ben-Othman and Kossentini, 2015; Nnadi and Soobaroyen, 2015), and is therefore considered as being influencial to foreign investment decisions (Efobi et al., 2014a). In terms of IFRS adoption, however, one might find that such adoption may be due to normative isomorphism, a segment of the institutional theory, due to pressures from local accounting regulators (Phan, 2014; Rodrigues and Craig, 2007), as well as the influencial role of the Big Four accounting firms (Gillis, 2011; Rodrigues and Craig, 2007), which indicate normative pressure from the broader accounting profession to adopt IFRS. It may therefore seem that IFRS adoption could be influenced by social pressure, which brings into question its validity as a predictor of foreign investment success.

However, research that investigated the association between IFRS and foreign investment hypothesised that IFRS adoption may favour foreign investment (Amiram, 2012; Efobi et al. 2014b). In developing this context, some studies investigated the association between foreign direct investment (FDI) and IFRS adoption (Amiram, 2012; Gordon et al., 2012; Chen et al. 2014; Ng, 2015; Nnadi and Soobaroyen, 2015; Efobi, 2017), while others focused on foreign portfolio investment (FPI) and IFRS adoption (Hong et al., 2014; Ben-Othman and Kossentini, 2015). Complementary hereto, some studies also considered African cases within this context (Efobi et al. 2014b; Nnadi and Soobaroyen, 2015; Efobi, 2017). The interest of IFRS adoption in Africa is explained by Boolaky et al. (2020) as relevant because only about one third of the African countries adopted IFRS in comparison with an almost two thirds adoption rate of countries at a global level.

The aforementioned studies mainly focused on relationship analyses using regression analysis in which a foreign investment indicator (either FDI or FPI) is typically used as the *dependent* variable with IFRS adoption being a dummy variable acting as the main *independent* variable. In ensuring higher deterministic relationships in the analyses efforts, various independent variables could be included as mediators together with IFRS adoption (Gordon et al., 2012; Gumus et al., 2013; Ng, 2015). For purpose of this study, they are split into two sections, namely:

- Economic indicators such as economic growth, capital markets, inflation rates, interest rates and exchange rates; and
- Governance indicators such as trade openness, corruption, regulatory quality index and corporate tax rates.

These above variables, in conjunction with IFRS adoption, are identified in the literature as the traditional (or yardstick) drivers of foreign investment, which indicates that changes therein will impact on foreign investment success. Therefore, these yardstick drivers may be used to some extent as a proxy for the success of IFRS adoption.

Nevertheless, the primary issue of this study is the limitation of using conventional regression analysis, namely that it can only determine which of the independent variables have a statistical (in)significant relationship with the sample countries' foreign investment success. Consequently, it cannot be assumed that IFRS adoption was equally beneficial in African countries in attracting foreign investment. Furthermore, regression analysis cannot indicate how efficient the other mentioned yardstick drivers (factors) in each country were in attracting foreign investment. That entails regression analysis cannot determine how successful the yardstick drivers are to attract foreign investment per country. To fill this gap the purpose of the study was to determine how successful IFRS-adopted African countries are to convert the yardstick drivers into FDI and FPI. To measure the degree of success, a model was needed to determine how efficient these countries' yardstick drivers were to contribute to attracting foreign investment.

In striving to develop a more robust model to evaluate foreign investment success, we consider data envelopment analysis (DEA). As a non-parametric mathematical programming-based method, DEA aggregates the relative efficiency of a decision-making unit (DMU) with multiple inputs and multiple outputs (Cook et al., 2014). It uses a linear programming approach that computes a comparative ratio of weighted inputs to weighted outputs for each DMU in defining a best practice frontier, which, in turn, is used to measure each DMU's relative efficiency (Avkiran, 2011). This efficiency frontier is established by a set of DMUs that demonstrate best practice, before determining an efficiency level of the non-frontier DMUs in relation to the efficiency frontier (Zhou et al., 2018).

In this study, 92 DMUs were obtained from six annual data points (2014 to 2019) for 16 IFRS-adopted countries in Africa. For each of the 92 DMUs, the relative performance was calculated of how the above multiple economic indicator-inputs and governance indicator-inputs are converted into two output indicators, FDI and FPI.

Within the conceptual framework of the institutional theory, and especially the institutional isomorphism process, which includes the pressure on countries to adopt IFRS, it was clear from the findings that the IFRS-adopted African countries experienced widely different degrees of success to attract FDI and FPI. In a recent study, Boolaky et al. (2020) found that social and political forces, rather than economic forces, are the primary drive for IFRS adoption in African countries. This study provides evidence of the importance of economic forces, namely the countries are significantly more efficient to convert the economic indicators into FDI and FPI than they are in the case of the governance indicators. The practical value of the study is that the IFRS adopted countries did not experienced equal success to attract foreign investment. Furthermore, economic forces and governance forces may provide extremely different foreign investment inflow yield. Finally, with this different approach to apply DEA rather than regression analysis, the path is paved to do further studies to compare countries' relative success when adopting IFRS.

The next section of the paper discusses the background of the study, including the conceptual scope and the principles of DEA. This is followed by a literature review, which is summarised by setting specific objectives for the study. The method explains the data and the DEA model, which is followed by the results and a discussion thereof. The study is concluded in the final section.

2. Conceptual framework

The adoption rate of IFRS has increased after the European Union (EU) mandated all EU-listed companies to comply with IFRS from 2005 onwards, which also prompted the adoption of IFRS by many other non-EU countries (Gordon et al., 2012). This move by the EU formed the basis of harmonising financial statements in the place of the national accounting standards of different countries (Marquez-Ramos, 2011). This was also the case in Africa, with many African countries abandoning their own national accounting standards in favour of IFRS. Amiram (2012) and Chen et al. (2014) believe that the adoption of IFRS will have economic consequences in the adopting countries, especially in improving the inflow of foreign investments.

As mentioned, the adoption of IFRS is conceptualised within the context of the institutional theory. The theory evolved from the work of various scholars, including Meyer and Brown (1977), DiMaggio and Powel (1983), and Friedland and Alford (1991). The premise for their research focused on understanding why organisations have the same degree of similarity and how an organisational structure can be embraced to bring acceptability to another organisation. Although the institutional theory provides a robust theoretical framework in organisational research, the theory has also been the focus of accounting researchers, such as Broardbent et al. (2001), Brignal and Modell (2000), Rollins and Bremser (1997) as well as Aldemir and Uvsal (2017), Fogarty (1996) and Phan (2014) specifically used the institutional theory as an examination tool for accounting standard-setting development. Research by Dillard et al. (2004) emphasised that institutional theory has gained more relevance in accounting research as a theoretical framework for the study of accounting practice in an entity. Iredele et al. (2020) investigated the influence of institutional isomorphism and organasational factors on environmental management accounting practices by comparing two African countries.

Fernando and Lawrence (2014), Dillard et al. (2004) as well as DiMaggio and Powel (1983) emphasise that the isomorphism dimension of institutional theory is a compelling process that forces one unit or organisation to adapt the *same* features and practices of another unit or organisation that operates in the same conditions or environment. DiMaggio and Powel (1983) identify the three types of isomorphic processes as coercive, mimetic and normative isomorphism. The latter is explained by DiMaggio and Powel (1983) as a pressure emanating from the norms, customs and beliefs of a (professional) group, to adopt a specific institutional practice for all the members in the group. As far as it relates to the adoption of IFRS, the anticipation that accountants will observe and comply with the generally accepted international accounting principles in the work environment could be seen as a form of normative isomorphism (Deegan, 2013).

In this study the African countries represent the "organisation". To focus on the question why countries adopt the same practices such as IFRS-adoption and enlightening economic and governance practices (measured by the indicated yardsticks), our argument is that they strive to obtain the same level of success or benefit. This study's purpose is to determine this degree of success on the hand of attracting FDI and FPI. The essence of this will be paramount to researchers in the field of accounting, especially when investigating the relative efficiency of yardstick drivers that are used in conjunction with IFRS adoption in terms of foreign investment success.

3. Data envelopment analysis

As a modelling approach, DEA aggregates multiple inputs and outputs of a sample of DMUs to define an efficiency frontier, which represents the sample benchmark. A DMU not on this frontier is considered as being inefficient, and the distance from the frontier determines the degree of such inefficiency. Anderson (1996) explains that the benchmark is based on the principle that if a specific DMU is capable of producing a specific output for a given set of inputs, the other DMUs in the sample should reasonably also be capable of doing the same. Therefore, in the DEA approach, all the DMUs are combined to find a composite (or virtual) DMU with composite inputs and composite outputs. In theory, therefore, the inefficient DMUs need to either reduce their inputs or increase their outputs, allowing them to move towards the best practice frontier.

To illustrate, the following example is based on an example in Anderson (1996). Say there are three DMUs, i.e. Country A, B and C, all with economic growth rates of 5%. Country A is best at attracting FDI, Country C is best at attracting FPI, while Country B falls somewhere in between.

- Country A: 5% growth rate, \$100m FDI, \$10m FPI
- Country B: 5% growth rate, \$40m FDI, \$15m FPI
- Country C: 5% growth rate, \$20m FDI, \$50m FPI

Per the above, Country A is efficient (1.0) in attracting FDI, while Country C is efficient (1.0) in attracting FPI. Country B, however, is inefficient since it could not attract either the highest FDI or FPI. For illustrative purposes, we use a 50:50 weighting of A and C to calculate a *virtual* vector (efficiency frontier) as a benchmark for B. This means *lambda* = [0.5, 0.5].

$$\lambda = [0.5 * 100 + 0.5 * 20, 0.5 * 10 + 0.5 * 50] = [60, 30]$$

Therefore, Country B needs to attract FDI and FPI of \$60m and \$30m, respectively, to move to the best practice frontier.

It is widely documented in the literature that Farrel (1957) was the first to address the problem of measuring the productive efficiency of an entity with multiple input variables and a single output variable. Charnes et al. (1978) developed the CCR DEA model to accommodate multiple inputs and multiple outputs, based on the constant return to scale (CRS) assumption. This implies that a DMU is considered fully scale efficient since the scale of operations does not influence the efficiency (Avkiran, 1999; Alvandi et al., 2013). This is perhaps an ambiguous assumption that would require some justification when using this model. Banker et al. (1984) improved on this DEA model by introducing the BCC model, which was based on the assumption of variable return to scale (VRS). This implies a disproportionate rise or fall in outputs when inputs are increased, for example when a DMU grows in size, its efficiency will not remain constant, but will either rise or fall.

For purposes of this paper, the VRS model was helpful in calculating the technical efficiency (TE) of the DMUs, which measures how well inputs are converted into outputs (Avkiran, 1999). In practice, the efficiency problem may be addressed by an input-oriented (input minimisation) approach or an output-oriented (output maximisation) approach. The former calculates the degree to which inputs can be

reduced while maintaining the output level, while the latter calculates the degree that outputs can be raised, given the current input levels (Avkiran, 1999; Cook et al., 2014). Relevant to this study, DEA is able to determine by how much inefficient DMUs' inputs (economic and governance indicators) must decrease to become efficient, or by how much the outputs (FDI and FPI) should increase to reach the efficiency frontier.

Finally, this study does not deal with a real production function, namely there is not a clear link to how multiple inputs (such as inflation rate, interest rate, exchange rate, economic growth rate, etc.) are converted to produce multiple outputs, FDI and FPI. In such a case, Cook et al. (2014) explain that the efficient DMUs do not necessarily form the 'production frontier', but it still yields information on the relative distance to the 'best-practice frontier'.

4. IFRS and foreign investment in Africa

Bughin and Chui (2013) observed that integration in global economies and advances in technology have led to a growth in international financial transactions. They also highlight that these developments require financial reporting information that is more transparent and comparable to ensure the efficient allocation of resources. Before the advent of IFRS, companies prepared their financial reports in accordance with local accounting standards (Cairns et al., 2011), resulting in *non-comparability* of accounting principles and financial reporting, which, in turn, hindered the flow of foreign investments, especially to developing economies (Nobes and Parker, 2008). The development of IFRS was prompted by the rapid growth in economic globalisation and an increase in global financial transactions (Nobes and Parker, 2008). These developments made national accounting standards somewhat irrelevant to the investment decisions of foreign investors. Given this, there was an increase in recognition of IFRS as more relevant in supporting cross-border investment decisions.

Researchers often disagree on an exact definition of, and distinction between, FPI and FDI (Makoni and Marozva, 2018). To conceptually understand foreign investment flow, one should consider the source thereof, which is the *financial account* in the balance of payments (BoP). The IMF (2021) categorises the financial account into (i) direct investment, assets and liabilities, (ii) portfolio investment, assets and liabilities. Within this context, the World Bank (2021) defines FDI as referring to direct investment equity flows, i.e. the sum of equity capital, reinvestment of earnings, and other capital together with ownership of at least 10 percent. In turn, the OECD (2013) defines FPI as the type of foreign investment that involves investment in equity and debt securities, which does not include instruments classified as direct investment or reserves. Therefore, the *influence of control* in management seems to be key in differentiating between FDI and FPI.

Even though many African countries gained independence by the late 1960s (Dupasquier and Osakwe, 2006), the continent was viewed as an area plagued with economic instability, weak governance, declining economic growth and social conflict.

During the 1970s and 1980s, many African countries showed very little increase in foreign investments (Ghosh et al., 2017). This period also witnessed fundamental economic policies that were primarily inward-looking economic strategies to encourage economic growth and development. These policies ranged from the protection of domestic industries, foreign exchange reserves and the nationalisation of foreign companies (Dupasquier and Osakwe, 2006). The study of Asfaw (2015) emphasised that these inward-looking strategies had a negative effect on the living standard of the people of Africa. Dupasquier and Osakwe (2006) also reported that the poor economic performance caused by these strategies did not allign with the globalisation activities worldwide. Many African countries tried to reverse the economic downturn and improve foreign investment by changing from inward-looking policies to more outward developing strategies. These efforts included embarking on policies to encourage foreign investments, among which was the adoption of IFRS.

Amaya and Rowland (2004) found that capital flows as a source of investment (in terms of FDI and FPI), increased significantly at the beginning of the 1990s in developing economies. The increase in capital flows to developing countries is arguably being attributed to changes in economic fundamentals and country-specific conditions (Ahmad and Zlate, 2014), which occurred due to the removal of various restrictions placed on foreign investments, and developments such as trade liberalisation and privatisation (Khayat, 2016)

Following the studies of Gordon et al. (2012), Gumus et al. (2013), and Ng (2015), we considered the following yardstick indicators that influence foreign investment, namely inflation rate, interest rate, exchange rate, economic growth rate, regulatory quality index, corruption, capital markets, trade openness, and corporate tax rate.

• Summary of argument and detail objectives

The argument of this study can be illustrated by the following scenario: Country A has low corruption levels, reflected in a good (high) corruption rating of 80%. It was also able to attract \$100m foreign investments. Country B has high corruption levels, reflected in a bad (low) rating of 40%. It was also able to attract foreign investments of \$100m. Therefore, even though Country A has low corruption levels, it can be argued that it is relatively *inefficient* when compared to Country B. From an output-oriented view, Country A should theoretically be able to attract twice as much foreign investment than Country B. Alternatively, from an input-oriented view, Country A's high corruption rating was not very helpful in attacting foreign investment and it could just as well have had the same low corruption rating as Country B. This argument is also valid for the other indicators, which can be used as input indicators to achieve the desired foreign investment inflow (output indicators). It may consequently be argued that the best practice frontier will be the country(ies) that can convert the *weakest* indicator (input) into the *highest* foreign investment (output).

To determine how African countries relatively benefit from IFRS, a model was needed to determine which set of countries demonstrate best practice attracting FDI and FPI, given their selected institutional environmental indicators. Therefore, the detailed sub-objectives of the paper are set out as follows:

- 1. Develop the requisite DEA models.
- 2. Extract data to calculate the technical efficiency of each of the 92 DMUs.
- 3. Determine whether there is a difference in technical efficiencies when economic indicators are used as input variables versus the governance indicators.
- 4. Rank the countries in sequence of their relative success to attract FDI and FPI.

5. Study population and data sources

The DEA approach is cognisant of evolving efficiency levels over time. Following the practice by Branken (2018), this study employed data for multiple years. The sample used was based on the 18 African countries that have adopted IFRS to date. As Senegal was the latest to adopt IFRS in 2014, annual data from 2014 to 2019 were extracted. The 2020 data were excluded because i) in many instances data points were not available yet, and ii) to avoid possible *abnormal* consequences due to Covid-19's effect. Furthermore, due to incomplete data from various sources from the IMF (2021), TheGlobalEconomy (2021) and the World Bank (2021), the countries Sierra Leone and Zimbabwe were excluded, while some years from Eswatini (2014 and 2015), Kenya (2019) and Senegal (2019) were also excluded due to incomplete data. The usable information of the 16 countries are listed in Table 2 and Table 3. In total, a dataset of 92 DMUs has been established.

FDI and FPI inflow data were extracted from the database of 'International Investment Position' on the IMF website (IMF, 2021). In respect of FDI inflows, 'Liabilities: Direct investment options' were selected, which include i) equity and investment fund shares and ii) debt instruments. In respect of FPI inflows, 'Liabilities: Portfolio investment options' were selected, which included i) equity and investment fund shares and ii) debt securities.

From TheGlobalEconomy (2021) website, the following indicators were extracted: Economic growth rate (EG – percentage of change in the GDP); inflation rate (INF – percentage change in the consumer price index); interest rate (INT – on bank credit to the private sector); trade openess (TOP – exports plus imports as percent of GDP), regulatory quality index (REG) and control of corruption (COR) (both converted to a scale from 0 to 5, where 5 represents a strong value, implying strong regulatory quality and strong corruption combat, and *vice versa*); and corporate tax rate (TAX – percent on commercial profits). As many countries did not indicate their market capitalisation, which is a measurement for capital markets, it was substituted with the *GDP*.

From the literature it is clear that input indicators such as i) economic growth rate (Zeghal and Mhedhbi, 2006), ii) market capitalisation (substituted by the *GDP*) (Gordon et al., 2012), iii) interest rates (Gumus et al., 2013), iv) governance factors, trade openess (Ramanna and Sletten, 2014), and v) regulatory quality index and corruption control (Gordon et al., 2012) are positively associated with foreign investment inflows. It may therefore be assumed that higher indicator values reflect a country scenario that is more attractive to foreign investors than countries with

lower indicators. In the DEA model, countries that can convert low (weak) inputindicators into high output levels (FDI and FPI) will be regarded as efficient, and will form the best practice frontier. Furthermore, literature also indicates that high inflation rates (Gumus et al., 2013) and high tax rates (Gordon et al., 2012) are negatively associated to foreign investment inflows. The expectation is that lower inflation and tax rates should increase foreign investments as investors perceive it as an indication of stability and an investment incentive. For example, Country A, which attracts \$100m foreign investment, where the tax rate is 30%, does better (is more efficient) than Country B, which also attracts \$100m, but with a tax rate of 20%. For the purpose of the DEA model, which seeks a low input value to convert into a high output value, the inverse of the inflation rate (1/inflation rate) and tax rate (1/tax rate) was used.

Exchange rate as a factor that may influence foreign investment makes sense, as a local currency weakens against the investor's currency, the investor's relative purhasing power increases. For the DEA model, the 16 currencies should be standardised to make them comparable. In doing so, the World Bank's Purchasing Power Parity (*PPP*) conversion factor was used. The PPP is defined as "the number of units of a country's currency required to buy the same amount of goods and services in the domestic market as a U.S. dollar would buy in the United States." (World Bank, 2021). In the literature, it is found that the higher PPP factor (per the exchange rate) will be negatively associated with foreign investment because an undervalued currency is *cheaper* in attracting foreign investment (Gordon et al., 2012). Similarly, the expectation is also that the lower the *PPP* factor is, the more it is attractive to foreign investors. For the purpose of the DEA model, which seeks efficieny, to convert a poor input value into a high output value, the inverse of the *PPP* factor (*1/PPP*) was used.

• DEA model and data

In attaining the first objective, 92 DMUs (datapoints) were considered to be sufficient for a single DEA model, which requires that the number of DMUs should be at least twice the size of inputs plus outputs (Cook et al., 2014); it was decided to develop two separate models to enhance the models' discrimination power. Model 1 included economic indicators as input variables, and Model 2 governance indicators as inputs variables. The models are specified as follows:

Model 1 Inputs:			x1 = TOP x2 = COR x3 = REG x4 = 1/TAX
Outputs:	y ₁ = FDI y ₂ = FPI	Outputs:	y1 = FDI y2 = FPI

Table 1 summarises the data, namely descriptive statistics of the input variables of both models, Model 1 and Model 2, and the output variables, which are the same for both models. The table exhibits the average, standard deviation, minimum and maximum values for each the nine input indicators and the two output indicators. There is a wide spread in the monetary data, *GDP*, *FDI* and *FPI*. For example, the *GDP* standard deviation (\$127.559bil.) is nearly twice the average value (\$72.059bil.). Since the DEA method was applied, these widely extreme data points were not problematic in this study, since DEA is a non-parametric method that uses ranked data instead of continuous data.

Table 1: Descriptive statistics of data

	Input							Output			
						Model 2					
	Model 1 (Economic indicators)			(Go\	(Governance indicators)						
	EG	GDP	INF*	INT	PPP*	TOP	COR	REG	TAX*	FDI	FPI
	%	\$bil.	%	%	0+	%	1-5	1-5	%	\$bil.	\$bil.
Avg.	4.0	72	6.6	14.8	0.42	71.2	2.3	2.3	31	42.5	19.3
S.D.	2.3	128	5.2	8.1	0.06	29.7	0.6	0.5	9	79.2	56.78
Min.	0.0	2	-1.1	5.1	0.31	20.7	1.2	1.6	14	0.26	0.001
Max.	9.4	547	23.8	44.4	0.59	143	3.4	3.6	55	331	292

* Note: In the DEA model, the inverse values of INF, PPP and TAX were used. Note: EG = economic growth; GDP = gross domestic product; INF = inflation rate; PPP = purchasing power parity; TOP = trade openness; COR = corruption; REG = regulatory index; TAX = tax rate; FDI = foreign direct investment; FPI = foreign portfolio investment

For purposes of this study, the following equation (Zhu, 2009) is the less restricted input-oriented VRS DEA model developed by Banker et al. (1984):

$$\begin{array}{l} \theta^* &= \min \theta\\ Subject \ to \end{array}$$

$$\sum_{\substack{j=1\\n}}^n \lambda_j \ x_{ij} \leq \theta x_{i0} \qquad i=1,2,\ldots,m;$$

$$\sum_{\substack{j=1\\n}}^n \lambda_j \ y_{rj} \geq y_{r0} \qquad r=1,2,\ldots,s;$$

$$\sum_{\substack{j=1\\\lambda_j}}^n \lambda_j = 1$$

$$\lambda_i \geq 0 \qquad j=1,2,\ldots n.$$

The value of θ represents the input-oriented efficiency score of DMU_0 If $\theta^* = 1$, DMU_0 lies on the (best practice) frontier. If $\theta^* < 1$, DMU_0 does not lie on the frontier and should decrease its input levels. DMU_0 represents one of the *n* DMUs under review and x_{i0} and y_{r0} are the *i*th input and *r*th output for DMU_0 , respectively. Each observation, DMU_i (j = 1,...n), uses *m* inputs x_{ij} (i = 1,2,...,m) to produce *s* outputs y_{rj} (r = 1,2,...,s). The efficiency frontier will be determined by these *n* observations.

6. Results and discussion

To enhance the reliability of the study, the software purposely developed by Zhu (2009) was used to calculate the input-oriented technical efficiency according to the VRS approach. Table 2 exhibits the results of the second objective, the relative technical efficiency estimates for the dataset of 92 DMUs.

Model 1: Using economic indicators as input data, the TE column shows that 40 of the 92 DMUs were fully efficient (1.000), with an average of 0.914 and the lowest estimate of 0.639 for Uganda in 2019. The sum of 1 - 0.914, namely 0.086 represents the average distance that DMUs are lying from the best-practice frontier. For a real production function applying the input-oriented approach, the average of 0.914 would be interpreted that, on average, the DMUs economic indicators (inputs) should be reduced by 8.6 percent (1 - 0.914) to become fully efficient, i.e. laying on the best-practice frontier. However, DEA was employed in this study to firstly find the benchmark DMUs (fully efficient ones) to establish the best practice frontier. Therefore, the interpretation for this study is that the inefficient DMUs have, on average, 8.6 percent better economic indicators, but were not able to gain any benefit from them to attract foreign investment. In the same vein, for the DMU of Uganda in 2019, a virtual DMU laying on the best-practice frontier that attracts exactly the same amount of FDI and FPI should have 36.1% weaker economic indicators. To summarise, the inefficient DMUs technical efficiencies are an indication how far they are from the best practice frontier. Therefore, the inefficiency number (1 - TE) indicates the degree that input indicators are not contributing (or in other words, are wasted) to attracting FDI and FPI inflows.

Model 2: Using governance indicators as input data, the technical efficiency column shows that 15 of the 92 DMUs were fully efficient, with an average of 0.870 and the lowest estimate of 0.593 for Botswana in 2014. Within the context of this study, the interpretation, from the input-oriented view is that the inefficient DMUs have, on average, 13 percent better governance indicators, but were not able to benefit from them to attract foreign investment. Furthermore, for Botswana in 2014, a virtual DMU laying on the best-practice frontier that attracts exactly the same amount of FDI and FPI would have 40.7% weaker governance indicators.

In attaining the third objective, i.e. determining differences in TEs between economic indicators and governance indicators, further analysis was performed to determine the difference in the results of Model 1 and Model 2. A t-test (paired two sample for means) was executed to determine whether there is a significant difference between the two models' averages, 0.914 and 0.870, respectively.

1 Botswana 2014 0.900 0.593 49 Namibia 2017 1.000 0.684 2 Botswana 2016 0.953 0.598 51 Namibia 2019 0.998 0.661 4 Botswana 2017 0.993 0.607 52 Nigeria 2014 1.000 1.000 5 Botswana 2019 1.000 0.618 54 Nigeria 2016 1.000 1.000 6 Botswana 2019 1.000 0.899 55 Nigeria 2018 0.899 0.993 8 Eswatini 2018 1.000 0.895 56 Nigeria 2018 0.899 0.993 9 Eswatini 2018 1.000 0.782 60 Rwanda 2011 0.845 0.744 1 Ghana 2015 1.000 0.782 60 Rwanda 2018 0.800 0.733 14 Ghana 2017 0.797 631 Rwanda 2018 1.000 0.741 15 Ghana 2019 0.752 1.000 65 Senegal 2011 1.000	No.	DMU	M1 TE	M2 TE	No.	DMU	M1 TE	M2 TE
2 Botswana 2015 1.000 0.609 50 Namibia 2018 1.000 0.663 3 Botswana 2017 0.993 0.607 52 Nigeria 2014 1.000 1.000 5 Botswana 2018 0.967 0.608 53 Nigeria 2016 1.000 1.000 6 Botswana 2019 1.000 0.818 54 Nigeria 2016 1.000 1.000 7 Eswatini 2016 1.000 0.895 56 Nigeria 2018 0.899 0.993 9 Eswatini 2018 1.000 0.917 57 Nigeria 2018 0.889 0.993 10 Eswatini 2018 0.000 0.735 59 Rwanda 2016 0.862 0.736 11 Ghana 2015 1.000 0.752 1.000 64 Senegal 2014 1.000 0.741 15 Ghana 2019 0.752 1.000 64 Senegal 2015 1.000 0.923 16 Kenya 2015 0.764 0.989 66	1	Botswana 2014	0.900	0.593	49	Namibia 2017	1.000	0.684
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Table 2: Technical efficiency (TE) of Model 1 and Model 2

Note: DMU = decision-making unit; M1 = Model 1; M2 = Model 2; TE = technical efficiency

In the process, the correlation between Model 1 and Model 2's technical efficiency scores have shown a correlation coefficient of 27.86 percent. Nevertheless, the t-test indicated (t-stat = 2.088) p = 0.0396, which implies that the difference in means is significant at 5%.

The software of Zhu (2009) also calculates a virtual vector as a benchmark for each inefficient DMU. Furthermore, it also set targets of either indicating how much each input variable should decrease and/or each output variable should increase that the inefficient DMU can move the shortest path towards the bestpractice frontier. For purposes of this study, this information does not provide any practical value. An input-oriented approach was chosen to calculate the degree to which inputs can be reduced while maintaining the output. Again, this was only to indicate which DMUs lie on the best-practice frontier and also to determine the distance that non-efficient DMUs are laying from this frontier. For example, it does not make sense to recommend to a non-efficient DMU to reduce their economic growth, reduce their GDP, increase tax rates, increase corruption levels, etc.

The final objective was to determine how IFRS-adopted African countries relatively to each other benefit to attract FDI and FPI. To reach the objective, the results in Table 2 were further analysed to calculate an average technical efficiency for each country. Table 3 exhibits the results in ranking order, from the most efficient to the least efficient.

Rank	Country	n	Model 1	Country	n	Model 2
1	Lesotho 6		1.000	Tanzania	6	0.999
2	Senegal	5	1.000	Nigeria	6	0.999
3	Eswatini	4	0.999	Kenya	5	0.972
4	Mauritius	6	0.998	Mauritius	6	0.967
5	South Africa	6	0.996	Uganda	6	0.957
6	Namibia	6	0.988	Malawi	6	0.949
7	Nigeria	6	0.971	Mozambique	6	0.949
8	Botswana	6	0.969	South Africa	6	0.947
9	Malawi	6	0.948	Senegal	5	0.929
10	Zambia	6	0.918	Eswatini	4	0.906
11	Mozambique	6	0.878	Ghana	6	0.823
12	Ghana	6	0.875	Zambia	6	0.786
13	Rwanda	6	0.863	Lesotho	6	0.763
14	Tanzania	6	0.769	Rwanda	6	0.741
15	Kenya	5	0.769	Namibia	6	0.660
16	Uganda	6	0.696	Botswana	6	0.605

Table 3: Ranking countries on the average TE of Model 1 and Model 2

Note: n = number of DMUs; M1 = Model 1; M2 = Model 2

The results in Model 1 indicate countries such as Lesotho, Senegal, Eswatini, Mauritius and South Africa are IFRS adopted countries that benefiting substantially more than the others. Consequently, the study concludes that it was easier for those mentioned countries to convert relatively poor economic indicators into FDI and FPI. The remaining countries' efforts to offer a good economic environment did not obtain relatively similar yields to attract FDI and FPI.

The results in Model 2 indicate that Tanzania and Nigeria were fully efficient, implying that the remaining countries with relatively better governance indicators could not obtain relatively similar yields to attract FDI and FPI.

Notably, there are no obvious patters in the ranking results between Model 1 and Model 2. For example, the three top ranking countries in Model 1, Lesotho, Senegal and Eswatini, are all at the bottom half in Model 2. Countries such as Tanzania and Kenya, which are ranked under the top three in Model 2, are ranked third and second last in Model 1. The lesson learnt from this exercise is that there would have been too many widely diverse input variables if a single combined model was applied. That would limit the discrimination power as, for example, a good economic indicator could be nullified by a poor governance indicator.

Following authors in accounting studies such as Broardbent et al. (2001), Brignal and Modell (2000), Rollins and Bremser (1997), Fogarty (1996), Phan (2014). Aldemir and Uvsal (2017) and Iredene et al. (2020), we have also used the institutional theory to conceptualise this study. Central to the theory is the concern why countries have the same degree of similarity and more specifically, institutional isomorphism is the concern why one country adopt the same features and practices of other countries which operate in the same conditions or environment. Central to the study was that there is pressure from society on countries to adopt IFRS. The common ground/similarity of the countries investigated is that they all adopted IFRS. We further argued that countries have the similarity to enlight forces such as the economic and governance vardstick driver. By doing so, the argument was that they would expect the same degree of success. However, the degree of success is diverse, between 69.6% and 100%, and 59.3% and 100%, where economic indicators and governance indicators were used as the input indicators, respectively. Furthermore, the TE estimates (on average 8.6% and 13.0%) are an indication of the degree that input variables were not fully efficient (or actually wasted) to attract foreign investment.

7. Conclusion

The purpose of the study was to determine how successful IFRS-adopted African countries relative to each other are in attracting FDI and FPI. Data envelopment analysis was supportive to reach the four objectives: 1) Develop two models using economic input indicators and governance input indicators; 2) Calculate the technical efficiency of each DMU; 3) Calculate whether there is a difference in technical efficiency when economic indicators are used as input variables versus the governance indicators; and 4) Rank the countries in order of their relative success to attract FDI and FPI.

The study found that the technical efficiencies of Model 1 and Model 2, using economic and governance indicators as input data, on average 8.6% and 13%, respectively, of the input indicators did not contribute to attracting foreign investment. Furthermore, there is a statistically significant difference in the average technical efficiencies of Model 1 and Model 2 at a 5% level. Finally, within the models, there is a wide difference between the average technical efficiencies between the different countries and there is no obvious pattern in the ranking of countries' technical efficiencies between Model 1 and Model 2.

Earlier we argued, due to institutional pressure, countries strive to obtain the same degree of success by adopting some practices. Within the conceptual frame of the institutional theory, the study concludes that with IFRS adoption as the similarity between the sample countries, they experienced different degrees of success to attracting foreign investment. The practical value hereof is that it provides valuable implications for a number of interested parties such as policymakers from Africa, policymakers from other developing countries and foreign investors. The lesson is that although there are similarities in countries structures, diverse different outcomes may occur. Furthermore, academic researchers and practitioners may use this study as a base for further research. With the aid of the DEA models, new insights were revealed that could not have been the case when regression analysis was applied. Key to be cognisent of is the understanding that IFRS adoption cannot, and does not, guarantee an equal degree of success to attract foreign investment.

A limitation of this study is that only IFRS-adopted countries were investigated and their success to attract foreign investment was only measured relative to each other. Therefore, no comparison could be made between IFRS adopted and non-adopted countries. Although DEA is a non-parametric method, the scale efficiencies of countries were not determined. That would require that both the VRS and CRS approaches of DEA are applied. Future research may address these limitations.

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