International Journal of Economics and Financial Issues

ISSN: 2146-4138

available at http: www.econjournals.com

International Journal of Economics and Financial Issues, 2026, 16(4), 23-31.

Trends and Growth Potential of the Attractiveness of African Countries to Chinese Foreign Direct Investment

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Received: 03 February 2026 **Accepted:** 01 May 2026 **DOI:** https://doi.org/10.32479/ijefi.23664

ABSTRACT

China has become one of the leading sources of FDI in Africa. However, the distribution of Chinese FDI across African countries is concentrated. This suggests that some countries are more attractive than others. In this study, we aimed to estimate the attractiveness of African countries to Chinese foreign direct investment, identify trends in attractiveness, and estimate the potential to improve country attractiveness to Chinese FDI. Our analysis is based on annual data for Chinese foreign direct investment in 42 African countries for the period 2008-2022. We used data envelopment analysis to generate efficiency scores that measure a host country's attractiveness relative to peers. Our analysis also identified potential to improve attractiveness based on input and output slacks for each country. The average efficiency score, based on variable returns-to-scale technology, was 84.8%, indicating that African countries are highly attractive to Chinese FDI. However, the efficiency scores fluctuated over the study period; only five countries had consistently high efficiency scores. These include Mauritius, South Africa, São Tomé and Principe, the Seychelles, and Zambia. Our analysis also reveals potential to enhance the attractiveness of African countries to Chinese FDI. Policy-makers should therefore benchmark their performance against peer countries to learn and assess the performance of their investment promotion strategies.

Keywords: Chinese FDI, Africa, DEA, Efficiency, Attractiveness, Slack
JEL Classifications: F21, C14

1. INTRODUCTION

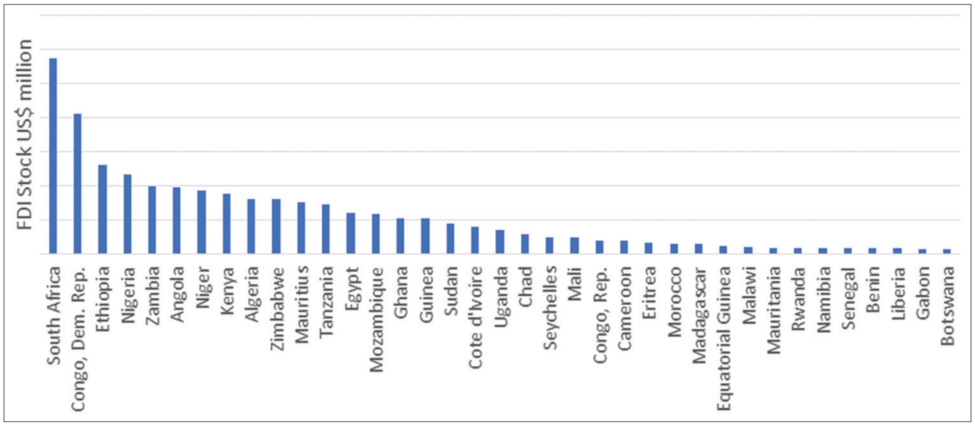
1.1. Background and Context

Over the last two decades, China has emerged not only as one of the largest economies in the world but also as a leading source of foreign direct investment (FDI). At the global level, the stock of outward Chinese FDI grew from $317,211 in 2010 to $2,939,100 (UNCTAD, 2024), a growth of slightly over 800%. Compared to other sources of FDI, China was the third-largest source of outward FDI stock in 2023, after the USA and the Netherlands, which were first and second, respectively (ibid). The growth of China as one of the leading sources of FDI globally accelerated following the reforms of the late 1990s and early 2000s, which saw China adopting the "Go Global" policy in 1999 and joining the world trade organisation (WTO) in 2001. With these two policy changes in place, China pursued more robust promotion of its FDI as well as the marketing of its products to the global economy.

The influence of China's FDI and trade policies has also been felt in Africa. Chinese FDI in Africa has increased by multiple folds in the last two decades. Between 2010 and 2022, the stock of Chinese FDI in Africa increased by 214%, rising from about USD13 billion in 2010 to about USD41 billion in 2022. Though dwarfed by the increase in Chinese FDI at the global level, which was estimated at 768% over the same period, such increases are nothing short of phenomenal, especially since the stock of FDI from the USA (the global leader in FDI) shrank by an estimated 16% during the same period.

While Chinese FDI has increased significantly in Africa, the FDI stock on the continent is highly concentrated (Figure 1). Some

Figure 1: Stock of Chinese FDI in top 37 African countries in 2022 (USD million in current prices)



Source: Johns Hopkins University SAIS China-Africa research Initiative (2025)

countries have received negligible amounts of FDI while others have received fairly large amounts. In 2022, close to 25% of the stock of Chinese FDI in Africa was in two countries – South Africa (14%) and the Democratic Republic of Congo (10%) – while 26 of the 54 countries shared 5% of the total FDI stock.

Several empirical studies have examined Chinese FDI in Africa. These studies have shown that, just like FDI from the West, Chinese FDI in Africa is motivated by the pursuit of markets, natural resources, and strategic assets (Drogendijk and Blomkvist, 2013; Kaplinsky and Morris, 2009; Utesch-Xiong and Kambhampati, 2022; Ross, 2015; Akatugba et al., 2023; Cheung et al., 2012; Gagne, 2018). While these studies have been helpful in analysing factors that make host countries attractive to Chinese FDI, they do not show the actual performance of host countries in attracting Chinese FDI. Hitherto, only three studies have estimated the actual performance of African countries in attracting Chinese FDI (Chompolola & Mbithi, 2026; Mohamued et al., 2022; Mourao, 2017). However, these too, do not analyse the trends and potential to improve in actual performance. This study sought to estimate African countries' actual performance in attracting Chinese FDI, trends in actual performance, and potential for improvement. Such information is important because it provides performance ranking, which can be used for benchmarking, assessing the performance of FDI promotion strategies, and analysing trends in the attractiveness of host countries. The study sought to address three specific objectives, which are:

i. To analyse the efficiency of the flow of Chinese FDI to African host countries
ii. To examine the trend in the efficiency of FDI flow from China to Africa
iii. To determine the potential for improving the flow of Chinese FDI to host countries in Africa.

1.2. Motivation and Significance

Currently, only three studies have assessed the attractiveness of African countries to Chinese FDI using efficiency analysis (Mourao, 2017; Mohamued et al., 2022; Chompolola & Mbithi, 2026). While the three studies showed the relative performance of each country, the efficiency scores used to estimate the level of attractiveness do not reveal trends over time. Estimating and analysing trends in attractiveness is important for policymakers as it can give a rough indication of performance over time. By estimating trends in attractiveness over time, our study provides policymakers with a tool to assess the evolution of their countries' attractiveness to FDI. This can serve as a basis for a more nuanced analysis of changes in attractiveness. Furthermore, our study can assess the potential to improve the inflow of Chinese FDI. Such information is important as it challenges policymakers to streamline existing policies and investment promotion strategies to optimise FDI inflow. The study also contributes to the growing body of efficiency studies in the FDI literature.

1.3. Contributions of the Paper

To the best of our knowledge, only three studies have attempted to analyse the attractiveness of African host countries to Chinese FDI (Mourao, 2017; Mohamued et al., 2022; Chompolola & Mbithi, 2026). However, two of these studies are based on the Stochastic Frontier Analysis approach, which does not show the trends in the attractiveness of African host countries (Mourao, 2017; Mohamued et al., 2022). Secondly, all three studies also fail to assess the potential to improve FDI inflows in host countries. Our study addresses these gaps by using the Data Envelopment Analysis (DEA) approach to answer the following three questions: (i) which African countries are more attractive to Chinese FDI?, (ii) how has the attractiveness of African countries to Chinese FDI evolved since the early 2000s? and (iii) what is the available potential for improving the inflow of Chinese FDI among African countries?

The rest of this paper is structured as follows: Section 4 discusses the existing literature on the subject matter, followed by a discussion of the methods and approaches in Section 5. The results of the study are presented and discussed in Section 6, followed by a conclusion in Section 7.

2. LITERATURE REVIEW

2.1. Empirical Literature

The empirical literature on FDI is quite extensive. However, most FDI studies have focused on the determinants of FDI. Similarly, studies on Chinese FDI in Africa, which have proliferated in the last two decades (Drogendijk and Blomkvist, 2013; Kaplinsky and

Morris, 2009; Utesch-Xiong and Kambhampati, 2022; Ross, 2015; Akatugba et al., 2023; Cheung et al., 2012; Gagne, 2018) have focused on determinants of FDI. Generally, studies measuring the attractiveness of FDI, which we shall refer to as the "efficiency of investment," have been limited.

Despite the paucity of efficiency studies in the FDI literature, interest in such studies has emerged over the last two decades. However, the existing studies are skewed. Out of the eleven empirical studies we reviewed, nine of them pertain to China or Chinese FDI (Qin & Song, 2009; Armstrong, 2011; Hualun Zhang et al., 2012; Lei et al., 2013; Fan et al., 2016; Mourao, 2017; Mohamued et al., 2022; Wang et al., 2023; Chompolola & Mbithi, 2026). Among these nine studies, only two analysed the efficiency of Chinese FDI in Africa (Mourao, 2017; Mohamued et al., 2022; Chompolola & Mbithi, 2026). Their specific focus was on the role of institutional distance (Mohamued et al., 2022; Mourao, 2017), the role of political and institutional attributes (Mourao, 2017), and the role of environmental variables (Chompolola & Mbithi, 2026).

The majority of the efficiency studies on FDI have relied mainly on parametric approaches, specifically the stochastic frontier analysis (SFA) (Armstrong, 2011; Stack et al., 2015; Fan et al., 2016; Mourao, 2017; Wang et al., 2022; Mohamued et al., 2022). Two of the empirical studies were based on data envelopment analysis (DEA) (Lei et al., 2013; Zhang et al., 2012). Each technique has its advantages and disadvantages. For example, SFA is more rigorous and can differentiate between noise and inefficiency, whereas DEA is unable to differentiate and, consequently, treats noise in the data as inefficiency (Coelli et al., 2005). Beyond the limited variability in analytical approaches, available studies are characterised by limited scope. Various measures of efficiency exist, including technical efficiency, allocative efficiency, cost efficiency, profit efficiency, and scale efficiency. Eight of the ten studies reviewed were based on technical efficiency, and only one study was based on allocative efficiency (Qin and Song, 2009), cost efficiency (Lei et al., 2013), and profit efficiency (Lei et al., 2013). The advantage of the limited variability in approaches and scope is that it facilitates easy comparison across studies and findings.

Available studies have used different units of analysis. Five of the ten studies reviewed used sovereign countries as their unit of analysis (Mourao, 2017; Fan et al., 2016; Stack et al., 2015; Armstrong, 2011; Mohamued et al., 2022). The remaining five studies used regions within countries as units of analysis (Qin and Song, 2007; Lei et al., 2013; Wang et al., 2022; Le and Dang, 2022; Zhang et al., 2012). This kind of heterogeneity, coupled with the relative paucity of efficiency studies on FDI, limits comparability. Additionally, the lack of homogeneity in units of analysis has implications for the types of input variables employed in the analyses and can limit the degree of comparability of results across studies. There is a need for more efficiency studies for scholarship as well as policy learning.

While the limited variability in the types of efficiency analysed in the literature makes it easy to compare findings across studies, comparisons may be constrained by heterogeneity in the number, type, and measurement of inputs and outputs. For example, while the DEA approach allows for multiple inputs and outputs (Afonso & Fernandes, 2008; Cook et al., 2014), SFA does not. Additionally, there is a lack of uniformity in the variables selected for the efficiency analyses in the reviewed papers. This is because the various studies had different research questions, which necessitated the variation in the choice of variables. For example, the study by Fan et al. (2016) used variables such as freedom, political stability, and property rights to explain the efficiency of Chinese FDI in the Belt and Road Initiative region. On the other hand, the study by Mourao (2017) employed political and regulatory variables, including indices of government effectiveness, corruption perception, political stability, and regulatory quality, to explain inefficiency in the second stage of the analysis. The study by Chompolola & Mbithi (2026) focused on the role of environmental variables in influencing efficiency. In the present study, we estimated trends in efficiency as well as the potential for efficiency improvement among African countries.

2.2. Knowledge Gaps

There is a relative paucity of empirical studies in the FDI efficiency literature. Existing studies are biased in their geographical spread, being concentrated on China or Chinese FDI. These studies do not reflect the disparate context associated with FDI in other countries. Secondly, the three existing studies that focus on Africa (Mourao, 2017; Mohamued et al., 2022; Chompolola & Mbithi, 2026) relied mainly on the basic SFA approach, which assumes time-invariant efficiency (Karagiannis & Tzouvelekas, 2009; Pitt & Lee, 1981). However, this assumption is unrealistic, as efficiency is bound to improve or deteriorate over time. We used the DEA approach to address these gaps. Furthermore, existing studies on the efficiency of Chinese FDI in Africa (Mourao, 2017; Mohamued et al., 2022; Chompolola & Mbithi, 2026) have not assessed the potential for improving the attractiveness of host countries to Chinese FDI. The DEA approach we adopted in this study can determine potential by computing input and output slacks.

3. METHODS AND PROCEDURES

This study is empirical in nature and uses quantitative methods to assess the attractiveness of African countries to Chinese FDI. We use the concept of technical efficiency as a proxy for attractiveness. To estimate technical efficiency, we employed the DEA approach. DEA is a widely used approach to assessing efficiency across production units. Its popularity stems from its flexibility: (i) DEA can handle multiple outputs (Afonso & Fernandes, 2008; Cook et al., 2014), (ii) it does not impose normality restrictions on the data, nor does it specify a functional form of a model, and (iii) it is atheoretical (Greene, 2008), making it flexible enough to assess technical efficiency even when there is no known theoretical link between the variables being considered.

3.1. Analytical Approach

We used the concept of technical efficiency to assess the attractiveness of African host countries to Chinese FDI. Based on the idea of efficiency, more efficient countries are deemed more attractive because they attract more FDI relative to peers.

Methods for assessing technical efficiency can be divided into two categories. Some are parametric and others are non-parametric.

In this study, we used a non-parametric approach called data envelopment analysis (DEA). DEA uses non-parametric approaches that construct an efficiency frontier using the output-input ratios of organisations or decision-making units (DMUs) under investigation. DMUs (here countries) with the output-input ratio equal to one are considered efficient and form the frontier against which the efficiency of all other units is gauged (Cooper et al., 2006). Measuring technical efficiency in a DEA framework involves solving the linear programming problem below:

$$\max\left(\frac{\sum_{s=1}^{S} u_s \times y_{s^0}}{\sum_{m=1}^{M} u_m \times x_{m^0}}\right) \quad 5.1$$

subject to

$$\frac{\sum_{s=1}^{S} u_s \times y_{s^0}}{\sum_{m=1}^{M} u_m \times x_{m^0}} \leq 1 \; i = 1,........, I$$

The inputs (x_{m0}) as well as outputs (y_{s0}) for DMU_0 are known. However, the weights u_s and v_m are not known and have to be determined by solving the optimisation problem 5.1. The optimisation problem 5.1 seeks to determine the values of u and v that maximise the technical efficiency measure of the ith DMU, subject to the constraint that the efficiency measures of all DMUs range from 0 to 1.

Two variants of the DEA model exist: the constant returns to scale (CRS) and variable returns to scale (VRS) variants. CRS is the simplest form of a DEA model and is attributed to Charnes et al., 1978). A DMU operating at CRS is operating optimally, implying that a change in the scale of production/operation is not likely to lead to efficiency gains (Kumar and Gulati, 2008). On the other hand, VRS technology implies that a DMU has the potential to improve its efficiency by changing its operations. VRS is more flexible as it accommodates differences in DMU sizes and allows for economies of scale (Banker et al., 1984). Further, the DEA optimization problem can be solved using output or input orientation. In this paper, we used output orientation because it is not in the best interest of DMUs (countries) to reduce inputs such as GDP. Instead, countries seek to maximise FDI inflows given their economic circumstances.

3.2. Data and Variable Selection

Data for this study were obtained from the World Development Indicators (WDIs) and the Statistical Bulletin produced by China's Ministry of Commerce (MOFCOM) (Table 1). All data pertained to annual time series for 42 African countries (Figure 2) spanning the period from 2008 to 2022. While the output variables (FDI stock and FDI inflow) were selected purposively, the input variables in Table 1, were selected based on the Isotonicity test (Avkiran, 2006). The isotonicity test, performed using correlation analysis (Table 2), ensures that the specification in a DEA model is valid. Considering that current investment decisions are based on historical context, all input variables were measured with a 1-year lag.

Table 1: Variable description and data sources

Variable type	Variable name (data source)	Variable description and measurement
Output variables	FDI stock (MOFCOM*)	This variable measures the total accumulated Chinese FDI in a given African host country at a point in time, expressed in real dollars.
	FDI inflow (MOFCOM)	This measures net Chinese FDI inflow into a given African host country in real dollars per year.
Input variables	Real GDP (WDI)	This is the host country's real GDP. The FDI literature uses it to represent market size (Asiedu, 2013; Anyanwu, 2011).
	Population (WDI)	The host country's population is another variable used to measure market size (Shah, 2014).
	Financial development (WDI)	The degree to which the financial sector is developed. In this paper, financial development it is measured as broad money (M2) expressed as a percentage of GDP (Ezeoha and Cattaneo, 2012).
	Infrastructure (ADB***)	This is measured as a composite index of availability of road, rail, electricity and water infrastructure (Chakrabarti et al., 2017).

*MOFCOM: Ministry of commerce, China, **WDI: World development indicators, ***ADB: African development bank

Based on the isotonicity test, only inputs that exhibit a positive, statistically significant correlation with the output variables are admissible in a DEA model. Isotonicity requires that increasing quantities of inputs should result in greater output. We conducted a correlation analysis of several candidate variables representing the various determinants of FDI, especially those whose theoretical relationship with FDI is expected to be positive. Based on the correlation matrix in Table 2, two input variables were admissible to our full DEA model for the period 2008-2022. These are: lagged Real GDP (Lreal GDP) and lagged Population (Lpopulation). Therefore, our DEA model for the pooled 2008-2022 data involved two outputs (FDI stock and FDI inflow) and two inputs (lagged Real GDP, and lagged Population).

To generate a set of efficiency scores for the period 2008-2022, we created sub-samples of the data. For purposes of smoothing the data to minimise annual fluctuations in data, each sub-sample was generated by averaging data over a 3-year period. For example, the first sub-sample was generated by averaging the data for the years 2008, 2009, and 2010. The last sub-sample was generated by averaging the data for 2020, 2021, and 2022. Including the full sample, we generated a total of six sub-samples. The isotonicity test was performed for each sub-sample to determine the input and output mix, as summarised in Table 3.

4. RESULTS AND DISCUSSION

4.1. Descriptive Statistics

The baseline model, which is based on the average of indicators over the period 2008-2022, was estimated using the four variables in Table 4. Between the two output variables, FDI stock and FDI

Figure 2: Trends in technical efficiency –2008-2022

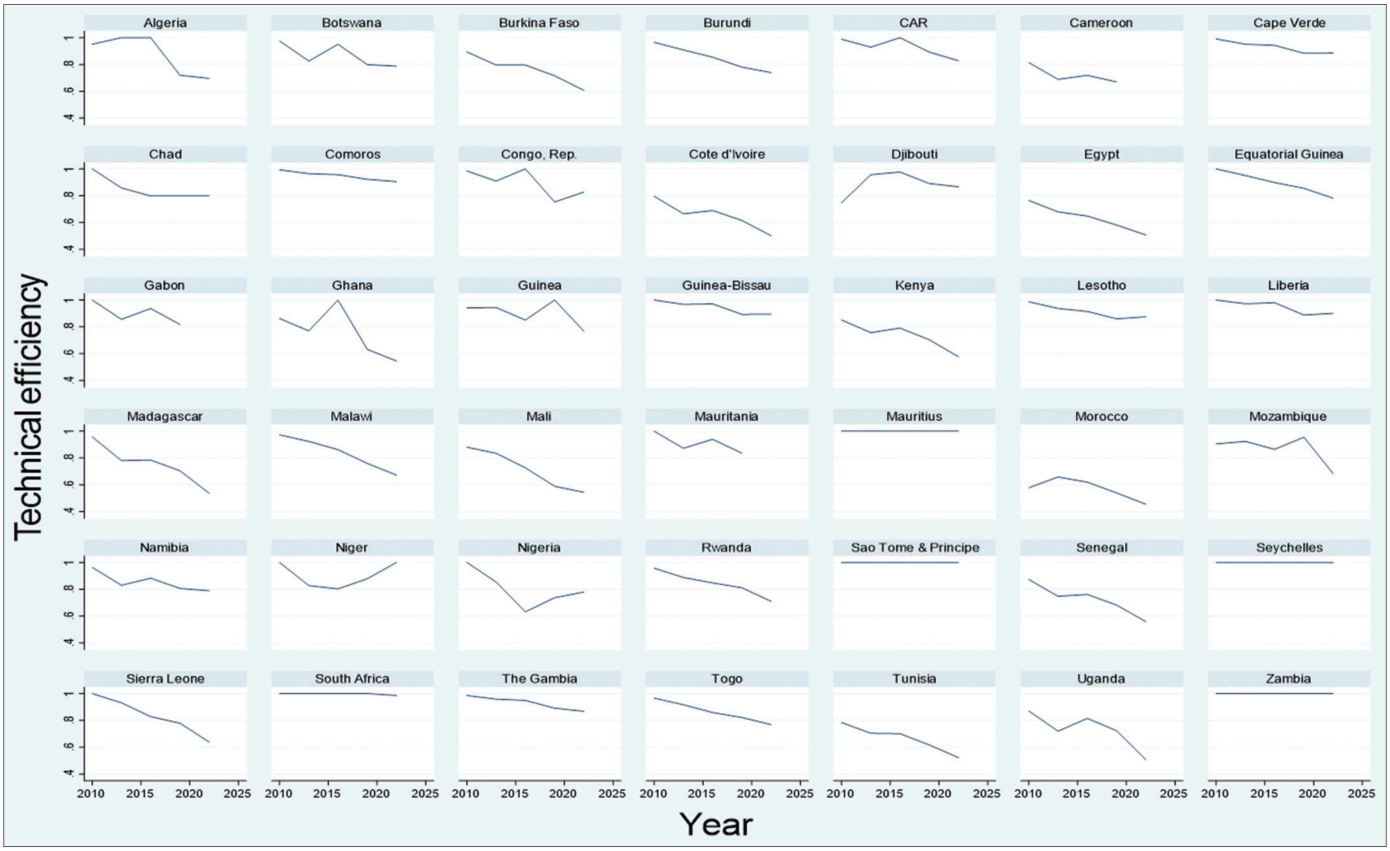


Table 2: Pairwise correlations (pooled 2008-2022 data)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) FDI stock	1.000						
(2) FDI inflow	0.969*	1.000					
	(0.000)						
(3) Linflation	0.126	0.101	1.000				
	(0.425)	(0.525)					
(4) Lpopulation	0.522*	0.468*	0.113	1.000			
	(0.000)	(0.002)	(0.475)				
(5) Lreal GDP	0.770*	0.651*	0.107	0.842*	1.000		
	(0.000)	(0.000)	(0.499)	(0.000)			
(6) Lfinancial dev	0.105	0.073	0.332*	0.063	0.195	1.000	
	(0.507)	(0.645)	(0.032)	(0.693)	(0.217)		
(7) Linfrastructure	0.255	0.232	0.172	0.148	0.291	0.811*	1.000
	(0.104)	(0.139)	(0.275)	(0.351)	(0.061)	(0.000)	

Source: Author's own work. *** P<0.01, ** P<0.05, * P<0.1

Table 3: Input and output mix for sub-samples

Sub-sample	Output	Inputs (All inputs are lagged)
2008-2022	FDI stock and flow	Real GDP and population
2008-2010	FDI stock and flow	Real GDP, population and infrastructure
2011-2013	FDI stock and flow	Real GDP and population
2014-2016	FDI stock and flow	Real GDP and population
2017-2019	FDI stock and flow	Real GDP and population
2020-2022	FDI stock and flow	Real GDP and population

Table 4: Descriptive statistics for pooled 2008-2022 data

Variable	Obs	Mean	Standard deviation	Min	Max
FDI stock	42	723.318	1,255.597	0.985	5,447.615
FDI inflow	42	775.624	118.411	701.127	1,199.134
Population	42	19.115	30.489	0.091	177.333
Real GDP	42	544,80.319	122,505.54	584.496	60,6626.81

Source: Author's own work

inflow, the former had greater variability, with a mean of $723 million and a standard deviation of $ 1,256 million. Variability was equally high in the population variable, with a mean of 19 million and a standard deviation of 30 million.

4.2. Technical Efficiency Scores

The technical efficiency (TE) scores presented in Table 5 are based on both variable returns to scale technology (VRS_TE) and constant returns to scale (CRS_TE) technology. In addition, we also present the scale efficiency (SCALE), returns to scale

(RTS) and efficiency rank (Rank) of each country. Generally, the efficiency scores for the 42 countries are relatively higher under VRS_TE (84.8%) than CRS_TE (22.4%). While the mean VRS_TE score is comparable to those of two DEA-based studies on FDI efficiency in 30 Chinese provinces, which determined average efficiency scores ranging from 88% to 95% (Zhang et al., 2012; Lei et al., 2013), it is higher than estimates from other studies on the efficiency of Chinese FDI in Africa. For example, using the SFA approach, studies by Mohamued et al. (2022) and Mourao (2017) estimated the efficiency of Chinese FDI in Africa at averages of between 25% and 73%. We can attribute the difference to the disparate analytical approaches, which have implications for the number and types of variables used in the analyses. For instance, while our DEA model employed two-factor inputs, the two SFA-based studies cannot handle multiple outputs.

Table 5: Efficiency scores and ranking based on aggregated data for 2008-2022

DMU or country	CRS_TE	VRS_TE	SCALE	RTS	Rank
Algeria	0.053359	0.877049	0.060839	DRS	21
Botswana	0.089925	0.866635	0.103763	IRS	23
Burkina Faso	0.04406	0.772726	0.057019	DRS	31
Burundi	0.100613	0.864181	0.116426	DRS	24
CAR	0.238113	0.9419	0.2528	DRS	8
Cameroon	0.037415	0.665816	0.056193	DRS	38
Cape Verde	0.352974	0.92986	0.379599	IRS	12
Chad	0.166402	0.839346	0.198251	DRS	28
Comoros	0.488694	0.938811	0.520546	IRS	10
Congo, Rep.	0.262454	0.898585	0.292074	DRS	15
Cote d'Ivoire	0.034332	0.640551	0.053597	DRS	41
Djibouti	0.103734	0.859503	0.120691	IRS	25
Egypt	0.017167	0.640841	0.026788	DRS	40
Equatorial Guinea	0.120401	0.893204	0.134797	DRS	17
Gabon	0.073652	0.894377	0.08235	DRS	16
Ghana	0.122265	0.74359	0.164425	DRS	32
Guinea	0.290736	0.922483	0.315167	DRS	13
Guinea-Bissau	0.584406	0.942832	0.619841	IRS	7
Kenya	0.093342	0.725671	0.128628	DRS	34
Lesotho	0.230537	0.917247	0.251336	IRS	14
Liberia	0.433741	0.952025	0.455598	IRS	6
Madagascar	0.167789	0.739389	0.226929	DRS	33
Malawi	0.144783	0.856556	0.16903	IRS	26
Mali	0.108863	0.700039	0.155511	DRS	37
Mauritania	0.109935	0.886574	0.124	DRS	18
Mauritius	0.399877	1	0.399877	DRS	1
Morocco	0.009603	0.6073	0.015813	IRS	42
Mozambique	0.306062	0.882856	0.346673	DRS	19
Namibia	0.158965	0.855591	0.185795	DRS	27
Niger	0.348688	0.940912	0.370586	DRS	9
Nigeria	0.029446	0.816002	0.036086	DRS	30
Rwanda	0.123844	0.86742	0.142772	IRS	22
Sao Tome and Principe	1	1	1	CRS	1
Senegal	0.052553	0.71453	0.073549	IRS	35
Seychelles	1	1	1	CRS	5
Sierra Leone	0.190731	0.829102	0.230046	DRS	29
South Africa	0.077642	1	0.077642	DRS	1
The Gambia	0.349018	0.932093	0.374445	IRS	11
Togo	0.141379	0.877647	0.161089	IRS	20
Tunisia	0.015364	0.660202	0.023271	IRS	39
Uganda	0.092041	0.706358	0.130303	DRS	36
Zambia	0.626294	1	0.626294	DRS	1
Mean	0.2236	0.847614	0.244296		

Source: Author's own work. VRS_TE: Technical efficiency from variable returns to scale DEA model, CRS_TE: Technical efficiency from variable returns to scale DEA model, RTS: Returns to scale, which can be increasing (IRS), decreasing (DRS) or constant (CRS)

The number of efficient countries under CRS_TE (2 or 5%) is lower than the number under VRS_TE (5 or 12%). However, the number of efficient countries is generally lower compared to other DEA-based studies in China. For example, one study determined that 37% of the provinces in the analysis were efficient (Zhang et al., 2012), while another determined that 82% of the DMUs in the analysis were efficient (Lei et al., 2013).

Based on VRS_TE, the technically efficient DMUs in this study were Mauritius, São Tomé and Principe, Seychelles, South Africa, and Zambia. These had an efficiency score of 1. The least efficient were Morocco, followed by Cote d'Ivoire and Egypt, whose efficiency scores were 60.7% for Morocco and 64.1% for Cote d'Ivoire and Egypt. The implication is that, with the right policies and strategies, these three countries can increase the inflow of Chinese FDI by 39.3% for Morocco, and 35.9% for Cote d'Ivoire and Egypt. Compared to the results from Mourao (2017), the top six efficient countries on Mourao's list include four of the five efficient countries from our list: Mauritius, Seychelles, South Africa, and Zambia. However, there is no similarity between our least efficient countries and the least efficient in Mourao's (2017) study. Nevertheless, the observed differences in the rankings between our findings and Mourao's (2017) can be partly explained by the differences in analytical approaches and data series. However, even among studies that have used similar analytical methods, comparability remains challenging due to differences in underlying objectives, which in turn influence the selection of variables and resultant empirical results. Further, even among studies conducted using DEA models, comparability of results across studies is problematic, partly due to the sensitivity of DEA models to noise and outliers (Clermont and Schaefer, 2019).

4.3. Trend in Technical Efficiency Scores

Based on five sub-samples, we generated a trend in efficiency scores over the period 2005-2022. Data for the sub-samples are based on 3-year averages to smooth short-term fluctuations. Table 6 provides a summary of the efficiency scores, along with their evolution from 2008 to 2022. Efficiency was generally high throughout the period, averaging 85%. However, fluctuations can be observed in both the efficiency scores and the number of efficient DMUs. The efficiency scores declined consistently from 93% in 2008-2010 to 75% in 2020-2022. The number of efficient DMUs averaged 8, and was characterised by a consistent decline.

Table 6: Evolution in technical efficiency scores between 2008 and 2022

Efficiency aspect	2008-2010	2011-2013	2014-2016	2017-2019	2020-2022	Average
VRS_TE	0.933466	0.87292	0.87034	0.804968	0.751611	0.846661
Efficient DMUs	14	6	9	6	5	8

Source: Author's own work

Table 7: Input and output slacks

DMU ID	Country	Input slack		Output slack	
		Population	Real GDP	FDI stock	FDI inflow
1	Algeria		164,373.00		29.69
2	Botswana		0.01	701.73	
3	Burkina Faso	9.57	0.00	1,270.31	
4	Burundi	6.33	0.00	710.47	
5	CAR	3.30	0.00	369.90	
6	Cameroon	5.40	0.00	2,138.57	
7	Cape Verde	0.16	0.00	263.13	
8	Chad	7.15	0.00	832.98	
9	Comoros	0.63		211.29	
10	Congo, Rep.		2,942.05	477.13	
11	Cote d'Ivoire	4.72	0.36	2,349.16	
12	Djibouti		0.01	741.05	
13	Egypt	37.56	0.10	2,428.01	
14	Equatorial Guinea		13,456.70	292.96	
15	Gabon		13,159.20	510.06	
16	Ghana	4.19	0.09	1,268.69	
17	Guinea	6.05	0.00	722.80	
18	Guinea-Bissau	1.42	0.00	165.24	
19	Kenya	16.69		1,876.26	
20	Lesotho	1.08		353.51	
21	Liberia	3.39	0.00	175.94	
22	Madagascar	9.88	0.00	1,218.43	
23	Malawi	12.88	0.00	590.55	
24	Mali	4.95	0.00	1,484.99	
25	Mauritania		4,061.08	747.83	
27	Morocco	5.14	0.03	2,475.88	
28	Mozambique	19.10	0.00	580.59	
29	Namibia		0.01	504.59	
30	Niger	14.27	0.00	520.32	
31	Nigeria	100.13	194,382.00	1,043.39	
32	Rwanda	7.06		648.27	
34	Senegal	3.86		1,523.24	
36	Sierra Leone	2.54	0.00	636.32	
38	The Gambia	1.55	0.00	261.17	
39	Togo	4.44	0.00	575.25	
40	Tunisia		12,195.30	1,980.98	
41	Uganda	15.43		1,874.35	
	Average	8.35	10,934.32	933.12	0.80

Countries in the sample are becoming less and less efficient in attracting Chinese FDI. This could be a sign of diminishing opportunities for multinational companies or ineffective investment promotion strategies.

In Figure 2, we present country-specific line graphs illustrating the trend in country-specific efficiency scores from 2008 to 2022. Of the 42 countries in the study, only five consistently maintained efficiency scores at the frontier throughout the period. This is shown by a consistent vertical efficiency line in Figure 2. The countries are Mauritius, South Africa, São Tomé and Principe, Zambia, and the Seychelles. While the rest of the country exhibited declining efficiency scores, some had relatively stable and less volatile scores. These include the Gambia, Comoros, Cape Verde, Guinea-Bissau, Lesotho and Liberia. Efficiency scores for these countries exhibited a consistent but gentle decline. The rest of the countries had relatively volatile efficiency scores characterised by kinks or rapid decline. Countries with high and stable efficiency scores are optimising their level of Chinese FDI given their economic circumstances. They can therefore serve as a source of policy lessons for peer countries seeking to optimise their attractiveness to Chinese FDI.

4.4. Potential for Efficiency Improvement

In the DEA literature, capacity for improvement is characterised by the presence of non-zero slack values, which can manifest as either input or output slacks or both (Markovits-Somogyi, 2011). The presence of slack entails the potential to enhance performance. Non-zero output slacks, for example, indicate the amount by which outputs can be increased without requiring additional inputs. On the other hand, input slacks denote the amount by which inputs can be reduced without affecting the current level of output. Slacks have been described as input excesses or output shortfalls after radial inefficiencies have been identified (Avkiran, 2006; Ozcan, 2014).

Based on the idea of slack, all five efficient countries had zero slack values. This indicates that these DMUs are strongly efficient, with no room to improve performance at the current level of factor inputs. The presence of non-zero input or output slacks, or both, characterised the remaining DMUs. Table 7 shows all non-zero input and output slacks. On average, the input slacks were 8.4 million for the population and $10,934.32 million for real GDP. This means that factor inputs can be reduced by 8.1 million population and $10,934.32 million worth of real GDP without affecting the current level of output. Nigeria had the highest input slacks, estimated at 100 million for the population and $194,382.00 worth of real GDP. Output slacks were primarily dominant for FDI stock, averaging $933.12 million. Morocco had the highest output slack, estimated at $2,475.88 million worth of FDI stock. On average, each inefficient DMU can increase FDI stock by $933.12 million with the current level of inputs.

5. CONCLUSION

5.1. Summary of Contributions and Key Findings

Efficiency studies in the FDI literature have gained some traction in the last two decades. However, such studies are still limited in Africa. Our analysis aimed to use a DEA approach to contribute to empirical literature on the attractiveness of Chinese FDI in Africa by addressing the following three questions: Which countries in Africa are relatively more attractive to Chinese FDI?, how has the attractiveness of Chinese FDI in Africa evolved between 2008 and 2022?, and to what extent do African countries have potential to increase their attractiveness to Chinese FDI? The use of the DEA approach represented a departure from the SFA approach employed in similar studies.

Based on the DEA efficiency scores of 42 countries, our study revealed that African countries are very attractive to Chinese FDI. The average efficiency score under VRS technology was 84.8%. However, the efficiency scores for most countries are characterised by fluctuations and general decline over the study period; only five countries had consistently high efficiency scores (Mauritius, South Africa, Sao Tome and Principe, the Seychelles, and Zambia. These can be used for benchmarking and peer learning. Slack-based analysis also revealed that less efficient African countries have the potential to enhance their attractiveness to Chinese FDI.

5.2. Suggestions for Future Research Directions

While this study was able to determine the level of attractiveness of individual African countries to Chinese FDI, the study is descriptive. It cannot explain the observed levels of attractiveness. Analytical studies are required to explain the estimated efficiencies and their trend. Comparative studies could also examine the attractiveness of Chinese FDI relative to FDI from the global North.

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