Technical Efficiency in the Services Sector of selected Sub-Saharan African Countries

Kenneth Kigundu Macharia

Research Paper 555

Bringing Rigour and Evidence to Economic Policy Making in Africa

AFRICAN ECONOMIC RESEARCH CONSORTIUM
CONSORTIUM POUR LA RECHERCHE ÉCONOMIQUE EN AFRIQUE

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AERC Research Paper 555
African Economic Research Consortium
April 2024

This research study was supported by a grant from the African Economic Research Consortium. The findings, opinions and recommendations are those of the author, however, and do not necessarily reflect the views of the Consortium, its individual members or the AERC Secretariat.

Published by: The African Economic Research Consortium
P.O. Box 62882 - City Square
Nairobi 00200, Kenya

ISBN 978-9966-61-260-1

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Abstract

While the service sector is increasingly playing a bigger role in the structural transformation of developing countries, the sector's level of technical efficiency remains understudied. This study analyses the level of technical efficiency in the service sector of selected sub-Saharan African countries and identifies covariates of this technical efficiency. Data are from the 2013 World Bank Enterprise survey for six countries, namely Kenya, Uganda, Tanzania, Ghana, Zambia and the Democratic Republic of the Congo. The estimation is performed by a two-stage bootstrap data envelopment analysis approach at the country and sub-sector levels. The sub-sectors of interest are retail, wholesale, hotel and restaurant, transport, motor vehicle services and IT. The findings show substantial opportunity to enhance technical efficiency in the selected sub-Saharan Africa service firms. The nature of the opportunity varies across countries and sub-sectors. Firm size, export, firm age, research and development, training, female firm ownership and top manager's experience have an influence on technical efficiency but this influence varies across countries. In general, the findings imply that there is a need to provide an enabling environment that allows the growth of service firms given that large service firms are more technically efficient compared to small firms.

1. Introduction

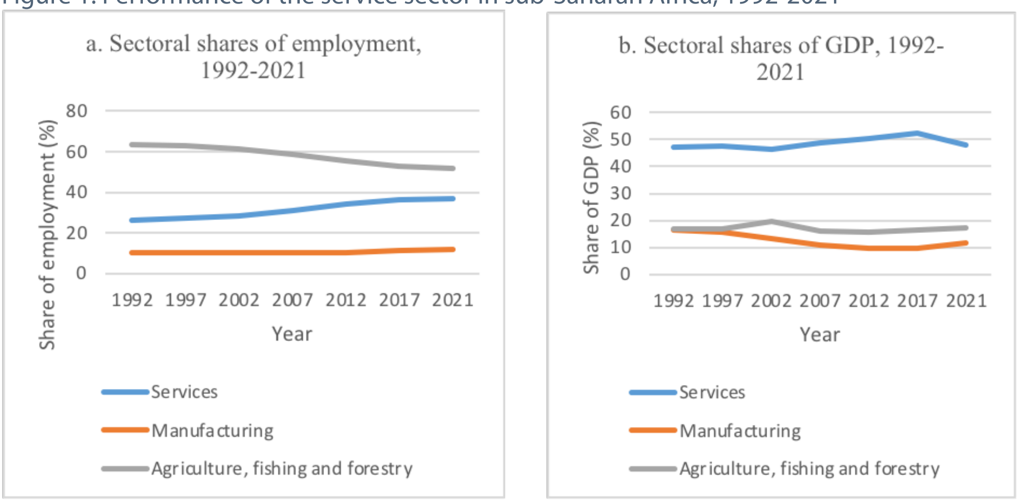
In recent years, the service sector has been at the centre of driving structural transformation across the globe. More specifically, low-income countries, especially in Africa and South Asia do not seem to follow the traditional path of development, but a new path in services making them grow faster than developed countries and hence converge more swiftly (Ghani and O'Connell, 2014). While services are increasingly playing an important role in economic performance and overall development in low-income countries, the role played by the manufacturing sector is shrinking as can be seen from the diminishing shares in both employment and real value-added since the 1980s (Rodrik, 2016; UNECA, 2021). The trends in structural transformation in low-income countries have nevertheless raised concern among a section of development economists who are of the view that these countries are experiencing "premature industrialization." As stated by Chenery (1960) and Kuznets (1971), if low-income countries were to follow the development path followed by developed countries, resources would move from agriculture to industrialization. After countries have industrialized and attained an advanced stage of development, the industrial sector's shares decline as those of the service sector rise. However, for low-income countries characterized by less industrialization, shares of manufacturing employment and value-added are observed to peak at lower levels and lower per capita GDP (Rodrik, 2016).

The increasing significance of services can be attributed to several factors. First, globalization and advancements in technology have made it possible to produce and trade services (Ghani and O'Connell, 2014). In addition, the low cost of trading services due to minimal customs and other administrative barriers has reinforced global trade in services making it grow faster than that of merchandise goods (Ghani and O'Connell, 2014). The entry of services into value chains has led to improved productivity of services. Second, services are now able to absorb a pool of highly skilled labour and offer significantly higher wages, ultimately leading to increased productivity. Third, service firms are less capital intensive, have a larger scope for mobility, are easily reachable for workers, require shorter lead times to establish and run effectively, and provide a marketplace across space and time for skills, expertise, and information (UNECA, 2021).

The service sector promotes development directly by contributing to GDP, trade, and job creation. A strong and efficient service sector also stimulates industrial growth by enhancing input-output linkages and demand between services, agriculture, and manufacturing. Globally, the sector contributes approximately 50% of the total GDP and a growing proportion to employment (Ghani and O'Connell, 2014). This has seen the sector employ more people than the agriculture and manufacturing sectors. For example, according to the International Labour Organization (ILO), the global workforce working in this sector in 2018 was slightly less than half of total employment (ILO, 2019). Agriculture stood at 28% which was a decline from 44% in 1991. The proportion of people working in the manufacturing sector is also declining at the global level (ILO, 2019). In global trade, the service sector provides at least 60% of total output, accounts for at least a fifth of gross trade volumes, and nearly 50% of the global trade in value-added terms (WTO, 2015).

In sub-Saharan Africa (SSA), the service sector has significantly stimulated economic growth in recent years. Agriculture, which is still the predominant economic activity, has reported a declining share in GDP while the manufacturing sector's contribution to GDP has either remained flat in some countries or dropped in others (Wamboye and Nyaronga, 2019). The range of businesses falling under the service sector both small and large is broad and highly heterogeneous. Based on the United Nations' International Standard of Industrial Classification of all Economic Activities (ISIC) the broad category of services encompasses from real estate, retail and wholesale, transport, finance, insurance, accommodation and food services, education, public administration, liberal professionals, and health to information and communications technology (ICT) (Nayyar et al, 2021). Among these services, financial and ICT services are some of the most vibrant and rapidly expanding services and their growth has been instrumental in accelerating demand for conventional services. Through its intermediation role, the internet has introduced new service platforms for e-commerce, e-business, and e-government, which are essential for efficiency and productivity improvements (UNECA, 2021).

Figure 1: Performance of the service sector in sub-Saharan Africa, 1992-2021



Source: World Bank Development Indicators (WDI)

Figure 1 shows the SSA service sector's contribution to employment and GDP for 30 years, from 1992 to 2021. The manufacturing sector's contribution to employment remained almost flat for more than two decades, but had a slight elevation in the last decade. Consequently, the increase in the service sector's share of total employment from 26% to 37% compensates for the fall in the agriculture, fishing and forestry sector's share, as indicated in Figure 1, Panel a. The service sector's contribution to GDP averaging 49% over the period remained significantly higher compared to that of the manufacturing sector at an average of 13% and the agriculture, fishing and forestry sector averaging 17%. The gradual improvements in manufacturing and agriculture, fishing, and forestry shares in the last five years compensated for the slight decline in the service sector's contribution to GDP over this period as shown in Figure 1, Panel b.

Even with this contribution, the service sector can still be a major driver of structural transformation in SSA (UNCTAD, 2015). Exploiting the sector's potential is essential for sustainable and inclusive economic development. However, the sector's performance in SSA remains suboptimal and services are delivered at a high cost, posing a threat to the realization of this potential (UNCTAD, 2015). The efficient application of limited resources is one of the approaches to enhance the sector's competitiveness and further employment creation, and the delivery of inclusive growth and sustainable development. The existence of low levels of technical efficiency implies that service firms could increase their output without necessarily consuming more inputs. Invariably, unravelling the potential of the service sector to enhance its competitiveness through technical efficiency enhancements requires an understanding of the kind of inefficiencies present and potential measures to moderate these inefficiencies.

Although useful and relevant for policymaking, technical efficiency in the service sector has not been assessed in depth in SSA. Some studies including those by Soderbom and Teal (2004), Chapelle and Plane (2005), Mukwate and Muchai (2012), Hailu and Tanaka (2015), Cheruiyot (2017) and Barasa et al (2019) have focused on the manufacturing sector. However, efficiency enhancements in a goods-domineering technique are inappropriate for services as service units uniquely transform inputs into output (Gronroos and Ojasalo, 2004). Only a few notable studies have focussed on the service sector, with most concentrating on financial services (Segun and Anjugam, 2013; Barros et al, 2014; Yannick et al, 2016), and a few concentrating on hotel services (Barros and Dieke, 2008), effectively ignoring other services such as retail and wholesale which are labour intensive.

This paper aims to address the research gap by focusing on three objectives. First, the study provides a rigorous assessment of technical efficiency in the service sector in selected SSA countries. Second, the study establishes the determinants of this efficiency. The study adopts a two-stage bootstrap data envelopment analysis (DEA) using data obtained from various 2013 World Bank Enterprise Surveys (WBES). The countries of interest are: Kenya, Uganda, Tanzania, Ghana, the Democratic Republic of the Congo (DRC) and Zambia. Although there are recent WBESs, there is not a common year for a significant number of SSA countries. This led to the choice of 2013, which has six country surveys allowing for cross-country comparisons. The empirical assessment is also at the sub-sector level given that sub-sectors differ in terms of production technology due to differences in input use, output and regulatory environment. The sub-sectors of interest are based on the WBES classification and include: hotels and restaurants, retail, wholesale trade, information technology (IT), motor vehicle services and transport. These are largely labour-intensive tradable services with great potential to spur employment and exports, and enhance poverty reduction.

The research adds to the current literature in several ways. First, the unique WBES provides room to contribute to the empirical literature by including a wide range of service firms located in selected SSA countries. Evidence is provided at the country and sub-sector levels. Such an empirical measure is useful in indicating the extent of gains realizable through technical efficiency enhancement at the country and sub-sector levels given the level of technology. The information could also be useful to less efficient firms in identifying their well-performing peers from whom they can learn to expand technical efficiency and converge to the benchmark frontier. Second, it provides evidence of the factors explaining technical efficiency in the selected SSA countries' service sectors. This could be important in providing key conclusions on the essential areas to be considered by policymakers when drafting policies to improve technical efficiency.

The rest of the paper is organized as follows: Section two is the literature review and Section three presents the methodology, definition, and measurement of variables and the data source. Section four provides a discussion of the results, and Section five concludes.

2. Literature review

Characteristics of services

With the increasing significance of the service sector in promoting the growth of economies, a need to measure productivity and efficiency in this sector is becoming more profound. The efficiency of a firm is a comparative measure of how well a firm applies inputs to attain output. While it is important to evaluate the level of technical efficiency in services, it is essential to acknowledge the unique nature of services that differentiates them from manufacturing firms in the conversion of inputs to output. Because of the unique differences, technical efficiency improvement measures under a goods-domineering production process cannot be applied to services, and therefore a need for services-specific studies. The unique characteristics include intangibility, inseparability, heterogeneity and perishability (Cowell, 1988; McLaughlin and Coffey, 1990; Klassen et al, 1998; Jaw et al, 2010; Roche et al, 2019). Intangibility means that it is generally impossible to taste, feel, see or smell services. Instead, services are valued activities, actions, or experiences. The intangible nature of services implies that services can easily proliferate as they are relatively easy to produce compared to products (Cowell, 1988).

Inseparability refers to the production and consumption of services occurring concurrently (Jaw et al, 2010). While goods are procured, sold and consumed, services are sold and then produced and consumed (Cowell, 1988). However, through innovations, some service organizations are progressively lowering the degree of service inseparability. For example, several years ago, no banking transaction could be processed when a bank was closed. However, with the introduction of ATMs, this inseparability problem was partially solved. Heterogeneity of services means that the delivery of a service may vary from time to time because different people are often engaged in supplying services to different customers. This implies that it is often difficult to ensure uniform standardization in the output of certain services (Cowell, 1988). However, some service-producing units, especially franchise entities where minimizing customer uncertainty is crucial, put a lot of effort into ensuring standards of conformity. Nevertheless, it is difficult to ensure uniformity in the quality of services compared to goods (Cowell, 1988). Perishability of services implies that services cannot be produced in advance and be stored to meet future demand (Jaw et al, 2010). For example, an empty hotel room represents capacity that is lost forever if the room remains unoccupied when it is vacant (Cowell, 1988). Furthermore, significant fluctuations in demand may hit certain services and this may exacerbate their perishability nature.

Theoretical review

In the standard classical theory, the long-run equilibrium of an industry refers to a situation where all firms in the industry are technically efficient and produce homogeneous products and quantities at a similar market price (Chappelle and Plane, 2005). However, economic reality provides little evidence of this theoretical assumption. Two firms may be identical in all aspects but produce varying amounts of output. The differences in firm performance can potentially be due to differences in the efficiency with which inputs are converted to output.

Researchers have made efforts to explain variations in efficiency across production units. One of the notable theoretical arguments is the Jovanovic (1982) theory which attributes differences in technical efficiency across firms to firm size and age. According to this theory, large firms are more efficient compared to small firms. This outcome is the result of a selection process where technically efficient firms grow and last, whilst technically inefficient firms stagnate or exit the market. Jovanovic assumed a competitive market where future output prices have a known time path and where all firms seek to maximize profits and have common cost functions that are convex in output. Further, firms were presumed to have varying fixed efficiency levels, but their efficiency levels were unknown when joining the industry. Instead, firms must deduce their efficiency levels by monitoring realized profits. However, this might take several periods as profits are distorted by random shocks. As time passes, firms become more accurate in estimating their efficiency levels and, based on the estimates, firms decide whether to expand, retain their current size, decrease, or leave the industry. Given that costs are convex, the profit-maximizing output is increasing in the efficiency parameter, which implies that technically efficient firms expand in size as inefficient firms reduce. Therefore, according to Jovanovic (1982), firm size and technical efficiency have a positive link in general. As a substantial period of time is involved in the process, large firms are not only more technically efficient compared to small firms, but also older, resulting in a positive relation between firm age and technical efficiency. This positive relation is augmented by learning by doing effects that make firms increasingly more efficient with time due to a more developed stock of experience.

However, the argument by Jovanovic (1982) has faced criticism from some researchers who argue that there exists a negative relationship between firm size and age, and technical efficiency. One of the arguments is that small firms may be more technically efficient compared to large firms because they are more exposed to competition. Second, unlike large firms, small firms leverage less diluted responsibilities and more flexible operations, leading to potentially better managerial performance (Chapelle and Plane, 2005). Conversely, large firms are characterized by rigidities in their management and operational environments and at times experience their own organizational weaknesses. Further, in small firms, it is common for owners to exercise direct participation in the production process and supervision appears easy (Chapelle and Plane, 2005). This context differs in large firms where output is jointly produced by many workers making it difficult to discern worker-specific contributions. Consequently, the incentive to free ride is present, necessitating more supervisors and bureaucratic costs to monitor staff performance. Regarding firm age, young firms could be more technically efficient compared to old firms because young firms join the market with more sophisticated and innovative technologies, while older firms apply durable equipment acquired in the past and may take time to acquire recent and superior technologies.

Other than firm age and size, the literature shows that differences in technical efficiency across firms could also be explained by the extent of investment in research and development (R&D), exporting status, and foreign ownership among other things (Van Biesebroeck, 2005; Wang and Wong, 2012; Moral-Pajares et al, 2015; Sadaf and Ishaq, 2018). The literature acknowledges that a firm's level of technical efficiency principally depends on the extent of technological advancement and the extent to which technology is absorbed and diffused. Firms innovate through implementing new and efficient technologies, high-quality output, production processes, or organization techniques provided by cumulative research and development efforts. A firm depends on own research efforts as well as on the R&D activities of support institutions such as research organizations, universities and trading partners. Hence, investment in R&D activities may be a key reason for technical efficiency improvements in many firms (Coe and Helpman, 1995; Sleuwaegen and Goedhuys, 2003; Wang and Wong, 2012).

International trade theories on export status have considered exporting firms over non-exporting firms as engines of economic growth. Exporting firms are considered to be more efficient owing to exposure to global competition and the absorption of foreign knowledge (Van Biesebroeck, 2005; Moral-Pajares et al, 2015). Exporting promotes product specialization, greater capacity utilization, leveraging economies of scale due to access to a larger market and assimilation of recent technologies and organizational norms, which are important in promoting technical efficiency (Ram, 1987). Van Biesebroeck (2005) and De Loecker (2007) link exports with indirect effects that encourage the absorption of foreign knowledge, a mechanism known as learning-by-exporting. The mechanism provides that once firms enter into foreign markets, they acquire new knowledge and expertise that propel them to enhance their technical efficiency levels. However, Van Biesebroeck (2005) and De Loecker (2007) consider the relation between exporting and technical efficiency to be bi-directional as technically efficient firms could self-select for exporting. According to this mechanism, export firms are more technically efficient compared to non-exporting firms before exporting, implying that only technically efficient firms participate in exporting activities and have a competitive edge in foreign markets. Improvements in the assignment and application of existing resources promote enhancements in competitiveness which boosts a firm's foreign commercial activities (Moral-Pajares et al, 2015).

On foreign ownership, foreign direct investment (FDI) is also considered a major driver of economic growth, particularly in developing countries. Consequently, host countries design a wide range of fiscal and financial incentives to attract FDI. FDI is considered important because it not only injects capital and adds employment to an economy but also infuses new knowledge into host economies (Suyanto and Salim, 2013). The new knowledge has been regarded as an important driver of improved technical efficiency in firms with foreign ownership. Moreover, foreign ownership comes with superior technology, better management expertise, and training to use recent technologies, which results in considerable improvements in technical efficiency (Esquivias and Harianto, 2020). Further, foreign ownership could have indirect effects on domestic firms through spillover effects in the form of new knowledge, recent technologies, better management expertise and training to apply recent technologies (Suyanto and Salim, 2013; Esquivias and Harianto, 2020). Spillover effects from foreign-owned firms could drive higher technical efficiency levels in domestic firms.

Measures of technical efficiency

The measurement of technical efficiency was pioneered by Debreu (1951) and Farrell (1957). It is described as the potential to produce more output using the same level of factors of production or the potential to produce a similar level of output but by engaging fewer amounts of factors of production. Advancements in the works of Debreu (1951) and Farrell (1957) have resulted in the formulation of two broad methods of measuring technical efficiency. The methods are the parametric and the non-parametric techniques. Under the parametric approach, efficiency is modelled by assuming the existence of a production function. The production function is defined as an analytical formulation expressing the highest amount of output that can be processed from a certain level of inputs or the minimum level of factors of production necessary to process a stated level of output. A production function that is commensurate with the full potential utilization of factor inputs defines a frontier. A frontier identifies all the feasible combinations of factors of production and output in production.

Following the seminal works by Farrel (1957), frontier production functions came into existence and a wide range of researchers have come to apply them. Estimation of technical efficiency under the parametric approach is dominated by the stochastic frontier analysis (SFA). The SFA was first coined in independent works of Aigner et al. (1977) and Meeusen and Van den Broeck (1977). These works were improvements on the works of Aigner and Chu (1968), Afriat (1972) and Richmond (1974). The earlier works used mathematical programming methods to compute technical efficiency by minimizing the absolute deviation of the optimal output from the actual output level (Kumbhakar and Lovell, 2000). However, this approach was problematic as it implicitly assumed a disturbance term making it very sensitive to outliers (Aigner et al, 1977). The SFA would solve this problem by introducing probabilities in the frontiers. In this case, a composite error term containing an inefficiency term and an error component is added to the deterministic frontier, hence allowing for a plausible estimation of technical efficiency (Kumbhakar et al, 2015).

The strength of the parametric approach is that, given its statistical nature, inferences can be made regarding the existence of inefficiency (Coelli et al, 2005). Additionally, confidence intervals can be determined for the levels of efficiency. Further, the approach can withstand measurement error as well as other disturbances. Nevertheless, the assumption of a production function is the main undoing of this approach. The functional form is unknown in most cases and making a wrong specification may lead to misleading results. The approach also suffers from common parametric estimation problems such as endogeneity.

The non-parametric approach can overcome these challenges as it requires no prior identification of the functional form and its non-statistical nature makes it immune from statistical issues, such as simultaneous-equation bias (Coelli et al., 2005). Moreover, the approach can fit in with multiple inputs and multiple outputs. At the helm of the non-parametric technique is the DEA initiated by the pioneering work of Charnes et al (1978). This approach measures the efficiency of decision-making units (DMUs) by adopting the linear programming mathematical technique. In this case, a benchmark frontier is developed from observed data. Technical efficiency scores are then computed relative to this frontier. Departures from the benchmark frontier are regarded as measures of inefficiency while DMUs that rest on the best linear frontier are argued to be technically efficient.

The literature describes two forms of DEA: The Charnes, Cooper and Rhodes (CCR) model that assumes constant returns to scale and the Banker, Charners and Cooper (BCC) model that assumes variable returns to scale. In constant returns to scale, DMUs are presumed to be functioning at an optimal scale. However, the variable returns to scale relaxes this assumption given that certain aspects, for example, imperfect competition, government regulations and financial constraints, could limit the possibility of firms operating optimally (Coelli et al, 2005). The major undoing of DEA is the deterministic nature that makes it treat all variations from the benchmark frontier as inefficiencies and ignores any possibility of random disturbances in the data (Coelli et al, 2005). From inception, DEA has been employed to analyse the technical efficiency of health facilities, banks, insurance firms, manufacturing firms, education institutions, crop farming and water utility firms, among others. As such, it is a desirable tool for evaluating the service sector's technical efficiency and even more so in a setting like the one being studied, where not much is known regarding production technologies.

In addition to the parametric and non-parametric techniques are the semi-parametric estimation techniques. These techniques are mainly applied in studies analysing the total factor productivity (TFP) of decision-making units. The analysis of TFP was pioneered in a seminal work by Solow (1957). In recent years, there has been a rise in both theoretical and empirical works on TFP with the revived attention being propelled by the increased availability of firm-level data and methodological developments. In general, firm-level productivity studies assume output to be a function of inputs applied by the firm and its productivity. TFP is then computed as a residual in this functional relationship.[1] However, applying traditional techniques, specifically ordinary least squares (OLS), in measuring TFP raises several methodological concerns. These include probable correlation between input amounts and simultaneity bias resulting from unobserved firm-specific productivity shocks (Levinsohn and Petrin, 2003). Several alternatives to OLS have been proposed. These include the Olley and Pakes (1996) (OP), Levinsohn and Petrin (2003) (LP), and Ackerberg et al. (2015) (ACF) techniques. Although these techniques have been developed to provide solutions to methodological issues, in practice some have proved to be more successful than others. The Olley and Pakes (1996) technique seeks to solve simultaneity bias by applying the firm's investment decision to proxy for idiosyncratic productivity disturbances.[2] The successful application of this technique requires several assumptions to be made. Among these is that the monotonicity condition is imposed on the investment covariate to allow for the invertibility of the investment demand function (Van Beveren, 2012). Consequently, this assumption requires that only non-negative values of the investment covariate are employed in the analysis. However, based on the available data, the requirement that only positive values of the investment variable can be applied in estimation can result in a considerable loss in efficiency (Van Beveren, 2012). Further, if zero values of investment are reported by firms, the monotonicity condition is cast in doubt. The LP technique solves the challenges faced by the OP technique by using intermediate inputs instead of investment as a proxy for unobserved productivity disturbance.[3] In this case, the monotonicity condition is likely to hold as most firms report positive values of energy and materials. However, according to Ackerberg et al. (2015), the OP and LP estimation procedures are subject to the functional dependence problem. This is because the OP and LP techniques invert investment and intermediate input demand functions that are unconditional on labour input in the first stage of the estimation. The ACF technique proposes to unravel this drawback by inverting investment or intermediate input demand functions that are conditional on labour input.[4]

Empirical review

The existing literature shows that although a significant number of studies have analyzed efficiency in the service sector, the evidence for SSA is limited. Existing studies have mainly focused on the manufacturing sector. Beginning with studies focusing on the manufacturing sector, Barasa et al (2019) investigate the innovation inputs and efficiency relationship in manufacturing firms in Kenya, Ghana, the DRC, Tanzania, Uganda and Zambia using a sample of 418 firms drawn from the 2013 WBES and the associated 2013 Innovation Follow-up Survey (IFS). The outcome of the research indicates that internal R&D and foreign technology negatively affect manufacturing firms' technical efficiency. Mazorodze (2020) investigates the trade and efficiency relation in South Africa's manufacturing industries using annual industrial data running from 1970 to 2016. The results indicate that the levels of technical and cost efficiency is 0.83 and 0.33, respectively, implying that South African manufacturing industries could continue producing the same level of output by reducing inputs by

17% and that these industries operate at 33% more than their cost minimizing level. Import penetration and export intensity are found to positively influence technical efficiency thereby reducing cost inefficiencies.

Mukwate and Muchai (2012) use SFA and data from an unbalanced panel of 276 firms from 1993 to 1995, and data of 282 firms from 2001 to 2003 from the WBES, to analyse differences in technical efficiency and efficiency distribution in Kenya's manufacturing sub-sectors which include food, metal and textile. The results show significant variation in technical efficiency across sub-sectors and for each sub-sector within the two periods. The efficiency distribution for firms in the food and textile sub-sectors was enhanced during the study period but declined for firms in the metal sub-sector. In Ivorian manufacturing firms, Chapelle and Plane (2005) investigate technical efficiency by applying the SFA technique to a sample of 186, with data from the WBES. The results show that the Ivorian manufacturing sector has great potential to improve efficiency. Large firms are found to perform better in technical efficiency compared to small firms.

In Ethiopia, Hailu and Tanaka (2015) apply a "true" random effects SFA to investigate technical efficiency in manufacturing firms using a micro-panel from 2000 to 2009. The results show significant variation in efficiency scores across firms, signalling considerable room for improvement. Using a two-stage non-parametric method, Cheruiyot (2017) investigates technical efficiency and sources of variation in this efficiency across Kenyan manufacturing firms using a sample of 396 firms using data from the 2007 WBES. The outcome of the study shows that technical efficiency in Kenya's manufacturing establishments is 68.3% on average. Firm age and size are observed to have a concave relation with technical efficiency implying that below a certain age and size, the efficiency of firms is low but increases after a certain threshold. Firms situated in Nairobi are found to have relatively higher efficiency compared to those located in Mombasa.

Turning to studies covering the service sector, Yannick et al (2016) investigate technical efficiency in the Ivorian banking sector with the application of the DEA technique and panel data from 2008 to 2010. The findings reveal that there is inefficiency in terms of loan applications in Ivorian banks. In addition, foreign-owned private banks are found to have a relatively high efficiency compared to public-owned banks. In Angola, Barros et al (2014) assess technical efficiency in 12 banks by employing the B-convex DEA model using panel data from 2005 to 2010. The findings show that bank efficiency in Angola is mixed and changes over the period of study. Segun and Anjugam (2013) investigate efficiency and its drivers in 70 microfinance institutions (MFIs) in 25 SSA countries by applying DEA to panel data from 2008-2010. It shows that MFIs in SSA are inefficient in the provision of microfinance-related services and inter-mediating funds between borrowers and depositors. In Luanda, Angola, Barros and Dieke (2008) investigate hotels' technical efficiency using DEA and panel data from 2000 to 2006. The outcome of the study shows heterogeneity in efficiency scores across the 12 hotels. The number of shares and group membership promoted the efficiency of hotels.

Considering other studies that have focused on the service sector globally: for the retail sector in the UK, Sena (2011) analyzes technical efficiency and investigates the degree to which county differences in human capital influence this efficiency using SFA. Applying panel data from 1997 to 2005, the results show that technical efficiency is relatively low across all retail sub-sectors. Efficiency scores are higher for retailers located in regions with well-developed human capital. Roche et al (2019) use the two-stage bootstrap DEA and panel data from 2006 to 2015 to estimate efficiency in retail services in 25 European Union countries and to establish the influence of exogenous covariates on this efficiency. The results reveal that there is potential to improve efficiency in retail services and this potential evolves. The variables responsible for enhancing efficiency are population density, the average size of retail stores, the ratio of foreign trade, and the proportion of the urban population.

Assaf et al. (2011) investigate Saudi banks' technical efficiency by employing a two-stage DEA technique for the 1999 to 2007. Data are drawn from annual reports where output is measured by customer loans, securities and interbank loans, and inputs measured by total employees, fixed assets, and total deposits are used. The findings indicate that the average efficiency across banks decreased between the period 1999 and 2003, but later increased up to 2007. Efficiency in banks is found to increase with the expansion of assets, net profit margin and liquidity ratio. Payout ratios are found to negatively influence technical efficiency, implying that shareholders should sacrifice their dividends and allow their profits to be re-invested. In contrast to the general view, foreign capital is found to negatively influence efficiency.

Jaloudi (2019) assesses the technical efficiency of Jordan's insurance companies and its drivers by employing DEA, slacks, and logit models. Panel data for 22 companies from 2000 to 2016 are extracted from annual financial reports where total operating expenses, debt, owner's equity, and total provisions are used as inputs, and net earned premiums and investment income are used as outputs. The findings show a gradual improvement in the efficiency of the companies over time. Significant efficiency differences are also observed across insurance companies. Efficiency is found to be enhanced by owners' equity, technical provisions, operating expenses, type, size and return on assets. Chaabouni (2019) applies the two-stage bootstrap DEA to analyse tourism efficiency in China from 2008 to 2013. The outcome of this analysis reveals that technical efficiency in this industry for the sampled period is generally low. An analysis of regional differences in tourism efficiency shows that East China performs better than Central and West China. The second-stage regression analysis reveals that China's tourism efficiency is positively influenced by trade openness, the strength of competition in the market and climate change.

From the review, it is evident that although several studies have concentrated on analysing technical efficiency in the service sector globally, evidence for the SSA is limited. Existing studies on SSA (Barasa et al, 2019; Mazorodze, 2020; Chapelle and Plane, 2005; Mukwate and Muchai, 2012; Hailu and Tanaka, 2015) have mainly focused on the manufacturing sector although efficiency improvements for physical goods are not suitable for services (Gronroos and Ojasalo, 2004). This is because service firms convert inputs to output differently compared to manufacturing firms due to their distinct characteristics that include intangibility, inseparability, heterogeneity, and perishability. This study fills this gap by focusing on the service sector in selected SSA countries. The focus on this sector is due to the sector's potential role in driving structural transformation in SSA economies. The studies that have focused on the service sector both globally and in SSA (Yannick et al, 2016; Barros et al, 2014; Segun and Anjugam, 2013; Barros and Dieke, 2008; Sena, 2011; Roche et al., 2019; Assaf et al., 2011; Jaloudi, 2019; Chaabouni, 2019) have a limited scope as they only focus on specific services, hence providing only a partial view of the service sector, which may not be representative of the overall sector. The present study fills this research gap by covering a wider scope of services. These include the retail, wholesale, IT, transport services, motor vehicle services, and hotel and restaurant sub-sectors.

The few studies that have focused on the service sector in SSA have mainly concentrated on a few services, mainly financial (Yannick et al, 2016; Barros et al, 2014; Segun and Anjugam, 2013) and hotel services (Barros and Dieke, 2008), effectively ignoring other services such as retail, wholesale, IT, motor vehicle and transport services. Yet these services play a key role in the economy, especially in driving the employment of low-skilled and semi-skilled workers, who form the majority of the workforce in SSA. The current study fills this gap by focusing on these services in addition to the hotel and restaurant sub-sector. The available studies have a limited scope in regional coverage as they concentrate on country-level analysis providing only a partial view of the region. The current study covers a wider regional scope by focusing on six SSA countries namely Kenya, Uganda, Tanzania, Zambia, Ghana, and DRC.

Finally, the methodological approach employed by some studies that applied DEA raises a concern that directly affects estimates of determinants of technical efficiency in the second stage of estimation. These studies (Yannick et al, 2016; Segun and Anjugam, 2013; Roche et al, 2019; Jaloudi, 2019) applied non-biased corrected technical efficiency estimates in the second stage of estimation. However, this poses a problem for inference (Simar and Wilson, 2007). This is because the technical efficiency estimates used in the second stage regression are potentially serially correlated given that they are computed from a common sample of data. Moreover, the environmental factors adopted in the second stage of estimation are potentially correlated with the inputs applied in the production process, yet these inputs are not included in this stage of estimation. This means that the environmental factors are potentially correlated with the error term given that information regarding input use is relayed through the error term. To address this problem, the current study applies the two-stage bootstrap DEA method.

3. Methodology

This paper adopts the DEA approach. The approach is very common in studies investigating the technical efficiency of firms in the services industry given that it does not need the initial presumption of a production function specification. DEA becomes appropriate in these studies because, in most cases, the production function specification is barely known. The results of this study are, therefore, free from misspecification errors that may be present in SFA. Further, DEA is immune from statistical problems such as simultaneity bias, which may be present under SFA.

The measurement of technical efficiency has two approaches: input-oriented output-oriented models (Kumbhakar et al, 2015). Under the input-oriented model, efficiency measurement seeks to determine the maximum probable proportional reduction in input application with the level of output remaining unchanged for each firm. By contrast, efficiency measurement under the output-oriented model sets out to establish the maximum possible proportional expansion in output with input usage remaining unchanged. Both models give similar findings of efficiency levels under constant returns to scale (CRS) but different results under variable returns to scale (VRS) (Coelli et al, 2005). Fundamentally, the choice of orientation should be rooted in what quantities the managers have control over (inputs or output). Improved output is deemed to be the goal of the service sector in the countries of interest in this study. This paper, therefore, endeavours to establish the extent to which firms can enhance their output by efficiently utilizing their limited resources. Consequently, the study focuses on the output-oriented model under the variable returns to scale assumption. The choice of the VRS assumption is guided by the reasoning that service firms in SSA could be operating in environments characterized by imperfect competition, government regulations, and financial constraints that could limit the possibility of firms operating optimally

Consider (w = 1, …, l) DMUs that employ a vector of factor inputs represented by x = $(x_1, \ldots, x_N) \in \mathfrak{R}^{N+}$ to process a positive vector of output represented by y = $(y_1, \ldots, y_M) \in \mathfrak{R}^{M+}$. The production possibility set (PPS), which denotes an assembly of all achievable input-output vectors of a DMU, is a subset T of the vector space $\mathfrak{R}^{N+M}$. A DMU may choose any input-output mix (x, y) ∈ T as its production plan. The PPS is formally presented as:

$$T = \{(y, x) : x \in \mathfrak{R}^{N+} \text{ can produce } \mathfrak{R}^{M+}\} \quad (1)$$

Some standard regularity features are assumed to hold for the PPS. According to Fare and Primont (1995) there are closedness, non-emptiness, scarcity, no free lunch and free disposability. Each DMU's technical efficiency is obtained by finding the solution to a linear programming problem that seeks to obtain the vector of weights that maximize the level of efficiency of the kth DMU subject to the constraint that no DMU has an efficiency score exceeding one. Assuming VRS the technical efficiency of a DMU is obtained by providing a solution to the following problem:

$$\begin{aligned} &\max_{\gamma,\delta_i} \delta_i \\ &\text{st} \quad -\delta y_i + Y\gamma \geq 0, \\ &x_i - X\gamma \geq 0, \qquad i = 1, 2, \ldots, I \\ &I1'\gamma = 1 \\ &\gamma \geq 0 \end{aligned} \tag{2}$$

where δ is a scaler and a measure of efficiency defined in the range $1 \leq \delta < \infty$ and δ-1 is the share by which the i-th firm's output increases while holding inputs constant. The ratio $1/\delta$ defines the efficiency score which ranges between 0 and 1. γ is an $I \times 1$vector of constants, y_i and x_i are the respective column vectors of output and inputs, and Y and X are the respective output and input matrices for all firms. The linear programming problem is solved I times (that is once for each DMU) after which a value of efficiency is obtained. $I1'\gamma = 1$ denotes the convexity constraint and I1 is a $I\times1$ vector of ones (Coelli et al, 2005). The convexity condition fundamentally ensures that an inefficient DMU is only gauged against like-sized DMUs. This means that the data points are enveloped more closely so that projected "peers" for a technically inefficient service firm are only efficient firms of the same size (Galanopoulos et al, 2006).

After the efficiency scores are obtained, the study establishes the variables that determine this efficiency under the second-stage bootstrap DEA approach.

Bootstrap-DEA

The bootstrap DEA method produces consistent estimates of the determinants of technical efficiency in the second-stage regression and, at the same time, constructs confidence intervals and standard errors for the DEA efficiency scores (Simar and Wilson, 2007). Consider that the degree of technical efficiency is dependent on several explanatory covariates denoted by z_i. Conventionally, the two-stage studies expressed technical efficiency as a function of explanatory covariates as follows:

$$\delta_i = z_i\alpha + \xi_i \tag{3}$$

where $\delta_i(x_i, y_i|\hat{T})$ and $x_i$are y_i are column vectors of inputs and output respectively Given that the efficiency scores δ_i are unobserved, these studies replace the unobserved δ_i by their estimates ($\widehat{\delta_i}$) obtained from the first stage. Consequently, the equation is

$$\widehat{\delta_i} = z_i\alpha + \varepsilon_i \qquad (4)$$

According to Simar and Wilson (2007), $\widehat{\delta_i}$ is a consistent estimator under certain assumptions[5] and the rate of convergence can be expressed as:

$$\widehat{\delta_i} = \delta_i + \vartheta_N(l^{-2/(M+N+1)}) \qquad (5)$$

However, the convergence rate is low as is common in non-parametric estimation and the rate becomes even lower as $M + N$ increases (Simar and Wilson, 2007).

Equation 4 is estimated using a tobit regression or, in a few instances, OLS. The choice of tobit specification is justified as, that normally, most of the efficiency estimates in a specified application are equal to one (Simar and Wilson, 2007). However, the two-stage specification presented in Equation 4 poses challenges for inference (Simar and Wilson, 2007). First, the $\widehat{\delta_i}$'s applied in the second-stage regression are serially correlated. This can be explained by the fact that $\delta_i = \delta_i(x_i, y_i|\widehat{T})$ is contingent on entire observations (x_i, y_i) through $\widehat{T}$ and, subsequently, the same happens to ε_i in Equation 4. In addition, x_i and y_i are correlated with z_i if they were not correlated, there would be no rationale for the second-stage regression. This, therefore, implies that the error term $\varepsilon_i\varepsilon_i$ in Equation 4 is correlated with z_i. Both the correlation among ε_is and z_i and ε_i vanish asymptotically, but this only happens at a similar slow rate in Equation 5 with which $\widehat{\delta_i}$ converges (Simar and Wilson, 2000a). This implies that the maximum likelihood estimates of α in the second-step regression will be consistent but will not converge at the normal non-parametric convergence rate (Simar and Wilson, 2007).[6]

A further review of Equation 4 signals another estimation issue. To understand this, note that the estimates $(\widehat{\delta_i})$ can be expressed as follows:

$$\widehat{\delta_i} = \mathrm{E}\,(\widehat{\delta_i}) + u_i \qquad (6)$$

where E $(\widehat{\delta_i})$= 0. Moreover, the bias of the estimator $\widehat{\delta_i}$ is expressed as:

$$\mathrm{BIAS}\,(\widehat{\delta_i}) \equiv \mathrm{E}\,(\widehat{\delta_i}) - \delta_i \qquad (7)$$

Substituting for E $(\widehat{\delta_i})$ from Equation 6 in Equation 7 and re-arranging gives:

$$\delta_i = \widehat{\delta_i} - \mathrm{BIAS}\,(\widehat{\delta_i}) - u_i \qquad (8)$$

Substituting for $\delta_i\delta_i$ in Equation 3 yields

$$\widehat{\delta_i} - \mathrm{BIAS}\,(\widehat{\delta_i}) - u_i = z_i\alpha + \xi_i \geq 1 \qquad (9)$$

Given that $\widehat{\delta_i}$ is a consistent estimator, u_i and BIAS $(\widehat{\delta_i})$ disappear asymptotically (Simar and Wilson, 2007). This provides the argument for writing Equation 3. Although u_i in Equations 6, 8 and 9 have zero means, that of BIAS ($\widehat{\delta_i}$) does not. Instead, BIAS ($\widehat{\delta_i}$) is usually negative in finite samples (Simar and Wilson, 2007). The $u_i's$ are not known and cannot be analyzed, but BIAS ($\widehat{\delta_i}$) can be analysed with bootstrap approaches[7].

The bootstrap bias estimate is expressed as the sum of the BIAS ($\widehat{\delta_i}$) and a residual v_i as follows:

$$\widehat{BIAS}(\widehat{\delta_i}) = \text{BIAS}\,(\widehat{\delta_i}) + v_i \tag{10}$$

Simar and Wilson (2007) opine that the variance of the residual v_i fades asymptotically and therefore, v_i is of a smaller amount compared to BIAS ($\widehat{\delta_i}$) for considerable sample sizes. From the bootstrap estimator, the bias-corrected estimator of δ_i is constructed as follows:

$$\widetilde{\delta_i} = \widehat{\delta_i} - \widehat{BIAS}(\widehat{\delta_i}) \tag{11}$$

Substituting for $\widehat{BIAS}(\widehat{\delta_i})$ from Equation 10 in 11, by rearranging terms and then substituting for BIAS ($\widehat{\delta_i}$) in Equation 9 results in:

$$\widetilde{\delta_i} + v_i - u_i = z_i\alpha + \xi_i \geq 1 \tag{12}$$

Given that v_i and u_i diminish asymptotically, the maximum likelihood estimation is on:

$$\widetilde{\delta_i} \approx z_i\alpha + \xi_i \tag{13}$$

which yields consistent estimates.

Simar and Wilson (2007) suggested the following steps to obtain the bootstrap estimates:

1) Using the original data, the estimates of δ are computed. That is $\widehat{\delta_i} = \hat{\delta}(x_i y_i \mid \hat{T})\forall$ 1, …, I

2) The maximum likelihood method is used to give an estimate $\hat{\alpha}$ of α and an estimate $\hat{\sigma}_\varepsilon$ of $\sigma_\varepsilon\sigma_\varepsilon$ in the truncated regression (left-truncation at 1) of $\hat{\delta}$ on z_i in Equation 3.

3) For each DMU i = 1, …, I the four steps (3.1) to (3.4) are repeated Q_1 times to derive I sets of bootstrap estimates $\mathcal{B}_i = \{\hat{\delta}^*_{ib}\}_{b=1}^{Q_1}$:

1.1) ε is drawn for each i = 1, …, I from the N (0, $\hat{\delta}^2_\varepsilon$) distribution with the left truncation at (1 - $z_i\hat{\alpha}$).

1.2) Then for each i = 1, …, I, $\delta_i{}^* = z_i\hat{\alpha} + \varepsilon_i$.

1.3) For all i = 1, …, l a pseudo dataset (x_i^* y_i^*) is calculated where x_i^*= x_i and y_i^*=y_i $\widehat{\delta_i}/\delta_i^*$.

1.4) For each i = 1, …, l, $\widehat{\delta_i}^*$ = δ ($x_i y_i$ | $\widehat{T_i}^*$)∀ 1, …, l, where $\widehat{T_i}^*$ is obtained by replacing Y= (y_1,…, y_l), X= (x,…, x_l) with Y^*= (y_1^*, … , y_l^*), X^* = (x_1^*, … , x_l^*).

4) For all i = 1, …, l, a bias-corrected estimator $\widetilde{\delta_i}$ using bootstrap estimates of $\mathcal{B}_i$ is derived in step 3.4 and the initial estimate $\widehat{\delta_i}$.

$\widetilde{\delta_i}$ = $\widehat{\delta_i}$- $\widehat{\text{Bias}_i}$

where $\widehat{\text{Bias}_i}$ = ($\frac{1}{Q_1}\sum_{b=1}^{Q}\hat{\delta}_{ib}^*$) - $\widehat{\delta_i}$.

5) The maximum likelihood method is then used to estimate the truncated regression of $\widetilde{\delta_i}$ on z_i to obtain estimates ($\tilde{\alpha}$, $\widetilde{\sigma_\varepsilon}$).

6) The three steps (6.1) to (6.3) are replicated Q_2 times to get a bootstrap set of estimates $\mathcal{H}$= $\{(\hat{\alpha}^*, \hat{\sigma}_\varepsilon^*)_b\}_{b=1}^{Q_2}$:

6.1) $\varepsilon_i \varepsilon_i$ is drawn for each i = 1, …, l from the N (0, $\widetilde{\sigma_\varepsilon}$) distribution with the left truncation at (1 - $z_i\tilde{\alpha}$).

6.2) Then for each i = 1, …, l, δ_i^{**}= $z_i\tilde{\alpha}$+ε_i.

6.3) The maximum likelihood method is used to estimate the truncated regression of δ_i^{**} on z_i, giving estimates ($\tilde{\alpha}^*$, $\widetilde{\sigma_\varepsilon}^*$).

7) Using the bootstrap figures in $\mathcal{H}$ and the initial estimates $\tilde{\alpha}$, $\widetilde{\sigma_\varepsilon}$, estimated confidence intervals are computed for every element of α and σ_ε. To show this, suppose the interest lies in finding the confidence interval of α_j the jth element of α estimated by $\tilde{\alpha}_j \tilde{\alpha}_j$ which is the jth element of $\tilde{\alpha}$. The (1- β) percent confidence is given by:

$$\Pr (Lower_{\beta,j} \leq \alpha_j \leq Upper_{\beta,j}) = 1 - \beta, \quad 0 < \beta < 1 \tag{14}$$

Where the lower and upper intervals are computed using the following empirical intervals

$$\Pr (-b^*_\beta \leq \tilde{\alpha}^*_j - \tilde{\alpha}_j \leq -a^*_\beta) \approx 1 - \beta \tag{15}$$

$$Lower_{\beta,j} = \tilde{\alpha}_j + b^*_\beta \tag{16}$$

$$Upper_{\beta,j} = \tilde{\alpha}_j + a^*_\beta \tag{17}$$

Definition and measurement of variables

To construct a DEA model for estimating the technical efficiency of service firms, the choice of inputs and output needs to be based on the considerations of a service firm. In general, major resources applied by a firm to produce output should be considered as inputs. In the empirical literature, the commonly applied inputs in efficiency and productivity analysis are capital, labour, energy, and material inputs. Given the availability of data in the WBES, this study includes the standard variables consisting of labour, capital, and energy as the inputs that are converted to output. Output is measured by the value of services produced. Labour is the physical and mental work done for wages and salaries and is quantified by the total cost of labour or wage bill. Capital is machinery and equipment employed in the production of goods and services quantified by the total value of machinery and other equipment. Energy is denoted by electricity, which is measured by the total cost of electricity. The choice of the output and input variables is guided by the availability of data. More information on the variable definition, measurement and source is provided in Table A1 in the appendix.

Following Assaf et al (2011), Barros et al. (2014), Lemi and Wright (2018), Jaloudi (2019), Roche et al (2019) and Mutarindwa et al (2021), this study adopts foreign ownership, R&D, exporting status, firm age and size, top manager's level of experience and female ownership in investigating drivers of technical efficiency. Foreign ownership is expressed by a dummy variable coded 1 if a firm is foreign-owned and 0 if not. The variable is projected to positively influence the technical efficiency of service firms. This is because foreign owners are more likely to use foreign equipment in enhancing technical efficiency. R&D is an undertaking by a firm to make a discovery that can result in the inception of new services or the enhancement of existing services. It is a dummy variable coded 1 if a firm engages in R&D and 0 if not. The covariate is projected to positively influence technical efficiency. This is because R&D activities improve firm innovativeness and firms learn new operation techniques.

Firm size is proxied by the number of workers in an establishment. The covariate is projected to have no clear effect on technical efficiency. On the one hand, Jovanovic's (1982) theory is that large-sized firms are more likely to hire a highly skilled workforce capable of producing services efficiently. On the other hand, small-sized firms are apt to be flexible in their decision-making and detect inefficiencies more easily unlike large firms that are apt to be characterized by bottlenecks in management. Further, small firms are prone to be more efficient as they are subjected to more competition compared to larger firms. Firm age is the number of years an establishment has been operating. It is computed as the difference between the year of data collection and the year of the establishment's inception. The covariate is projected to have an ambiguous effect on technical efficiency. On the one hand, Jovanovic (1982) holds that old firms are likely to have a large stock of experience obtained through learning by doing, which would make them more efficient than young firms. On the other, young firms could be more technically efficient compared to old firms because young firms are likely to adopt recent production techniques while old firms use old techniques.

The top manager's level of experience is the total number of years the top leader of the establishment has worked. The variable is likely to positively promote technical efficiency. A manager who has a large wealth of experience is likely to lead the organization efficiently. Exporting activity is the activity of selling services abroad. Exporting is expressed as a dummy covariate of 1 if a firm exports and 0 if not. The covariate is expected to positively affect technical efficiency. A firm with access to a foreign market is likely to learn new technologies that may help enhance technical efficiency. Further, such firms' management is likely to be exposed to better management practices, which may also help them enhance technical efficiency. Female ownership is expressed as a dummy covariate of 1 if there is a presence of female members among firm owners and 0 if not.

One aspect of this study's novelty is the inclusion of training in the assessment of determinants of technical efficiency. Although Blundell et al (1999) opine that on-the-job training programmes equip workers with skills, competencies and expertise crucial to enhancing labour productivity, efficiency, competitiveness and profitability in firms, existing studies have failed to empirically investigate its effect on technical efficiency. Training is expressed as a dummy variable of 1 if a firm has a training programme and 0 if not. The covariate is projected to positively influence technical efficiency.

Data source and descriptive statistics

The study applies cross-sectional data from the 2013 WBES for Kenya, Uganda, Tanzania, Ghana, Zambia and the DRC. The focus on the six countries is guided by the availability of data. Although there are more recent surveys, they are in different years for most of the countries, making it difficult to conduct a comparative analysis. The WBESs make use of standardized instruments and data are collected through stratified random sampling. The surveys are conducted in two stages. The first stage involves screening via phone where the firm's eligibility is established. In the second stage, data are collected using a questionnaire that contains 14 sections. These surveys are done to provide important business environment indicators and to establish the limiting factors to the private sector and growth, among other things. The surveys present information on individual firm features, infrastructure and services, sales and supplies, competition, finance, performance and business environment relations, crime, labour, and land. The surveys are available in different waves for 169,000 firms in 146 countries for both manufacturing and service firms. The use of standardized instruments and common indicators across countries provides an opportunity for comparative studies.

This study focuses on a total of 2005 service firms spread across the six countries of interest: Kenya (361), Tanzania (365), Uganda (364), Ghana (308), Zambia (332) and the DRC (275). The study adopts the World Bank's categorization of service firms into retail, wholesale, hotel and restaurants, transport, motor vehicle services and IT sub-sectors. The WBESs provide financial information in local currency units. To facilitate comparative analysis, this study uses the Penn World Tables purchasing power parity (PPP) exchange rates for deflating capital, labour, and capital.

The descriptive statistics in Table 1 show that Kenya had the highest average level of output valued at US$ 2,119,340, Zambia had the lowest, valued at US$ 863,220 thousand. Kenya had the highest average capital investment valued at US$ 239,170 thousand and Zambia had the lowest average investment valued at US$ 124,490 thousand. Kenya paid the highest average wages valued at US $ 125,970 thousand and Uganda paid the lowest at US$ 39,600 thousand. Kenyan service firms had the highest spending on energy at US$ 19,710 thousand and the DRC had the lowest spending at US$ 2,810 thousand. The huge variation in energy spending could potentially reflect differences in electricity tariffs. Kenya has relatively higher electricity tariffs compared to other countries of interest. The difference in electricity spending across countries could also be a result of the extent of electricity connection across countries. Kenya is among the leading countries in electricity connection in SSA, implying that most of the service firms are connected to the grid, which explains the higher spending on energy. The World Bank Development Indicators show that in 2013, Kenya's electricity connection in urban regions, where most service firms are located, was at 72.92% while that of the DRC, which has the least spending on energy, was at 42.49%.

Table 1:Descriptive Statistics

Statistics	Output	Capital	Labour	Energy	Firm size	Firm Age	TME	Training	FO	FM	Ex	R&D
Kenya (N=367)												
Mean	2119.34	239.17	125.97	19.71	37.52	16.92	16.03	0.411	0.076	0.446	0.256	0.253
SD	8174.82	820.49	314.69	77.60	81.64	15.24	10.35	0.493	0.266	0.497	0.436	0.436
Minimum	1.974	0.001	0.168	0.059	1	1	1	0	0	0	0	0
Maximum	116117	7721.78	2496.52	673.48	1000	105	57	1	1	1	1	1
Uganda(N=364)												
Mean	1088.65	140.85	39.60	5.182	29.55	13.01	11.80	0.291	0.107	0.346	0.170	0.253
SD	5352.07	808.05	289.59	39.42	111.42	9.840	7.579	0.455	0.310	0.476	0.376	0.435
Minimum	0.171	0.011	0.016	0.007	1	1	1	0	0	0	0	0
Maximum	50819.1	5710.01	3997.01	571.00	1500	86	41	1	1	1	1	1
Tanzania(N=365)												
Mean	1400.93	151.11	55.99	4.052	23.58	13.34	12.18	0.312	0.096	0.282	0.167	0.132
SD	11886.51	847.73	211.70	12.86	72.44	9.646	8.209	0.464	0.295	0.451	0.374	0.338
Minimum	0.438	0.143	0.001	0.001	1	1	1	0	0	0	0	0
Maximum	132500	8565.02	2036.25	157.5	1200	60	50	1	1	1	1	1
Ghana(N=308)												
Mean	1674.00	171.32	69.22	8.542	24.62	14.34	15.23	0.435	0.153	0.318	0.140	0.179
SD	6332.58	311.46	147.45	44.99	37.95	10.59	8.448	0.497	0.360	0.467	0.347	0.384
Minimum	1.5	0.152	0.152	0.032	1	4	1	0	0	0	0	0
Maximum	64925	5500.00	1000.00	500	350	104	54	1	1	1	1	1
DRC(N=275)												

Mean	1253.63	138.63	43.17	2.812	20.16	10.15	12.32	0.229	0.164	0.164	0.091	0.229
SD	6027.99	607.92	123.18	8.965	43.49	8.949	8.490	0.421	0.371	0.371	0.288	0.421
Minimum	0.141	0.143	0.033	0.011	1	1	1	0	0	0	0	0
Maximum	54347.83	5853.87	1087.61	89.02	480	60	50	1	1	1	1	1
Zambia (N=624)												
Mean	863.22	124.49	44.14	6.519	27.60	12.73	12.16	0.324	0.309	0.447	0.181	0.242
SD	4950.87	508.81	135.58	26.01	70.24	12.84	9.111	0.469	0.463	0.498	0.385	0.429
Minimum	0.835	0.001	0.021	0.001	1	1	1	0	0	0	0	0
Maximum	76437.99	3821.9	1146.57	259.89	750	83	50	1	1	1	1	1

Note: The values of the variables output, capital, and labour are expressed in thousands of U.S. dollars. SD denotes standard deviation.

Source: Own computations from WBES data.

Kenya had the highest average firm size measured by the total number of employees at 37.52 and the DRC had the lowest at 20.16. Kenya had the oldest firms with an average age of 16.92 years, while the DRC had the youngest service firms with an average age of 10.15 years. Kenyan service firms had top managers with the highest experience at an average of 16.03 years and Rwandan firms had the least experienced top managers at an average of 11.80 years. Ghana had the highest number of service firms with training programmes at an average of 43.50%, and the DRC had the least at number of programmes at 22.90%. Zambian service firms had the highest foreign ownership of about 30.90% and Kenyan firms had the least at 7.60%. This statistic is surprising because despite Zambia enjoying the highest proportion of foreign-owned firms, the service firms in this country have the lowest value of capital investments compared to other countries in the study. It is expected that foreign ownership brings with it capital investments and the flow of superior technologies. Zambian service firms had the highest proportion of female ownership at 44.70% and the DRC had the least at 16.40%. Kenya had the highest number of exporting service firms at 25.60% and the DRC had the least at 9.10%. Kenya and Uganda had the highest number of firms that invested in R&D at an average of 25.30 % and Tanzania had the lowest number at an average of 13.20%. The majority of the variables had standard deviations that were larger than the mean values implying that the observations were spread over a broad span of values.

Table 2 presents the correlation matrix of the covariates of interest. The results show that nearly all correlations are statistically significant. All the factor inputs and output have a positive relationship. The correlations in the explanatory variables are also largely positive. However, the degree of association between variables is weak because the correlation coefficients are low in general. This signals little risk of multicollinearity among explanatory variables.

Table 2:Variables Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Output	1.000											
(2) Capital	0.346***	1.000										
(3) Labour	0.573***	0.240***	1.000									
(4) Energy	0.406***	0.322***	0.309***	1.000								
(5) Female-owned	0.131***	0.058***	0.096***	0.039*	1.000							
(6) Firm age	0.086***	0.076***	0.051**	0.079***	0.079***	1.000						
(7) TME	0.042*	0.056**	0.033	0.062***	0.057***	0.500***	1.000					
(8) Export	0.120***	0.084***	0.085***	0.071***	0.063***	0.066***	0.041*	1.000				
(9) Firm size	0.236***	0.197***	0.192***	0.237***	0.034	0.165***	0.161***	0.146***	1.000			
(10) Training	0.114***	0.052**	0.089***	0.092***	0.101***	0.090***	0.075***	0.089***	0.212***	1.000		
(11) Foreign	0.167***	0.065***	0.147***	0.167***	0.007	0.000	0.001	0.148***	0.113***	0.118***	1.000	
(12) R & D	0.112***	0.080***	0.079***	0.068***	0.046**	0.049**	0.014	0.065***	0.132***	0.228***	0.052**	1.000

*** p<0.01, ** p<0.05, * p<0.1

Note: TME denotes the top manager's experience

Source: Own computations from WBES data.

4. Results and discussion

Table 3 provides the average VRS technical efficiency scores for the six countries of interest, obtained from 2,000 bootstrap iterations as recommended by Simar and Wilson (2007). Technical efficiency has been estimated separately for each country. Table 3 reports both the original (non-bootstrapped) and bootstrapped efficiency estimates to aid the comparison of the conventional DEA model and the bootstrapped DEA model. Findings of the level of bias and lower and upper confidence intervals at a 5% level of significance are also presented.

Table 3:Average technical efficiency scores

Country	N	Original	Bootstrapped	Bias	Lower confidence interval	Upper confidence interval
Kenya	367	0.804	0.768	0.036	0.742	0.803
Uganda	364	0.684	0.631	0.052	0.591	0.686
Tanzania	365	0.652	0.565	0.087	0.514	0.633
Ghana	308	0.824	0.775	0.048	0.747	0.810
DRC	275	0.673	0.618	0.055	0.570	0.677
Zambia	333	0.769	0.721	0.048	0.692	0.756

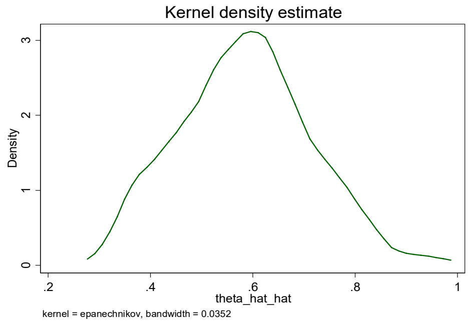
Source: Own computation from WBES data.

The results in Table 3 show that the original DEA estimates are greater than those of the bias-corrected approach. The original DEA estimates are biased upwards as all the bias is positive. Because of the bootstrap correction in the confidence intervals, the original DEA estimates lie outside the lower and upper confidence intervals. Nonetheless, every observation in the bias-corrected DEA estimates lies within the confidence interval. It is important to note that the while Simar and Wilson (2007) bootstrapping technique corrects for bias in efficiency scores, the bootstrapped DEA estimates could potentially be biased due to measurement error in inputs and output. This is because the DEA technique does not control for potential random disturbances in the data, such as measurement error, as it treats all deviations from the benchmark frontier as inefficiencies. Like many surveys, the WBES data are subject to measurement error as some covariates are difficult to measure with sufficient accuracy. For example, information on inputs and output in the WBES is collected by asking respondents to recall details of events occurring in previous financial year(s). This is prone to introducing recall bias. Further, input measures are often based on accounting information, yet the definition of accounting cost is different from that of the economic cost (that is, opportunity cost). Consequently, the results provided in this study should be interpreted with caution.

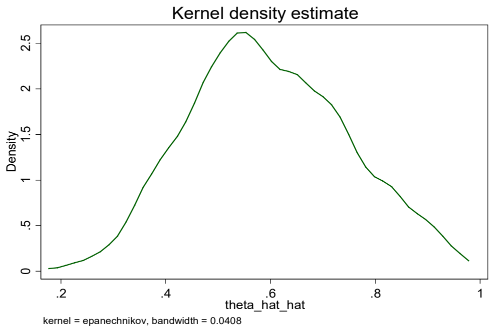
The bias-corrected results indicate heterogeneity in efficiency scores across the six countries. The bias-corrected VRS scores vary between 0.57 in Tanzania and 0.78 in Ghana. This means that the respective countries could expand their output by 43 and 22% while consuming the same level of inputs. The bias-corrected VRS scores for the DRC, Uganda, Zambia, and Kenya are 0.62, 0.63, 0.72 and 0.77. These countries could bolster their output by 38%, 37%, 28% and 23%, respectively, without increasing the uptake of inputs. Heterogeneity in efficiency scores is confirmed in the input-oriented approach as provided in Table A2 in the Appendix. However, the efficiency scores of the input-oriented approach are lower than those of the output-oriented approach. The differences in efficiency scores between the two orientations is in line with the theoretical argument that technical efficiency varies between the input-oriented approach and the output-oriented approach under the variable returns to scale assumption (Coelli et al, 2005). The input-oriented scores for Ghana, Kenya, Uganda, the DRC, Tanzania and Zambia are 0.77, 0.72, 0.62, 0.60, 0.54 and 0.52 respectively. This indicates that the respective countries could achieve the same level of output by applying 23%, 28%, 38%, 40%, 46% and 48% fewer inputs, on average. Potential reasons explaining why there are variations in technical efficiency across countries are provided in "Determinants of Technical Efficiency in the Service Sector."

Heterogeneity in efficiency scores across firms is also notable within countries as indicated in the kernel density distributions presented in Figure 2. Of concern in the kernel density distribution is the dispersion and skewness of the plots. The plots for Kenya, Uganda, Tanzania, Ghana, and the DRC are widely dispersed indicating greater heterogeneity in the technical efficiency of service firms within each of the listed countries. The plot for Zambia is less dispersed indicating less heterogeneity in the technical efficiency of service firms in this country as firms are concentrated in the same area. The plots also show that for all countries, apart from Kenya, technical efficiency scores range from as low as less than 0.20 to about 0.90. However, there are only a few firms at both extremes signalling the existence of very low efficiency firms and very highly efficient firms. In Kenya, the distribution ranges between 0.31 and 0.95 indicating that the Kenyan service sector does not have very low efficiency firms but it also signals the existence of very highly efficient firms. In all the plots, apart from that for Zambia, the majority of the firms appear to fall within the 0.40 and 0.80 range, indicating that there is an average efficiency shared by many service firms. In Zambia, the majority of firms fall in the area between 0.60 and 0.80 indicating that the majority of the firms' technical efficiency is above average.

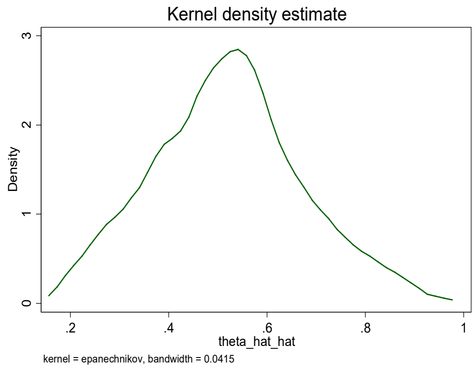
Figure 2: Kernel density estimates of technical efficiency scores at the country level



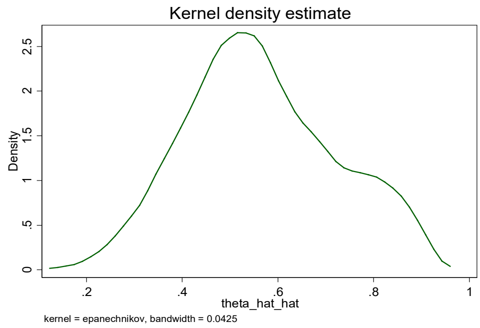
Kenya



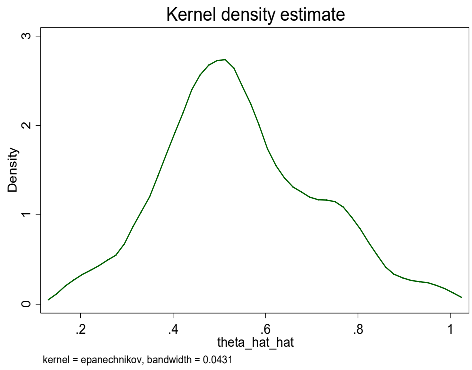
Uganda



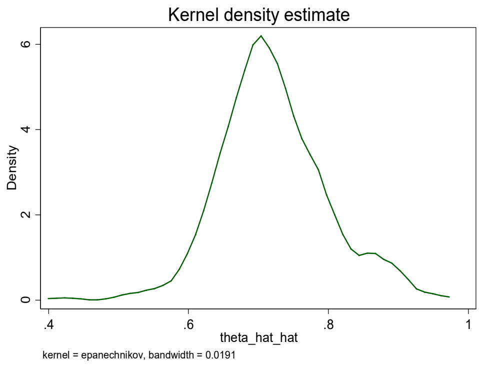
Tanzania



Ghana



DRC



Zambia

Sub-sector average technical efficiency scores

Table 4 provides the sub-sector average VRS efficiency scores obtained from 2,000 bootstrap iterations. The sub-sectors of interest are based on the WBES categorization. They include hotels and restaurants, retail, wholesale, motor vehicle services (MVS), transport and information technology (IT). As noted earlier, these are labour-intensive trade services with significant potential to employ many people and alleviate poverty. Given the structural differences across sub-sectors, technical efficiency has been estimated separately for each sub-sector. To aid the comparison of the original (non-bootstrapped) and bootstrapped efficiency estimates, the conventional DEA model and the bootstrapped DEA model are provided. In addition, Table 4 presents findings of the level of bias and lower and upper confidence intervals at a 5% level of significance.

Table 4: Sub-sector average technical efficiency scores

Sub-sector	N	Original	Bootstrapped	Bias	Lower confidence Interval	Upper confidence interval
Retail	826	0.546	0.480	0.066	0.443	0.528
Wholesale	266	0.684	0.619	0.065	0.576	0.670
Hotel and restaurant	543	0.695	0.649	0.046	0.619	0.687
Transport	131	0.792	0.724	0.068	0.677	0.791
Motor vehicle services	189	0.712	0.656	0.056	0.613	0.714
IT	86	0.873	0.785	0.088	0.733	0.863

Source: Own computation from WBES data.

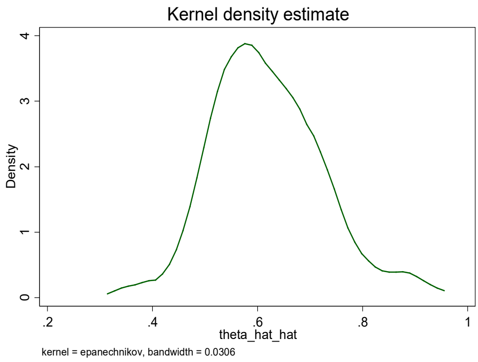
The findings in Table 4 also show that the original sub-sector DEA scores are biased upwards. Given the bootstrap correction in the confidence intervals, the original sub-sector DEA scores also lie outside the lower and upper bounds. However, every observation in the bias-corrected DEA scores lies within the lower and upper bound. Nevertheless, as noted earlier, the results of this study should be interpreted with caution as they could be biased due to potential measurement error in inputs and output in the WBES dataset.

The findings reveal significant heterogeneity in DEA scores across the six sub-sectors. The bias-corrected VRS scores range from 0.48 in the retail sub-sector to 0.79 in the IT sub-sector. This implies that respective sub-sectors could continue using the same level of inputs but expand their output by 52% and 21%, respectively. The bias-corrected VRS scores for the wholesale, hotel and restaurant, motor vehicle services and transport sub-sectors were 0.62, 0.65, 0.66, and 0.72 respectively. The respective sub-sectors could therefore increase their output levels by 38%, 35%, 34% and 27% respectively, without changing the level of input application. Comparing the output-oriented DEA results to those of the input-oriented approach presented in Table A3 in the Appendix, the findings also show heterogeneity in efficiency scores across sub-sectors in the input-oriented approach. Nevertheless, the input-oriented efficiency scores are lower than those of the output-oriented approach. Again, this points out the expected differences in technical efficiency scores between the input-oriented approach and output-oriented approach owing to the assumption of variable returns to scale in estimation. The input-oriented efficiency scores for the IT, transport, motor vehicle services, wholesale, hotel and restaurant and retail sub-sectors are 0.77, 0.71, 0.63, 0.57, 0.53, and 0.46 respectively. These scores imply that the respective sub-sectors could continue producing the same level of output by using 23%, 29%, 37%, 43%, 47% and 54% fewer inputs, on average. Potential explanations for variations in technical efficiency across sub-sectors are provided later in the discussion on "Determinants of technical efficiency in the service sector."

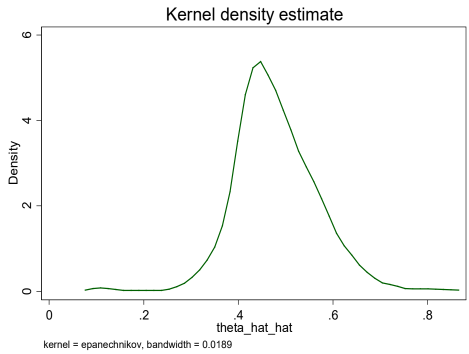
The study also considers the heterogeneity in technical efficiency scores within sub-sectors as provided in the kernel density distribution plots in Figure 3. Comparing the dispersion of the sub-sector plots to those of country plots, sub-sector level plots appear to have less dispersion implying that there is less heterogeneity in technical efficiency scores within sub-sectors compared to technical efficiency within countries. This could potentially signal similarities in the service production technologies in sub-sectors across different countries. Intuitively, this could signal that there should be more emphasis on the sub-sector level analysis when estimating the technical efficiency of service firms. The kernel distribution plots are relatively more widely dispersed in the wholesale, transport and IT sub-sectors compared to the retail, hotel and restaurant, and motor vehicle services. This means that there is more heterogeneity in technical efficiency scores in the wholesale, transport and IT services compared to retail, hotel and restaurant, and motor vehicle services.

In the wholesale, hotel and restaurant, transport, and motor vehicle services, only a few firms have efficiency scores that are below 0.40. The majority of the firms in the wholesale and hotel and restaurant sub-sectors have efficiency scores ranging between 0.40 and 0.80. In motor vehicle services, technical efficiency in the majority of the firms falls between 0.40 and 0.90. In the transport and IT sub-sectors, technical efficiency scores in the majority of the firms are more than 0.60 and 0.70, respectively, implying that many of the firms in these sub-sectors are highly efficient. However, for the retail sub-sector, technical efficiency scores range from as low as less than 0.20, signalling the existence of very low efficiency firms in the sub-sector. A large number of firms fall between 0.40 and 0.60 implying that a large section of the firms are average performers in technical efficiency, but the existence of the very low efficiency firms causes the overall technical efficiency score to be slightly below average.

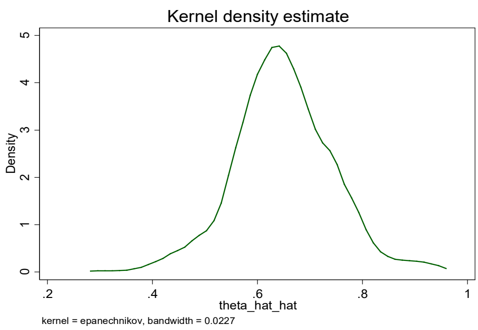
Figure 3: Kernel density estimates of technical efficiency scores at sub-sector level



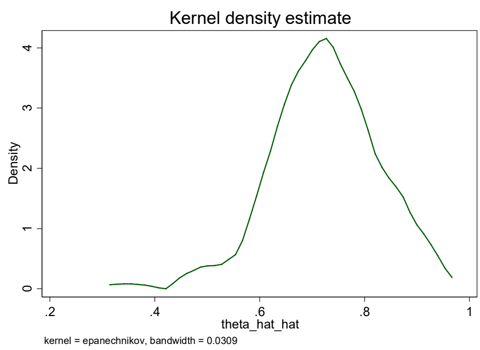
Retail sub-sector



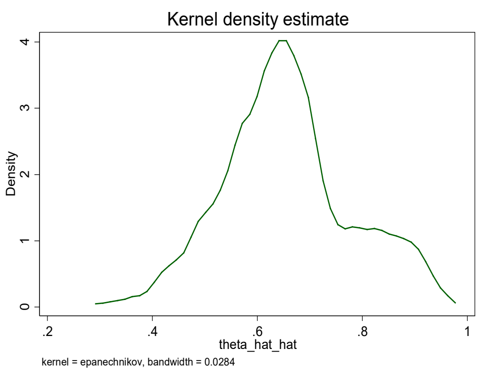
Wholesale sub-sector



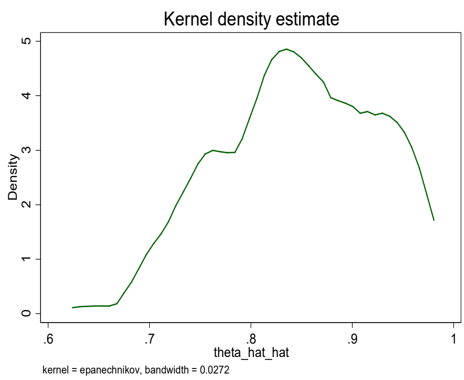
Hotel and restaurant sub-sector



Transport sub-sector



Motor vehicle services sub-sector



IT sub-sector

4.2 Determinants of technical efficiency in the service sector

Table 5 provides the bootstrap regression results of determinants of technical efficiency in the service sector. This section helps in providing potential explanations for variations in technical efficiency across countries.

Table 5:Determinants of technical efficiency in the service sector

	Kenya	Uganda	Tanzania	Ghana	DRC	Zambia
Foreign-owned	0.0169	0.0523**	-0.00209	0.0154	0.0733***	0.0226***
	(0.0180)	(0.0210)	(0.0194)	(0.0136)	(0.0169)	(0.00829)
Female-owned	-0.00276	-0.00869	-0.0122	0.00407	-0.0135	0.0137*
	(0.00905)	(0.0138)	(0.0124)	(0.00953)	(0.0170)	(0.00772)
Firm age	0.000583*	0.00563	0.0146	0.00392	0.00218**	0.00723
	(0.000330)	(0.00921)	(0.00962)	(0.00686)	(0.000985)	(0.00646)
Firm size	0.000149**	0.000347***	0.0118**	0.000322**	0.000533***	0.000277***
	(0.0000682)	(0.000108)	(0.00541)	(0.000145)	(0.000155)	(0.0000699)
Export	0.0152	0.0607***	-0.00651	-0.00408	0.0416*	0.00866
	(0.0110)	(0.0174)	(0.0159)	(0.0139)	(0.0216)	(0.0101)
Training	0.00511	-0.00177	0.00654	0.0200**	0.0254*	0.0143
	(0.0102)	(0.0143)	(0.0133)	(0.00957)	(0.0152)	(0.00899)
R&D	0.00163	0.0260*	0.0188	0.0128	-0.0220	-0.0123
	(0.0116)	(0.0149)	(0.0174)	(0.0123)	(0.0144)	(0.00890)
TME	0.00884	0.00444	0.0220**	0.00105*	0.00241**	0.0102*
	0.00649	(0.0101)	(0.00945)	(0.000625)	(0.000982)	(0.00609)
No. of observations	367	364	365	308	275	333
Wald statistics	25.71	43.21	21.84	16.01	60.18	60.13
No. of iterations	2000	2000	2000	2000	2000	2000

Dependent variable: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Note: Female-owned, foreign-owned and TME denote female ownership, foreign ownership and top manager's experience respectively.

Source: Own computation from WBES data.

Exporting has a positive and significant coefficient in Uganda and DRC. This implies that exporting positively influences the technical efficiency of service firms in these countries. The positive influence of exporting could be a result of the premiums associated with learning by exporting. Through exporting, particularly to developed countries, firms learn modern techniques that help them bolster technical efficiency. In addition, exporting exposes the management in firms to improved management practices which go a long way in enhancing technical efficiency. This finding is in line with Lemi and Wright (2018).

Research and development has a positive and significant coefficient in Uganda. This means that R&D investments lead to improvements in the technical efficiency of service firms in this country. R&D activities expose firms to innovations which, among other things lead, to product development and improvement, and new operation techniques that bolster technical efficiency. Female firm ownership has a positive and significant coefficient in Zambia. The finding reveals that service firms in Zambia with female ownership have higher technical efficiency compared to service firms with no female ownership. The International Labour Organization (ILO) postulates that women infuse an organization with teamwork, problem-solving expertise, creativeness, innovation, and openness (ILO, 2019). Such attributes are key to promoting technical efficiency in service firms.

Training has a positive and significant coefficient in Ghana and the DRC. This means that service firms that have formal training programmes have higher technical efficiency compared to firms with no formal training programmes. Through job training programmes, workers acquire skills, competencies, and expertise, that are essential to promoting labor productivity, efficiency, competitiveness, and profitability of firms (Blundell et al, 1999). Given rapidly changing production requirements, a successful launch of new technologies obliges firm managers to be backed by highly skilled technical staff. Such staff have been found to adapt more swiftly and efficiently to changing roles and technologies.

Foreign firm ownership has a positive coefficient in Uganda, the DRC and Zambia. This means that firms with foreign ownership in these countries are more technically efficient compared to firms with no foreign ownership, signifying that foreign ownership is essential in local service firms. The presence of foreign ownership, particularly in developed countries, in local service firms is likely to improve managerial skills and technical assistance as well as promote technology transfer, which are key to bolstering technical efficiency. In addition, foreign firms have more exposure to international markets making them more sensitive to competition from abroad (Sleuwaegen and Goedhuys, 2003). This outcome supports Barros et al (2014). Nevertheless, the finding contradicts Assaf et al (2011) who find foreign ownership to negatively influence the technical efficiency of Saudi banks.

Firm size has a positive and significant coefficient in all six countries. However, the estimated coefficients are very low suggesting that the extent of influence of firm size on technical efficiency is very low. Even with the low estimated coefficients, the finding implies that large service firms are more technically efficient compared to small service firms. This result supports the Jovanovic (1982) theory which states that large firms are likely to perform better in technical efficiency compared to small firms. According to the theory, firms self-select. They discover their levels of efficiency over time and, consequently, accustom their scale of operations. Highly technical efficient firms grow larger while low technical efficiency firms remain sluggish or exit the market. In addition, large firms have the financial ability to hire a high-skilled workforce, purchase recent technologies and realize the benefits of economies of scale and scope in terms of lower production cost per unit of output (Barros et al, 2014; Jaloudi, 2019). The outcome corroborates Assaf et al (2011), Roche et al (2019), and Jaloudi (2019).

Firm age has a positive and significant coefficient in Kenya and the DRC. Nevertheless, the estimated coefficients of firm age are very low, signalling that firm age's influence on technical efficiency is very low. However, the finding reveals that old service firms are more technically efficient compared to young firms, a finding that supports the Jovanovic (1982) theory. The theory states that old firms are likely to be more technically efficient compared to young firms because they reap the benefits of learning by doing. Therefore, over time, low technically efficient firms leave the industry and the more technically efficient firms remain in each age group. Conversely, young firms have inadequate knowledge of their capability and require time to recognize this capability. The finding is also in line with Mutarindwa et al (2021).

Top manager's experience has a positive and significant coefficient in Tanzania, Ghana, the DRC and Zambia. However, for Ghana and DRC, the estimated coefficients are very low, suggesting that the impact of top manager's experience on technical efficiency is quite limited. Nonetheless, the finding implies that service firms with highly experienced top managers have higher technical efficiency compared to firms with low experienced top managers. According to Lemi and Wright (2018), highly experienced managers have a wealth of skills and techniques that are essential for bolstering technical efficiency. The outcome is in line with Lemi and Wright (2018).

An estimation of the determinants of technical efficiency was also performed at the sub-sector level to help explain variations in technical efficiency across sub-sectors, the results of which are provided in Table 6. Exporting is found to have a positive and significant coefficient in the retail, transport and motor vehicle services sub-sectors. This implies that exporting firms in these sub-sectors have higher technical efficiencies compared to non-exporting firms. The finding suggests that these sub-sectors could produce more output without engaging more inputs by participating in exporting activities. This is important in improving the performance and competitiveness of the sub-sectors of interest in the face of increasing competition and globalization because these sub-sectors, especially the retail sub-sector, are characterized by low participation in international trading activities.

Table 6:Determinants of technical efficiency in the service sector, results by sub-sector

	Retail	Wholesale	Transport	H and R	IT	MVS
Foreign-owned	0.0208**	0.0463***	0.00603	0.0233**	0.0179	0.0116
	(0.00908)	(0.0153)	(0.0194)	(0.0116)	(0.0260)	(0.0233)
Female-owned	-0.000570	0.0100	-0.00169	0.00142	0.01044	-0.00230
	(0.00606)	(0.0124)	(0.0180)	(0.00812)	(0.01081)	(0.0203)
Firm age	0.00937**	-0.00322	0.00160**	0.000209	-0.00849	-0.000490
	(0.00449)	(0.00836)	(0.000743)	(0.000377)	(0.01330)	(0.000970)
TME	0.0158***	0.0000672	-0.00422	-0.00224	-0.00102	0.0240*
	(0.00475)	(0.000793)	(0.0133)	(0.00510)	(0.00139)	(0.0145)
Firm size	0.000221***	0.0339***	0.0178***	0.0194***	0.0334*	0.0367***
	(0.0000437)	(0.00567)	(0.00683)	(0.00386)	(0.0192)	(0.0101)
Export	0.0193**	0.0136	0.0522***	0.00527	-0.0079	0.0491**
	(0.00880)	(0.0147)	(0.0172)	(0.00988)	(0.02025)	(0.0250)
Training	0.0169**	0.0114	-0.00102	0.00500	-0.0154	0.00377
	(0.00670)	(0.0133)	(0.0169)	(0.00896)	(0.01817)	(0.0199)
R&D	0.0111	-0.0190	0.00826	0.00958	0.00883	0.0314
	(0.00743)	(0.0135)	(0.0193)	(0.00924)	(0.0317)	(0.0242)
No. of observations	826	266	131	543	51	189
Wald statistics	96.68	71.27	31.75	51.48	8.70	34.79
No. of iterations	2000	2000	2000	2000	2000	2000

Dependent variable: Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Female-own, foreign-owned and TME denote female ownership, foreign ownership, and top manager's experience respectively. "H and R" and "MVS" denote hotel and restaurant and motor vehicle services respectively.

Source: Own computation from WBES data.

The coefficient of training is positive and statistically significant in the retail sub-sector implying that this sub-sector could enjoy technical efficiency gains by introducing training programmes for its staff. This finding is particularly important given that the sector is often characterized by low-skilled workers (Branstetter et al, 2018). Equipping low-skilled workers with regular training could go a long way in enhancing their skills, competencies and expertise thereby promoting labour productivity, efficiency, competitiveness, and profitability of firms (Blundell et al, 1999). Foreign ownership has a positive and significant coefficient in the retail, wholesale, and hotel and restaurant sub-sectors. This implies that service firms with foreign ownership in these sub-sectors have higher technical efficiency compared to firms with no foreign ownership. These sub-sectors could be enjoying the technical efficiency gains of foreign ownership given that such ownership injects new knowledge to firms. Further, through foreign ownership, these sub-sectors are likely to be exposed to superior technologies, better management practices and training to use modern technologies, which are key to better technical efficiency.

Firm size has a positive and significant coefficient across all sub-sectors, signalling the significant role this covariate plays in determining the technical efficiency of service firms. The finding implies that large service firms across all the sub-sectors have better technical efficiency compared to small firms. This variable appears to have a higher impact on technical efficiency at the sub-sector level analysis compared to the country-level analysis. The only exception is the retail sub-sector where the coefficient is relatively small. The better performance in the large firms could be linked to self-selection, a case where technically efficient firms grow in size while inefficient firms exit the market. In addition, the relatively higher technical efficiency in large firms could partly be explained by their better financial ability to acquire modern technologies and hire highly skilled staff.

Firm age has a positive and significant coefficient in the retail and transport sub-sectors. This implies that older firms in these sub-sectors have higher technical efficiency compared to young firms. This could partly be explained by learning-by-doing effects. However, the impact of firm age on technical efficiency in the two sub-sectors is very low, as was the case for the country-level analysis. Top manager's experience has a positive and significant coefficient in the retail and motor vehicle services sub-sectors. This suggests that these two sub-sectors could enjoy technical efficiency gains by hiring highly experienced top managers given that such managers have a wealth of skills and techniques to appropriately manage the conversion of inputs to output. This variable also appears to have higher coefficients at the sub-sector level analysis compared to the country-level analysis.

5. Conclusion and policy implications

Although the service sector is progressively taking on a bigger role in structural transformation in developing countries compared to the manufacturing sector, the performance of the sector has not been studied in depth. This study employs a double bootstrap DEA, a non-parametric approach, on firm-level data obtained from the WBES to analyse technical efficiency and its determinants in selected SSA countries' service sectors. The empirical analysis is at the country and sub-sector levels. Countries of interest are Kenya, Uganda, Tanzania, Ghana, DRC and Zambia. The sub-sectors identified are hotel and restaurants, retail, wholesale, information technology (IT), motor vehicle services, and transport. The findings show the existence of a considerable opportunity to enhance technical efficiency in SSA. This finding applies across countries and within the sub-sectors studied. Exporting status, R&D, female firm ownership, top manager's experience, training, foreign ownership, firm size, and firm age are found to influence technical efficiency. However, the influence of these covariates is country-specific.

Several policy implications can be drawn from the findings of this study. First, there is a need for the selected SSA governments to provide an enabling environment to allow the growth of service firms. This is because of the striking finding that large service firms demonstrate higher technical efficiency compared to small firms. Small service firms could be supported with capital and access to finance to expand activities. These strategies will enable small firms to grow into the size necessary to leverage competitiveness. Second, there is a need for service firms to incorporate customized training programmes as part of their staff development initiatives. This is especially true for Ghana and the DRC where this variable is found to positively influence technical efficiency. Such programmes equip workers with skills and core competencies that help promote productivity and technical efficiency in firms. Third, there is a need for the selected SSA governments to intensify export promotion policies. More emphasis should be on Uganda and the DRC where exporting is found to promote technical efficiency. The search for international markets is a particular imperative. By exporting, firms learn recent production techniques, which are important in promoting technical efficiency.

Fourth, there is a need to promote foreign direct investment (FDI) in SSA. It is especially true for Uganda, the DRC and Zambia where firms with foreign ownership have higher technical efficiency compared to firms with no foreign ownership. This is because foreign-owned service firms are found to perform better in technical efficiency in almost all the countries studied. Foreign direct investment flowing from developed countries bring with them advanced technology, capital investments and entry to international markets. Locally owned firms also benefit from the spillover effects of advanced technologies and access to international markets. Fifth, service firms should take great care in hiring top managers as they play an integral role in technical efficiency. The findings of this study show that the top manager's experience influenced technical efficiency in most countries. Service firms should therefore hire experienced top managers because they possess the managerial abilities necessary to accelerate technical efficiency.

Finally, there is a need for governments to promote female firm ownership. This is most pertinent for Ghana where female firm ownership is found to positively influence technical efficiency. Rigorous education and training programmes in business skills increased awareness of profitable opportunities, and financial support could go a long way in increasing the visibility of women in firm ownership. Further, there is a need to promote research and development. This is especially true for Uganda where R&D is found to promote technical efficiency. The successful roll-out of research and development activities largely depends on access to internal and external resources. Governments can enhance R&D in service firms by offering financial incentives, for example, low-cost loans and subsidies for firms engaging in R&D activities. On their part, service firms need to work with research institutions, such as universities. R&D activities could result in a lower cost of production and high-quality services, thus promoting the competitiveness of firms.

Notes

1 For a more detailed discussion, see Van Beveren (2012).

2 A detailed explanation can be found in Olley and Pakes (1996).

3 For more detailed information, see Levinsohn and Petrin (2003).

4 For mor explanation, see Ackerberg et al. (2015).

5 For a detailed explanation, see Simar and Wilson (2007).

6 For more details, see Simar and Wilson (2000a) and Kneip et al. (1998).

7 For more details, see Efron and Tibshirani (1993) and Simar and Wilson (2000a)

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Appendix

Table A1: Definition, measurement, and source of variables and data

Variable	Definition and measurement	Source of variable and data
Output	Services produced by service firms. Measured as the value of services (Ksh).	Mukwate and Muchai (2012), World Bank Enterprise Survey (WBES).
Capital	Physical machinery and equipment used in production. Quantified by the total value of machinery and equipment (Ksh).	Mukwate and Muchai (2012), WBES.
Labour	Physical and mental workforce provided for wages and salaries. Quantified by the total cost of labour (Ksh).	Mukwate and Muchai (2012), WBES.
Energy	Electricity used in the production of services. Quantified by the total cost of electricity (Ksh).	Mukwate and Muchai (2012), WBES.
Firm age	Number of years an establishment has been operating	Mutarindwa et al. (2021). WBES.
Firm size	Number of workers in an establishment	Roche et al. (2019) WBES.
R&D	An undertaking by a firm to make a discovery that can result in the inception of new services or enhancement of existing services. Measured as a dummy variable, 1 if a firm engages in R&D and 0 if not.	Chaddad and Mondelli (2012), WBES.
Foreign ownership	Ownership of a local establishment by foreigners. Measured as a dummy variable coded 1 if foreign-owned and 0 if not.	Sleuwaegen and Goedhuys, (2003). WBES.

Exporting status	The activity of selling services in foreign countries. Measured as a dummy variable coded 1 if a firm exports and 0 if not.	Lemi and Wright (2018) WBES.
Top manager's experience	The total number of years the top manager has worked	Lemi and Wright (2018), WBES.
Female firm ownership	Whether a firm has female ownership or not. Measured as a dummy variable, 1 if there is a female member in firm ownership and 0 if not.	WBES.

Table A2: Average technical efficiency scores - input-oriented approach

Country	N	Original	Bootstrapped	Bias	Lower Confidence Interval	Upper Confidence Interval
Kenya	367	0.762	0.720	0.042	0.687	0.761
Uganda	364	0.652	0.620	0.032	0.601	0.676
Tanzania	365	0.607	0.540	0.067	0.487	0.603
Ghana	308	0.825	0.773	0.052	0.743	0.809
DRC	275	0.673	0.602	0.071	0.580	0.652
Zambia	333	0.623	0.527	0.096	0.462	0.595

Source: Own computation from the WBES data.

Table A3: Sub-sector average technical efficiency scores - input-oriented approach

Sub-sector	N	Original	Bootstrapped	Bias	Lower Confidence Interval	Upper Confidence Interval
Retail	826	0.532	0.456	0.076	0.409	0.517
Wholesale	266	0.666	0.570	0.096	0.510	0.638
Hotel and Restaurant	543	0.606	0.532	0.074	0.489	0.582
Transport	131	0.775	0.711	0.064	0.656	0.779
Motor vehicle services	189	0.719	0.633	0.086	0.584	0.693
IT	86	0.860	0.772	0.088	0.720	0.850

Source: Own computation from the WBES data.

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