TECHNICAL AND SCALE EFFICIENCY OF PUBLIC SECONDARY SCHOOLS IN KENYA: A DATA ENVELOPMENT ANALYSIS OF COUNTIES

VICTOR ELIKANA ONGAYA

A RESEARCH PROJECT SUBMITTED TO THE DEPARTMENT OF ECONOMETRICS AND STATISTICS IN THE SCHOOL OF BUSINESS, ECONOMICS AND TOURISM IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF MASTER OF ECONOMICS (ECONOMETRICS) OF KENYATTA UNIVERSITY

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DECLARATION

This research project is my original work and has not been presented for a degree in any other university or any other award.

Signature:............................ Date:...03/05/2024...

Victor Elikana Ongaya

Bachelor of Economics and Statistics

K102/CTY/PT/31010/2015

I confirm that the work reported in this project was carried out by the candidate under my supervision.

Signature:............................ Date:...3-05-24...

Dianah Ngui M. (PhD)

Senior Lecturer

Department of Econometrics and Statistics

School of Business, Economics and Tourism

Kenyatta University

DEDICATION

To my sons Avin, Bravin and Caven. May this be an encouragement to you for academic excellence.

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I appreciate the Almighty God for guiding me throughout my academic journey despite the many obstacles I faced. Many are the times I almost gave up on any further academic progress, but the Lord Almighty came through. I will never waver in my faith in him as I continue on my path to greater academic success.

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LIST OF ACRONYMS AND ABBREVIATIONS

AL	Aridity Level
ASAL	Arid and Semi-Arid Lands
BPS	Budget Policy Statement
CDF	Constituency Development Fund
CRS	Constant Returns to Scale
DEA	Data Envelopment Analysis
DEAP	Data Envelopment Analysis Program
DMU	Decision making unit
ECDE	Early Childhood Development Education
ERS	Economic Recovery Strategy
FDSE	Free Day Secondary Education
FPE	Free Primary Education
GDP	Gross Domestic Product
GOK	Government of Kenya
GPI	Gender Parity Index
KACE	Kenya Advanced Certificate of Education
KCPE	Kenya Certificate of Primary Education
KCSE	Kenya Certificate of Secondary Education
KESSP	Kenya Education Sector Support Program
KNBS	Kenya National Bureau of Statistics
KNEC	Kenya National Examination Council
LR	Literacy Rate
MDGs	Millennium Development Goals
MODA	Ministry of Devolution and ASALs

MOE	Ministry of Education
MOEST	Ministry of Education, Science and Technology
NEMIS	National Education Management Information System
PPS	Production Possibilities Set
RDEA	Robust Data Envelopment Analysis
ROK	Republic of Kenya
SDGs	Sustainable Development Goals
SD	School Density
SE	Scale efficiency
SFA	Stochastic Frontier Analysis
TE	Technical efficiency
TSC	Teachers Service Commission
TIMMS	Trends in International Mathematics and Science Study
UN	United Nations
UNESCO	United Nations Education, Scientific and Cultural Organization
UNICEF	United Nations Children Education Fund
VRS	Variable Returns to Scale

OPERATIONAL DEFINITION OF TERMS

Data envelopment analysis: A non-parametric approach to estimation of efficiency.

Learning: The process of acquiring new knowledge and skills as a result of attending school.

Scale efficiency: Is a measure used to express whether a firm/ decision making unit is operating at its optimal size.

School county: Is a geographical political unit established by the Fourth Schedule of the Constitution of Kenya, 2010 within which public secondary schools are found.

Schooling: The act of attending school.

Technical efficiency: Is the ability of a firm/decision making unit to obtain maximum output from a given set of inputs.

ABSTRACT

Kenya is working towards achieving a rapidly growing upper-middle income economy status by 2030. Education and training have been identified as among the enablers of this vision and have subsequently seen their public spending sustained at above 4% of the GDP over the last decade. Although there have been deliberate efforts which have yielded tremendous progress towards improving access to public education in the country over the years, there still remain direct challenges facing public secondary education. Notable among them is the coexistence of overutilization and underutilization of educational resources, and significant disparities in academic achievements of students across the 47 counties. This points to inefficiency in public secondary education, whose determinants are unknown. This study therefore sought to fill this gap by making use of the data envelopment analysis model approach to assess the technical efficiency levels of public secondary schools in Kenya and their determinants. The model was estimated using secondary cross-sectional data on one output and three input variables for the 2019 academic year, collected from public secondary schools across the country and using the 47 counties as decision making units. The output variable used was the number of form four candidates who scored a mean grade C+ and above in the 2019 Kenya Certificate of Secondary Education examinations. The inputs used were the county student-teacher ratio, county textbook-student ratio and county average school size. Results revealed that public secondary schools were inefficient, and could improve their efficiency by 51% using the available resources; there was a huge variability in efficiency levels of public secondary schools across the counties; public secondary schools were operating sub-optimally, and could improve on their unutilized capacity by 11.1%; counties with more secondary schools were more efficient than those with fewer secondary schools, and also counties with higher literacy rates were more efficient that those with lower literacy rates. Gender parity index and county aridity level were not found to significantly affect inefficiency The study recommends that policies that will ensure effective management of public schools, for instance benchmarking, should be implemented by the Ministry of Education. It also recommends opening of more secondary schools by the Ministry of Education in counties with fewer schools to encourage competition. The study additionally recommends inclusion of literacy programs into other community focused programs being funded by both the government and non-governmental partners, and application of technology to promote continuous learning among communities, especially those in the ASALs.

CHAPTER ONE

INTRODUCTION

1.1 Background

The journey towards achieving global quality education started way back in September 2000, where the 191 members of the United Nations adopted the Millennium Declaration which aimed at forging a global collaborative approach for overcoming the challenges that faced the future global development (UNESCO, 2002). The meeting came up with a framework of 8 goals, 21 targets and 60 indicators that came to be known as the Millennium Development Goals (MDGs). Goal number two aimed at achieving universal primary education and ensuring that by the year 2015, all children of both genders across the globe were able to complete a full course of primary schooling. These goals have since been succeeded by the Sustainable Development Goals (SDGs) which are a set of 17 goals and 169 targets that are to be achieved by 2030.

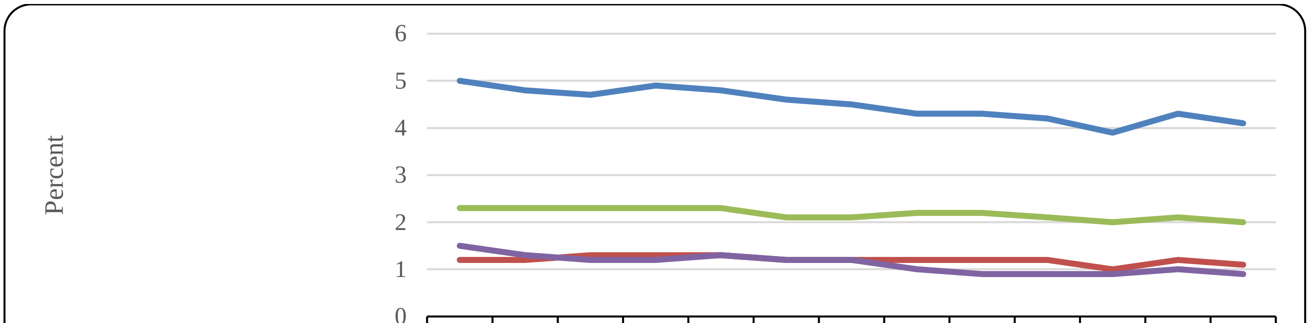
Kenya took up this challenge in 2003 with the implementation of free primary education (FPE) programme in public primary schools. Initiatives to streamline the programme saw the development of the Sessional Paper No. 1 of 2005. The paper noted that despite increased enrolment levels between the years 1963 and 2003 at all the three levels of basic education (ECDE, public primary and public secondary school), the sector still faced challenges with respect to access, equity and quality (MOE, 2005). A five-year plan known as the Kenya Education Sector Support Program (2005-2010) was later developed to operationalize the sessional paper.

1.1.1 Macroeconomic Context of Education in Kenya

The Kenya Vision 2030 was launched in 2008 as a blueprint for transforming the country into a newly industrializing middle-income economy by the year 2030. Prior to this, the government had been implementing the Economic Recovery Strategy (ERS) from 2003 to 2007 as an action plan that was meant to guide the government's economic policies over the implementation period. In its five years' implementation term, the ERS transformed the country's economy into a steady recovery path by reversing the poor economic performance experienced as a result of mismanagement of economic policies aimed at addressing structural problems affecting the economy and weak governance institutions (GOK, 2003).

Vision 2030 was aligned to the then UN global development agenda (the MDGs) and is anchored on three main pillars namely; the economic, social and political pillars - each with several key sectors under it. The education and training sector is appropriately placed under the social pillar. The overall goal for the sector, initially meant to be achieved by 2012 under the first medium term plan, was to reduce illiteracy by increasing access to education, improving the transition rate from primary to secondary schools, and raising the quality and relevance of education (GoK, 2007). A key flagship project under the sector involved building and equipping of 560 new public secondary schools. This project was prioritized so as to accommodate the growing number of students graduating from primary schools as a spillover effect of introduction of free primary education (FPE) earlier in the year 2003.

In order to keep up with the global goal of achieving basic education for all, the government continued to support the education sector by consecutively allocating higher amounts of budget, which led to the sector's massive expansion in both enrolment levels and number of educational institutions over time. Budgetary allocations from the government averaged about 4.5% of the GDP between the years 2010 and 2022. Over the same period, the contribution of the primary, secondary and higher education subsectors to GDP averaged 2.2%, 1.2% and 1.1% respectively. Figure 1.1 shows the annual contribution of the sector and subsectors to GDP.



	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Education Sector	5	4.8	4.7	4.9	4.8	4.6	4.5	4.3	4.3	4.2	3.9	4.3	4.1
Primary Education Subsector	2.3	2.3	2.3	2.3	2.3	2.1	2.1	2.2	2.2	2.1	2	2.1	2
Secondary Education Subsector	1.2	1.2	1.3	1.3	1.3	1.2	1.2	1.2	1.2	1.2	1	1.2	1.1
Higher education Sub sector	1.5	1.3	1.2	1.2	1.3	1.2	1.2	1	0.9	0.9	0.9	1	0.9

Figure 1.1: Contribution of the education sector and subsectors to Kenya's GDP, 2010 – 2022
Source: Statistical Abstract, 2023;

Total spending by the government on education sector grew from Ksh. 154.41 billion to 465.69 billion between fiscal year 2009/2010 and 2022/2023, representing a 255.1% rise. Out of this, spending on secondary education subsector grew by 432.8% over the same period, rising from Ksh. 15.28 billion to Ksh. 81.41 billion. The spending on teacher salaries, which is one of the most critical inputs in the sector, also grew by 166.1%, from Ksh. 92.33 billion in the fiscal year 2009/2010 to Ksh. 289.97 billion on account of additional teachers hired over the period as shown in table 1.1.

Table 1.1: Government spending on the education sector, 2009/10 – 2022/23 (Millions, Ksh.)

Financial Year	Total spending on education sector	Spending on Secondary education only	Pay to teachers & other personnel
2009/2010	154,405.85	15,279.30	92,330.44
2010/2011	179,000.03	3,026.60	118,657.64
2011/2012	207,460.09	19,198.13	112,982.41
2012/2013	260,122.37	25,075.93	147,122.08
2013/2014	251,212.59	22,802.88	161,000.89
2014/2015	284,164.89	29,861.89	179,627.30
2015/2016	319,425.24	32,996.51	170,665.00
2016/2017	315,578.67	34,853.20	187,874.00
2017/2018	412,454.95	35,956.00	195,301.00
2018/2019	455,079.84	69,334.20	219,711.00

Financial Year	Total spending on education sector	Spending on Secondary education only	Pay to teachers & other personnel
2019/2020	464,692.19	68,458.90	245,719.90
2020/2021	472,376.00	70,818.20	257,973.40
2021/2022	511,917.00	75,219.80	273,234.30
2022/2023	548,249.67	81,414.80	289,973.30

Source: Economic Survey, 2014, 2018, 2023 & BPS, 2020, 2023
**Estimates*

These allocations, complemented by other institutional reforms like the introduction of the constituency development fund (CDF) and assistance from development partners and private providers led to increased enrolment in both primary and secondary schools across the country.

1.1.2 Role of Government in Promoting Efficiency of Secondary Education

The Constitution of Kenya 2010 created 47 devolved units of governance, known as county governments, which were operationalized in 2013. The counties were allocated various functions and powers under the fourth schedule of the constitution. With respect to education, the County governments are mandated to coordinate preprimary education, village polytechnics, homecraft centres and childcare facilities while the national government coordinates education policy, standards, examinations and curricular and also the running of higher education institutions, secondary and primary schools (ROK, 2010).

Worthington (2001) defines technical efficiency, in the context of the education system, as the utilization of educational productive resources in a way that enables obtaining the maximum possible educational output from them. Educational institutions are comparable to a firm that transforms raw materials into final outputs. The educational resources referred to here may be capital or labour, while the outputs may be students' achievements, categorized into either intermediate outputs (standardized test scores), or final outcomes from education (for instance transition rates to higher levels of education).

Kenya's secondary schools are inefficient, according to Sitati (2017). Overall efficiency was estimated to be 63%, with only 8% of the 377 sampled schools being fully efficient. Regionally, Mombasa, Laikipia and Nairobi counties jointly recorded the highest efficiency score, at 83% while Mandera, Wajir and Tana

River counties had the lowest efficiency scores at 51%, 49% and 41% respectively, showing a wide variability in the scores, which could be a pointer to the existing disparities in opportunities for education among the counties.

Whereas one might attribute this inefficiency to resources constraints, the results seem to diagnose a different cause, since with the existing resources, the schools still had room for improving their output, and thus efficiency, by about 37%. Public secondary schools, small sized schools and those based in the rural areas had a negative impact on efficiency. The schools were also operating sub-optimally, leaving about 26% of unused capacity. The MOE (2018) agreed that though there have been concerted efforts by government to increase the number of teachers in schools, their utilization remains a key challenge, as there were still imbalances in teacher distribution, with ASAL counties facing a shortage, mainly due to the insecurity in most of the ASAL areas. Additionally, climate challenges have also led to sub optimal use of schools, especially during seasons of drought, where nomadic families have to migrate to look for food and water for their animals, leaving schools deserted. Still within some of these areas with harsh climatic conditions, learning only takes place for a few hours due to high temperatures that make it unbearable to stay is classes during the day.

1.1.2.1 Situation Analysis of Kenya's Educational Inputs and Outputs

In considering education as a production process where the society invests key variables through the schooling system expecting educational outputs, the quality and quantity of these variables becomes the key determinant of the quality and quantity of the outputs. The common factors of production in the education system include labour (teachers) and capital (classrooms and teaching aids).

In Kenya, the national examinations taken by students at the end of secondary education is the main output of the secondary education system. The Kenya Certificate of Secondary Education (KCSE) was first administered in 1989 to replace the Kenya Advanced Certificate of Education (KACE). Since its inception, performance of students in the KCSE has been receiving much public attention, partly due to its importance in the criteria for admission to higher education within the country and abroad. The reason for use of results obtained in cognitive tests to measure educational output may be largely attributed to the perception that they are difficult to manipulate (Yawe, 2014). Because of this centrality, the integrity of the exams is therefore a major policy concern for all education stakeholders.

Cases of malpractices in national secondary examinations have however been reported from as far way back as the mid-nineties, a factor that continues to cause great concern among stakeholders in the education sector. In response to this challenge, the Kenya National Examinations Council (KNEC) has over the years formulated, reviewed and enforced strict exam rules and regulations that have gone a long way in minimizing the prevalence of these malpractices. The penalties for exam malpractices have included, inter alia, cancellation of students' results, prosecution and dismissal of teachers and other government officers found to have colluded with students to cheat in exams.

KCSE performance trend shows a 114.9% rise in the total number of candidates who met the minimum threshold for joining universities in Kenya, by attaining a mean grade of C+ and above, from 82,135 in 2010 to 174,505 in 2022. The percentage of candidates who scored a grade C+ and above to the total number of candidates who sat for KCSE over the twelve-year period ranged between 18% and 27% (KNBS, 2014; KNBS, 2018; KNBS, 2023). A look at the performance in the 2019 KCSE by counties revealed that Nakuru had the highest number of candidates scoring C+ and above at 7,005 while Tana River had the least, at 41. A total of 11 counties had less than 1,000 candidates scoring C+ and above. Out of the 11 counties, 8 are located in the arid lands of the country, suggesting that aridity negatively affects student performance.

On the inputs side, evidence has shown that good physical learning facilities can positively impact student achievement as they enhance school attendance throughout the academic year. However, despite consistent investments in school infrastructural development over the years, there are still inadequacies. This is more pronounced in the Arid and Semi-Arid areas, poor rural areas and the urban informal settlement areas where supply of students has exceeded the available classrooms. The investments, largely funded by the Constituency Development Fund (CDF) and the now defunct Local Authority Transfer Fund (LATF) led to an increase in the number of public secondary schools from 5,019 in 2009 to 7,680 in 2014, to a further 9,247 by the year 2022 (KNBS, 2014; KNBS, 2018; KNBS, 2023). This was against an increase of enrolment in public secondary schools, which grew from 926,149 students in 2004 to 3,858,079 in 2022, representing a 315.6% increase over the period.

In 2014, Kakamega county had the highest number of public secondary schools (381), followed by Kitui (372) and Makueni (356). Isiolo, Tana River and Samburu had the least number of public secondary schools at 17 schools and 20 each, respectively (MOEST, 2014). By the year 2019, a total of 8,933 public secondary schools existed. Kitui county had increased its tally to 483 schools to top the list as the county with the highest number of public secondary schools. On the other hand, Lamu county had the least number of schools, at 21, having been overtaken by Isiolo, which had increased its tally to 32 schools from 17 in 2014.

The government's drive to progressively increase the number of public secondary schools over the years was necessitated by the introduction of Free Primary Education (FPE) earlier in 2003 and later, Free Day Secondary Education (FDSE) in 2008. These policies led to significant increments in school enrollments which also overstretched the existing facilities, some of which had very little or no space for expansion. The introduction of the FDSE, for instance, increased enrollment by about 300,000 secondary school leaners in its first term of implementation in 2008, subsequently presenting twin challenges; an acute shortage in the number of classrooms to accommodate the extra learners, and insufficient teachers to teach the extra learners (Khamati and Nyongesa, 2013). The short-term measure introduced to address these challenges while longer term measures were being explored saw the MOE raise the classroom capacity to 45 students per class from 40, thereby altering upwards the recommended teacher to student ratio from 1:40 to 1:45 (Oyaro, 2008).

The government later in 2018 rolled out implementation of mass transition programme, which meant that all candidates who sat for the 2017 Kenya Certificate of Primary Education (KCPE) were to be admitted in secondary schools regardless of the grade attained. Considering that public schools didn’t have enough classrooms and the number of teachers was still way lower than the recommended international standards for teacher to learner ratio, this worsened the then teacher to student ratio of 1:41, since public secondary schools required about 47,576 more teachers (Mbaka, 2017).

Studies have shown that teacher to learner ratio has a significant influence on the performance of students in academics (Ajani and Akinyele, 2014; Koc and Celik, 2015; Waita et.al., 2016). This is because learners in small classes benefit from closer supervision and individualized attention offered by the teachers, helping them to better understand what they are taught. The Kenyan context was however different considering the 2019 KCSE examinations. Whereas Nairobi County with a teacher to students ratio of 1:42 had 5,857 students scoring C+ and above, Tana River County, with a much better ratio of 1:25 had only 41 students managing C+ and above. This therefore means that besides the ratio, other factors also contribute to performance. As Ajani and Akinyele (2014) contend, the teacher to student ratio is not equivalent to amount of instruction time, hence performance will also be dependent on the amount of time a teacher spends with the students.

Another key input into the education system is the instructional materials. These supplement the role of teachers in imparting knowledge and enable learners achieve their full potential. Textbook to student ratio is among the indicators of internal quality in education. Cognizant of this, the government, in line with Kenya's development blueprint targeted the reduction of the text book to student ratio from 1:3 to 1:1. Achievement of this target has however not been easy, with the education ministry facing various challenges that include inadequate financing, high year on year enrollment, high rate of book wear and tear especially in rural schools and loss/ theft of text books in some schools. (MOEST, 2015).

To counter some of the above challenges, a new arrangement for acquisition of text books was adopted in 2019 by the government. On top of the centralized procurement of books and distribution by the education ministry, schools were also allowed to procure the books directly through the capitation amounts advanced to them. At secondary school level, the focus was on acquisition of textbooks for core subjects offered, including English, Kiswahili, Physics, Biology, Chemistry and Mathematics. A total of 4,162,459 texts were acquired to serve the 3,025,774 enrolled public secondary school students, translating to a text book to student ratio of 1:1.31. Only three counties, namely Marsabit (1:1.23), Nyeri (1:1.27) and Isiolo (1:1.29) had better ratios than the national average. Mombasa county had the highest ratio at 1:1.47 (MOE, 2019).

Equity in access to education is a key policy concern across the globe. This is because of the transformative potential of educating girls in the community, including its contribution to reduction in inequality and ability of women to be included in making decisions that affect them. It is therefore important to ensure gender parity is achieved at all levels of the schooling profile of learners. UNICEF (2022) reported that about 76% of countries globally had not achieved gender parity in upper secondary education. Gender parity is achieved when the ratio of the number of school girls to school boys, also known as gender parity index (GPI), is between 0.97 and 1.03 (UNESCO, 2015). An index above the upper limit means more girls than boys, while an index below the lower limit means more boys than girls.

According to MOE (2019) Kenya had achieved gender parity in secondary schools (GPI=1), with slightly more girls than boys enrolled for the 2019 academic year. Among the counties, Wajir recorded the highest GPI score at 1.89 while Vihiga had the lowest at 0.82. An interesting finding is that the top five counties were all arid counties, while the bottom five counties were all non-arid, suggesting that more girls than boys were enrolled in secondary schools found in arid counties, while more boys than girls were enrolled in secondary schools found in non-arid counties.

1.2 Statement of the Problem

Concerted efforts by the government and other education stakeholders have led to policy changes which have resulted in greater investments in the education sector over the years. The share of secondary education spending to the MOEST recurrent expenditure averaged about 25% between 2012 and 2017 (KNBS, 2017) and contributed to improving access to education. Despite this however, there still remained direct challenges facing public secondary education, notable among them being the coexistence of overutilization and underutilization of educational resources, and significant disparities in academic achievements of students across the counties.

MOEST (2015) admitted that the performance of the education sector had been less than optimal, attributing this to constraints posed by implementation of FPE and FDSE. The two programmes resulted in increased enrollments in public secondary schools without a commensurate increase in both personnel and facilities. This led to classroom overcrowding and increased workload for the available teachers, hence affecting the quality of education at both primary and secondary school level.

The National Education Sector Plan 2018-2022 further affirms that the basic education sub sector in general still faces a number of challenges that have contributed to internal inefficiencies. The plan notes that about 4 out of every ten children who enroll for grade 1 in primary school do not finish secondary education; a substantial number of children eligible for schooling in the Arid and Semi-Arid Lands (ASALs) counties, mostly girls, are not in school; and, upper primary school (grade 6) completion rate is lower for students from poor backgrounds (60%) compared to children from rich backgrounds (90%). More importantly, most children already enrolled in basic education institutions are schooling but not learning, as evidenced by performance in the KCSE exams, where for the academic years 2016 through to 2018, less than a fifth of those who sat for the exam managed a mean grade of C+ and above.

Previous studies (Baba et al., 2020; Kaur, 2021) have shown that the need for efficiency in education stems from a number of factors, among them, dwindling academic performance; financial constraints; declining satisfaction levels among stakeholders; and loss of public confidence in the education system. Public secondary education in Kenya has over the years experienced expansion, marked by increased enrollments of students, increased number of secondary schools and increased levels of public funding. Interestingly, even with this significant allocation of public funds, students are still performing below the anticipated level.

Sitati (2017), using a sample of 377 schools, established that Kenyan public secondary schools were a significant determinant of school technical inefficiency. This study aimed to measure the technical efficiency of public secondary education by using the entire population of the existing public secondary schools in Kenya, and determine the contributors to inefficiency.

1.3 Research Questions

The study was guided by the following questions;

i. What are the technical efficiency scores and corresponding scale efficiency scores in public secondary schools across Kenya’s counties?

ii. What are the determinants of technical inefficiency in public secondary schools across Kenya's counties?

1.4 Objectives of the Study

The main objective of this study was to measure the levels at which public secondary schools in Kenya are using the available scarce resources to produce maximum educational output.

The specific objectives were;

i. To estimate the technical efficiency scores and the corresponding scale efficiency scores in public secondary schools across Kenya's counties.
ii. To establish the determinants of technical inefficiency in public secondary schools across Kenya's counties.

1.5 Significance of the study

The findings of the study are of core importance to various stakeholders. First to the Kenyan government and policy makers at both the national and county level, the findings provide empirical results as a basis for the design and administration of relevant policies that affect allocation of resources to the education sector. This study also provides an important empirical reference to inform public – private partnership engagements between the government and the private sector. The findings of this study also contribute to the already existing literature in the disciplines of economics and education and hence a reference point for scholarly work by students and researchers.

1.6 Scope of the study

This study evaluated the technical efficiency of all the registered public secondary schools in Kenya that were operational in the 2019 academic year and captured in the 2019 basic education census by MOE. A total of 8,933 public secondary schools across all the 47 counties in Kenya were considered. The decision to use the population as opposed to using a sample of public schools was favoured by the ease of availability of data from the 2019 basic education statistical booklet. The year 2019 was chosen because it was the latest academic year that had core education reference data for this study that is disaggregated up to county level.

1.7 Limitations of the study

The study did not calculate the allocative efficiency of public secondary schools. This was because of the difficulty in accessing data concerning expenditures on educational inputs disaggregated upto the county level.

1.8 Organization of the study

The study is organized into five chapters. Chapter one introduces the study by giving the background information, statement of the problem, the objectives and significance of the study. Chapter two reviews some of the available theoretical and empirical literature on the measurement of efficiency in education. Chapter three explains the research methodology employed for conducting the study. Chapter four presents the empirical findings, while chapter five presents the summary, conclusion and policy implications arising from the study.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter provides a review of literature on estimation of technical efficiency, with a bias to the education sector. The review is divided into theoretical literature which provides the microeconomic foundation of technical efficiency measurement, and empirical literature which critically reviews empirical studies carried out to estimate the technical efficiency scores of schools.

2.2 Theoretical Literature

Efficiency measurement is embedded in the economic theory of production. This is a microeconomic theory that is concerned with the behavior and interactions of two types of economic units, that is, consumers and firms. These units have a common objective, which is optimization, subject to certain constraints. Firms are modeled as having the objective of profit maximization subject to market and technological constraints, while consumers aim to maximize utility subject to a budget constraint.

The theory of the firm is directly related to efficiency measurement, since efficiency is concerned with the performance of a decision-making unit that utilizes inputs to produce outputs. The technological constraint faced by a firm when trying to maximize profits concerns getting the best combination of inputs to maximize the output and hence its profit. This interaction of inputs and outputs is best described using a production function.

2.2.1 The Production Function

This is the simplest way to represent the technology of a firm, as it shows the maximum output that can be produced using a given set of inputs. The function mathematically expresses the quantity of output produced as a function of inputs. The inputs are either capital, labour or other raw materials.

$$Q = f\,(inputs)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.1)$$

$$Q = f\,(K,L,R)\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2.2)$$

where Q represents the output of the firm; K represents the amount of capital employed to produce the output; L represents the amount of labour in form of people and skills used to produce the output; and R represents the amount of other raw materials used in the production process (Varian, 2006). This relationship can be presented graphically as shown below.

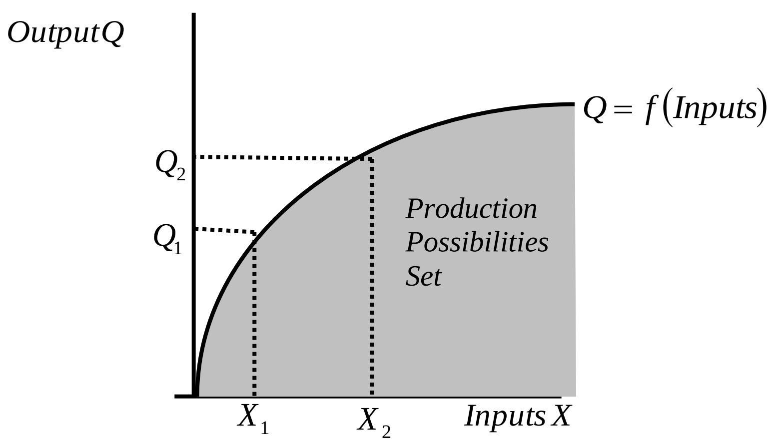


Figure 2.1: Graphical representation of the production function

Source: Gachanja, 2016.

Given a vector of inputs X_1, the maximum possible vector of outputs is Q_1. Besides this, there are other technologically feasible sets of production plans that fall under the production function, known as the production possibilities set (PPS) (Varian, 2006).

Since the firm's objective is to maximize profit, there are two main ways to achieve this. The firm can either increase the amount of output Q produced, or reduce the cost of producing Q. Both of these depend entirely on how the firm plays around with the input combinations. The study of getting the right input mix that will produce the maximum amount of output is the main stay of efficiency measurement.

2.2.2 The Concept of Efficiency

Productive efficiency is the ability of a decision-making unit to produce maximum attainable output from a given set of inputs (Farrell, 1957). It can be decomposed into two components, technical efficiency and price/ allocative efficiency. Technical efficiency is the ability of a given firm to maximize its output from a fixed set of inputs, while price/ allocative efficiency is the ability of a given firm to optimally utilize the inputs at its disposal given their respective prices.

There are two main orientations for measuring technical efficiency, the output orientation and the input orientation (Coelli et al., 1996). Output orientation is where the output vector is held constant while no reduction in any input is considered feasible. The aim is to maximize the level of output. On the other hand, input orientation is where the input vector is held constant and no increase in any output is considered feasible. The aim is to minimize the amount of inputs used (Koopmans, 1951). These can be mathematically represented as:

Output orientation - TEO $(x,) = [max\ \{\phi: \phi y \in P(x)\}]-1$ ………………………... (2.3)

Input orientation - TEI (y, x) = $min\ \{\Theta: \Theta y \in L(y)\}$……………………….…….. (2.4)

The decision on which of the two orientations to adopt will mainly depend on which of the factors the decision-making unit has control over, whether it is the inputs or outputs. These two orientations are presented graphically below.

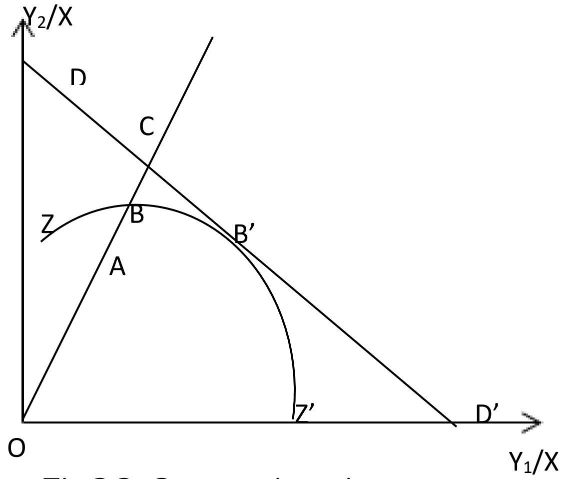


Fig 2.2: Output orientation

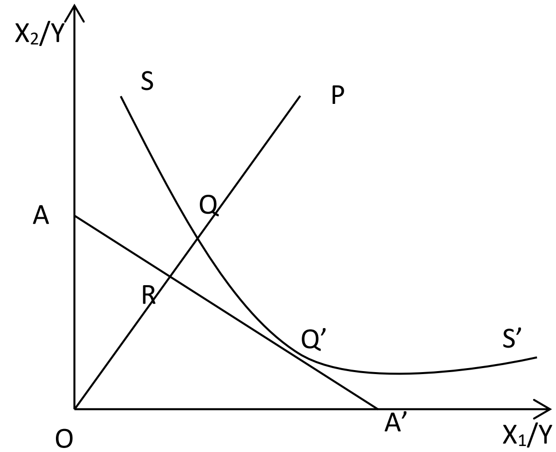


Fig 2.3: Input orientation

Source: Coelli, 1996

In figure 2.2, the curve ZZ' represents the production possibilities frontier and point A depicts an inefficient firm since it lies below the production possibilities curve which represents the upper bound of the production possibilities set. Technical efficiency is represented by the ratio OA/OB, while AB is technical inefficiency.

In figure 2.3, for a given firm using quantities of inputs P to produce a unit output, the distance QP represents technical inefficiency, while the ratio OQ/OP represents the technical efficiency.

2.2.3 Measurement of Efficiency

Literature provides two main ways of estimating efficiency. The first approach is parametric or economic approach, which utilizes the production function and assumes suitable assumptions to the function. Parametric approaches are commonly used in describing models that have a homogenous structure. In this case, the specified production model determines the combination of inputs and outputs. Stochastic Frontier Analysis (SFA) is the most popular method for parametric estimation of efficiency. Other methods include distribution free approach and thick frontier approach (Ćwiąkała-Małys, Nowak 2009a). Distance functions are also applied in economic estimation of efficiency.

Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) are credited with the introduction of SFA. It is an efficiency estimation method that acknowledges the error term, which accounts for the effects of producer specific random shocks on the production process. Its main strength lies in its ability to accommodate approximation errors and statistical noise (O'Donnell, 2010). Its main disadvantage is that it cannot differentiate between inefficiency and effects of the random noise since the two are combined into one error term (Nguyen, 2020).

The second approach for measuring efficiency is non-parametric approach, which uses linear programming methods (Baran, 2007). Data Envelopment Analysis (DEA) is the widely used method for non-parametric estimation of efficiency, besides its other alternative, the free disposal hull (Ćwiąkała-Małys, Nowak 2009a).

Charnes, Cooper and Rhodes are credited with the introduction of DEA in 1978. It is a mathematical programming technique used in estimating the relative efficiency of decision-making units that are homogenous in nature. The DEA efficiency evaluation process entails analyzing the empirical observations obtained from the units under study in order to identify the productive ones as defined by common outputs arising from use of designated inputs (Soteriou *et al*., 1998). This is corroborated by Worthington (2001) who submits that DEA evaluates an organization's efficiency relative to the best performing organization(s) in the sample under investigation. This technique is superior where multiple outputs are produced using multiple inputs, and the input-output transformation relationships are known (Charnes *et al*., 1978).

DEA has obvious advantages that make it suitable for this study. One is its computational simplicity, which means that it can be implemented without specifying the frontier functional form (Kariuki *et al*., 2015) and does not it require any assumptions to be made concerning the error term (O'Donnell, 2010). It also focuses on each decision-making unit in contrast to the population averages hence producing a single efficiency measure for each decision-making unit (Kirigia, 2013). Ogada *et al*. (2014) note the third advantage as being its ability to compute TE scores with inputs and outputs in their natural physical units without having to normalize them into some common metric. Lastly, DEA's flexibility also enables it to take care of exogenous variables that are beyond the control of the decision-making unit under consideration.

Scale efficiency under DEA relates to the size of operation of a DMU. A unit is scale efficient if its size of operation is optimal, so that any modification on its size renders the unit less efficient (Coelli et al., 1996). It can also be considered as the amount of productivity gain as a result of adjustment in the scale of production (Coelli et al., 2005). Therefore, if a unit is not operating at optimal size, it is also possible to know whether it is too large or too small. Scale efficiency may take on one of two assumptions, that is, constant returns to scale (CRS) or variable returns to scale (VRS). In CRS, there is proportional change for input and output, meaning that a unit adjustment in input leads to an equal adjustment in the output. In VRS, change in input and output variables is disproportional, meaning a unit adjustment in the input may lead to a higher or lower adjustment in the output.

From theory, the CRS assumption when calculating technical efficiency is appropriate only when all DMUs under observation are operating at an optimal production size. However, due to issues like market imperfection, government intervention and resource constraints, a firm may not operate at an optimal scale in reality. As such, applying the constant returns to scale assumption where decision-making units under study are not all operating optimally leads to technical efficiency scores that are confounded (Coelli *et al*, 2005).

2.3 Empirical Literature

Sitati (2017) sought to establish the determinants of technical efficiency in Kenya's secondary schools using two steps of analysis, where DEA and Tobit regression analysis were applied. Output-oriented DEA was applied to a sample of 377 public and private secondary schools spread across the county's 47 counties to estimate the schools' efficiencies. Three inputs (pupils to teacher ratio, pupils to classroom ratio and book to student ratio) and two outputs (KCSE mean scores and school completion rate) were used for the DEA analysis, while three environmental factors (school size, location and school type) were regressed against the calculated efficiency scores.

The study established that secondary schools were operating at an average efficiency of 62.7% with about 26% of unused capacity. In terms of determinants, it was established that smaller schools, which were rural-based were less efficient compared to larger urban-based schools, while also public schools were found to negatively affect efficiency, compared to their private counterparts. Similar to this study, the present study has been done in Kenya, and examines secondary schools using a two-step analysis process, where DEA is first used and later Tobit regression is applied. The difference is that Sitati (2017) included in her sample both public and private schools and had two output variables, while the present study only examines public secondary schools and had one output variable.

Mahmudah et al. (2018) applied the robust data envelopment analysis model (RDEA) to assess Indonesia's high schools' technical efficiency. The decision to use RDEA over DEA was informed by the former's advantage of being able remove bias from results in cases where the dataset is contaminated by outliers, which is common in highly aggregated data, for instance provincial data. The researchers used data from senior secondary schools for the 2015 and 2016 years in 34 Indonesian provinces which acted as DMUs. A total of eight input variables and six output variables were used, giving an average efficiency of 93.6%, with 10 of the 34 provinces being fully efficient. The study found the robust DEA efficiency scores tended to follow the traditional DEA scores, with only a very small bias efficiency score of 0.04. The present study didn't apply RDEA because of its computational difficulties. However, as concluded in the reviewed literature, only a small bias efficiency which is insignificant exists between DEA and RDEA scores, making the choice of DEA valid.

Sabine (2018) systematically reviewed literature that estimated the efficiency of university education using SFA. The review focused on establishing the underlying assumptions and specifications used, including their strengths and weaknesses, and also the commonly used input variables, output variables and environmental factors of efficiency. The author examined 63 studies published in peer reviewed journals between the years 1998 and 2017. The commonly used inputs factors were budget, physical capital, students, research funds, personnel structure, and other factors, for instance students' feedback. The commonly used output factors were research grants, publications, graduates, personnel structure, students and other factors, for instance teaching hours. For the determinants of efficiency, the author notes that in line with Coelli et al. (2005), these variables should neither have been used in estimating the DEA efficiency scores nor be within the control of the producer, but still have the potential to affect the production process. The common determinant factors were students, personnel structure, resource allocation, institution type, region and education quality. The present study, which applied DEA, benefitted greatly from the variable categorization, which enabled to author to choose the appropriate input, output and environmental variables.

Halkiotis et al., (2018) measured the degree of technical efficiency of 23 high schools in Greece using a combination of 3 inputs and 4 outputs. The methodology employed was an output-oriented DEA model. One of the outputs was the number of graduates from high school that were not admitted in tertiary education. This was introduced in the model using a negative sign so as to be in line with the maximization principle of the output-oriented model, since a higher number of students not admitted indicates lower quality/ low output. Results showed that a low percentage of the schools (34.8%) achieved maximum technical efficiency. The similarity with the present study is that both studies employed an output-oriented DEA model and used high school graduates as an output. The difference is that the present study had only one output.

Mutuku and Korir (2019) studied the effect of government expenditure on the performance of public primary schools in Kenya. The study aimed to establish how government expenditure had affected enrolment in public primary schools; determine the effect of government expenditure on the quality of public primary education; and, estimate the contribution made by government spending to the technical efficiency of public primary schools in Kenya. The fixed effects model was used for objective one and two, while DEA combined with the two stage least squares regression was used for the third objective. From the findings, there was an improvement in the calculated efficiencies from the year 2000 through 2004 to 2012 across all the counties. The authors established that the determinants of efficiency were infrastructural facilities, location of school and amount of government budget. Similar to the present study, this literature applied DEA, and benefitted the present study in the application of two stage analysis for estimating technical efficiency and identifying the factors affecting efficiency. However, whereas Mutuku and Korir (2019) used two stage least squares regression, the present study applied Tobit regression to estimate the determinants of inefficiency.

Chlebounova (2019) used DEA to calculate the technical efficiency of 36 secondary schools in the Pardubice region of the Czech Republic. The study used made use of one input variable –salaries paid to teachers; and three output variables – pupil's pass percentage in mathematics and English language Czech language exams. Results showed that 33.3% of the schools were fully efficient. It was further established that grammar schools were operating at 80% efficiency, while vocational secondary schools were operating at 60% efficiency. Similar to this reviewed literature, the current study sought to establish the efficiency levels of secondary school education using DEA, though on a much larger scope, and not only concentrated on one region of the country.

Sahnoun and Abdennadher (2019) examined how corruption affects the efficiency of education expenditure across a sample of 75 countries comprising of 40 developing and 35 developed countries. The authors applied stochastic frontier analysis (SFA) because of its ability to isolate technical inefficiency from random shocks outside the producer's control, to data of 1,200 annual observations collected from the countries over a 16-year period. Their choices of variables were: one output variable (ratio of education expenditure to GDP), three input variables (ratio of GDP to population in 2010; population aged 0 to 14 years; and, political stability) and two inefficiency correlation variables (corruption perception index and Kaufmann corruption index).

From their findings, the authors were able to empirically demonstrate that corruption had a positive influence on the technical inefficiency of educational expenditure, which was more evident in the developing countries. This literature varies from the present study in that the literature used SFA, while the present used DEA.

Baba et al. (2020) estimated the technical efficiency and its determinants for Malaysian secondary schools. For this study, a sample of 626 secondary schools was used, and panel data for the period 2010 to 2014 was collected. The researchers employed DEA and static panel data analysis for first stage and second stage analysis, respectively, to first establish the technical efficiency and then its determinants. Average school grade was used as the output variable while student teacher ratio and per student expenditure were used as the input variables. As per the findings, secondary schools in Malaysia operated at an average efficiency level of 67%, with rural and undeveloped state schools performing better than urban and developed state schools overall. This was attributed to factors like school size which negatively affected efficiency and per capita income which positively affected efficiency. Citizen's average wage was not found to significantly affect efficiency. Similar to the reviewed literature, the present study estimated the technical efficiency for secondary school and its determinates using DEA, though it used cross sectional data collected in the year 2019, and not panel data.

Kaur (2021) employed an output-oriented DEA technique to a sample of 28 Indian states and used secondary data gathered over a five-year period from ministry publications, official websites, and national polls to evaluate the technical effectiveness of higher education in India. The author used public spending on university education and number of university lecturers as input variables, and student enrolment numbers and graduation numbers as output variables. The findings showed that all the 28 states were performing at a modest level of efficiency, with the recommendation that the states should increase how effectively they used the public monies that were given to them in order to increase their output. This study is similar to the present one in various ways. First, Kaur (2021) chose the education sector for efficiency estimation, just like the present study. Secondly, both studies applied output-oriented DEA approach for efficiency estimation. As well, the two studies used states/ counties as the DMUs for efficiency estimation.

Andersson and Sund (2021) used six-year data from 68 higher education institutions located in six Nordic countries to estimate productivity of higher education. They followed a two-stage analysis, where a CRS DEA model with output orientation was used in the first stage to estimate the efficiency levels, and correlation analysis was used in the second stage to determine the sources of inefficiency.

The study established that average efficiencies for the six in the region of 89.9% and that productivity increased yearly at the rate 0.4%. Correlation analysis showed a positive correlation between inefficiency and staff turnover. The authors also noted that using DEA to measure efficiency of higher educational units presents three main problems. First is the need to modify the efficiency scores to match the quality of inputs. Second is the challenge of heterogeneity among the DMUs under study and, lastly, is the inability for generalization because of the biasness of DEA estimators. To overcome problem one, they used upper-secondary schooling grades; to overcome problem two, they used weighted students' achievements according to subject mix; and to overcome problem three, they used bootstrapping. This study has both similarities and differences with the present study. On similarities, the two studies applied output-oriented DEA approach and two stage analysis. On differences, whereas Anderson and Sund (2021) modelled DEA with CRS, the present study modelled DEA with VRS. As well, for the second stage analysis, whereas the authors used correlation analysis for identification of sources of efficiency, the present study used Tobit regression analysis to achieve the same.

D'elia and Ferro (2021) employed SFA, while considering heterogeneity, to study the technical efficiency of Argentina's public higher education. Using a panel of 37 national universities over the period 2005 to 2013, they made a comparison of between heterogeneity extended SFA models and those that don't factor heterogeneity. To estimate the technical efficiency more accurately, the authors modelled university specific observed and unobserved heterogeneity and also included sensitivity analysis in checking for the robustness of results. This was done to account for university specific differences and so as to avoid bias in the efficiency scores. Results showed that SFA extended models reported the highest mean levels of technical efficiency, which ranged between 75 and 82 per cent over the period of study. This study differs from the present study as it used SFA, while the present study used DEA.

Tran et al. (2022) applied DEA to a sample of 172 Vietnamese higher education institutions to examine their economic efficiency. Using data for the period 2012 to 2016 comprising of both financial and academic statistics, the researchers first estimated the economic efficiency of the institutions and then compared the institutions under the following categories; whether they were publicly or privately owned;

whether they offered one or multiple disciplines; whether they were independent or not; and, whether they offered international programs or not. The study established that over the 5-year period, the higher education institutions decreased their operational efficiency, with private institutions recording a higher efficiency than the public ones. As well, higher education institutions that offered international programmes were observed to more efficient than those without. This study differs from the present study because the present study does not compare the DMUs under various classifications.

2.4 Overview of Literature

The theoretical literature has presented and compared the two most popular approaches for estimating technical efficiency of educational institutions, that is DEA and SFA approaches. DEA is a non-parametric method that estimates technical efficiency of a given decision making unit relative to other units operating in the same industry. It makes the assumption that the error term is equal to zero and hence attributes all the unexplained variations to represent inefficiency. SFA on the other hand is a parametric approach to estimating efficiency which takes into account the effects of random shocks on the production process.

Empirical literature has revealed that both approaches can be used to calculate TE scores in cases where multiple inputs are used to produce multiple outputs. However, DEA's computational simplicity gives it an edge over SFA. DEA can also compute TE scores using inputs and outputs in their natural physical units without having to transform them into a common unit of measure, which works well for educational units where inputs and outputs have different metrics. Furthermore, DEA can still be applied to nonhomogeneous units provided appropriate adjustments are made to account for differences in site characteristics. DEA's main limitation lies in its inadequacy to estimate efficiencies without bias, necessitating the application of additional methods like regression analysis and panel data analysis for establishing the determinants of efficiency or inefficiency.

The empirical literature reviewed further affirms the choice of input variables as: student – teacher ratios, number of texts books available to students, student characteristics, school characteristics, teacher characteristics, cost per teacher, cost per student and education expenditure as a percentage of GDP. The choice output variable was performance in national or international standardized tests and number of graduates progressing or not progressing to the next level of education. This study adopted and modified some of the proposed inputs and outputs from this list. These inputs were: student-teacher ratio, textbook-student ratio and average school size. The output was KCSE transition, representing the number of candidates who qualified for progress to university. The review did not find any specific empirical literature for studies done in Kenya estimating county efficiency scores, and therefore this study contributed to filling this gap.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter provides an insight into the methodology employed by the study following the review of both theoretical and empirical literature. It covers the research design, the theoretical framework, definition and measurement of variables, study area and target population, population size, data type and source and data analysis.

3.2 Research Design

The study employed a non – experimental research design and further adopted a cross sectional design since the data used was from a secondary source where data was collected on same set of variables across the 47 counties of Kenya with reference to the same year. DEA, a non-parametric model, was used to estimate the efficiency scores, which were later regressed against environmental variables using a Tobit regression model, to establish the determinants of technical inefficiency.

3.3 Theoretical Model

To estimate the TE of public secondary schools in Kenya, the study adopted a framework based on a firm's production theory. The firm's production technology uses a vector of non-negative real inputs; $x = (x_1, \ldots, x_n)$ to produce a non-negative vector of real outputs; $q = (q_1, \ldots, q_m)$. Its production possibilities set (PPS), which is a collection of all the feasible input-output vectors, is specified as;

$$S = \{(x, q): x \text{ can produce } q\} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.1)$$

The firm may select any input-output combination in the PPS *S* as its production plan. An output set P(x), representing the set of all feasible output vectors, q, that can be produced using the input vector, x, is defined as;

$$P(x) = \{q: x \text{ can produce } q\} = \{q: (x, q) \in S\} \ldots\ldots \text{ (3.2)}$$

Specification of the technical relationship reflecting the choice combination of inputs that will yield the most output for the firm is necessary, since the firm faces an optimization problem (Varian, 1992), This is represented as;

$$q_i = f(x_i) \ldots\ldots\ldots\ldots \text{ (3.3)}$$

Theoretically, this production function represents the boundary of the PPS, implying that a firm operating on its production function can be considered to be efficient in the use of its inputs. Thus, the firm's efficiency reflects the choice of technology that leaves it with the most output given its feasible output set. For a simple production process where a single input is used to produce a single output, this efficiency is defined as:

$$\text{Efficiency} = \frac{\text{Output}}{\text{Input}} \ldots\ldots\ldots \text{ (3.4)}$$

However, in practice, production processes will mainly include multiple disproportionate inputs and outputs. This provides a complexity in measuring performance, which requires modification of the definition of efficiency to:

$$\text{Efficiency} = \frac{\text{Total weighted outputs}}{\text{Total weighted inputs}} \ldots\ldots\ldots\ldots \text{ (3.5)}$$

Thus, assuming we have data on *N* inputs and *M* outputs of a firm, efficiency will be defined as:

$$\text{Efficiency} = \sum_{i-1}^{m} \mathbf{q}\text{i}\ \mathbf{u}\text{i}\ /\ \sum_{j-1}^{n} \mathbf{x}\text{j}\ \mathbf{v}\text{j} \ldots\ldots\ldots\ldots\ldots \quad (3.6)$$

where $\mathbf{q}_i$ represents the quantity of output i; $\mathbf{u}_i$ is the weight attached to output i; $\mathbf{x}_j$ represents the quantity of input j and $\mathbf{v}_j$ is the weight attached to the input j. This is what characterizes TE in traditional economic theory whose scores can then be estimated using the non-parametric DEA methodology. The scores are constrained between zero (completely inefficient) and one (completely efficient).

3.4 Empirical Model

The study hypothesized that each public secondary school represented in the school county maximizes output subject to available inputs. This is because the public secondary schools have greater control over the outputs than the inputs, which are provided by the government. Following Coelli *et al's*. (2005) simple definition of TE as the ratio of all weighted outputs over all weighted inputs, equation 3.6 was transformed into the mathematical programming problem in 3.7. To obtain the optimal weights for the three inputs and one output of each of the 47 school counties the mathematical programming problem below was solved;

$$\text{Max}_{u,v}\ (\mathbf{u'q}_i/\mathbf{v'x}_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (3.7)$$

$$\text{st} \quad \mathbf{v'x}_i = 1$$

$$\mathbf{u'q}_j/\mathbf{v'x}_j \leq 1, \quad j = 1,2,\ldots I$$

$$\mathbf{u}, \mathbf{v} \geq \mathbf{0}.$$

where $\mathbf{x}$ is an input column vector for the i^{th} school county; $\mathbf{q}$ is an output column vector for the i^{th} school county; $\mathbf{u}$ is an M*1 vector of output weights for all the school counties, where M=1; and, $\mathbf{v}$ is an N*1 vector of input weights for all the school counties, where N=3.

This linear programming problem was solved I times, once for each of the school county in the sample under study (Coelli *et al*., 2005). In this case, it was solved 47 times.

To achieve the study's first objective, equations 3.8 and 3.9 were estimated. The output oriented DEA with variable returns to scale was specified in the envelopment form as:

$$\text{Max}_{\phi,\lambda}\ \phi, \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (3.8)$$

$$\text{st} \quad -\phi \mathbf{q}_i + \mathbf{Q}\lambda \geq 0,$$

$$\mathbf{x}_i - \mathbf{X}\lambda \geq 0,$$

$$\mathbf{I1'\lambda}=1$$

$$\lambda \geq 0.$$

$$1 \leq \phi < \infty$$

where **I1** is an *I*1* vector of ones; **I1'λ**=1 is a convexity constraint, meant to ensure that an inefficient school county is only benchmarked against counties of the same size; ***λ*** is an *I*1* vector of constants representing weights assigned to each school county; **X** is an *N*I* input matrix for all the school counties, where N=3 inputs (county student-teacher ratio, county average school size and county textbook-student ratio); **Q** is an *M*I* output matrix for all the school counties, where M=1 input (county student transition); $\mathbf{x}_i$ is a column vector representing inputs for the i^{th} school county; $\mathbf{q}_i$ is a column vector representing outputs for the i^{th} school county; and, $1/\phi$ is the technical efficiency score for the i^{th} school county, and varies between 0 and 1 (the output oriented TE score reported by DEAP);

The scale efficiency for each school county was calculated after obtaining both the CRS and VRS technical efficiency scores, where a difference between the CRS and VRS TE scores indicated presence of scale inefficiency. Scale efficiency was therefore given by:

$$Scale\ efficiency = \frac{CRS\ Technical\ Efficiency}{VRS\ Technical\ Efficiency} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (3.9)$$

and scale inefficiency was:

$$\text{Scale inefficiency (SI)} = 1 - \text{scale efficiency (SE)} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ (3.10)$$

The CRS TE can therefore be decomposed into pure technical efficiency (VRS TE) and scale efficiency.

$$TE_{CRS} = TE_{VRS} \times SE \quad \text{……} \quad (3.11)$$

The study's second objective was to establish the determinants of technical inefficiency. This was achieved through regression analysis, where efficiency scores obtained through equation 3.8 were first converted to inefficiency scores through equation 3.12, and then regressed against environmental variables presumed to influence performance of schools.

$$\text{Technical inefficiency (TI)} = 1 - \text{technical efficiency (TE)} \quad \text{……} \quad (3.12)$$

These inefficiency scores were then regressed against the identified environmental variables, using the Tobit regression specification;

$$y_i = x_i\beta + e_i \quad \text{……} \quad (3.13)$$

Where y_i is the DEA technical inefficiency score, x_i are the independent environmental variables, β is a vector of parameters to be estimated and e_i is the error term. Tobit model was preferred because it is a censored regression model, applicable where the dependent variable is censored, as is the case with efficiency scores which range between a minimum of 0 and a maximum of 1.

The influence of the independent environmental variables on the inefficiency scores was therefore analyzed as;

$$TI_i = \alpha + \beta_1 GPI_i + \beta_2 AL_i + \beta_3 SD_i + \beta_4 LR_i + e_i \quad \text{……} \quad (3.14)$$

Where TI_i is the technical inefficiency score for school county *i*, GPI_i is the county gender parity index for school county *i*, AL_i is the aridity level for school county *i*, SD_i is the county school density for school county *i*, LR_i is the literacy rate for school county *i*, and e_i is the error term for school county *i*.

3.5 Definition and Measurement of Variables

The study used the following input and output variables.

Table 3.1: Definition and measurement of variables

VARIABLE	DEFINITION	MEASUREMENT
Input Variables		
County student-teacher ratio	This is the number of students per teacher in a public school classroom within the county.	Total number of public school students in a county divided by the total number of teachers in a county.
County average school size	This is the average number of students per public school within a county.	The total number of public school students in a county divided by the total number of public secondary schools in a county.
County textbook-student ratio	This is the number of students per textbook in a given school year within a county public school. The textbooks considered are for six major subjects namely, English, Mathematics, Kiswahili, Biology, Physics and Chemistry.	The total number of textbooks in a county divided by the total number of students in the county.
Output Variables		
County student transition	This is the number of students in a county who sat for the 2019 KCSE in a public school and scored a mean grade of C+ and above and hence directly qualified to join university.	Sum of the number of students within a county who scored a minimum mean grade of C+ in the 2019 KCSE.
Environmental Variables		
County gender parity index	Ratio of female to male students	Total number of female students divided by the total number of male students enrolled in a public secondary school.
Aridity level	This is the degree to which a climate lacks effective and life promoting moisture.	Quotient of long-term average water supply (precipitation) to long-term average water demand (evapotranspiration).
County literacy rate	This represents the education level of the local population.	The population with secondary education as the highest attained qualification divided by total population aged three years and above in the county.
County school density	The total number of schools within a county	Sum of both public and private secondary schools in a county.

Source: Author’s computation

3.6 Study Area Profile and Target Population

The study covered the entire territory of the Republic of Kenya, disaggregated into 47 counties as established under the first schedule of the Constitution of Kenya, 2010. The target population was all the public secondary schools within the 47 counties whose information was captured in the National Education Management Information System (NEMIS) in the 2019 academic year. NEMIS is a web-based data management platform developed and operated by the Ministry of Education to collect data from educational institutions at the primary and secondary school level, process it and provide reports with key educational indicators.

3.7 Population Size

According to the MOE, a total of 10,487 secondary schools were registered in the NEMIS system in the 2019 academic year, out of which 8,933 were public secondary schools and 1,554 were private secondary schools. The total enrollment for that year was 3,262,951 students, out of which 3,045,227 were in public secondary schools while the remaining 217,724 were enrolled in private secondary schools. This study used data from the 8,933 public secondary schools which was aggregated to county level data. The total study population was therefore 47 entries.

3.8 Data Type and Source

The study used secondary quantitative data of input, output and environmental variables. The main sources of the secondary data were records from MOE, KNEC, KNBS and MODA. These sources were relied upon to provide data on the number of operational public secondary schools in the country for the academic year 2019, their enrollment numbers disaggregated by gender, the number of textbooks availed to them, the academic staff numbers and the performance of candidates in the 2019 KCSE examination. Additionally, data on the literacy levels and climatic zone distribution of counties were collected as part of environmental variables. The main reference document for this study was the 2019 Basic Education Statistical Booklet prepared by MOE. The booklet was prepared based on data extracted from NEMIS.

3.9 Diagnostic Tests

A number of diagnostic tests were conducted to investigate whether the data used and the model estimated were consistent with the assumptions of ordinary least squares econometric analysis. These included normality tests, correlation analysis, multicollinearity test and heteroscedasticity test. The tests were used to establish whether the assumptions were violated, in which case the results would be spurious or misleading.

3.10 Data Collection and Analysis.

Data collection involved extracting the required figures from both administrative records and reports published by the above-named sources. Data processing began with verification and cleaning of the data before analysis, which was conducted using DEAP version 2.1 for DEA analysis and STATA version 14 for descriptive and Tobit analysis.

CHAPTER FOUR

EMPIRICAL FINDINGS

4.1 Introduction

This chapter presents the empirical findings of the study. Analysis was undertaken in two stages, where DEA analysis was first employed to obtain the technical efficiency and scale efficiency scores, and then Tobit regression analysis was applied to establish the determinants of technical inefficiency. The two-step analysis strategy has also been applied in other previous studies (Sitati, 2017, Mutuku and Korir, 2019; Baba et al., 2020; Andersson and Sund, 2021). The section is therefore divided into two sub sections, 4.2 in which efficiency estimates are presented and 4.3 where results of the regression analysis are presented and discussed.

4.2 Efficiency Estimation

The section is dedicated to achieving the first study objective, through estimation of equations 3.8 and 3.9.

4.2.1 Descriptive Statistics for Input and Output Variables

Table 4.1 presents an overview of the summary statistics which describes the key characteristics of the secondary data used in the analysis.

Table 4.1: Descriptive statistics for the for input and output variables

	Minimum	Maximum	Mean	Median	Std. Dev.
Output					
County student transition	41	7,005	2,675	2,784	1,915
Inputs					
County student-teacher ratio	19	43	30	29	5.41
County textbook-student ratio	1.23	1.47	1.39	1.39	0.05
County average school size	179	644	347	333	89
Total observations	47	47	47	47	47

Source: Author’s computation

According to the results of the summary statistics, there was only a minimal amount of heterogeneity among the school counties at the time that the study was conducted because the standard deviation for all of the input and output variables is smaller than the mean value.

4.2.2 Diagnostic Tests for Input and Output Variables

4.2.2.1 Normality Test

This test establishes whether the residuals follow a normal distribution. The skewness kurtosis normality test was conducted and returned the results shown in table 4.2.

Table 4.2: Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis) adj	chi2(2)	Prob>chi2
resid	47	0.3199	0.0497	4.81	0.0902

The null and alternative hypothesis for the test were:

H_o: residuals are normally distributed

H_a: residuals are not normally distributed

The decision criteria for this test is that the null hypothesis is rejected if the Prob>chi2 value is less than the 0.05. Based on the test results, the Prob>chi2 = 0.0902 is greater than 0.05, hence we fail to reject the null hypothesis and conclude that the residuals follow a normal distribution.

4.2.2.2 Correlation Analysis

Results of the correlation between the input and output are presented in table 4.3.

Table 4.3: Correlation results for input and output variables

	County student transition	County student-teacher ratio	County textbook-student ratio	County average school size
County student transition	1			
County student-teacher ratio	0.0004	1		
County textbook-student ratio	0.1096	-0.1974	1	
County average school size	-0.0272	0.2730	-0.1886	1

Source: Author's computation

Results indicated presence of a weak association between the three input variables and the output variable. A very low positive correlation of 0.0004 was found between the output variable and county student-teacher ratio, suggesting there exists almost no association between the number of teachers and student performance. Another positive correlation of 0.1096 was recorded between the output variable and textbook-student ratio, suggesting a very week relationship between textbook availability and student performance. Average size of school was weakly and negatively correlated with student performance suggesting that higher student numbers reduce student performance.

There is also a weak relationship among the three input variables, ranging from a low of 0.1886 for correlation between county average school size and county textbook-student ratio to a high of 0.2730 for correlation between county average school size and county student-teacher ratio, suggesting there is no problem of multicollinearity. This finding is similar to the finding by Sitati, 2017.

4.2.2.3 Heteroscedasticity Test

This test was conducted to determine whether the residual variances were constant over a range of measured values. The Breusch Pagan test was conducted and returned the following results.

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity

Ho: Constant variance

Variables: fitted values of Cutoff

chi2(1) = 0.06

Prob > chi2 = 0.8011

The null and alternative hypothesis for the test were:

H_o: the variance of the residuals is constant

H_a: the variance of the residuals in not constant

The decision criteria for this test is that the null hypothesis is rejected if the Prob>chi2 value is less than the 0.05. Based on the test results, the Prob>chi2 = 0.8011 is greater than 0.05, hence we fail to reject the null hypothesis and conclude that the variance of the residuals is constant, and therefore homoscedastic.

4.2.3 Technical Efficiency Estimation

For the purpose of estimating the technical efficiency scores, this study adopted the VRS assumption as presented in equation 3.8. According to this assumption, technical efficiency is divided into two separate parts. The first is pure technical efficiency, which reflects the managerial performance in the running of a given DMU through allocation of resources to create outputs. The second part is scale efficiency, which assesses a DMU's capacity to reach the optimal scale of operation and indicates whether a certain DMU is running at the optimal scale.

Data analysis was carried out using the Data Envelopment Analysis Program (DEAP) with the instruction set to output orientation, using the multi-stage DEA mode in order to acquire the technical and scale efficiency scores. Results (see appendix 3) indicated that only 8 out of the 47 school counties were VRS technically efficient, accounting for 17% of the study population. These constituted the group from which a given set of inputs produced the highest output. On the other hand, only 1 of the 47 school counties, accounting for 2.1%, was found to exhibit mix efficiency, implying that it was both CRS and VRS efficient. This therefore means that, public secondary schools in 46 counties exhibited some type of inefficiency. Table 4.4 presents the summary statistics of the efficiency scores obtained from the analysis.

Table 4.4: Descriptive statistics for efficiency scores

	Minimum	Maximum	Mean	Median	SD	OBS
				Overall		
VRS TE	0.007	1.000	0.490	0.448	0.338	48
CRS TE	0.006	1.000	0.410	0.412	0.292	48
				Inefficient		
VRS TE	0.007	0.943	0.385	0.361	0.269	39
CRS TE	0.006	0.860	0.365	0.350	0.253	39
				Efficient		
VRS TE	1.000	1.000	1.000	1.000	0.000	8
CRS TE	0.009	1.000	0.607	0.729	0.397	8

Source: Author's calculation

The mean VRS technical efficiency for all the school counties was found to be 0.49 (49%), implying that on average, the counties could improve their output (county student transition) by 0.51 (51%) and operate on the efficient frontier, without increasing their level of inputs. The collective mean efficiency for the 39 VRS inefficient school counties was found to be 0.385 (38.5%), suggesting that using the same level of inputs, they could still improve their output by 0.615 (61.5%) and achieve efficiency. These school counties had their efficiency scores ranging between 0.007 (0.7%) and 0.943 (94.3%). This difference of 0.936 (93.6%), which is by all means a wide variation, corresponds with the findings of other studies on school efficiency that have been discussed under literature review. According to Sitati (2017), the wide difference in efficiency implies that there could be other factors affecting efficiency across the different schools which may include school management structure, location, type, size, among others.

4.2.4 Scale Efficiency Estimation

Returns to scale, according to Tolga et al. (2009), is a crucial measure that gives an indication of the possibility of realizing further efficiency improvements by changing the size of a DMU. This was estimated using equation 3.9. Appendix 3 presents the scale efficiency results, from which the distribution of DEA results on scale efficiency was summarized and presented in table 4.5.

Table 4.5: Frequency distribution of Returns to Scale

Returns to scale	**Frequency**	**Percent**	**Mean S.E**
Optimal returns to scale	4	8.5%	100.0%
Increasing returns to scale	39	83.0%	86.7%
Decreasing returns to scale	4	8.5%	99.1%
Total	**47**	**100.00%**	

Source: Author's computation

On average, the scale efficiency was recorded at 88.9%, suggesting there was 11.1% unused capacity of the factors of production (inputs) by the counties. 4 school counties (8.5%) were fully scale efficient, suggesting that compared to the rest, they were operating optimally as they had employed all their inputs at full capacity. A majority of the school counties 39 (83%) depicted increasing returns to scale, suggesting that they enjoyed economies of scale, and could therefore increase their resource use efficiency through capacity improvement of their inputs. However, as Tolga et al., (2009) also found out in their study, the high level of mean scale efficiency for this category (in this case 86.7%) leaves fairly little scope for improving the capacity of their inputs. On the other hand, public secondary schools in 4 other school counties (8.5%) depicted decreasing returns to scale, pointing to diseconomies of scale among them, where a unitary increase in inputs yields a below unitary increase in output. For this category, the counties could improve their efficiency and operate optimally by not stretching their inputs beyond their capacity. Due to their very high mean S.E. (in this case 99.1%) however, the school counties have only 0.9% unused capacity, giving them also very little scope to change their scale of operation.

These findings demonstrate empirically that scale efficiency varies across public secondary schools within the 47 counties, and that scale of operation is an important contributor to this variation. Generally, inefficiency results from either inappropriate scale of operation, which requires long term strategies to correct, or inappropriate allocation of resources, which can be corrected in the short run. For the case of inappropriate scale of operation, this happens where a DMU fails to take advantage of economies of scale. Inappropriate allocation of resources on the other hand is where there is improper combination of inputs by the DMUs. In this study, results have indicated high scale efficiency scores (averaging 88.9%) pointing to the possibility that inefficiency could be as a result of improper input combination, as Oren & Alexander (2006), and Tolga et al. (2009) also established.

4.3 Determinants of Technical Inefficiency

In order to further investigate and establish the external factors that explain the differences in public secondary schools' efficiencies, the obtained DEA efficiency scores were used as a regressand in a regression analysis where external variables that were not directly included in the DEA analysis were used as regressors.

4.3.1 Descriptive Statistics for Environmental Variables

Table 4.6: Descriptive statistics for environmental variables

	Minimum	Maximum	Mean	Median	Std. Dev.
Dependent Variable					
VRS technical inefficiency	0	0.99	0.51	0.55	0.34
Independent Variables					
County GPI	0.81	1.99	1.08	1	0.24
Aridity Level	0	1	0.38	0	0.49
County school density	24	532	223.13	197	135.46
County literacy level	14.43	33.93	22.53	22.08	4.85
Total observations	47	47	47	47	47

Results of the descriptive statistics show there was a minimal amount of heterogeneity among all the independent and dependent variables because the standard deviation for all of the 4 environmental variables and independent variable is smaller than the corresponding mean value.

4.3.2 Diagnostic Tests for Environmental Variables

4.3.2.1 Normality Test

The skewness kurtosis normality test was conducted to establishes whether the residuals follow a normal distribution, and returned the below results.

Table 4.7: Skewness/Kurtosis tests for Normality

Variable	Obs	Pr(Skewness)	Pr(Kurtosis) adj	chi2(2)	Prob>chi2
resid	47	0.5569	0.3972	1.11	0.5743

The null and alternative hypothesis for the test were:

H_o: residuals are normally distributed

H_a: residuals are not normally distributed

The decision criteria for this test is that the null hypothesis is rejected if the Prob>chi2 value is less than the 0.05. Based on the test results, the Prob>chi2 = 0.5743 is greater than 0.05, hence we fail to reject the null hypothesis and conclude that the residuals follow a normal distribution.

4.3.2.2 Correlation Analysis

Results of the correlation between the input and output variables are presented in table 4.8.

Table 4.8: Correlation results for environmental variables

	VRS technical inefficiency	GPI	Aridity – Non ASAL	School density	Literacy level
VRS technical inefficiency	1				
GPI	0.5264	1			
Aridity – Non ASAL	-0.3140	-0.3711	1		
School density	-0.6443	-0.4875	0.2148	1	
Literacy level	-0.4990	0.3885	0.3339	0.3502	1

Source: Author’s computation

Results indicated presence of a weak to moderate association between the four environmental variables and the dependent variable. A moderate positive correlation of 0.5264 was found between the dependent variable and GPI, suggesting higher GPI led to higher technical inefficiency scores. A weak negative correlation of -0.3140 was recorded between the dependent variable and aridity level (non ASAL), suggesting low and inverse association between non-aridity and technical inefficiency. School density was also moderately negatively correlated with the dependent variable suggesting that higher school numbers reduce technical inefficiency. Another moderate negative association was recorded between the dependent variable and literacy levels, suggesting that higher literacy levels led to lower technical inefficiency scores.

Relationship among the environmental variables was low, erasing any chances of the problem of multicollinearity among the predictors. The highest recorded correlation was -0.4875, between GPI and school density, suggesting a moderate negative association between the two variables..

4.3.2.3 Heteroscedasticity Test

The Tobit Multiplicative Heteroscedasticity test (tobithetm) was applied to the data. The summary test results are presented below.

Table 4.9: Heteroscedasticity test

Tobit NormaL Regression	Number of obs = 47
	LR chi2(1) = 64.21
Log likelihood = 34.77274	Prob > chi2 = 0.0000

The null and alternative hypothesis for the test were:

H_o: the residual variances of the model are heteroscedastic

H_a: the residual variances of the model are homoscedastic

The decision criteria for this test is that the null hypothesis is rejected if the Prob>chi2 value is less than the 0.05. Based on the test results, the Prob>chi2 = 0.0000 is less than 0.05, hence we reject the null hypothesis and conclude that the residual variances of the model are homoscedastic.

4.3.3 Tobit Regression Analysis

The study utilized a truncated Tobit regression model that was specified in equation 3.14, since the DEA efficiency scores have a lower (0.000) and upper (1.000) bound.

For purposes of estimation, and following the works of Kantabutra and Trag (2006), the obtained efficiency scores were transformed through equation 3.12 into inefficiency scores, by subtracting them from 1. Table 4.10 presents results of the regression analysis.

Table 4.10: Tobit regression results

				Number of obs = 47		
				LR chi2 (4) = 30.83		
				Prob > chi2 = 0.0000		
Log likelihood =		-12.800746		Pseudo R2 = 0.5464		
Tech Inefficiency	**Coef.**	**Std. Err.**	**t**	**P > |t|**	**(95% Conf. interval)**	
GPI	.262117	.2062697	1.27	0.211	-.1538656	.6780995
Aridity – Non ASAL	-.0057748	.0917115	-0.06	0.950	-.1907286	.179179
School density	-.0012341	.000354	-3.49	0.001	-.0019479	-.0005202
Literacy level	-.0229784	.0096485	-2.38	0.022	-.0424364	-.0035203
Constant	.9971188	.3633676	2.74	0.009	.2643183	1.729919
Sigma	.2678817	.0318655			.2036187	.3321446
8	left-censored observations at technical inefficiency <=0					
39	uncensored observations					
0	right-censored observation					

The log likelihood of the fitted model was estimated at -12.800746. This is used in the likelihood ratio chi square test to test whether all the coefficients of the predictor variables are simultaneously equal to 0. The likelihood ratio (LR) chi-square therefore tests the following hypothesis.

Ho: all predictor variable coefficients are equal to 0

Ha: at least one predictor variable coefficient is not equal to 0

The null hypothesis is rejected if the Prob>chi2 is less than 0.05.

From the results, the LR chi2 at 4 degrees of freedom was estimated to be 30.83, with the Prob>chi2 = 0.0000, implying that we reject the null hypothesis in favour of the alternative hypothesis that at least one of the predictor variable coefficients is not equal to 0. This leads to the conclusion that the estimated model as a whole fits significantly better in explaining the determinants of technical inefficiency than an empty model.

The Pseudo R2 = 0.5464 is used to compare the estimated model with another estimated model using the same data to determine which model better fits the outcome data.

The p-values for the coefficients of the independent variables indicate that two out of the four environmental factors considered had a significant effect on the calculated scores of technical inefficiencies at the 5% significance level. These were, school density and literacy level.

The coefficient for total number of secondary schools in the county, measured by school density, was negative at -0.0012 and significant at 5% significance level. This means that an increase in the school density by addition of one extra secondary school leads to a decrease in technical inefficiency by 0.12%. This result suggests that the more the number of secondary schools in a county, whether public or private, the higher would be the performance of students, hence counties with more schools are associated with lower levels of inefficiency (higher efficiency) than their counterparts with fewer schools. This can be attributed to the potential effect of many schools fostering competition among themselves, leading to better overall performance. This finding is similar to that of Sherron and Kenny (2017), who also established that when competition among public school districts is restricted, it results in adverse effects on student learning.

The coefficient for literacy level was also negative at -0.023 and significant at 5% significance level, implying that an increment in the county literacy level by 1% leads to a decrease in technical inefficiency by 2.3%. Literacy is considered to be among the key factors used in measuring the effectiveness of an education system (Zua, 2021). A high societal literacy rate is therefore an indication of a robust education system that provides the population with useful knowledge, skills and competencies. As such, it is more likely that literate parents who are more engaged in their children's education in and out of school will be found in a county with a higher level of education. This result is in line with that of Drajea (2015) and Ghanney (2018), who contend that parents with higher levels of education are more likely to be involved in their children's education and have a more beneficial impact on them as a result than parents with lower levels of education.

The coefficients for the gender parity index (GPI) and Aridity level were not significant at the 5% significance level implying that the influence of the two factors on the technical inefficiency of public secondary schools in Kenya was insignificant. With regards to gender parity index, the results are contradictory to the findings of Nauzeer et al. (2018), who established that for the case of Mauritian secondary schools, gender of students as an explanatory variable had a significant and positive effect on the variations of the schools technical efficiency scores. Girls'–only schools contributed to about 14% increase in academic performance compared to boys-only schools. The difference with our Kenyan situation could be because the country has managed to achieve gender parity in education.

With regard to the aridity level explanatory variable, the result also conflicts with the findings of other works previously done by Brink et al. (2020) and Arroyo et al. (2023) who observed that climatic conditions affect students' academic performance and also that environmental comfort has a direct influence on learning by students. The Kenyan unique situation may be attributed to fact that societies living in ASALs have over the years built resilience and devised adaptation mechanisms to overcome the challenges of formal schooling, which include quality and accessibility (Villiers et al., 2015).

CHAPTER FIVE

SUMMARY, CONCLUSION AND POLICY IMPLICATIONS

5.1 Introduction

This chapter presents the summary of the study findings, conclusions, policy implications of the study findings, the study's contribution to knowledge and areas identified for further research.

5.2 Summary of the Study

Kenya's Vision 2030 has identified education and training as one of its enablers. As a result, the sector's public spending has continued to increase, and was maintained at an average of 4.5% of GDP from 2010 to 2019. However, despite these concerted efforts that have led to significant improvements in the country's access to public education throughout the years, there are still specific challenges that plague public secondary education in Kenya, which include the coexisting overutilization and underutilization of educational resources, as well as stark differences in students' academic performance across the 47 counties. This illustrates the unmeasured inefficiencies of public secondary education.

This study applied the DEA model to fill this knowledge gap through assessment of Kenya's public secondary schools' technical efficiencies. Using an output-oriented DEA model, technical efficiency scores for public secondary schools grouped in the 47 counties and their relative scale efficiencies were estimated. The study further examined the external factors that were associated with technical inefficiency in the school counties.

To address the first study objective, results of the DEA analysis established the average VRS technical efficiency score to be 0.49. The highest recorded efficiency score was 1.000 while the lowest was 0.07. 8 out of the 47 school counties were found to be VRS technically efficient, representing 17% of the sample.

Public secondary education within the 47 school counties was found not to be scale neutral. The average scale efficiency was estimated at 0.889 with a majority of the school counties (83%) exhibiting increasing returns to scale. Only 8% of the school counties were found to be operating optimally.

The second study objective was addressed by regressing technical inefficiency scores against four external environmental factors namely, gender parity index, aridity level, literacy rate and school density. From the analysis, only two factors were found to be significant determinants of the school county's inefficiency. These were: school density and literacy level.

5.3 Conclusions

The study has confirmed that there exist challenges of technical inefficiency in public secondary schools across the country, which have hindered 100% transition of secondary school graduates to university, because they do not meet the minimum cutoff grade of C+. Only a quarter of the 47 school counties were found to be technically efficient. It was also evident from the findings that majority of the school counties were operating below their optimal scale that would make them fully employ all the educational resources at their disposal. This situation presents opportunities for them to improve their performance (student transition to universities) by simply reallocating their resources to achieve the best input combination for maximum output. To also ensure full employment of the available resources, the schools can work around their scale of operation by either increasing or reducing their size.

5.4 Policy Implications/ Practice

The study's findings and subsequent conclusions point towards policy proposals that aim to boost the efficiency of Kenya's public secondary schools while keeping input levels constant. DEA results showed that many public-school counties were operating sub optimally. To address this, the study recommends that the Ministry of Education implements policies that promote efficient administration of public schools.

These include promoting benchmarking among schools to afford the school heads and boards an opportunity to learn and interchange best practices among themselves, and continuous training for school heads and boards to equip them with the requisite management skills to make them better stewards of the schools.

The study also recommends to the Ministry of Education to put measures that will encourage opening of more secondary schools, both public and private, especially in counties with fewer secondary schools since evidence has shown that more schools promote competition among them and students, that can lead to better overall student performance. Further and in line with the study findings that a high literacy rate is a reflection of the education sector's robustness, the study recommends to the Ministry of Education and the Ministry in charge of ICT and Digital Economy that adult literacy programs and application of technology should be embedded into other community support programs being funded by both state and non-state partners in order to promote continuous learning among communities, especially those in the ASALs.

5.5 Contribution to Knowledge

This study has been able to estimate the actual value of technical efficiency, and clearly bring out the disparities in efficiency levels of public education across the counties, including identifying their drivers.

It is envisaged that the findings of this study will offer important insights and benefits to the relevant parties involved in public secondary education. The study will enrich the existing body literature on education efficiency and also offer guidance to the ongoing educational reforms in the country under the competency-based curriculum. Further, the study can also inform public discourses on resource allocation to public schools; determination of "best practices" in school administration, running, and goal-setting, especially for the schools with low performance.

5.6 Areas for Further Research

The study could not measure the total economic efficiency due to constraints in accessing data, specifically that on educational expenditures disaggregated by county. Instead, partial economic efficiency was measured through estimation of technical efficiency. Budgetary constraints further hindered collection of primary data which would have provided more specific and updated school-level data on other external factors that influence schooling, including student's socio-economic background information. This would have further enriched the study.

In light of the mentioned delimitations, a number of areas for further exploration through research exist. These include: widening the scope of this study to estimate the total economic efficiency; estimating the influence of other socio-economic factors like poverty, use of technology, sanitation amenities and corruption on technical efficiency; and a comparison of technical efficiencies between public and private secondary schools.

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APPENDICES

Appendix 1: Input and Output Variables Dataset

County	County Student Transition	County Student-teacher ratio	County Textbook-student ratio	County Average School Size
BARINGO	1814	25	1.43	374
BOMET	4146	35	1.40	385
BUNGOMA	4831	25	1.32	377
BUSIA	1789	28	1.33	644
ELGEYO MARAKWET	1963	29	1.35	484
EMBU	2398	29	1.40	291
GARISSA	286	26	1.41	321
HOMA BAY	4806	34	1.41	307
ISIOLO	60	28	1.29	371
KAJIADO	1285	33	1.36	257
KAKAMEGA	5819	36	1.42	413
KERICHO	4088	34	1.38	545
KIAMBU	6210	40	1.35	283
KILIFI	1489	35	1.36	321
KIRINYAGA	2939	27	1.45	289
KISII	5206	25	1.44	276
KISUMU	3790	27	1.44	342
KITUI	3298	29	1.44	205
KWALE	685	38	1.42	378
LAIKIPIA	1787	35	1.37	407
LAMU	117	32	1.43	431
MACHAKOS	4005	26	1.39	472
MAKUENI	4532	19	1.34	184
MANDERA	180	38	1.37	361
MARSABIT	127	39	1.23	362
MERU	3503	29	1.42	470
MIGORI	2986	22	1.38	333
MOMBASA	1239	26	1.47	297
MURANG'A	5269	27	1.31	330
NAIROBI	5857	38	1.39	410
NAKURU	7005	26	1.43	255
NANDI	2896	29	1.44	285
NAROK	1039	32	1.42	367
NYAMIRA	2602	20	1.38	179
NYANDARUA	2784	26	1.38	331

County	County Student Transition	County Student-teacher ratio	County Textbook-student ratio	County Average School Size
NYERI	3958	43	1.27	413
SAMBURU	296	26	1.34	240
SIAYA	4426	26	1.35	320
TAITA TAVETA	806	26	1.33	450
TANA RIVER	41	33	1.36	247
THARAKANITHI	2154	37	1.44	311
TRANSNZOIA	3402	31	1.39	399
TURKANA	410	28	1.41	283
UASIN GISHU	3133	26	1.43	314
VIHIGA	3145	32	1.42	347
WAJIR	126	27	1.35	319
WEST POKOT	1019	25	1.46	335

Appendix 2: Environmental Variables Dataset

County	County GPI	Aridity level	County school density	County literacy rate
BARINGO	0.98	0	183	22.64
BOMET	1.05	1	297	20.82
BUNGOMA	0.95	1	389	22.30
BUSIA	0.96	1	156	18.99
ELGEYO MARAKWET	0.94	0	129	21.48
EMBU	1.05	0	212	25.48
GARISSA	1.37	0	86	21.45
HOMA BAY	1.15	0	353	19.77
ISIOLO	1.02	0	39	22.08
KAJIADO	1.14	0	172	26.89
KAKAMEGA	0.92	1	443	19.99
KERICHO	1.02	1	158	22.94
KIAMBU	0.94	0	378	32.34
KILIFI	1.10	0	254	16.71
KIRINYAGA	0.93	1	165	28.79
KISII	1.01	1	368	27.40
KISUMU	0.92	1	252	24.23
KITUI	0.93	0	494	17.38
KWALE	1.01	0	106	14.43
LAIKIPIA	1.00	0	135	26.88
LAMU	1.25	0	24	19.42
MACHAKOS	0.97	0	460	26.85
MAKUENI	0.98	0	417	23.32
MANDERA	1.99	0	81	18.06
MARSABIT	1.08	0	52	17.81
MERU	0.89	0	400	20.47
MIGORI	1.13	0	305	18.27
MOMBASA	1.11	1	149	28.47
MURANG'A	0.97	1	340	26.83
NAIROBI	0.98	1	386	33.93
NAKURU	1.02	0	532	27.42
NANDI	0.97	1	246	20.50
NAROK	1.12	0	171	16.31
NYAMIRA	1.00	1	197	30.16
NYANDARUA	0.96	1	211	26.52
NYERI	0.98	0	242	31.83
SAMBURU	1.51	0	24	17.26
SIAYA	1.02	1	246	19.09

County	County GPI	Aridity level	County school density	County literacy rate
TAITA TAVETA	0.95	0	94	23.12
TANA RIVER	1.43	0	40	15.84
THARAKA NITHI	0.96	0	157	22.57
TRANSNZOIA	1.00	1	261	22.60
TURKANA	1.47	0	63	17.35
UASIN GISHU	0.91	1	248	27.09
VIHIGA	0.81	1	162	21.42
WAJIR	1.91	0	51	18.48
WEST POKOT	1.09	0	159	14.75

Appendix 3: County Technical and Scale Efficiency Scores

COUNTY	CRS - TE	VRS - TE	SE	RTS
BARINGO	0.269	0.273	0.988	irs
BOMET	0.605	0.618	0.978	irs
BUNGOMA	0.747	0.943	0.792	irs
BUSIA	0.275	0.320	0.858	irs
ELGEYO MARAKWET	0.297	0.332	0.894	irs
EMBU	0.350	0.361	0.969	irs
GARISSA	0.041	0.043	0.969	irs
HOMA BAY	0.696	0.706	0.985	irs
ISIOLO	0.009	1.000	0.009	irs
KAJIADO	0.193	0.216	0.894	irs
KAKAMEGA	0.837	0.843	0.993	irs
KERICHO	0.605	0.630	0.960	irs
KIAMBU	0.939	1.000	0.939	irs
KILIFI	0.224	0.239	0.934	irs
KIRINYAGA	0.414	0.420	0.986	drs
KISII	0.773	0.783	0.988	irs
KISUMU	0.537	0.541	0.993	drs
KITUI	0.586	0.627	0.935	irs
KWALE	0.098	0.099	0.993	irs
LAIKIPIA	0.266	0.281	0.949	irs
LAMU	0.017	0.017	1.000	-
MACHAKOS	0.588	0.628	0.936	irs
MAKUENI	0.897	1.000	0.897	irs
MANDERA	0.027	0.028	0.955	irs
MARSABIT	0.021	1.000	0.021	irs
MERU	0.504	0.507	0.993	irs
MIGORI	0.504	0.534	0.943	irs
MOMBASA	0.177	0.177	1.000	-
MURANG'A	0.821	1.000	0.821	irs
NAIROBI	0.860	0.886	0.970	irs
NAKURU	1.000	1.000	1.000	-
NANDI	0.411	0.413	0.993	drs
NAROK	0.149	0.150	0.993	irs
NYAMIRA	0.529	1.000	0.529	irs
NYANDARUA	0.412	0.448	0.920	irs
NYERI	0.636	1.000	0.636	irs
SAMBURU	0.045	0.057	0.790	irs
SIAYA	0.669	0.770	0.869	irs
TAITA TAVETA	0.124	0.148	0.834	irs
TANA RIVER	0.006	0.007	0.872	irs
THARAKA NITHI	0.305	0.307	0.993	drs
TRANSNZOIA	0.500	0.519	0.962	irs

COUNTY	**CRS - TE**	**VRS - TE**	**SE**	**RTS**
TURKANA	0.059	0.061	0.980	irs
UASIN GISHU	0.447	0.447	1.000	-
VIHIGA	0.452	0.455	0.993	irs
WAJIR	0.019	0.022	0.886	irs
WEST POKOT	0.151	0.153	0.988	irs
MEAN EFFICIENCY SCORES	**0.406**	**0.49**	**0.889**	