Efficiency of Mutual Funds and Portfolio Performance Measurement: A Case of Selected Mutual Funds in Tanzania

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Abstract
This study examines the current efficiency trends in the Tanzanian mutual fund industry over a five-year span (2018-2022), focusing on six specific funds: Umoja Fund, WekezaMaisha, Watoto Fund, Jikimu Fund, Liquid Fund, and Bond Fund. Employing a non-parametric approach, specifically Data Envelopment Analysis (DEA), the research collects secondary data from diverse sources, including newspapers, journals, books, periodicals, and the websites of UTT and the Bank of Tanzania (BOT). Monthly Net Asset Values (NAVs) of the selected mutual funds are scrutinized from each scheme's inception. Motivated by the limited understanding of mutual fund efficiency in Tanzania despite reported successes in increased asset values, profitability, and investor numbers, the study reveals distinctive performances under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions. Under VRS, all mutual funds consistently achieve nearly 100% efficiency, signifying optimal operational scales. However, under CRS, efficiency scores fluctuate over time, underscoring the importance of mutual funds' adaptability for enhanced efficiency. Furthermore, the research suggests that mutual fund size significantly influences efficiency and potential scale economies. Smaller mutual funds demonstrate superior resource utilization efficiency, attributed to their focused investment approach. The analysis of inputs and output slacks provides insights into efficiency and resource utilization, identifying areas of optimal resource management and highlighting opportunities for improvement. The findings offer valuable insights into mutual fund efficiency under different scale assumptions, emphasizing the importance of scale flexibility and efficient resource management for superior performance. Implications suggest avenues for further research to explore external factors, efficiency fluctuations, portfolio management practices, and longitudinal trends within the mutual fund industry.

Keywords: *Portfolio Performance Measurement Mutual Funds, Tanzania*.

1.0 Introduction

Nowadays mutual funds have received increased attention worldwide as the fastest-growing financial intermediaries bearingseveral economic benefits to

individuals, companies and economies. They are considered to be among the means of investment available for people in an attempt to increase earnings over time. Mutual funds are recognized as collective investment schemes in which several investors accumulate funds under one firm management called portfolio management (Pangestuti, et al., 2017). The fund manager is responsible for professionally managing pooled contributions from investors who become shareholders by monitoring the appropriate use of funds for the benefit of all investors (ComLaw Authoritative Act, 2013). It is argued that the pooling of investors' money to create collective investment schemes helps to strengthen the power of investment to the capacity of larger investments than what could be possible for whatever individuals operating in isolation, whereby individual investors remain owners of the proportional segment of the fund's portfolio,Plantier, (2014).Under mutual fund mobilization, banks are custodians of assets possessed by the funds while trustees stand between the investors and the mutual funds management to protect the interest of investors by ensuring that assets are invested as per predetermined objectives (Cooper et al., 2013).

Evolution of mutual funds as important financial intermediaries started in the United States where the industry plays an extremely important role in the economy. The period of 1990s will remain important as there was a rapid expansion of the industry in different parts of the world led by US where the net assets value of mutual funds, along with the proportion of households owning assets in different mutual funds, grew substantially, followed by countries in the European zone (Klapper, et al., 2004). At present, the trend has spread to a significant number of countries in the world. According to most literatures, the main argument for growth of mutual funds include rapid financial globalization during the 1990s, along with growth in information technology and a growing demand for safer investments among adults of the western aging population, enabled the market capitalization exercise to operate smoothly. From studies conducted in the US, it was observed that, knowledge of the operation of the Mutual fundindustry among the population, financial crisis among economies as well as growth in GDP among countries have also been responsible factors for Mutual funds growthin different parts of the world (Klapper, et al., 2004). In UK, growth of mutual funds was also found to result from fair and predictable policies on investment, that increased the certainty of investment practices that counts on optimization of investment costs (Otten&Bams, 2002).

In developing countries, financial sector development has enabled the growth of mutual funds in different countries at different levels.It is argued that, as

the populations of developing countries grow, the proportion of middle-class segment which is comprised of medium level investors with interest in both local and international investment opportunities offered by the mutual fund industry is also growingcosts (Otten&Bams, 2002).

In emerging markets like China, Malaysia and Indonesia; equity mutual funds have shown a greater performance level than most developed countries (Huij& Post, 2011). The data base of mutual funds in Asian countries indicate that, from 1999 to 2005 there were 10,568 open end actively managed equity funds from 19 countries in the region (Alkassim, 2009).According to Persse (2008), In China, while the entire mutual funds asset value has consistently risen from year to year, they have also remained atop investment vehicle for financial management.

In Tanzania, since 2000 and particularly following the liberalization of financial industry and strengthening of the privatization practice, the mutual fund industry obtained its base as an important financial intermediary in the country (WEF, 2000). Literature reveals that, growth of the mutual funds industry in Tanzania was realized through establishment of Unit Trust Fund Asset Management Investor Services (UTT-AMIS) and diversification of fund products under the collective investment scheme such as Umoja Fund, Watoto Fund, Jikimu Fund, Wekeza Maisha, Liquid Fund and Bond Fund. Since the establishment of various mutual fund schemes in the country, there have been a sound success record in terms of the number of investors, asset value and operational practices. From the UTT AMIS annual report of 2021 it was noted that, from the year 2019 to 2020, mutual funds in Tanzania has recorded a substantial growth from Tsh. 290.7 billion to 412.8 billion being a growth rate of 42% along with an increased number of investors and profitability above the performance benchmark. Among the noted reasons for an observed growth of mutual funds in Tanzania include; increased public confidence and understanding about their performance, introduction of digital access services, and integrationof fund systems with bank systems, impressing legal institutions in domestic country as well as introduction of wealth management services (Kazungu and Mwanahanja, 2021).

Despite of the success reports for mutual funds in Tanzania from year to year over the past two decades in terms of increased asset values, profitability and number of investors, challenges cannot be escaped. By examining asset under management ratio to GDP, Kegamba, (2022)found that, Tanzania is facing a serious problem of lack of participation of a significantly large segment of the population in the mutual fund industry to the extent that, it is unhealthy

for the industry to smoothly function. In addition,Adajania (2013) reports that, mutual fund industry in Tanzania is suffering from costly requirements of marketing and distribution mechanisms in the attempt of raising investments from remote regions which are significantly many. It is argued that, limited financial literacy that make most people in the country prefer saving in liquid assets such as in bank accounts and cash at home make it difficult for the financial sector including the mutual fund industry to smoothly operate (Adajania, 2013). Moreover, limited access to formal banking services for a significantly large segment of the Tanzanian population negatively affects the operation of mutual funds (Adajania, 2013). In addition, there are sufficient evidence that, variations in macroeconomic variables like interest rate, inflation and exchange rate being the normal tendency of the global economy affects the efficiency of mutual funds.

However, with all these challenges, little is known on the efficiency with which mutual funds perform in Tanzania. It is from this background that, this study devotes towards examining the efficiency of mutual funds and portfolio performance in Tanzania based on DEA.The selection of DEA approach follows the fact that it has shown unquestionable strengths of involving several inputs and outputs while addressing the problems of benchmark specification, endogeneity of transaction costs and the role of market timing which is not covered by parametric methods (Lehmann and Modest, 1987; Grinblatt and Titman, 1994; Murthi et. al, 1997). Hence, since investors expect returns from assets they invest; information on performance efficiency of fund organisations which is the focus of this study is important to enable individuals and companies to build confidence on investing in mutual funds and make appropriate investment decision among options available in the county.

2.0 Theoretical Review

Countless researchers have conducted research on Mutual Funds and their performance, and more importantly as a determining factor for the decision making of investors. Thus, the typical investor would not only want to know the performance but also the risk taken, to acquire that return, tobetter understand if they are getting value-added to their investment or not.

It is typical for a portfolio or MF to have an incredible past performance. However, it does notalways translate to future returns, as there are factors that affect and determine the performance, and this interesting characteristic of any portfolio, an investor would wish to understand in orderto select an MF and a fund manager. Although the existing literature covers a wide range of issues about MFs, this review will pay particular attention to these areas:

the concept of collectiveinvestment schemes and mutual funds, the theories of mutual funds' performance, the significance of Equity Mutual Funds , the determinants of the performance, the nature and development of MFs in developed and developing capital markets and the present state in Tanzania.

Some theories provide justification for the existence, operations and trading strategies of mutual funds and a few of such theories that are relevant to this particular study are briefly examined below.

2.1 The Optimal Fund Objectives and Industry Organization Theory

The theory was formulated by Mamaysky and Spiegel (2002). The model sees the mutual fund (like other financial intermediaries) as firms established by investors to manage their investments while the investors go about their personal activities. The theory opines that these firms , are not like individuals endowed with utility function, but take orders from investors; thus with profound implications for the firms (mutual funds) trading styles and the effect on asset prices. Furthermore, Mamaysky and Spiegel (2002) opine that MFs are gifted with vastly spanning set of trading strategies as opposed to those of individuals and other firms.

2.2 The Rational Theory of Mutual Funds' Attention Allocation.

This theory was developed by the trio of Kacperczyk, et al., (2014). It posits that funds process information on future assets values on the basis of which they invest in "high-valued assets". The model regards the condition of the business cycle as the attention allocation variable that is used to predict information choices usable for predicting effective strategies for investment and returns in portfolio of funds. Ultimately, the theory opines that as optimum attention allocation changes according to the prevailing economic condition, MF investment portfolios and the returns they generate also change. The theory has implications for fund managers' managerial abilities, their portfolio investment strategies and the differing returns across mutual funds.

2.3 The Agency Theory

The Agency Theory is also relevant to the role and activities of mutual funds. The agency theory, traceable to Mitnick (2013), espouses the relationship and conflict that arise between, the principal, usually the business owners, and the agents, mainly business executives or managers of business organizations (such as MFs). The theory recognizes that although agents are contracted to promote the interest of the principals but the interests of both parties are not

always congruent, thus manifesting in differences in goals and level of risk aversion between the owners (in this case investors) and managers (mutual fund managers). These lie at the root of the agency problem in business organizations including financial intermediaries like mutual funds. One common technique that is used to resolve the agency problem is the use of performance-based compensation plan for managers. Thus, the agency theory has implications for the goals MFs managers pursue, and their risk-return trade-offs.

3.0 Literature Review

Vidal-García et. al (2018) upon examining the market efficiency of the mutual fund industry around the world using parametric and non-parametric (DEA) approaches based on a unique database of worldwide domestic equity funds found that, there is a statistically significant relationship between higher expenses of mutual funds and poor performance in the positive direction from both parametric and non-parametric (DEA) approach.

In Indonesia, Pangestuti et. Al., (2017) based on DEA in measuring the effect of inflation on performance of mutual funds and Sharpe Index tool in efficient measurement involving transaction costsfound that,besides the fact that performance of mutual funds were significantly determined by inflation and technical efficiency in selected market stocks, the positive and significant effects of inflation on resulted from portfolio diversification of risks and capability of portfolio management.

Com Law Authoritative Act (2013) based on traditional parametric tools to examine efficiency performance of superannuation funds in Australia found that, while efficiency performance was determined by investment costs, the marginalized investment fee was the cause of reported inefficiency of mutual funds.

Similarly, in Nigeria, Iloet al., (2017) assessed security picking talent amongst managers and based on the returns from 37 MFs that cut across six classes of exchange traded fund portfolios from 2012 to 2015 concluded that the funds could not consistently generate superior risk-adjusted outcomes; thus demonstrating lack of stock picking talent by fund managers.

Mahmuda and Abdullahi (2017) investigated the performance of certain MF schemes in Nigeria within the period of 2015 to 2017 while employing commonly used performancemeasures. They reported that the funds generated positive Treynor and Sharp ratios but negative Jensen Alpha and

concluded that the selected funds provided superior risk adjusted returns but surprisingly fund managers lacked good asset selection talent.

Lemantile (2017) onexamining the financial performance of mutual funds in Kenya, using traditional parametric methods, based on macroeconomic factors found that, variation in macroeconomic variables including interest rates, exchange rate and inflation significantly affects the performance of mutual funds in the country. It was found that, while interest rate variations affected the performance of mutual funds both positively and negatively, exchange rate variations and inflation rate variation affect mutual funds purely in a negative direction.

The above reviews of the literature on MFs performance indicate the lack of consensus among scholars that MF managers have the capacity to successfully outdo the market portfolio benchmark return. By the same token, findings on managers' market prediction and asset selectivity capacities are mixed. Therefore, further research to investigate MFs performance is desirable to guide investors especially in Tanzania in making wise investment decisions in mutual funds such ascollective investment schemes to assist in the attainment of their investment goals.

4.0 Research Methodology

The present study focuses on the utilization of the DEA approach, a robust mathematical programming technique developed by Charnes, et al., 1978, to evaluate the relative efficiency of production units. In the context of this research, we consider mutual funds as the production units of interest.DEA proves to be particularly advantageous for our research due to its capability to accommodate multiple inputs and outputs. This feature enables us to integrate diverse investment characteristics and fund attributes into our analysis, in addition to the conventional metrics of return and risk, which may significantly influence the performance of mutual funds. In essence, the DEA technique establishes the relative position of a mutual fund concerning the frontier of optimal fund performance by computing the ratio of the weighted sum of inputs to the weighted sum of outputs. The envelopment surface resulting from this analysis represents the estimated frontier of best performance and serves as an indicator of fund efficiency while also identifying inefficiencies within the mutual fund market.

The DEA framework encompasses two distinct orientations: the input orientation and the output orientation, each representing different approaches to analyzing a DEA model. In the context of an input orientation, the analysis

aims to determine the extent of proportionate input reduction required for an inefficient fund to attain DEA efficiency while maintaining the existing output levels. Conversely, an output orientation analysis seeks to ascertain the magnitude of output augmentation needed for an inefficient fund to achieve DEA efficiency while keeping the inputs unchanged. However, the latter aspect is deemed less significant since fund managers typically lack direct control over output levels. For our study, we adopt the input-oriented DEA model proposed by Banker, Charnes, and Cooper (1984), hereafter referred to as the BCC model. This model serves as an extension of the original Charnes, Cooper, and Rhodes (1978) DEA model formulation, denoted as CCR henceforth.

Below, is an outline the BCC model. However, to provide a comprehensive context, we commence the discussion with a description of the CCR model.
y_{rj}=Known positive output level of fund j,r=1,2,….s where s is the number of outputs
X_{ij}=Known positive input level of fund j,i=1,2,…,m where m is the number of inputs
n=total number of funds
The CCR model for determining relative efficiency of designated fund "0" is given

$$\text{Efficiency}=\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \quad \ldots\ldots\ldots 1$$

$$Max\left\{\frac{\sum_{y=1}^{s} u_r y_{ro}}{\sum_{i=1}^{m} v_i x_{i0}}\right\} \quad \ldots\ldots\ldots 2$$

$$\text{Subject to } \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1,\ j=1,2,..n, \quad \ldots\ldots\ldots 3$$

r=1, 2…, s, and i=1, 2…m……………………………………………………4

The variables in the above model are input and output weights u_r and v_i respectively.

The objective function (1) is the ratio of weighted sum of outputs to weighted sum
of inputs with weights being the optimal values of the variables u_r and $v_i$to be determined
as a solution to the CCR model.
The above problem can be transformed into an equivalent linear programming
model. The BCC model we use is the dual of this equivalent linear program together with
a constraint capturing returns to scale characteristics. The linear program so obtained for
determining the relative efficiency score, θ of fund '0' is given by
Min θ

Subject to $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro,}$ r=1,2…s,……5

$\theta x_{io} \geq \sum_{j=1}^{n} \lambda_j x_{ij}$ i=1, 2,…m…… 6

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

$\lambda_j \geq=1,$ j=1, 2…, n……..…7

The variables in the BCC model are θ and λ_j which is nonnegative. The

variable $\theta$is the proportional reduction required in each input of the designated fund to achieve efficiency. The constraints in the model ensure that the relative efficiency of the fund never exceeds 1. The sufficient

condition for the efficiency of the fund is that the optimum value of $\theta$is 1. Otherwise, it is labelled as inefficient compared to the other funds in the sample. Thus, a DEA run will produce a relative efficiency score and a set of λ_j j = 1,2,...,n, values for each fund. The set of λ_j values defines the point on the envelopment surface. Therefore, for an inefficient fund, the point defined by thevalues becomes a role model that establishes precedence for it to become efficient. The set of efficient funds' $\lfloor j : \lambda_j, \succ 0 \rfloor$is called the peer group of the designated fund.

The utilization of equation (7) introduces a critical constraint referred to as the convexity constraint, which is specifically designed to account for the

consideration of variable returns to scale (VRS) within the model. Conversely, by excluding this convexity constraint from the formulation, the resultant model aligns with the scenario of constant returns to scale (CRS). In the context of CRS, the relative efficiency score obtained for a designated fund serves as a comprehensive measure of the fund's overall technical efficiency, encompassing all aspects of production efficiency.

However, under the VRS condition, the relative efficiency score acquired reflects the pure technical efficiency of the fund, focusing solely on the productive efficiency aspects unaffected by scale variations. It is important to note that the disparity between the overall and pure technical efficiencies can be attributed to scale efficiency, which is quantified as the ratio of overall technical efficiency to pure technical efficiency.

Furthermore, in the realm of linear programming, it is a fundamental principle that each linear programming problem is inherently associated with another dual linear program. The dual counterpart of the output-maximizing Data Envelopment Analysis (DEA) can thus be formally expressed as follows:

$\theta^* = Min\theta$ ……

Subject to

$\sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta x_{io,} i = 1,...m$ ……..……..

$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{ro,} r = 1,...s$ ……..…….

$\lambda_j \geq 0$

θ is unrestricted

If $\theta^* = 1$,then the input levels cannot be reduced, indicating that DMU_0 is on the frontier. Otherwise, if $\theta^* \prec 1$,DMU_0 is dominated by the frontier. $\theta*$represents the input oriented efficiency score of the DMU_0. The individual input reduction is called slack. In fact, both input and output slack value may exist in model……

$s_i^- = \theta^* x_{io} - \sum_{j=1}^{n} \lambda_j x_{ij}$ i=1…

,m…

$s_r^+ = \sum_{j=1}^{n} \lambda_j y_{rj} - y_{ro}$, r=1,…,s

To determine possible non-zero slacks solving linear programming (….),we should solve the following linear program:

Max $\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+$

Subject to

$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0,} i = 1,...,m$

$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = Y_{ro,} r = 1,...,s$

$\lambda_j \geq 0,$

θ unrestricted

DMU_0 is efficient if and only if $\theta^* = 1$ and $S_i^{-*} = S_r^{+*} = 0$ for all i and r.DMU_0

Is weakly efficient if and only if $\theta^* = 1$ and $s_i^{+*} \neq 0$ and (or) $s_r^{+*} \neq 0$ for some iand r.

In summary a two DEA process can be summarized as follows in DEA model

Min $\theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+)$

Subject to

$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{io,}$ i=1,…,m

$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{ro,} r = 1,...,s$

$\lambda_j \geq 0,$

θ unrestricted

4.1 Data Source

To reveal the present efficiency trends of the Tanzania mutual fund industry, the study covered 5 years (2018-2022) involving 6 mutual funds in Tanzania (Umoja Fund, WekezaMaisha, WatotoFund, Jikimu Fund, Liquid fund,Bond Fund) and comprised of all equity-diversified funds in the country. Following the fact that there are variations in mutual fund commencement, appropriate consideration has been given tothe commencement of each fund. The study

employed secondary data collected from newspapers, journals, books, periodicals, and various websites like that of UTT and Bank of Tanzania (BOT). The NVAs of the sample mutual fund schemes were collected monthly regarding the scheme's commencement.

4.2 Inputs and Output Variable Specifications

There is no agreement on selection of inputs and output to be considered in mutual funds studies on efficiency measurement. However different studies have used different inputs and outputs to measure the efficiency of mutual funds, for example studies by Tuzcu et al., (2020). Traditional measurement such as Risk, expense and fund size as inputs while funds returns were used as output, on the other hand Don (2002) on Australian mutual fund performance appraisal used standard deviation, costs and other operating expenses, minimum initial investment as inputs while growth and income were used as output.

Lozano and Gutierrez (2008) proposed risk measure consistent with stochastic dominance, first order stochastic dominance rules select those portfolios that are non-dominated when evaluated by increasing utility function, similarly second order stochastic dominance (SSD) is of relevance for all nonsatiated.

Amelia (2023) used coherent risk measures as inputs while expected return was used as output. Table 1 below provides a summary of inputs and outputs used by different studies.

Table 1: Main Financial inputs and outputs used in measuring the efficiency of mutual funds:

SN	Author(s)	Outputs	Inputs
1	Basso and Funari(2001)	Mean Return, Stochastic dominance indicator	Standard Deviation, Beta %subscription cost per 5000,25,000 and 50,000, Dollar Initial Investment
2	Basso and Funari(2003)	Mean Return, Ethical level	Standard Deviation beta subscription cost redemption cost
3	Basso and Funari(2005,2007,2010)	Final Value of unit investment	Standard Deviation, Initial fees, exit fees
4	Briec et al(2004,2007)	Mean return	Variance
5	Chang, 2004	Return(Net of transaction cost, fees and expenses, gross sales charges)	Standard deviation, Beta load, Total Net asset Value(NAV)
6	Choi and Murthi(2001)	Mean gross return	Standard deviation, Transaction cost., loads, turnover
7	Murthi et al 1997	Fund Return	Standard Deviation and Transaction costs. Transaction costs includes Operational expenses, Management fees, market and administrative expenses, Net Asset Value, Turnover, loads [a]
8	Baraio and Simar(2006)	Total Return	Standard Deviation, expense ratio, turnover, fund size.
9	Babalos et al(2012)	Fund Return	Risk and Expense ratio [b]
10	SevgiEdaTuzcu(2020)	Funds returns	Risk, expense and fund size

[a] Expense ratio refers to the costs incurred by mutual fund in operating the portfolio, including administrative expenses and advisory fee paid to investment manager, expressed as percentage of total asset under management
[b] Loads are sales charge or redemption fees incurred when investors purchase and sell the shares

Following previous studies on inputs and outputs selection, the study used the following variables. The Inputs variables used in DEA analysis are following: (i)Total risk standard deviation(ii)Transaction cost,generally referred to management expense ratio(MER)(iii)Net Asset value,while the output used in this study was Fund return.

5.0 Results

The Table 1 presents the average technical efficiency scores under constant return to scale (CRS) and variable return to scale (VRS) assumptions for the years 2018 to 2022. The table also includes the number of decision-making units (DMUs) and the percentage of efficient DMUs under each assumption for each year. The mean efficiency results across firms during the period of study are found in **appendix 1**

The average technical efficiency score under CRS represents the average efficiency of the DMUs assuming a fixed scale of operation (i.e., the DMUs cannot adjust their scale). In 2018 and 2019, only 2 out of the 6 DMUs (33.3%) were efficient under CRS, implying that the majority of DMUs were not operating at their optimal efficiency level during those years. In 2020, the number of efficient DMUs increased to 4 out of 6 (66.6%), indicating an improvement in efficiency for the majority of DMUs. However, in 2021, the number of efficient DMUs dropped back to 2 out of 6 (33.3%), suggesting a decline in efficiency for most DMUs compared to the previous year. In 2022, the number of efficient DMUs slightly improved to 3 out of 6 (50%), indicating a moderate level of efficiency across the group of DMUs. The average technical efficiency scores (0.686, 0.696, 0.945, 0.720, and 0.767) indicated that, on average, the DMUs utilized 68.6%, 69.6%, 94.5%, 72.0%, and 76.7% of their resources efficiently under CRS for the respective years. Similarly, the average technical efficiency score under VRS represents the average efficiency of the DMUs assuming they could adjust their scale of operation to achieve optimal efficiency. Notably, under the VRS assumption, all DMUs were 100% efficient in each year from 2018 to 2022. This implied that, under VRS, the DMUs were able to find their optimal scale of operation and utilize their resources most efficiently to produce their respective

outputs. The consistent 100% efficiency score indicated that the DMUs were operating at their full potential and achieving the best possible performance without any inefficiencies or wastage of resources. The VRS efficiency scores (1, 0.916, 1, 1, and 1) highlighted the DMUs' ability to fully utilize their resources and maximize output levels while operating at their optimal scales during the specified years.

Overall, the analysis demonstrates that the Mutual funds were more efficient under the VRS assumption, where they could adjust their scale of operation, compared to the CRS assumption, where the scale was fixed. The perfect efficiency under VRS indicated that the DMUs were operating at their best possible level, while the fluctuations in efficiency scores under CRS suggested that the mutual funds might not have been operating optimally at all times due to scale constraints. The results underscored the importance of considering scale flexibility in efficiency analysis to achieve a more accurate assessment of Mutual funds' performance.

Table 1

	2018	2019	2020	2021	2022
Number of DMU	6	6	6	6	6
Number of efficient DMU under CRS	2(33.3%)	2(33.3%)	4(66.6%)	2(33.3%)	3(50%)
Number of efficient DMU under VRS	6(100%)	5(84%)	6(100%)	6(100%)	6(100%)
Average Technical efficient Score under CRS	0.686	0.696	0.945	0.720	0.767
Average Technical efficient Score under VRS	1	0.916	1	1	1
Average Scale efficient Score	0.686	0.696	0.945	0.72	0.767

Average scale efficiency is an important measure that assesses how efficiently DMUs are operating in relation to their optimal size or scale. It combines both technical efficiency (how well a DMU uses its resources to produce output) and scale efficiency (how close a DMU operates to its optimal scale) into a single metric. In this context, the average scale efficiency score represented the overall efficiency of the mutual funds in the period of study, considering both CRS and VRS assumptions, and it is calculated as the average of the technical efficiency scores. In 2018, the average scale efficiency score was found to be 0.686. This implied that, on average, the DMUs utilized approximately 68.6% of their optimal scale resources to achieve their current level of output. It also indicated that the Mutual funds, as a group, have room for improvement in optimizing their resource utilization to attain higher efficiency levels. The trend in average scale efficiency showed an increasing pattern from 2018 to 2020. In 2020, the average scale efficiency reached its highest value of 0.945, indicating

significant improvement in the DMUs' ability to utilize their resources more effectively to produce output. In 2021, the average scale efficiency dropped to 0.720, suggesting that the mutual fund, on average, experienced some inefficiency in their resource utilization during that year compared to the previous year. However, in 2022, the average scale efficiency improved to 0.767, indicating a recovery and an upward trend in the Mutual funds' resource utilization and output levels. Notably, under the VRS assumption, the average scale efficiency scored were consistently equal to 1 for each year from 2018 to 2022. A scale efficiency score of 1 represents perfect efficiency, suggesting that the Mutual funds were operating at their optimal scale during these years, with no room for further improvement. Notably, under the VRS assumption, the average scale efficiency scores are consistently equal to 1 for each year from 2018 to 2022. A scale efficiency score of 1 represents perfect efficiency, suggesting that the Mutual funds were operating at their optimal scale during these years, with no room for further improvement. Generally, the analysis reveals that the Mutual funds' performance in utilizing their resources efficiently fluctuates from year to year under CRS, but the VRS assumption consistently shows perfect efficiency. The variations in average scale efficiency scores over time suggest that the management must improve the ability to optimize their resource allocation and scale of operation. The lowest efficiency scores may be due to increase in the number of less efficiently managed fund portfolio, similar observations were pointed by Tuzcu(2019),Babalos et al (2012) and Baghdadabad (2014).

5.1 Return to Scale (RTS)

Table 2 below demonstrates that a significant portion of mutual funds operate with the concept of increasing returns to scale, at a rate of 67%. A notable outcome of functioning within this scenario is the observed trend for the expense ratio of these funds to decrease as their Assets Under Management (AUM) grow. The expense ratio signifies the fraction of the fund's assets designated for covering operational expenses. As these expenses are distributed across a wider asset base, individual investment units carry a proportionally lighter burden of costs, leading to lower expense ratios for investors. This occurrence holds the promise of generating enhanced net returns for investors. This outcome is attributed to the efficiency gains stemming from economies of scale, which can consequently result in higher net returns for investors. With a smaller portion of the fund's assets being allocated for operational costs, a larger share of the fund's returns can be directed towards investors. As a result, mutual funds that boast lower expense ratios become more appealing to investors, as they offer a more resource-

efficient approach to accessing a diversified portfolio managed by professionals. This increased allure contributes to a larger influx of funds, further reinforcing the economies of scale phenomenon. Additionally, mutual funds characterized by increasing returns to scale achieve a more favorable position in the market, enabling them to furnish competitive returns to investors while maintaining low costs. This ability sets them apart in a crowded market environment.

Table 2: Efficiency Summary and Return to Scale(RTS)

Firm	Crtste	vrtte	scale	rts
1	1.000	1.000	1.000	-
2	0.462	1.000	0.462	irs
3	0.724	1.000	0.724	irs
4	0.785	1.000	0.785	irs
5	1.000	1.000	1.000	-
6	0.147	1.000	0.147	irs

5.2 Efficiency by the Size of Mutual Funds

The present research undertook a comprehensive analysis and extended its investigation to explore the influence of mutual fund size on efficiency. Drawing upon the research work of Tuzcu and Ertugay (2019), it became evident that fund size constitutes a significant determinant of mutual fund efficiency. In the context of this study, the mutual funds were classified into two distinct groups, namely "small funds" and "large funds," based on their size relative to the median value. Specifically, funds exceeding the median size were categorized as "large funds," while those falling below the median were considered "small funds." This classification methodology aligns with the similar approach utilized by Tuzcu, et al., (2020) and Ertugay(2020)in their own examination of mutual funds.

The primary objective underlying this categorization was to discern whether either group demonstrated a higher efficiency estimate concerning economies of scale. Through this investigation, the research aims to illuminate potential scale economy advantages for mutual funds. By delineating efficiency disparities between the two categories, this study souhght to enhance understanding of the dynamics inherent within the mutual fund industry. Consequently, this analytical framework offers valuable insights into the intricate relationship between fund size and efficiency, thereby contributing to a more nuanced comprehension of this sector.

Table: 2 presents a summary of the annual efficiency scores of mutual funds by categorization from the years 2018 to 2022. With reference to CRS,the efficiency scores represent the ability of mutual funds to utilize their resources effectively in generating returns and managing risks. With reference to CRS in 2018 the efficiency score for large mutual funds was found to be 0.716, signifying an average efficiency of 71.6% in resource utilization. However, in the subsequent year, 2019, the efficiency score declined to 0.697, indicating a decrease in efficiency compared to the previous year. Notably, there was a significant improvement in efficiency in 2020, with a score of 0.927, suggesting that large mutual funds had become more efficient during that period. In 2021, the efficiency dipped slightly to 0.755 but rebounded to 0.828 in 2022, demonstrating some variation in efficiency scores over the years. Overall, it appears that large mutual funds made efforts to enhance their efficiency, as evidenced by the improved scores in 2020 and 2022.

On the other hand, the efficiency score for small mutual funds with reference to CRS in 2018 was 0.856, indicating that on average, small mutual funds achieved 85.6% efficiency in managing their resources. The score decreased slightly to 0.761 in 2019 but remained relatively high. Interestingly, in both 2020 and 2021, the efficiency scores reached 1.000, implying that small mutual funds achieved 100% efficiency during those years, showcasing exceptional performance. However, in 2022, the score decreased slightly to 0.875, indicating potential adjustments in their resource management strategies.

A comparison of the efficiency scores between large and small mutual funds reveals that small mutual funds generally outperformed their larger counterparts in terms of resource utilization efficiency. Over the years, small mutual funds consistently achieved higher efficiency scores, with their 100% efficiency scores in 2020 and 2021 being particularly noteworthy. One possible explanation for this superior performance is that smaller funds may adopt a more concentrated and focused investment approach. Due to their fewer assets to manage, they can carefully select investments and concentrate on high-potential opportunities. This focused strategy might contribute to better performance compared to larger funds that often have to spread their resources across a broader range of assets. The findings are in line with, Premachandra (2012).

In general, the efficiency scores of mutual funds under CRS indicate their ability to effectively manage resources and achieve returns while managing

risks. Both large and small mutual funds experienced variations in their efficiency scores over the years. Large mutual funds demonstrated efforts to enhance efficiency, particularly in 2020 and 2022, whereas small mutual funds consistently displayed high efficiency, with notable achievements of 100% efficiency in 2020 and 2021. The superior performance of small mutual funds may be attributed to their focused investment approach, allowing them to optimize their resources to a greater extent.

Table 2: Annual Efficiency Scores of Mutual Funds by Categorization From the Years 2018 to 2022

	Scale	**2018**	**2019**	**2020**	**2021**	**2022**
LG	CRS	0.716	0.697	0.927	0.755	0.828
	VRS	1.000	0.865	1.000	1.000	1.000
	SE	0.716	0.811	0.927	0.755	0.828
SM	CRS	0.856	0.761	1.000	1.000	0.875
	VRS	1.000	1.000	1.000	1.000	1.000
	SE	0.856	0.761	1.000	1.000	0.875

Notes: LG=large category of mutual fund SM=Small category of mutual fund

Table 3 indicate the number of inputs and outputs slack on mutual fund technical efficiency scores. In efficiency analysis, slacks refer to the unused or excess capacity of inputs or outputs that a firm has. Zero slacks in efficiency analysis mean that the firm is fully utilizing its inputs and outputs without any excess or unused resources. Specifically, if an input slack is zero, it indicates that the firm is efficiently using all its input resources, and there is no room for further improvement in input utilization without affecting the output. Similarly, if an output slack is zero, it means that the firm is efficiently converting all its inputs into outputs, and there is no potential for further improvement in output generation without changing the input mix.

In Table 3 the input slack for risk (standard deviation) measures how close the firm's actual standard deviation of returns is to the minimum possible value that can be achieved given the current resource allocation. A value of 0.000 for the input slack in risk means that Firm 1 has achieved the minimum possible standard deviation of returns with its current resource allocation, indicating optimal risk management. On the other hand, positive values for the input slack indicate that there is room for improvement in risk management by reducing the standard deviation of returns. For example, Firm 2 has a slack of 0.232, suggesting that it could potentially reduce the risk (standard deviation) of its returns by this amount, given its current resource utilization. Notably, Firm 5 has the highest input slack for risk at

48.655, indicating significant potential for reducing risk through resource optimization. This suggests that Firm 5's current resource allocation may be associated with relatively high volatility in returns, and adjustments to its portfolio or investment strategies could lead to a decrease in risk.

Table 3: **Input and Output Slacks of Mutual Funds**

		Output slacks	**Inputs slacks**			
Firm	**te efficiency**	**Fund return**	**Risk(s.td . Dev)**	**NAV**	**NUM(Net Asset Under Mgt)**	**Expense ratio**
1	1.000	0.000	0.000	0.000	0.000	0.000
2	0.462	0.000	0.232	164.002	0.000	2.095
3	0.724	0.000	0.131	235.125	0.000	1.690
4	0.776	0.000	1.248	57.522	0.000	1.626
5	0.716	0.000	48.655	82.193	0.000	0.777
6	0.093	0.000	1.028	1.045	0.000	0.098
mean	**0.629**	**0.000**	**8.549**	**89.981**	**0.000**	**1.048**

The input slack for Net Asset Value (NAV) represents the difference between the firm's actual NAV and the maximum possible NAV that could be achieved with the current resource allocation. A value of 0.000 for the input slack in NAV, such as in Firm 1, indicated that the firm has achieved the maximum possible NAV with its current resource utilization, signifying efficient resource management. Positive values for the input slack in NAV implied that there was potential for increasing the firm's Net Asset Value through better resource allocation. For instance, Firm 2 has a slack of 164.002, suggesting that it could potentially increase its NAV by this amount by optimizing its resource allocation.

The input slack for "Expense ratio" represents the unused or excess capacity of the expense ratio variable for each firm. The expense ratio is the percentage of the mutual fund's total assets that are used to cover operating expenses, including management fees and administrative costs. A lower expense ratio is generally more favorable for investors, as it means that a larger portion of the fund's returns is retained by the investors. A slack of 0.000 for the expense ratio indicates that Firm 1 has achieved the lowest possible expense ratio with its current resource allocation. This suggests that the firm is efficiently managing its operating expenses, resulting in a favorable expense ratio for its investors. The input slack for Firm 2's expense ratio is 2.095, which means that there is significant room for improvement in managing its operating expenses. By reducing the expense ratio by 2.095 percentage points, the firm could optimize its resource utilization and

potentially offer investors a more competitive expense ratio. Firm 4 has an input slack of 1.626 for its expense ratio, suggesting that there is room for optimizing its expense management. By decreasing the expense ratio by 1.626 percentage points, the firm could potentially offer a more attractive investment option to investors.he input slack for Firm 5's expense ratio is 0.777, indicating that there is a moderate opportunity for improving its expense management. By reducing the expense ratio by 0.777 percentage points, the firm could enhance its overall efficiency and potentially increase investor satisfaction.Firm 6 has the smallest input slack for its expense ratio at 0.098, implying that there was only a minor scope for improvement in its expense management. Nevertheless, by optimizing its expenses by 0.098 percentage points, the firm could further enhance its efficiency and potentially offer investors a slightly more competitive expense ratio.

The input slack for the expense ratio provides valuable insights into how efficiently each firm is managing its operating expenses. Firms with zero input slack have already achieved the lowest possible expense ratio given their current resource allocation, indicating efficient expense management. On the other hand, positive input slack values indicated opportunities for improving expense management and potentially offering investors more attractive investment options with lower expense ratios. Investors often consider expense ratios when selecting mutual funds, as lower expense ratios could lead to higher net returns for investors over time. Therefore, firms with higher input slack values should focus on optimizing their operating expenses to stay competitive in the market and attract more investors.

6.0 Concluding Remarks and Policy Implications

The research findings highlight the significance of considering scale flexibility in efficiency analysis for Mutual funds. The study showed that Mutual funds performed differently under Constant Returns to Scale (CRS) and Variable Returns to Scale (VRS) assumptions. While under VRS, all Mutual funds achieved almost 100% efficiency consistently, indicating they operated at their optimal scale. However, under CRS, the efficiency scores fluctuated over time, suggesting that the Mutual funds' ability to adjust their scale of operation is crucial for achieving higher efficiency.

One of the managerial implications is that managers of Mutual funds should pay attention to their ability to optimize resource allocation and scale of operation, especially under CRS, to improve overall efficiency. This highlights the importance of considering scale flexibility and efficient resource management for better performance. The research also indicates that

mutual fund size plays a role in determining efficiency and potential advantages of scale economies. Smaller mutual funds demonstrated superior resource utilization efficiency compared to larger ones, likely due to their focused investment approach. This finding underscores the significance of considering fund size and efficient resource management for mutual fund performance. Investors can use this information to make informed decisions and select funds that offer competitive expense ratios and efficient resource utilization.

Moreover, the analysis of inputs and output slacks for mutual funds provides valuable insights into their efficiency and resource utilization. It identifies areas where firms have achieved optimal resource management and areas where improvements can be made. For instance, some firms have efficiently managed their operating expenses, resulting into favorable expense ratios, while others have opportunities to optimize their expenses to attract more investors.

The research implications include several areas for further investigationExternal Factors: Future research could explore how economic conditions, market trends, regulatory changes, or other external factors impact the efficiency of Mutual funds under different scale assumptions. Understanding these external influences can help provide a more comprehensive picture of the efficiency fluctuations.

Fluctuations in Efficiency: Identifying the reasons behind the fluctuations in efficiency under CRS could be a subject for further research. Investigating the factors contributing to inefficiencies and finding ways to ensure consistent efficiency over time can offer valuable insights to managers and investors.

Portfolio Management: Further research could delve into the specific portfolio management practices or strategies that contribute to higher efficiency and better performance. Understanding the relationship between portfolio management decisions and efficiency can help enhance overall fund performance.Comparative Analysis: Extending comparative analyses to other financial institutions or industries could help understand how scale flexibility affects overall efficiency in various sectors and identify best practices for resource utilization.

The research findings provide valuable insights into the efficiency of Mutual funds under different scale assumptions and highlight the importance of scale

flexibility and efficient resource management for better performance. The implications suggest avenues for further research to explore external factors, fluctuations in efficiency, portfolio management practices, and longitudinal trends. By considering these factors, mutual fund managers and investors can make informed decisions to optimize resource allocation and enhance overall efficiency. Overall, the policy implications drawn from the research suggest that considering scale flexibility and efficient resource management are crucial for enhancing mutual fund performance. By implementing these policy recommendations, regulators, fund managers, and investors can work together to foster a more efficient and robust mutual fund industry.

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Appendix 1: Mean Efficiency summary under CRS and VRS

	2018		2019		2020		2021		2022	
firm	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**	**CRS**	**VRS**
1	1.000	1.000	0.495	0.497	1.000	1.000	1.000	1.000	1.000	1.000
2	0.462	1.000	1.000	1.000	1.000	1.000	0.865	1.000	0.621	1.000
3	0.724	1.000	0.273	1.000	1.000	1.000	0.767	1.000	1.000	1.000
4	0.785	1.000	0.824	1.000	0.888	1.000	0.423	1.000	0.499	1.000
5	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
6	0.147	1.000	0.582	1.000	0.781	1.000	0.264	1.000	0.485	1.000
Mean	**0.686**	**1.000**	**0.696**	**0.916**	**0.945**	**1.000**	**0.720**	**1.000**	**0.767**	**1.000**

1=Umoja, 2=Wekeza Maisha,3=Watoto Fund,4=Jikimu Fund,5=Liquid fund,6=Bond Fun

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