

Research Article

Assets Selection and Portfolio Optimization in a Developing Economy Using Linear Programming

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Abstract

Portfolio construction in developing economies such as Nigeria is often complicated by market inefficiencies, high volatility, limited diversification opportunities, and inadequate analytical approaches for optimal asset allocation. This study develops an optimal investment portfolio model using Linear Programming (LP) to support rational asset selection and fund allocation in the Nigerian stock market. The model seeks to maximize portfolio performance by simultaneously considering return, liquidity, and risk. Financial data were obtained from the annual reports of five selected companies listed on the Nigerian Exchange Group, namely Zenith Bank Plc, United Bank for Africa (UBA), TotalEnergies Marketing Nigeria Plc, Fidelity Bank Plc, and Nigerian Breweries Plc. The objective function was formulated as the ratio of the product of return and liquidity to risk, while the constraints were specified using the relative proportions of each firm's return, liquidity, and risk. The resulting LP model was solved using the simplex algorithm implemented in LINGO 17.0 (64-bit) software. The results identified United Bank for Africa and Nigerian Breweries as the constituents of the optimal portfolio, with Nigerian Breweries accounting for the larger allocation and providing the greatest contribution to portfolio performance. Sensitivity analysis was subsequently performed to assess the robustness and stability of the optimal solution under possible changes in investment parameters. The analysis of reduced costs indicated that the assets excluded from the optimal portfolio would require sufficiently favorable changes in their performance coefficients before becoming economically attractive for inclusion in the portfolio. Furthermore, the shadow prices associated with the right-hand-side constraints provided information on the marginal effect of changes in the available investment resources and model constraints on the optimal objective value. The sensitivity results demonstrated that the optimal portfolio remained stable within specified ranges of variation in the objective coefficients and constraint values, implying that moderate fluctuations in market conditions would not alter the composition of the portfolio. This robustness highlights the ability of the proposed model to provide reliable investment decisions even under uncertain and dynamic market environments.

1. Introduction

Asset selection and portfolio optimization constitute important aspects of financial decision-making, involving the determination of an appropriate combination of investment assets and the allocation of available funds in a manner that maximizes returns while controlling

exposure to risk. The increasing complexity of financial markets and the need to achieve optimal utilization of scarce resources have made the application of mathematical optimization techniques indispensable in investment management [1, 2]. Portfolio optimization provides investors with a systematic framework for constructing efficient portfolios capable of balancing profitability, risk, and liquidity requirements.

In practice, investors seek to maximize wealth while minimizing exposure to adverse market fluctuations and maintaining adequate liquidity to meet short-term financial obligations. Consequently, portfolio optimization has become an essential tool for individual and institutional investors in achieving sustainable investment performance [3]. However, attaining efficient portfolio allocation is particularly challenging in developing economies due to structural inefficiencies, information asymmetry, limited diversification opportunities, low market depth, and heightened volatility. Empirical studies have shown that emerging and developing financial markets, including Nigeria, are characterized by greater uncertainty and vulnerability to macroeconomic and political shocks, thereby complicating investment decisions [4–6]. These challenges necessitate the adoption of robust analytical models capable of supporting rational asset selection and efficient fund allocation.

The pioneering work of Markowitz [7] introduced the Mean-Variance (MV) framework and established the concept of the efficient frontier, which identifies portfolios that provide the highest expected return for a given level of risk. The expected portfolio return and portfolio variance are expressed respectively as:

$$R_p = \sum_{i=1}^N x_i R_i, \quad \sigma_p^2 = \sum_{i=1}^N \sum_{j=1}^N x_i x_j \sigma_{ij} \quad (1)$$

where,

x_i is the proportion of fund invested in i^{th} asset

x_j is the proportion of fund invested in j^{th} asset

$R_i = \sum_{t=1}^N R_{it}$ is the total investment return on i^{th} asset

R_{it} is the investment return on i^{th} asset over a time period, t

N is the total number of available assets.

Although the Markowitz model remains a cornerstone of modern portfolio theory, its reliance on only two criteria: expected return and risk limits its applicability in real-world investment environments where additional factors such as liquidity, transaction costs, and investment constraints significantly influence investors' decisions [8]. Moreover, the assumptions underlying the mean-variance framework, including normally distributed returns and stable covariance structures, are often violated in emerging markets characterized by high volatility and market imperfections [2]. Consequently, there has been increasing interest in alternative optimization approaches, including linear programming, that are more flexible and capable of accommodating practical constraints.

Linear Programming (LP) is a mathematical optimization technique that has gained considerable attention in financial decision-making because of its ability to optimize objective functions subject to multiple constraints [9]. Unlike traditional mean-variance models, LP provides a flexible framework for asset selection and capital allocation while incorporating practical considerations such as budget limitations, minimum and maximum investment requirements, and liquidity constraints. Recent studies have demonstrated the effectiveness of linear programming models in solving portfolio optimization problems and improving investment performance, particularly in uncertain and resource-constrained environments [8, 10, 11]. Owing to its simplicity, computational efficiency, and adaptability, LP represents a suitable approach for portfolio construction in developing economies.

An important advantage of linear programming is its sensitivity analysis capability, which examines the effects of changes in model parameters on the optimal solution. Sensitivity analysis provides valuable information regarding the robustness of investment decisions by identifying the range within which objective coefficients and right-hand-side constraint values may vary without altering the optimal portfolio structure [12]. This feature is particularly important in financial markets where returns, risk levels, and liquidity conditions are dynamic and subject to continuous fluctuations. Through sensitivity analysis, investors can assess the implications of changing market conditions and make informed adjustments to their investment strategies.

Against this backdrop, this study applies Linear Programming to the problem of asset selection and portfolio optimization in the Nigerian stock market. Using selected publicly listed companies as investment alternatives, the study seeks to determine the optimal allocation of funds based on key investment criteria, namely expected return, risk, and liquidity. Furthermore, sensitivity analysis is conducted to evaluate the stability of the optimal solution and to provide insights into how variations in investment parameters may affect portfolio composition. By integrating mathematical optimization with the realities of a developing economy, the study contributes to the growing body of literature on portfolio management and provides a practical framework for enhancing investment decision-making in emerging financial markets.

2. Method

This study employs Linear Programming (LP) as a mathematical optimization technique to determine an optimal investment portfolio that balances return, liquidity, and risk. Linear programming has been widely applied in financial decision-making because of its ability to optimize an objective function subject to a set of practical constraints. Compared with traditional mean-variance approaches, LP offers greater flexibility in accommodating real-world investment requirements and multiple performance measures [8, 12] (Sharma & Mehra, 2024). Owing to its computational efficiency and adaptability, LP is particularly suitable for portfolio optimization problems in developing economies characterized by market imperfections and limited investment opportunities.

This section of the work describes the data used in the study and the modeling approach adopted for portfolio optimization.

2.1. Data Description

The data used for this study were collected on the three investment criteria considered, which include the investment return, liquidity and risk. The data were the annual averages, in millions of naira, obtained from the annual reports of the five organizations considered, which are Zenith bank plc, UBA, TOTAL, Fidelity bank plc and Nigerian Breweries. The data are as shown in Table 1.

Table 1: Annual average data from the involved organizations

	Zenith Bank	UBA	TOTAL	Fidelity Bank	Nigerian Breweries
Return (₦ billion)	34.1	23.76	25.32	16.01	33.17
Liquidity(₦ billion)	71.03	76.85	60.12	80.92	82.38
Risk(%)	17.3	10.6	13.11	12.04	15.27

Annual Report of Zenith bank plc, UBA, TOTAL, Fidelity bank plc and Nigerian Breweries

2.2. Methodology

This study applies Linear Programming (LP) as a mathematical optimization technique to determine the optimal investment portfolio that balances return, liquidity, and risk. Linear programming is particularly suitable for portfolio selection problems because it allows for the systematic evaluation of multiple investment options under well-defined constraints and criteria [13].

Formulation of Decision Variables and Objective Function

Let x_i represent the proportion of total investment allocated to asset i , where $i = 1, 2, \dots, N$ and N is the number of available investment alternatives. In order to formulate the objective function, the three key financial parameters: return, liquidity, and risk, are considered. For each asset, the ratios of the individual values for return, liquidity, and risk to the respective total values across all assets are calculated as follows:

$$\text{Total Return: } \sum_{i=1}^N R_i = 132.36 \text{ million Naira}$$

$$\text{Total Liquidity: } \sum_{i=1}^N L_i = 371.3 \text{ million Naira}$$

$$\text{Total Risk: } \sum_{i=1}^N K_i = 68.32 \text{ million Naira}$$

Then, for each company (asset) i , a performance coefficient, C_i , is computed as follows:

$$C_i = \frac{R_i \times L_i}{K_i} \quad (2)$$

where,

R_i is the return on investment for asset i ; L_i is the liquidity of asset i ; K_i is the associated risk for asset i . These coefficients capture the trade-offs between maximizing return and liquidity while minimizing risk. The objective function aims to maximize the total performance score across all assets and it is given as:

$$\text{Maximize } Z = \sum_{i=1}^N \frac{(R_i \times L_i)}{K_i} x_i \quad (3)$$

The choice of the objective function is motivated by the need to achieve an optimal trade-off among return, liquidity, and risk. Investors generally seek assets that generate high returns, possess sufficient liquidity, and exhibit relatively low risk. By considering the product of return and liquidity and dividing by risk, the proposed formulation simultaneously rewards profitable and easily tradable assets while discouraging excessive exposure to uncertainty.

This approach is consistent with the principles of multi-criteria portfolio optimization, which recognize that investment decisions are influenced by several performance indicators rather than return alone [8, 14]. In particular, Konno and Yamazaki [15] proposed the mean absolute deviation model as an alternative to the mean-variance framework, emphasizing risk minimization while maintaining desirable returns. Subsequent studies have demonstrated the effectiveness of mathematical programming techniques in addressing portfolio optimization problems involving multiple criteria and practical constraints [3, 8].

Recent developments in portfolio optimization have further highlighted the importance of incorporating additional dimensions such as liquidity, transaction costs, and market uncertainty into optimization models, especially in emerging markets where volatility and information asymmetry are prevalent [2, 10] (Sharma & Mehra, 2024). These studies advocate the use of flexible optimization frameworks capable of integrating several financial performance measures into a single decision-support model.

This linear programming model is subject to the following constraints:

1. Budget Constraint (Total investment allocation must equal 1):

$$\sum_{i=1}^N x_i = 1$$

2. Minimum asset diversification constraint (To avoid concentration risk, at least two assets must be selected):

$$y_i \geq 2 \text{ where } y_i \in \{0, 1\}, \text{ and } x_i \leq y_i$$

3. Maximum allocation constraint (No more than 60% of the portfolio should be allocated to a single asset):

$$x_i \leq 0.6, \forall i$$

4. Non-negativity constraint (No negative allocations):

$$x_i \geq 0, \forall i$$

All input data: return, liquidity, and risk, are normalized relative to their total values to ensure comparability and eliminate scale bias. The model does not assume any short-selling. Additionally, liquidity is treated as a resource to be optimized (where higher liquidity is preferred), while risk is penalized within the objective function via its role in the denominator of C_i . Therefore reflects practical investment considerations. Specifically:

1. **Return** serves as the primary indicator of profitability and wealth creation.
2. **Liquidity** ensures that assets can be converted into cash quickly with minimal loss in value, an important consideration in volatile and relatively underdeveloped financial markets.
3. **Risk** represents the uncertainty associated with expected returns and must be controlled to avoid excessive exposure.

By combining these factors in a multiplicative-divisive structure, the model promotes portfolios that achieve a balanced compromise among profitability, liquidity, and risk. Such an approach is consistent with the theory of portfolio selection introduced by Markowitz [7] and with the broader literature on multi-objective optimization, which recognizes that investors pursue multiple, often conflicting, objectives simultaneously [3, 14].

Overall, the proposed objective function provides a practical and structured framework for portfolio optimization by integrating three fundamental investment criteria into a single performance measure. Consequently, it offers a rational basis for asset selection and fund allocation and serves as an effective decision-support tool for investors operating in developing economies.

The chosen form of the objective function, maximizing the ratio of the product of return and liquidity to risk for each asset, is grounded in the principle of achieving an optimal trade-off among key financial performance indicators: return, liquidity, and risk. This formulation recognizes that investors typically aim to maximize returns and liquidity, while minimizing exposure to risk. The product of return and liquidity rewards assets that are both profitable and easily tradable, while dividing by risk penalizes highly volatile or uncertain investments.

This objective function aligns with prior applications of multi-criteria financial optimization using linear programming models. For instance, [15] proposed a mean-absolute deviation (MAD) model that focuses on minimizing risk while maintaining a maximum return. This indicates that risk minimization plays a central role in LP-based models. Mbah and Onwukwe [13] which inspired this study used a composite objective function in which return and liquidity are directly weighted and risk is inversely weighted. The formulation, $\frac{(R_i \times L_i)}{K_i} x_i$ therefore reflects a practical consideration for real-world investors who must balance multiple dimensions of investment performance. The rationale behind this structure is that: (1) Return is the primary driver of investor interest and indicates the profitability of an asset. (2) Liquidity ensures that assets can be converted to cash quickly without significant price loss, which is crucial in volatile or underdeveloped markets. (3) Risk captures the uncertainty or volatility in expected returns and must be minimized or counterbalanced. By incorporating all the three in a multiplicative-divisive form, the objective function promotes efficient portfolios that do not overly concentrate on high-return, high-risk assets, nor on highly liquid but low-return options. This formulation is consistent with financial decision-making literature that advocates for multi-criteria utility functions [7, 14]. Such models recognize that investors seek not only return maximization but also favorable risk and liquidity profiles. In summary, the chosen objective function form reflects real-world investor preferences and is grounded in established multi-objective optimization principles, supported by empirical and theoretical studies in financial optimization. This approach offers a structured decision-support framework that integrates key financial performance indicators into a single optimization model, thereby enabling rational, data-driven investment decisions.

Sensitivity Analysis

The major components of sensitivity analysis include the shadow price of the right-hand side (RHS) of the constraint and the reduced cost of the asset the allocation variable. The shadow Price tells how much the objective function value would change per unit increase in the RHS of a constraint, while keeping every other constraint constant. For example, increasing the total allowable return or liquidity or decreasing the total allowable risk may yield a better objective value. Shadow price therefore shows how RHS constraints affect the objective function. Reduced costs on the other hand, indicate how much an objective coefficient must improve (increase for maximization or decrease for minimization case) before that variable could enter the optimal solution at a positive level if the variable is not in the current solution (i.e., asset allocation, $x_i = 0$, in the optimal solution) [12]. Reduced cost therefore decides whether an asset could enter the portfolio or not [16]. The reduced cost is calculated thus:

$$\text{Reduced cost } j = C_j - \sum_{i=1}^N y_i a_{ij}, \quad j = 1, 2, \dots, N$$

where,

C_j is the objective coefficient of the variable, x_j ; y_i is the shadow price of constraint i ; a_{ij} is the coefficient of variable x_j in constraint i .

Table 2: Choosing the stock to be included in the portfolio

	Y	Z	U	T	F	N	S_1	S_2	S_3	Solution.
Y	1	140.01	172.26	116.11	107.60	178.95	0	0	0	0
S_1	0	0.26	0.18	0.19	0.12	0.25	1	0	0	132.36
S_2	0	0.19	0.21	0.16	0.22	0.22	0	1	0	371.3
S_3	0	0.25	0.16	0.19	0.18	0.22	0	0	1	68.32

Model Formulation using the Investment Data

Let

x_1 be the proportion of investment in Z; x_2 be the proportion of investment in U
 x_3 be the proportion of investment in T; x_4 be the proportion of investment in F
 x_5 be the proportion of investment in N

The objective function coefficients (that is, the performance score),

$$C_i = \frac{R_i \times L_i}{K_i} \text{ for each asset.} \quad (4)$$

Using the normalize data in Table 2, the linear programming model for the problem under study is as given in Equation (5)

$$\begin{aligned} \text{Maximize } Z &= 140.01 x_1 + 172.26 x_2 + 116.11 x_3 + 107.60 x_4 + 178.95 x_5 \\ \text{Subject to } &0.26 x_1 + 0.18 x_2 + 0.19 x_3 + 0.12 x_4 + 0.25 x_5 \leq 132.36 \\ &0.25 x_1 + 0.16 x_2 + 0.19 x_3 + 0.18 x_4 + 0.22 x_5 \leq 68.32 \\ &x_1 + x_2 + x_3 + x_4 + x_5 = 1 \\ &0 \leq x_i \leq 0.6 \forall i = 1 \text{ to } 5 \\ &y_i \geq 2 \end{aligned} \quad (5)$$

2.3. Solution Approach

The formulated LP model is solved using the simplex algorithm implemented in optimization software (Lingo 17 $\times$ 64.0). The solution is obtained after three iterations. The summary of the results is given in Table 3.

Table 3: Summary results of sensitivity analysis for objective coefficients and RHS constraints

Company	Allocation	Coefficient	Contribution to Obj. value	Reduced cost	Shadow price
Zenith Bank	0.00	140.01	₦0 m	66.47	Return = 0.09
UBA	0.40	172.26	₦68.90 m	0.00	Liqu=1076.63
TOTAL	0.00	116.11	₦0 m	42.19	Risk = 6.88
Fidelity Bank	0.00	107.60	₦0 m	36.94	-
N. Breweries	0.60	178.95	₦107.37 m	0.00	-

3. Discussion of Results

The major objectives of this study were to determine the assets that constitute an optimal portfolio, their corresponding allocations, and the resulting portfolio yield. The results showed that United Bank for Africa (UBA) and Nigerian Breweries (NB) constitute the optimal portfolio, with allocations of 0.4 and 0.6 respectively, producing an optimal objective value of ₦176.27 million. This result supports the central proposition of Modern Portfolio Theory (MPT) introduced by Markowitz [7], which posits that efficient portfolio construction involves allocating resources among selected assets in such a way that the expected return is maximized for a given level of risk. Similarly, Kolm et al. [3] observed that portfolio optimization techniques seek to identify efficient asset combinations rather than investing uniformly across all available securities. The concentration of investment in only two assets therefore reflects the efficiency principle underlying portfolio selection.

The zero allocations assigned to Zenith Bank, TotalEnergies' and Fidelity Bank indicate that, although these assets possess positive performance coefficients, they are relatively inefficient compared with UBA and Nigerian Breweries under the prevailing constraints. Such sparse portfolio structures are common in mathematical programming approaches to portfolio optimization. Mansini et al. [8] noted that linear and mixed-integer programming models frequently generate portfolios containing only a subset of available assets because the optimization process naturally selects securities with superior risk-return characteristics and excludes comparatively inefficient alternatives. Likewise, Konno and Yamazaki [15] demonstrated that linear programming-based portfolio models tend to favour assets that provide the best trade-offs between profitability and risk, resulting in concentrated but efficient portfolios.

The sensitivity analysis results further revealed that UBA and Nigerian Breweries possess zero reduced costs, indicating that they belong to the optimal basis and remain profitable under the existing constraints. In contrast, Zenith Bank (66.47), Total Energies (42.19), and Fidelity Bank (36.94) exhibit positive reduced costs, implying that their inclusion in the portfolio would decrease the objective value unless their performance coefficients improve by at least the magnitude of the corresponding reduced costs. According to Hillier and Lieberman [12], a positive reduced cost in linear programming signifies that a non-basic variable must experience a sufficiently favourable change in its objective coefficient before it can enter the optimal solution. Consequently, these assets would become attractive only if their expected returns increase, their liquidity positions improve, or their risk exposures decline substantially.

These findings are particularly relevant in developing economies, where market volatility, liquidity constraints, and information asymmetry often affect investment performance. Bodie et al. [2] emphasized that the attractiveness of financial assets depends not only on their returns but also on their liquidity characteristics and exposure to risk. Similarly, Adekoya et al. [6] argued that emerging markets are characterized by heightened uncertainty and greater vulnerability to economic shocks, making the trade-off among return, liquidity, and risk particularly important. The relatively high reduced costs associated with Zenith Bank, TotalEnergies, and Fidelity Bank therefore suggest that these assets are unable to compete effectively for limited investment funds under current market conditions.

The shadow price analysis also provided useful insights into the sensitivity of the optimal portfolio to changes in the model parameters. Zenith Bank exhibited a shadow price of 0.09 associated with the return constraint, indicating that the model is sensitive to changes in its return and that a marginal improvement in return could make the asset competitive. According to Taha [9] and Hillier and Lieberman [12], shadow prices represent the marginal contribution of relaxing a binding constraint and therefore provide valuable information regarding the economic significance of scarce resources. UBA recorded a large shadow price of 1076.63 for liquidity, suggesting that the liquidity constraint is strongly binding and explaining why the asset is included in the optimal portfolio. This result highlights the importance of liquidity in portfolio selection, especially in less developed financial markets where investors value assets that can easily be converted into cash. Bodie et al. [2] similarly emphasized that liquidity constitutes a critical dimension of investment performance and plays an increasingly important role during periods of market uncertainty.

Furthermore, the shadow price associated with TotalEnergies' risk constraint (6.88) suggests that risk considerations significantly influence the exclusion of the stock from the optimal portfolio. Thus, any reduction in its risk level would enhance its competitiveness. This finding is consistent with the observations of Kolm et al. [3], who reported that risk remains one of the principal determinants of optimal asset allocation and that optimization models inherently penalize securities with unfavourable risk characteristics. Assets with inactive constraints exhibited no shadow prices because they do not participate in determining the optimal solution. This agrees with the theory of sensitivity analysis in linear programming, which states that only binding constraints possess non-zero shadow prices [12].

Overall, these findings underscore the importance of balancing return, liquidity, and risk in investment decisions, particularly within developing economies where market inefficiencies, low market depth, and regulatory challenges impose additional constraints on portfolio construction. The results corroborate the findings of Mansini et al. [8] and Chand et al. [10], who observed that linear programming techniques are capable of generating efficient portfolios by simultaneously accounting for multiple investment criteria and practical constraints. Therefore, the optimal portfolio obtained in this study demonstrates the effectiveness of linear programming as a decision-support tool for asset selection and fund allocation in emerging financial markets.

4. Conclusion

This study aimed to develop an optimal investment using LP to guide asset selection and portfolio construction in a developing economy. The simplex method of LP was used, with lingo software to choose the best assets to make up the needed investment portfolio. The results revealed the ideal assets, the allocation for each asset, the optimal investment and the expected yield. Assets like Zenith Bank, TOTAL, and Fidelity Bank have zero allocations, suggesting that their performance ratios ($\text{return} \times \text{liquidity} \div \text{risk}$) were not strong enough compared to UBA and Nigerian Breweries. If their returns or liquidity increase, or if their associated risks decrease, they may become viable in a future allocation. Nonetheless, this does not imply that only one stock offers the highest potential yield; rather, diversification remains a key strategy to minimize risk and loss. The study concludes that Linear Programming constitutes an effective decision-support tool for asset selection and portfolio optimization in developing economies. It is therefore recommended that investors emphasize assets characterized by strong liquidity, favorable returns, and manageable risk profiles, while also utilizing sensitivity analysis to evaluate the resilience of portfolio decisions to changing market conditions.

Recommendations

Based on the results obtained from this study, the following recommendations are made:

1. Investors should prioritize assets with high liquidity and stable returns to minimize risk in volatile markets.
2. Companies with high reduced costs should improve financial performance to remain competitive for institutional investment.
3. Future research should incorporate diversification constraints, stochastic programming, or fuzzy LP to address market uncertainty.

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