

Static and Dynamic Portfolio Selection Approaches and the Application of Portfolio Strategies: Evidence from the Ghana Stock Exchange

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Abstract: This study investigates portfolio selection under both static and dynamic approaches, with an application to the Ghana Stock Exchange. The static approach evaluates asset performance using historical wealth accumulation over the past 120 trading days, the Sharpe ratio, and the Gini performance ratio. In contrast, the dynamic approach emphasizes investor preferences and the asymptotic properties of wealth evolution, with ranking indicators including the Expected Power Utility, the Sharpe ratio based on forecasted wealth, and the Optimum Asset (OA)-Stable ratio. Assets preselected under these two approaches are subsequently subjected to portfolio strategies such as the Markov strategy—implemented through a transition matrix to compute wealth paths—the Sharpe ratio strategy, and the uniform strategy. Using historical data from the Ghana Stock Exchange from January, 2015 to October, 2016, the results show that the static and dynamic approaches do not necessarily select the same set of assets. Moreover, results reveal that the Markov strategy outperforms both the uniform and Sharpe ratio strategies in terms of wealth accumulation. These findings underscore the relevance of Markov chains in portfolio allocation, particularly in enhancing financial returns within illiquid markets such as Ghana.

Keywords: Preselection, Static Framework, Dynamic Framework, Portfolio Strategy, Markov Chain Strategy, Sharpe Strategy

1 Introduction

Portfolio selection is a cornerstone of modern finance, originating with Markowitz's mean–variance framework [1]. Subsequent developments introduced refinements distinguishing between static approaches, which rely on historical performance measures such as the Sharpe ratio and utility-based indicators [2], and dynamic approaches, which incorporate investor preferences, stochastic processes, and the forward-looking properties of wealth evolution [3,4,5]. These models guide how investors allocate assets to balance risk and return.

Although extensively applied in developed markets, portfolio selection models face limitations in emerging markets, where conditions such as low liquidity, volatility, and thin trading complicate investment decisions [6]. The Ghana Stock Exchange, in particular, provides a setting in which conventional methods may not fully capture market realities, underscoring the need to test both static and dynamic approaches in such contexts [7].

This study examines portfolio selection under static and dynamic approaches using Ghanaian market data. The static framework is evaluated through wealth accumulation, the Sharpe ratio, and the Gini performance ratio, while the dynamic framework is guided by investor preferences and asymptotic wealth properties, assessed through Expected Power Utility, forecast-based Sharpe ratios, and the Optimum Asset (OA)-Stable ratio. Once assets are preselected under each approach, we apply portfolio strategies—including uniform allocation, Sharpe ratio maximization, and a Markov chain-based strategy—to analyze comparative performance.

By integrating static and dynamic selection with strategy evaluation, this paper contributes to the literature on portfolio optimization in emerging markets. It highlights the interplay between selection frameworks and allocation strategies and provides practical insights for investors navigating illiquid markets such as Ghana.

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Portfolio selection theory has its foundations in [1], who introduced mean–variance optimization and established the classical static framework. Static selection methods rely on historical data and performance metrics such as wealth accumulation, the Sharpe ratio, and dispersion measures like the Gini index. While widely used, static methods may overlook evolving market conditions, particularly in dynamic or illiquid environments [8,9].

Dynamic approaches address this limitation by incorporating forward-looking variables and investor preferences [3, 4]. [10] studies portfolio selection in stochastic environments, emphasizing the role of learning, predictability, and state variables in dynamic portfolio rules. More recently, [11] develop equilibrium approaches for time-consistent mean–variance portfolio selection, yielding allocation policies that avoid pre-commitment and better reflect dynamic investment behavior.

In parallel, robust portfolio methods seek to mitigate estimation error and model risk [12,13]. [14] propose robust portfolio optimization procedures based on risk-sensitive performance measures under parameter uncertainty. Extending this line of research, [15] introduce *Set–Portfolio Selection with the Use of Market Stochastic Bounds*, where assets are preselected according to stochastic dominance and market state behavior, emphasizing robustness in portfolio evaluation.

Algorithmic and state-aware allocation frameworks have also been developed. Dynamic programming and stochastic control methods provide tractable ways to derive adaptive portfolio allocation rules under uncertainty [16,17,3]. Similarly, regime-switching and state-dependent models have been applied to capture changing economic conditions and market decoupling effects [18,19]. These models offer flexible mechanisms for adjusting allocations under regime shifts and tail-risk events.

Despite their theoretical advancements, such approaches remain underexplored in emerging markets, where liquidity constraints, volatility, and structural inefficiencies prevail. For instance, the Ghana Stock Exchange (GSE) is characterized by low turnover and sudden swings, making it an appropriate setting to test static versus dynamic preselection criteria and compare allocation strategies such as uniform weighting, Sharpe maximization, and Markov chain–based methods [7].

This study contributes to the literature by applying both static and dynamic preselection criteria grounded in wealth metrics, investor preferences, stochastic bounds, and state-dependent portfolio dynamics, while empirically evaluating their associated portfolio strategies in the context of an emerging and relatively illiquid market. The rest of the paper is organized as follows: Section II outlines the mathematical preliminaries. Section III describes the model formulation and methodology. Section IV presents the empirical analysis and discussion of results. Section V concludes the paper and highlights policy implications and directions for future research.

2 Basic definitions and Mathematical preliminaries

Definition 1(Preselection criteria).

A preselection criteria for portfolio refers to a set of guidelines or standards used to evaluate and select assets for inclusion in an investment portfolio. These guidelines are designed to guarantee that selected assets align with the investor's objectives, risk tolerance, and financial plans.

Definition 2(Portfolio strategy).

A portfolio strategy is a method for managing a collection of financial assets with the goal of achieving specific financial objectives.

Definition 3(Markov Chain Strategy).

The Markov Chain portfolio strategy is based on modeling asset transitions through a Markov process. Let $P = (p_{ij})$ denote the transition probability matrix estimated from historical returns, where p_{ij} represents the probability of moving from asset i to asset j . The strategy begins with an initial asset, and at each step, the next asset is selected according to the probabilities in P , thereby capturing the temporal dynamics of asset performance.

Definition 4(Sharpe Strategy). *The Sharpe portfolio strategy selects, at each decision point, the asset that maximizes the Sharpe ratio. For asset i , the Sharpe ratio is defined as*

$$S_i = \frac{\mu_i - r_f}{\sigma_i},$$

where μ_i is the mean return of the asset, σ_i is its standard deviation, and r_f is the risk-free rate. In the absence of a risk-free rate, $r_f = 0$ is typically assumed.

Definition 5(Uniform Strategy). *The Uniform portfolio strategy allocates wealth equally across all N available assets. Formally, if $w = (w_1, w_2, \dots, w_N)$ denotes the vector of portfolio weights, then*

$$w_i = \frac{1}{N}, \quad i = 1, 2, \dots, N.$$

This represents a naive diversification rule that ensures no single asset dominates the portfolio.

Definition 6(Static Preselection criteria). Let $\mathcal{A}$ denote a finite universe of assets, and let

$$\phi : \mathcal{A} \rightarrow \mathbb{R}$$

be a selection score constructed from predetermined selection criteria evaluated over a fixed historical window. For each asset $a \in \mathcal{A}$, let $\phi(a)$ denote its resulting composite score or rank. The static preselected set is defined as

$$\mathcal{A}_s = \{a \in \mathcal{A} : \phi(a) \text{ meets the prescribed selection rule}\}.$$

In this study, the selection rule is based on the composite ranking obtained from the selected criteria. The individual criterion ranks are aggregated to produce a total rank for each asset, and the assets with the lowest total ranks are retained. Specifically, if R_{ij} denotes the rank of asset i under criterion j , the composite rank is

$$C_i = \sum_{j=1}^m R_{ij},$$

where m is the number of selection criteria. The static preselected universe consists of the ten assets with the smallest values of C_i :

$$\mathcal{A}_s = \arg \min_{\substack{B \subseteq \mathcal{A} \\ |B|=10}} \sum_{i \in B} C_i.$$

Thus, the selected set remains fixed over the subsequent portfolio construction period unless the selection criteria, historical evaluation period, or selection rule is recomputed.

Definition 7(Stability of Static preselection criteria). Let $\mathcal{A} = a_1, \dots, a_m$ denote a finite set of assets and let K static selection criteria be used to evaluate them. Let R_{ij} denote the rank assigned to asset a_i under criterion j . The composite rank of asset a_i is defined as

$$C_i = \sum_{j=1}^K R_{ij}.$$

The static preselected set of size q is given by

$$\mathcal{A}_s = \{a_i \in \mathcal{A} : C_i \text{ belongs to the } q \text{ smallest composite ranks}\}.$$

The static criteria are said to be stable when the same asset rankings and selection set are obtained when the criteria are applied repeatedly over the same fixed evaluation sample, without changing the underlying data, criteria, or selection rule.

The definition formalizes the stability of the static preselection procedure such that when the same criteria, evaluation sample, ranking procedure and selection rule are applied without modification, the resulting asset rankings and preselected set remain unchanged.

Definition 8(Dynamic preselection criteria). Let $\mathcal{A}$ denote a finite universe of assets and let $\mathcal{A}_d \subseteq \mathcal{A}$ denote the set of assets selected using dynamic selection criteria. Unlike static preselection, which evaluates assets using statistics calculated over a fixed historical period, dynamic preselection incorporates information that evolves over time or over a specified rolling horizon.

For each asset $i \in \mathcal{A}$, let

$$C_{ij}(t), \quad j = 1, \dots, m,$$

denote the value of the j th dynamic selection criterion at time t . The assets are ranked according to each criterion and the individual ranks are aggregated to obtain a composite rank

$$C_i(t) = \sum_{j=1}^m R_{ij}(t),$$

where $R_{ij}(t)$ denotes the rank assigned to asset i under criterion j at time t .

The dynamic preselected set is then obtained by retaining the assets satisfying the prescribed composite-ranking rule. In this study, the dynamic criteria incorporate expected power utility, the OA-Stable ratio and a Sharpe-based criterion constructed using a 20-observation horizon. The resulting composite ranking is used to identify the ten assets retained for subsequent portfolio construction. The purpose of the dynamic procedure is therefore to incorporate information from the evolving return distribution and short-horizon performance of the assets when forming the candidate investment universe. We state and prove the following relevant theorem:

Theorem 1(Invariance of Static Rank-Based Preselection criteria). *Let $\mathcal{A} = a_1, a_2, \dots, a_m$ be a finite set of assets, and let*

$$\phi_j : \mathcal{A} \rightarrow \mathbb{R}, \quad j = 1, 2, \dots, K,$$

denote K selection criteria used to evaluate the assets. For each criterion ϕ_j , let R_{ij} denote the rank assigned to asset a_i , and define the composite rank of asset a_i by

$$C_i = \sum_{j=1}^K R_{ij}.$$

Let A_q denote the set of q assets having the smallest composite ranks. For each criterion j , let

$$g_j : \mathbb{R} \rightarrow \mathbb{R}$$

be a strictly increasing function, and define the transformed criterion by

$$\tilde{\phi}_j(a_i) = g_j(\phi_j(a_i)).$$

If the same ranking convention and tie-breaking rule are used before and after transformation, then the ranks and composite ranks remain unchanged. Consequently,

$$\tilde{A}_q = A_q.$$

Hence, the static rank-based preselection procedure is invariant under strictly increasing transformations of its individual selection criteria.

Proof. We prove the result in three steps.

Step 1: Preservation of the ordering under each criterion. Fix an arbitrary criterion $j \in 1, \dots, K$ and consider any two assets $a_r, a_s \in \mathcal{A}$. Since g_j is strictly increasing, it preserves the ordering of real numbers. Therefore,

$$\phi_j(a_r) < \phi_j(a_s) \iff g_j(\phi_j(a_r)) < g_j(\phi_j(a_s)).$$

Similarly,

$$\phi_j(a_r) > \phi_j(a_s) \iff g_j(\phi_j(a_r)) > g_j(\phi_j(a_s)).$$

If

$$\phi_j(a_r) = \phi_j(a_s),$$

then, because g_j is a function,

$$g_j(\phi_j(a_r)) = g_j(\phi_j(a_s)).$$

Thus, the transformation g_j preserves both the ordering and equality relationships among all asset values under criterion j . Consequently, the relative position of every asset in the ranking is unchanged.

Hence,

$$\tilde{R}_{ij} = R_{ij}, \quad i = 1, \dots, m, \quad j = 1, \dots, K.$$

Step 2: Preservation of the composite ranks. The composite rank of asset a_i before transformation is

$$C_i = \sum_{j=1}^K R_{ij}.$$

After transforming the criteria, the composite rank becomes

$$\tilde{C}_i = \sum_{j=1}^K \tilde{R}_{ij}.$$

From Step 1, we have

$$\tilde{R}_{ij} = R_{ij}$$

for every i and j . Therefore,

$$\tilde{C}_i = \sum_{j=1}^K R_{ij} = C_i.$$

Thus,

$$\boxed{\tilde{C}_i = C_i}$$

for every asset $a_i \in \mathcal{A}$.

It follows that the relative ordering of the assets according to their composite ranks is also unchanged. In particular, if

$$C_r < C_s,$$

then

$$\tilde{C}_r = C_r < C_s = \tilde{C}_s.$$

Therefore, an asset that has a smaller composite rank than another asset before the transformation continues to have a smaller composite rank after the transformation.

Step 3: Preservation of the selected asset set. By definition, the static preselected set is

$$\mathcal{A}_q = \{a_i \in \mathcal{A} : C_i \text{ belongs to the } q \text{ smallest composite ranks}\}.$$

After transformation, the corresponding set is

$$\tilde{\mathcal{A}}_q = \{a_i \in \mathcal{A} : \tilde{C}_i \text{ belongs to the } q \text{ smallest composite ranks}\}.$$

From Step 2,

$$\tilde{C}_i = C_i$$

for every i . Therefore, the q assets having the smallest composite ranks before transformation are exactly the same q assets having the smallest composite ranks after transformation.

Hence,

$$\tilde{\mathcal{A}}_q = \mathcal{A}_q.$$

Since the functions $g_1, \dots, g_K$ were arbitrary strictly increasing functions, the result holds for any collection of strictly increasing transformations applied to the individual selection criteria.

Therefore, the static rank-based preselection procedure is invariant under strictly increasing transformations of its individual selection criteria.

Remark. The theorem establishes that the static preselection procedure depends on the relative ordering of the assets under the selection criteria rather than on the numerical scale of the criteria. Consequently, replacing any criterion by a strictly increasing transformation does not change the individual ranks, the composite ranks, or the resulting set of selected assets.

3 Model Formulation

In this section, we present the model formulation and the methodology employed in this study. It is essential that assets selected for a portfolio satisfy several optimality criteria, taking into account various aspects of wealth dynamics. The following factors should be taken into account as preselection criteria: Asymptotic behavior of wealth [9], Alignment with investor preferences [9] and relationship with market stochastic boundaries. In terms of portfolio interaction with market stochastic boundaries, Investors typically aim to maximize the correlation with the upper stochastic bound while reducing the correlation with the lower bound. This approach reflects the goal of enhancing wealth while reducing the risk of substantial losses. Hence, it becomes imperative to consider the investor's preferences to select a sizeable number of assets. We classify the preselection criteria as either static or dynamic approach. With these preselection criteria, the future wealth can be generalized as either static or dynamic:

1. In the static approach, it is assumed that historical observations are equally distributed. The investor aims to maximize a functional of future wealth that does not depend on the temporal horizon $[0, T]$. Specifically, the problem is formulated as:

$$\max_{\mathbf{x} \in S} f(z_{(x),t+1}).$$

This static approach represents the traditional myopic approach, where the time evolution of the wealth process is not considered.

2. In the dynamic approach, it is assumed that gross returns follow a Markov chain. Consequently, the investor seeks to maximize a functional of future wealth, taking into account this assumption. The problem is then formulated as:

$$\max_{\mathbf{x} \in S} f(W_T(z_{(x)})).$$

Here, $W_T(z_{(x)})$ represents the wealth predicted after T working days, given the portfolio $z_{(x)} = x'z$. In the dynamic context, the focus shifts to the set of all admissible Markovian wealth processes:

$$W(z_{(x)}) = \{W_t(z_{(x)})\}_{t \geq 0}.$$

These processes are defined on a filtered probability space, with the starting portfolio weights $\mathbf{x} \in S$.

Now, it is crucial to incorporate both approaches for asset preselection due to the following reasons:

1. A significant portion of portfolio models presented in existing literature are primarily based on one of these two hypotheses [14].
2. Empirical tests shows two distinct groups of "optimal" assets. Specifically, the assets identified as optimal by the dynamic approach are not necessarily the same as those identified by the static approach, and vice versa [14].

3.1 Preselection under the Static framework

Considers consistency with investor preferences and association with market stochastic boundaries. Assets are ordered based on:

1. **Wealth obtained in the last 120 working days:**

$$\frac{P_{j,t}}{P_{j,t-120}}$$

where $P_{j,t}$ represents the price of the j^{th} asset at time t , and $P_{j,t-120}$ is the price of the same asset 120 working days earlier, approximately equivalent to a six-month period.

2. **Sharpe Ratio:**

$$\frac{\mu(z_j - z_f)}{\sigma_j}$$

where the parameters for drift (μ) and volatility (σ) of the j -th asset are estimated using the observed returns over the most recent 120 trading days. It is also assumed that the risk-free rate is zero, meaning $z_f = 1$.

$$\mu(z_j) \approx \frac{1}{120} \sum_{t=1}^{120} z_{j,t},$$

and

$$\sigma(z_j) \approx \sqrt{\frac{1}{120} \sum_{t=1}^{120} (z_{j,t} - \mu(z_j))^2}.$$

3. Gini Performance Ratio:

$$\text{GPR}_j = \frac{\gamma(z_j, \max_{1 \leq k \leq m} z_k)}{1.1 + \gamma(z_j, \min_{1 \leq k \leq m} z_k)}.$$

The Gini Performance Ratio (GPR) evaluates the performance of asset j by considering its concordance with the best- and worst-performing assets in the investment universe. The numerator measures the Gini concordance between the return series of asset j and the best-performing reference series, while the denominator incorporates the concordance between asset j and the worst-performing reference series. The constant 1.1 is included in the denominator to avoid division by zero and to maintain numerical stability.

The empirical Gini concordance between two variables X and Y is computed as

$$\gamma(X, Y) = \frac{1}{n^2/2} \sum_{h=1}^n [|p_h - q_h - 1| - |p_1 - q_1| (p_h q_h)],$$

where $n = 120$ denotes the number of observations in the evaluation window, while p_h and q_h represent the ranks of X and Y , respectively, at observation h .

Thus, the Gini Performance Ratio incorporates the relative concordance of an asset with both the strongest and weakest performers in the investment universe, rather than relying solely on the asset's own return series.

The first two indicators—the six-month wealth growth and the Sharpe ratio—align with the preferences of investors who aim to maximize returns without bounds. On the other hand, the Gini performance ratio serves to enhance the alignment of a portfolio with the upper boundary of market returns while reducing exposure to the lower boundary. This dual focus ensures a better balance of gain-seeking behavior and risk avoidance.

These three metrics collectively serve as the foundation for selecting favorable assets, particularly those that cater to the preferences of return-maximizing investors. The final selection consists of the assets among the available m that demonstrate superior performance across all three evaluation measures.

3.2 Preselection Criteria under the Dynamic Framework

In the context of the dynamic approach, asset selection is guided by criteria that reflect investors' preferences, the asset's behavior in relation to market stochastic boundaries, and the underlying Markovian and asymptotic properties of wealth evolution. This approach assumes that the return process for each asset can be modeled as a Markov chain. Consequently, the selection of assets is based on the following three ranking indicators:

1. Expected Power Utility:

$$E[u(W_T(z_j))] = E\left(\frac{W_T(z_j)^g}{g}\right)$$

where $W_T(z_j)$ denotes the projected wealth generated from investing in the j^{th} asset over a horizon of $T = 20$ trading days, and the utility function is defined as $u(W) = \frac{W^g}{g}$, with $g = 0.95$ capturing the investor's degree of risk aversion.

2. Sharpe Ratio:

$$\frac{\mu(W_T(z_j)) - W_0}{\sigma(W_T(z_j))}$$

Here, the Sharpe ratio is calculated using the forecasted wealth $W_T(z_j)$ after 20 trading days, where $\mu(W_T(z_j))$ is the mean of the predicted wealth, $\sigma(W_T(z_j))$ is its standard deviation, and W_0 denotes the initial investment. This ratio serves to evaluate the expected risk-adjusted return of each asset.

3. OA-Stable Ratio:

$$\text{OA-Stable}_i = \frac{\delta_i}{\text{ETL}_{0.05,i} - \delta_i},$$

where

$$\delta_i = \frac{1}{n} \sum_{t=1}^n W_t(z_i)$$

denotes the mean wealth associated with asset z_i . The expected tail loss is computed from the lower 5% tail of the wealth distribution as

$$\text{ETL}_{0.05,i} = \frac{1}{|\mathcal{T}_i|} \sum_{t \in \mathcal{T}_i} W_t(z_i),$$

where

$$\mathcal{T}_i = \{t : W_t(z_i) \leq Q_{0.05}(W(z_i))\},$$

and $Q_{0.05}(W(z_i))$ denotes the 5% quantile of the wealth observations for asset z_i . Thus, the OA-Stable Ratio incorporates both the average level of wealth and the behaviour of the lower tail of the wealth distribution.

The criterion combines a location measure of the wealth distribution with a lower-tail measure of risk. The numerator reflects the central location of the wealth distribution, whereas the denominator captures the distance between the lower-tail loss and the mean wealth level. Consequently, the criterion incorporates information about both the typical level of wealth and the adverse-tail behaviour of the wealth distribution.

Asset selection under the dynamic approach involves identifying the top-performing assets (among m) based on shared indicators of predicted wealth performance—namely, expected power utility, the Sharpe ratio, and the OA-stable ratio. Some assets may qualify under both the static and dynamic selection frameworks, as observed in [14]

4 Discussion and Analysis

We begin by outlining the dataset and analyzing how the choice of preselection strategy influences the results. Specifically, the analysis is based on a selection of equities that were actively traded between January 2015 and October 2016. The data source is the Ghana Stock Exchange, with returns valued in Ghanaian cedis. The study used 36 stocks on the Ghana stock exchange market within the stated period. The assets were **ACI, ALW, AADs, AGA, AYRTN, BOPP, CAL, CMLT, CYLD, CPC, EGH, ETL, EGL, FML, GCB, GOIL, GSR, GWEB, GGBL, REPUBLIC, MLC, PKL, PBC, PZC, SWL, SOGEGH, SIC, SCB, SPL, TOTAL, TRANSOL, TBL, TLW, UNIL, UTB** and **MAC**. For the analysis conducted in this study, we focus solely on data from the past six months, as it is assumed to have the greatest influence on future decisions [9].

The price data were converted to a standard datetime format and daily returns were computed from consecutive closing prices. The missing observation generated for the first return of each series was removed. No imputation, interpolation, or forward-filling was applied. Other potential data issues including duplicate dates, extreme observations, and trading suspensions were not separately adjusted for in the computational procedure. The results should therefore be interpreted in light of the characteristics and quality of the underlying GSE dataset.

Survivorship bias may arise if the dataset excludes securities that were delisted, suspended, or otherwise absent during the sample period. In addition, the ten assets were selected using their full-sample Sharpe ratios and the same observations were used for subsequent strategy evaluation. This introduces potential in-sample selection or look-ahead bias. Therefore, the reported results should be interpreted as an empirical comparison within the study period rather than as an out-of-sample assessment of future performance.

Result 1: Top Ten Preselected Stocks Using Static Criteria

Static preselection is performed by evaluating each asset over a 120-observation historical window using three selection criteria: the Wealth Ratio, Sharpe Ratio and Gini Performance Ratio. At each observation, assets are ranked separately according to each criterion, with higher criterion values receiving better ranks. The three ranks are then aggregated to obtain a composite rank for each asset. The average composite rank over the evaluation sample is subsequently calculated, and the ten assets with the lowest average composite ranks are selected for the subsequent portfolio construction stage. The result is shown in Table 1. The observed performance differences should be interpreted in light of the in-sample asset-selection procedure and the potential survivorship limitations discussed in Section 4

Table 1: Top Ten Preselected Stocks Using Static Criteria

Stock	Wealth Ratio	Sharpe Ratio	Gini Performance Ratio
AADs	0.999319	-0.004024	24.358696
ALW	1.649091	0.088904	13.391350
FML	1.204862	0.161896	4.180211
EGL	1.147210	0.079784	20.478239
MAC	1.082950	0.106133	1.109776
UNIL	1.011589	0.031120	33.893860
SIC	0.908089	-0.008655	53.573925
GOIL	1.071733	0.045883	10.056498
CAL	0.928287	-0.042776	64.158063
CPC	1.147493	0.044129	5.599307

Table 1 displays the top ten preselected stocks using static criteria based on three metrics: Wealth Ratio, Sharpe Ratio, and Gini Performance Ratio. **Wealth Ratio** reflects the cumulative return of an asset over the considered horizon. ALW (1.649), FML (1.205), and CPC (1.147) top the list, indicating their strong ability to grow wealth over time. In contrast, SIC (0.908) and CAL (0.928) show lower wealth ratios, suggesting more modest returns.

Sharpe Ratio assesses performance relative to risk. FML (0.162) and MAC (0.106) show the highest positive Sharpe ratios, identifying them as attractive investments on a risk-adjusted basis. Meanwhile, AADs, SIC, and CAL exhibit negative Sharpe ratios, suggesting underperformance relative to the risk-free rate.

For the **Gini Performance Ratio**, CAL (64.16), SIC (53.57), and UNIL (33.89) have the highest Gini values, implying higher variability in returns, possibly due to volatility or sporadic price movements. Conversely, MAC and FML show relatively low Gini ratios, indicating more stable return distributions.

In summary, FML, ALW and MAC stand out as promising stocks due to their balanced performance across wealth accumulation, risk-adjusted return, and return stability. While CAL and SIC appear in the top ten based on wealth or Gini ranking, their negative Sharpe ratios and high dispersion suggest potential instability or downside risk in a static investment context. Figure 1 provides a graphical representation of the results shown in Table 1

We also present the order of preference when an investor relies solely on asset returns and assigns equal weights to all top 10 assets preselected over the same investment period. However, such an approach may not adequately capture the risk associated with stock-market investments. The resulting order of preference from the top ten preselected is given by:

Order of Preference : FML > MAC > ALW > CPC > EGL > GOIL > UNIL > AADS > SIC > CAL.

Result 2: Top 10 Stocks selected by Dynamic approach

The dynamic selection procedure evaluates each asset using three criteria: expected power utility, the OA-Stable ratio and a Sharpe-based criterion constructed from a 20-observation rolling horizon. The criteria are calculated for the available asset price series and used to assess the relative performance of the assets. For each criterion, the assets are ranked and the resulting ranks are combined to obtain a composite rank for each asset. The assets are then ordered according to their composite ranks and the ten assets with the lowest total ranks are selected for subsequent portfolio construction. This approach provides a multi-criteria selection framework in which asset selection incorporates utility, stability and short-horizon performance information. The result is displayed in Table 2

Table 2 presents the performance evaluation of the top ten selected stocks based on three dynamic selection criteria: Expected Power Utility, OA-Stable Ratio and Sharpe Ratio. Among the stocks, **EGH** exhibits the highest Expected Power Utility (6.6636), suggesting strong performance under power utility preferences. However, its OA-Stable Ratio remains negative, indicating some instability in its return profile. **GCB** also demonstrates a relatively high utility value (3.9560) and a moderately negative OA-Stable Ratio (−3.7563), positioning it as a fairly robust asset in both return and stability dimensions. **SCB** and **UNIL** rank next, driven primarily by strong utility scores (14.1938 and 7.4332, respectively), although both exhibit significantly negative Sharpe Ratios. This reflects considerable return volatility relative to their mean returns, and may caution risk-averse investors. In contrast, assets such as **AADs** despite their earlier selection, display poor performance across all three metrics with the lowest Expected Power Utility (0.6165) and a substantially negative OA-Stable Ratio (−26.3311). This raises concerns about their inclusion in a robust portfolio especially under adverse market conditions. The result of Table 2 is plotted as Figure 2.

Among the ten assets selected using the dynamic criteria, the order of returns for each asset over the same investment period is presented below. This ranking reflects the returns obtained under an equal-weight allocation and provides a basis for comparing the performance of the selected assets over the investment period. The results also indicate that returns

Static Portfolio Performance Metrics



Fig. 1: Top 10 preselected stocks out of 36 using static criteria

Table 2: Top 10 Stocks Selected by Dynamic Approach

Stock	Expected Power Utility	OA-Stable Ratio	Sharpe Ratio
SCB	14.1938	-5.7733	-0.5254
GSR	2.1344	-7.7677	-0.2419
GGBL	2.3805	-3.6052	-0.5402
SOGEGH	0.9664	-5.7333	-0.3056
UNIL	7.4332	-8.6809	-0.1657
TOTAL	4.6250	-1.8006	-0.6339
AADs	0.6165	-26.3311	0.0032
GCB	3.9560	-3.7563	-0.1773
EGH	6.6636	-7.3924	-0.0474
UTB	0.1656	-1.3272	-0.3654

alone may not provide sufficient information for selecting a particular asset for portfolio inclusion, as they do not fully account for the associated risk and other characteristics of the investment.

Order of Preference: $EGH > GCB > SCB = UNIL > TOTAL > GGBL = UTB > GSR = SOGEGH = AADS$.

Dynamic performance Metrics of Top 10 Stocks

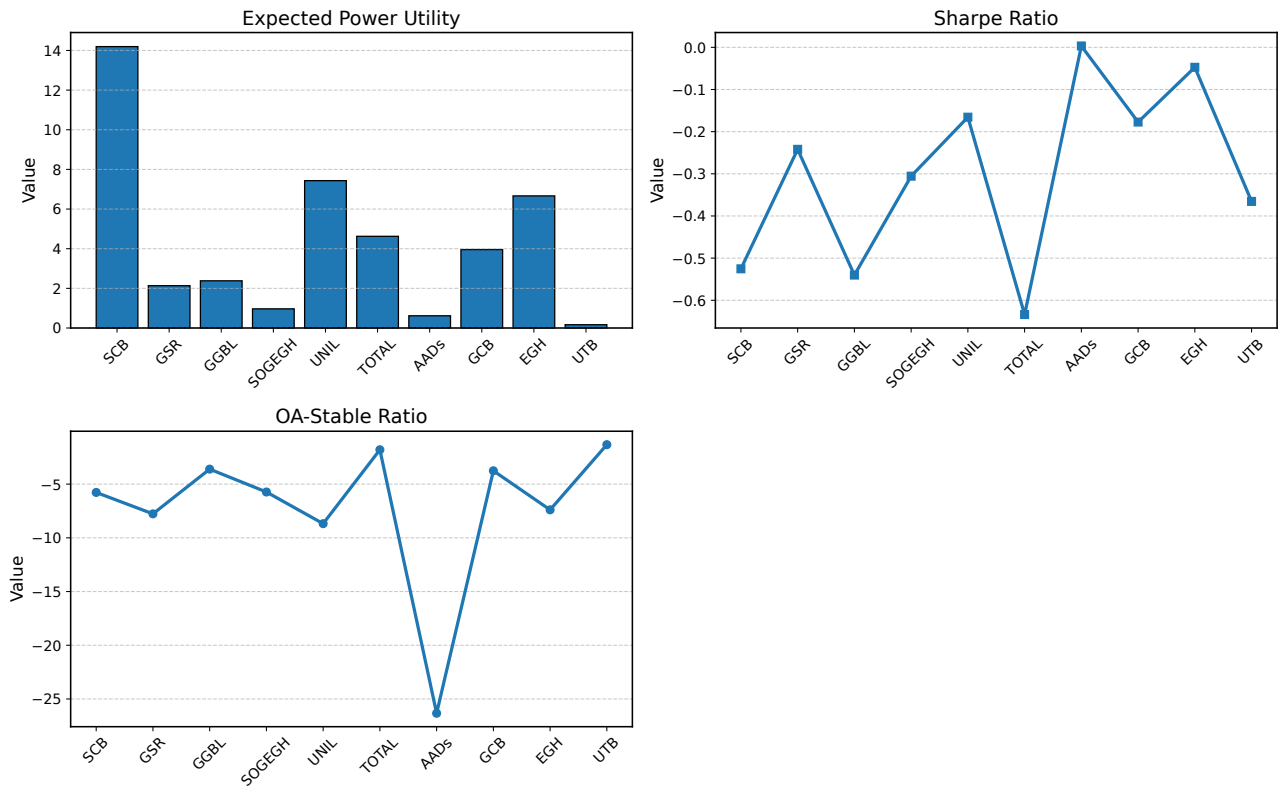


Fig. 2: Top 10 preselected out of 25 stocks using dynamic criteria

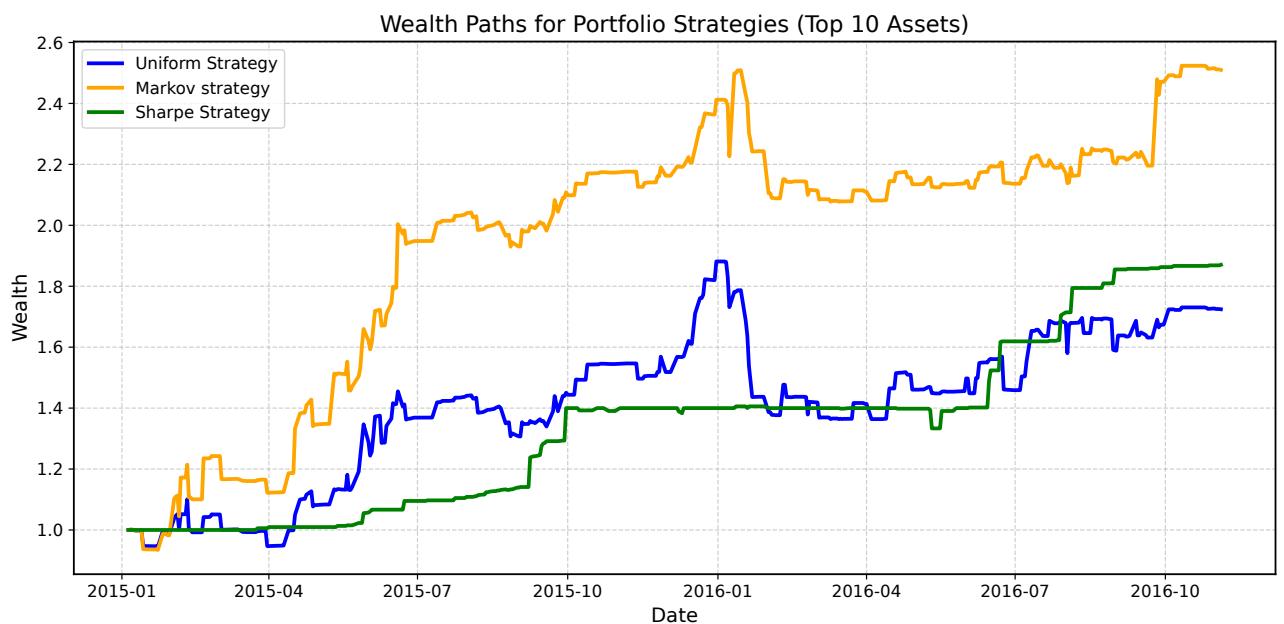


Fig. 3: Comparison of Markov Strategy vs Other Strategies

Result 3: Comparison of Markov Strategy Vrs Other strategies

4.1 Discussion of Results

Figure 3 presents the wealth paths generated by three distinct portfolio strategies—Uniform Strategy, Markov strategy, and Sharpe Strategy—applied to the top 10 preselected assets over a six-month period. The comparison highlights clear differences in performance, stability, and risk–return trade-offs among the strategies.

First, the *Uniform Strategy* (blue line) exhibits moderate growth, with wealth values fluctuating between 0.9 and 1.8. This behavior reflects its equal-weighted allocation principle, which ensures diversification but does not exploit asset-specific risk–return profiles. The volatility of the path indicates that diversification alone does not eliminate exposure to market shocks, yet the strategy provides a baseline against which more sophisticated methods can be compared.

Second, the *Markov strategy* (orange line) outperforms the other strategies in terms of terminal wealth, reaching a value close to 2.1. Its superior performance arises from dynamically reallocating wealth based on a Markov chain model constructed from historical transition probabilities. By adapting to regime shifts in asset behavior, the strategy captures momentum effects and avoids extended drawdowns. Notably, the Markov-based allocation demonstrates both rapid growth phases (e.g., around mid-2015) and resilience during periods of market stagnation (mid-2016), which supports the effectiveness of regime-aware modeling in enhancing portfolio returns.

Third, the *Sharpe Strategy* (green line) produces relatively stable but slower growth, ending with terminal wealth around 1.85. By construction, the strategy favors assets with the highest risk-adjusted returns, as measured by the Sharpe ratio. This selection criterion offers downside protection and avoids highly volatile assets, resulting in fewer sharp drawdowns. However, compared to the Markov approach, the Sharpe strategy is less adaptive to market regime changes, leading to more gradual wealth accumulation.

Overall, the results underscore that the *Markov-based Strategy delivers the best performance in terms of total wealth accumulation*, albeit with occasional short-term volatility. The *Sharpe Strategy provides a conservative, risk-adjusted pathway*, making it more suitable for investors prioritizing stability. Meanwhile, the *Uniform Strategy remains the simplest benchmark*, highlighting the trade-offs between naive diversification and model-driven allocation.

These findings contribute to the broader literature on portfolio optimization by demonstrating that dynamic, regime-aware strategies (such as those based on Markov chains) can outperform both static equal-weighting and single-metric selection approaches. The results also suggest that incorporating both *asset preselection and dynamic allocation* significantly enhances portfolio outcomes in emerging markets.

5 Conclusion

This study examined the role of static and dynamic preselection strategies in portfolio construction and evaluated their implications for subsequent portfolio performance. The results show that the two preselection strategies rarely select the same assets, indicating substantial differences in their selection outcomes. This finding suggests that the choice of preselection method can materially influence portfolio composition and subsequent performance. Consequently, practitioners may benefit from assessing portfolio robustness across alternative preselection frameworks and selecting an approach that is consistent with their investment objectives and risk preferences.

The results further show that the portfolio allocation strategies considered in the study do not generate identical wealth outcomes. In particular, under the Markovian maximum-diversification framework, the resulting portfolios generated higher wealth than the Uniform strategy and the Sharpe-ratio-based strategy over the evaluation periods considered. This finding indicates that incorporating market-state information into portfolio allocation can provide useful information for dynamic portfolio management. The results also highlight the importance of accurately estimating transition probabilities within the Markov-chain framework, since these probabilities determine the estimated evolution of market states and consequently influence dynamic asset selection and allocation.

The findings have implications for practitioners and institutional investors. First, the observed differences between static and dynamic preselection suggest that portfolio evaluation may benefit from considering multiple preselection frameworks. Examining the consistency of asset selection and portfolio performance across alternative approaches can provide additional information about the robustness of an investment strategy and help reduce reliance on a single selection procedure. Second, the results provide support for considering adaptive portfolio strategies that incorporate information about changing market conditions. The observed performance of the Markov-based framework suggests that regime-dependent information can be relevant to portfolio construction, particularly when market conditions evolve over time.

The findings also have implications for risk management. Dynamic asset selection provides a framework through which changes in market conditions can be incorporated into portfolio decisions rather than relying exclusively on static allocation rules. For emerging markets, where market conditions may be affected by liquidity constraints, information

asymmetries, and changing market regimes, such adaptive approaches may provide a useful basis for further portfolio research and investment analysis. However, the practical implementation of these strategies should also account for transaction costs, liquidity constraints, estimation uncertainty, and model risk.

Overall, the results indicate that portfolio outcomes depend not only on the allocation rule but also on the preselection framework through which assets enter the portfolio. The findings therefore support greater consideration of dynamic and regime-sensitive approaches to portfolio construction while recognizing that their effectiveness depends on the market environment and modelling assumptions. The results should be interpreted within the context of the assets, sample period, and empirical framework examined in this study.

Several avenues for future research remain. First, the analysis could be extended by incorporating alternative portfolio selection criteria, including downside-risk measures, liquidity-adjusted criteria, and entropy-based measures. Such extensions would allow the robustness of the observed results to be examined under different definitions of portfolio attractiveness and risk. Second, future research could investigate the scalability of static and dynamic preselection methods in high-dimensional portfolios. As the number of assets increases, the estimation of transition probabilities and the associated portfolio allocation problem may become computationally more demanding.

Finally, although the Markov-chain framework provides a useful representation of regime-dependent market behaviour, financial markets may also exhibit memory and long-range dependence that cannot be fully captured by conventional Markov processes. Future studies could therefore incorporate fractional processes, semi-Markov models, or other non-Markovian state dynamics to investigate whether they provide improved representations of asset-selection and market-state dynamics. These extensions could provide further insight into the robustness and applicability of dynamic preselection and portfolio allocation strategies in emerging financial markets.

Limitations of the study

Despite the findings of this study, and its contribution to knowledge, some limitations should be acknowledged. Although the analysis covers 36 of the available assets in the Ghana Stock Exchange (GSE) dataset, the findings are largely specific to the GSE. Given the emerging-market context of the GSE, the findings may not necessarily generalize to other markets with different market structures and characteristics, particularly developed markets. In addition, the Markov-based strategy depends on the definition of market states, estimated transition probabilities, and selected assets, which may vary under different market conditions. The higher wealth observed for the Markov strategy therefore represents an empirical finding for the study period rather than evidence of general theoretical dominance. Furthermore, full-sample asset selection may introduce selection or look-ahead bias. These limitations provide scope for future studies using larger datasets and out-of-sample evaluation.

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