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Portfolio Optimization Using ANNs and Mean-Semi Variance Markowitz Model: A Comparative Study of South Asian Economies

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ABSTRACT

This study uses many portfolio approaches to optimize mean semi-variance portfolios using artificial neural networks for South Asian investors. These methods include the mean-semi variance strategy, minimal variance approach, limited portfolios with transaction costs and turnover constraints, constrained portfolios with risk and return diversification limits, and the equally weighted approach. These portfolio strategies are analysed using the excess Sharpe ratio and the Information Ratio for financial efficiency and diversity, respectively, and validated using the 130/30 portfolio strategy. The Pakistan Stock Exchange (PSX), Bombay Stock Exchange (BSE), Dhaka Stock Exchange (DSE), Columbo Stock Exchange (CSE), and Nepal Stock Exchange (NEPSE) supply daily data for empirical research. We use a large data collection from 2017 to 2021. The study found that ANN-generated estimators using a mean semi-variance optimization strategy outperformed alternative portfolio optimization methods in South Asian markets. The research reveals that ANN-based returns outperform correlation statistics, descriptive analysis, and mean square prediction error (MPSE). The study suggests utilizing naive diversification as a benchmark for other portfolio optimization methodologies.

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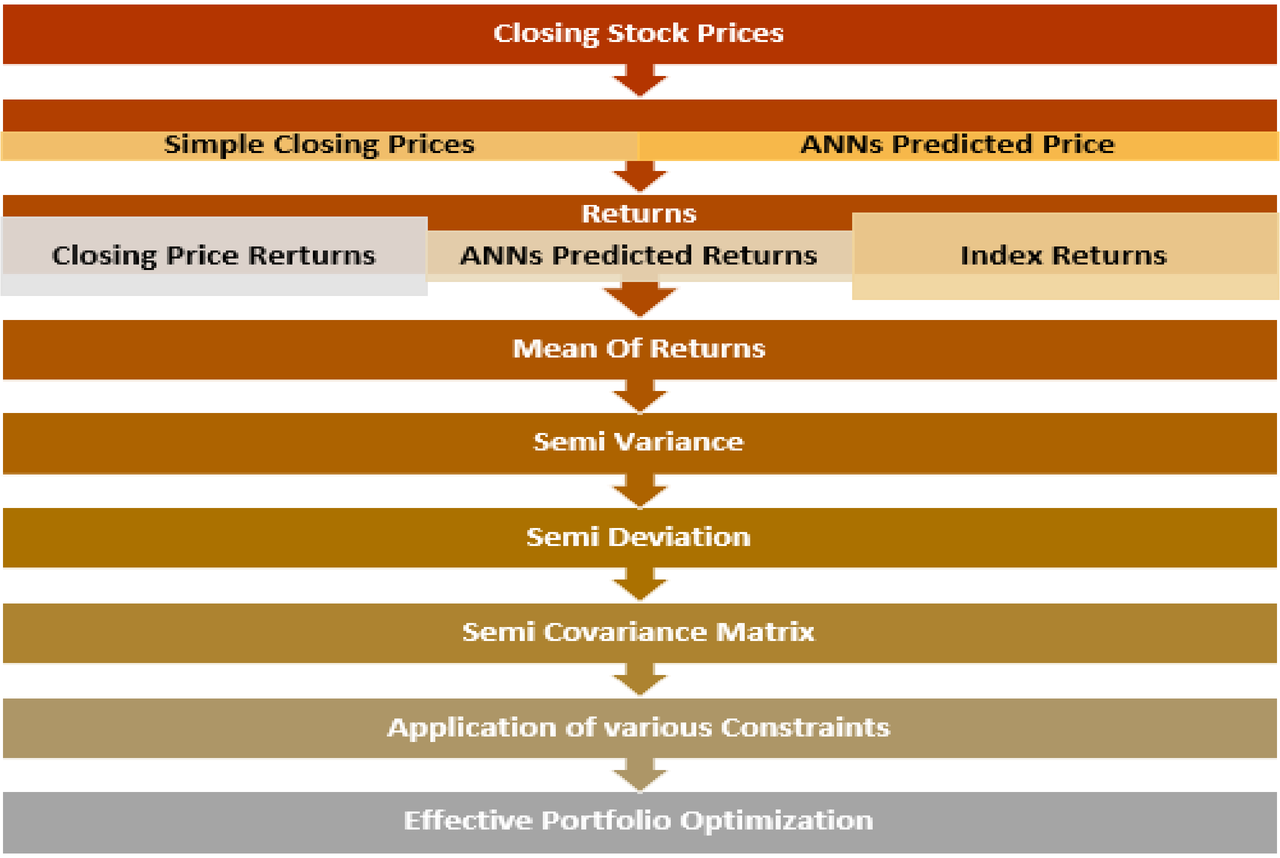
1. Introduction

South Asian stock exchanges are the most accurate, efficient, safe, and honest. With banking services becoming more digital and convenient, customers are gravitating towards online exchange. Online bank accounts allow customers to trade stocks without a broker. An investor wants to know how to minimize risk and maximize reward before investing. In economic theory and practice, investment technique selection is critical because it affects future tool performance, particularly predicted returns. When stocks are unclear, the selection frame must include a quantifiable measurement of risk to achieve the expected return. Financial exchanges are important; therefore, speculation usually follows a projection. However, predicting the securities exchange is important. First, show the non-linear stock price pattern. To prepare input data for optimal processing, it is appealing to delete some highlights (Hajizadeh, Seifi, Zarandi, & Turksen, 2012). Karimi, Kisi, Shiri, and Makarynskyy (2013) provide four financial exchange estimate procedures, including specialized inquiry. Huang and Jane (2009) claim that specialized research manages authentic value development to predict future venture decisions. Deng, Zhao, and Li (2018) recorded ROC, MACD, and inclination moment indicators. Number two is a basic investigation, defined by Ko and Lin (2008) as the evaluation of financial data and other company facts like stock or income growth.

The time series method forecasts time series levels using past functionality. Timeseries run a succession of numbers from an examination to determine periodic allocation (Zhang et al. 2008). Regression, auto-regression, and ARIMA are further time series analytic forecasting methods. Current studies focus on historical data since time-series depend on time frames (Neto, Da Costa, & Maia, 2009). Therefore, AI effectiveness is the last method. Delegates—probably learning delegates—solved its problems. Delegates can learn more. Based on delegate responses, knowledge learning is provided in three forms. In unsupervised learning, the delegate recognizes forms without explicit reaction, while in reinforcement learning, incentives and penalties increase knowledge. During learning through supervision, the delegate is given inputs and outputs to plan for Genetic Algorithms (GA) and Artificial Neural Networks (ANNs). For portfolio optimization, we will use ANNs to anticipate stock prices.

In the semi-variance pattern, risk is a convex mixture of semi-variances (beneath and beyond the anticipated return) that helps investors overcome the reduced risk of any investment, indicating the need for this research. We predict R (Stock returns) using the combinational model combining mean-semi variance Markowitz version and ANNs feedforward backpropagation set of rules with time-series external inputs to make an ideal selection decision. From daily cost data, a neural framework estimator estimates future costs (Bai, Liu, & Wong, 2009), and coming attributes are employed to process expected returns. Markovian structure's projected stock returns were these anticipated returns. This research is based on traces of prediction and quadratic framework (Freitas, De Souza, & De Almeida, 2009; Iqbal, Sandhu, Amin, & Manzoor, 2019; Manzoor & Nosheen, 2022). This study optimizes South Asian portfolios to help investors choose firms with higher returns and reduced risk. Design of the study is mentioned in Figure 1

Figure 1: Design of the Study tracked for Mean-SemiVariance Portfolio Optimization through ANNs



2. Significance of Artificial Intelligence in South Asian Economies

Empirical finance research focuses on predicting stock market volatility. Previous studies were inspired by "Black Monday," the 1987 stock market meltdown. Recurring market calamities emphasize the need to understand volatility. Twenty-three major markets fell on Black Monday. The 2007 global financial crisis (GFC) and the March 2020 COVID-19 pandemic caused global equity markets to crash. Global equity markets plummeted after these occurrences. The DJIA index fell 26% in four trading days, while WTI crude oil entered negative territory for the first time in pricing data history. Global stock markets lost US$16 trillion in 52 trading days. History shows that stock market volatility lead to uncertainty and the prospect of an economic disaster. Thus, financial market modelling and prediction has grown over time to better comprehend crises, tail occurrences, and systemic risk. Because of current information technology advances and machine learning's success in pattern recognition. One of the most successful AI applications in financial markets is Medallion Fund, which has returned 66% annually for 20 years (Kamalov, 2020).

These models approximate universal functions (Hornik et al., 1989; Kosko, 1994). They can learn non-linear patterns and functions. Several studies have examined the efficacy of various ANN and hybrid models. Roh (2007) proposes a hybrid KOSPI Index model using ANN and time series econometric approaches. The hybrid volatility model predicts well. Guresen, Kayakutlu, and Daim (2011) investigate daily NASDAQ returns and find that hybrid models perform worse than ANN models. Roh (2007) disagrees. Kristjanpoller, Fadic, and Minutolo (2014) use ANN-GARCH hybrid models to anticipate three growing Latin American stock markets and find that hybrid models outperform traditional models. Hao and Gao (2020); Kim and Won (2018); Mingyue, Cheng, and Yu (2016); Rather, Agarwal, and Sastry (2015) are researching hybrid models.

Luo, Li, Peng, and Fan (2018) show that deep learning models are far less predictive than classic ANN algorithms. D'Amato, Levantesi, and Piscopo (2022) show that deep learning models work in the chaotic crypto market. Koo and Kim (2023) combine GARCH, LSTM, and volume-upped (VU) distribution methods to create a new model. This improves forecasting. The proposed approach outperforms standalone deep learning methods by 21.03%. Ahamed and Ravi (2021) focus on the optimising problem to assess deep learning network drawbacks. The literature does not show a clear advantage in ANN models or conventional forecasting methodologies. Literature suggests no clear advantages. Ravichandra and Thingom (2016) and Chopra et al. (2021) show that AI models can better predict stock market prices, hence they deserve further study. This study compares Mean semi variance models to standard stock price forecasting models. It analyses more ANNs, uses portfolio optimisation metrics, and discusses the economic ramifications.

2.1. Downside Risk Measurements

2.1.1. Semivariance as a Measure of Downside Risk

The semivariance below the mean value and below the target return are important measures of downside risk in finance. Markowitz suggested them. Despite preferring semivariance conceptually, Markowitz used variance as the risk metric since lower semivariance was harder to quantify. The hardest part of investment diversification is estimating the correlation of Lower Partial Moments (LPM), the most important provision. Researchers and academics continue to examine downside risk quantification despite the computation's complexity. Fishburn (1977); Harlow and Rao (1989) created a generalized form of lower partial moments (LPM) and developed the "(-t)" model, in which 't' represents the investor's risk aversion and Roy (1952)'s desired return of investment or disaster level.

Downside risk underpinned both contributions. An investor's risk tolerance decreases with value. For risk-neutral investors, ɑ = 1; for risk seeking investors, ɑ < 1; and for risk averse investors, ɑ > 1. In addition, Fishburn (1977) presented the Mean-Lower Partial Moment model, often known as the MLPM-model. Note that the (-t) " model is stated as an LPM model when = 2 and t equates to the mean value of the investment return. This is important to keep in mind. The LPM was utilised by Harlow (1991) as a downside risk measurement tool in portfolio decisions. He gave the following definition of LPM: He defined LPM as:

$$\text{n}LPM_n = \sum_{R_p=-x}^{T} P_p\left(\tau - R_p)^n\right) \tag{1}$$

where P_p is the probability that return, R_p occurs. He emphasized that the type of "moment," n, that is described in the LPM equation describes an investor's preferences.

3. Statistical Techniques and Methodology

3.1. Dataset Description for the Research

We utilized the Closing prices data of Stocks for effective portfolio choice and Optimization. Only those organizations for examination were selected, whose trading days were in concordance having equivalent observations in time frame of five years from January 2017 to December 2021. We used T Bills rates and use them as Risk Free Rates. All market share indices of the overall industry Index were utilized as a benchmark to continue with examination.

The constituent' data availability from start date of 02 January 2017 is checked, which leaves us with 100 companies that had a long record of trading history in South Asian Exchanges. The data start date is 2 January 2017 and end date is 30 December 2021 which covers 1200 trading days.

3.2. Statistical Techniques to Accomplish the Exploration

In this segment, we properly rationalize what techniques are to be used in completing our findings from start till portfolio optimization. We describe them in detail in progression as we persist to our anticipated conclusions.

3.3. Proposed Model of ANNs (NARX)

NARX version and its way of forecasting prices is portrayed in subsequent equation.

$$Output\ series = \{h(x(t-1), x(t-2), \dots, x(t-d), y(t-1), y(t-2), \dots, y(t-d)) + \varepsilon(t)\} \quad (2)$$

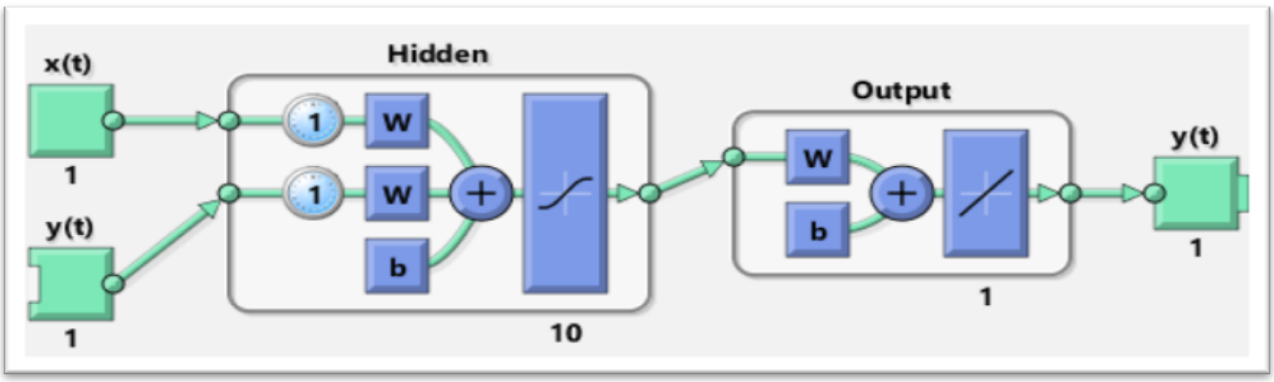
Figure 2: NARX Functionality

3.4. Stages to Forecast Prices of Stocks by using NARX

Subsequent stages are finalized to get the expected prices from ANNs timeseries forecast procedure with NARX modelling process (Carriero, Mumtaz, Theodoridis, & Theophilopoulou, 2015; Iqbal et al., 2019; Ruiz, Cuéllar, Calvo-Flores, & Jiménez, 2016; Weron, 2014).

Stage 1. Choosing the Input variables
Stage 2. Validation and Data Testing
Stage 3. Creating the Architecture of the ANNs
Stage 4. Network Training of ANNs

Figure 3: NARX Architecture. Source: ANNs time series tool using Matlab



NARX net follows Levenberg-Marquardt backpropagate approach (LMBP) which is the universally acknowledged and quickest learning calculation (Chauvin & Rumelhart, 2013; Hagan & Menhaj, 1994; Rumelhart, Hinton, & Williams, 1986). The LMBP calculation is planned to rough approximation second-request subsidiaries having no need to figure the 'Hessian framework' is drawn closer by as uncovered in given eq. 6 and its inclination is made sense of as offered here in eq.8

$$h = J^T J \tag{3}$$
$$g = J^T e \tag{4}$$

LMBP systems backpropagation technique to guesstimate Matrix by Jacobian in the following equation

$$x_{t+1} = x_k - [J^T J + \mu I]^{-1} J^T e \tag{5}$$
$$where, \quad \mu I = fixed\ effects$$

This procedure put into practice Jacobian matrix for determining outcomes. Hereafter, this network utilizes error estimates like MSE, and SSE as stipulated in subsequent comparations (Ruiz et al., 2016; Weron, 2014). The disparity amongst objective and projected cost is computed by applying the LMBP

$$SSE = \sum_{i=1}^{n} (target\ value - output\ value)^2 \tag{6}$$
$$MSE = \frac{\sum_{i=1}^{n} (target\ value - output\ value)^2}{no.of\ data\ samples\ for\ training} \tag{7}$$

Later, we will protect the output value identified as sign of performance by MSE and Regression component 'R' for assessment (LeSage, 1999). (Script attached in Appendix).

3.5. Forecasting Returns Using ANNs

Subsequent method is applied to determine ANNs profits by employing natural logarithm of the Projected prices, $\hat{P}$ and real prices P_t.

$$ANNs\ Predicted\ returns \quad \hat{R} = ln \left[\!\left[\frac{\hat{P}}{P_t} \right]\!\right] \tag{8}$$

3.6. Proposed Model for Optimizing Portfolios using Mean Semi Variance Model with ANNs

The returns from ANNs $\hat{R}$, calculated with ANNs timeseries forecaster are utilized as anticipated returns in our ANNs version, whilst the risk and return for portfolio are computed as;

$$ANNs\ Portfolio\ Risk \quad \hat{v} = \sigma^2 = \frac{1}{N} \sum_{t=1}^{N} (R_t - \hat{R})^2 \tag{9}$$
$$ANNs\ Portfolio\ returns \quad R_p = \sum_{i=1}^{M} X_i \hat{R}_i \tag{10}$$
$$\text{Semi variance} = \frac{1}{n} \times \sum_{rt<Average}^{n} (Average - rt)^2 \tag{11}$$

Where, n is total number of observations below the mean, rt is observed value, and Average is mean or target value of the dataset. The extent of interactive risk $\hat{\gamma}_{ij}$ is expounded as:

$$Interactive\ Risk(Covariance)\hat{\gamma}_{ij} = \frac{1}{N} \sum_{t=1}^{N} (R_{i_t} - \hat{R}_i)^1 (R_{j_t} - \hat{R}_j) \tag{12}$$

After updating all the parameters and formulas we are proposing our model as:

$$Minimize \quad \hat{V} = \sum_{i=1o}^{M} {X_i}^2\, \hat{v}_i + \sum_{i=1o}^{M} \sum_{j=1o, i \neq . j}^{M} X_i X_j \hat{\gamma}_{ij} \tag{13}$$
$$where, \quad \sum_{i=1o}^{M} X_i \hat{R}_i = R, \tag{14}$$
$$also \quad \sum_{i=1o}^{M} X_i = 1\ and \tag{15}$$
$$and, \quad X_{io} \geq 0, i = 1, \ldots, M \tag{16}$$

4. Results and Findings

4.1. Descriptive Statistics

Through the use of descriptive analysis, we were able to better understand the characteristics of the data by calculating the mean and the standard deviation.

Table 1: Descriptive Statistics for Returns of South Asian Countries

Country	Mean	Std. Dev.	Max	Min	JB-[P]*	Obs.
Nepal	0.0149	0.0856	0.3473	-0.2409	9.7 [0.01]	1200
Pakistan	0.0129	0.1	0.3158	-0.2931	2.1[0.35]	1200
Bangladesh	0.018	0.1179	0.4709	-0.339	23.2[0]	1200
India	0.0256	0.1115	0.6344	-0.3718	61.9[0]	1200
Sri Lanka	0.007	0.0696	0.2697	-0.2341	73.6[0]	1200

*Large values for Jarque-Bera test indicates deviation from normality

Looking at the maximum and minimum values, India has maximum value of 63.4 percent while Sri Lanka has minimum value of 27 percent. The Jarque–Bera stats confirm rejection of null hypothesis for normal distribution of the data. Overall, the quantitative feature obtained through the descriptive statistics confirms that the data is systemically good and does not have any abnormality in it.

4.2. Confirmation or Refutation of Our Hypothesis

4.2.1. The Results of Hypothesis 1

"By applying an equal weighted portfolio, the use of Artificial Neural Networks results in significantly higher portfolio returns than the use of the mean-semi variance model."

To begin, we determined the relative weights of our 100 stocks by assigning each stock an equal weight of 1/100, which is equivalent to 0.01. After that, we determined the weighted average returns to the portfolio by multiplying the average returns of 1200 observations by each weight.

Table 2: Risk and return for Naive Portfolio

Equally weighted Portfolio (1/N)			
Country		**MSV**	**ANNs**
Pakistan	Eret (return)	0.003239	0.004412
	Ersk (risk)	0.001341	0.000826
India	Eret (return)	0.005239	0.006406
	Ersk (risk)	0.001279	0.001209
Bangladesh	Eret (return)	0.002589	0.002491
	Ersk (risk)	0.010560	0.001026
Nepal	Eret (return)	0.004238	0.004306
	Ersk (risk)	0.001042	0.001179
Sri Lanka	Eret (return)	0.001546	0.001406
	Ersk (risk)	0.001841	0.001626

In a basic mean-semi variance model for Pakistan, investing one dollar yields 1.6 dollars after five years. Our investment's predicted return. However, ANNs will give investors 2.6 dollars per rupee after five years. Asset-backed note (ANN). If we accept a naive-portfolio, simple mean-semi variance returns will be lower than neural networks returns on the South Asian stock market. Thus, our initial hypothesis is false.

4.2.2. Results of Hypothesis 2

"When compared to a standard mean-semi variance model, the use of neural networks with budget restrictions results in a considerable boost in the portfolio's returns".

Table 3: Risk and return based on Budget constraint

Country		Portfolio without constraints		With Budget Constraint		
		MV	**ANN**		**MV**	**ANN**
Pakistan	Prsk	0.1618	0.189	Qrsk	0.114	0.171
	Pret	0.822	0.626	Qret	0.618	0.607
India	Prsk	0.1668	0.184	Qrsk	0.109	0.166
	Pret	0.917	0.621	Qret	0.613	0.602
Bangladesh	Prsk	0.1568	0.184	Qrsk	0.152	0.157
	Pret	0.817	0.621	Qret	0.513	0.594
Nepal	Prsk	0.1518	0.179	Qrsk	0.104	0.161
	Pret	0.812	0.616	Qret	0.608	0.597
Sri Lanka	Prsk	0.1448	0.172	Qrsk	0.097	0.154
	Pret	0.805	0.609	Qret	0.601	0.592

ANNs prices return 0.189 (annualizing risk daily returns by multiplying by 360), whereas plain closing prices return 0.126. Actual prices return 0.630, while ANN returns 0.619. Based on these parameters, ANNs and actual prices offer similar risk and profit when budgets are limited. ANNs have lower returns than a mean-variance framework with a simple mean and semivariance. This disproves our theory.

4.2.3. Results of Hypothesis 3

"When compared to a standard mean-semi variance model, Portfolio Returns Increase Significantly Using ANNs with Constraints of Target Risks and Target Returns."

We obtained some of the projected portfolios with values that were lower than the desired values by setting the target levels of risk and return at 15% and 20% respectively. The graphs show the effectiveness of the individual stocks in providing investors with the best answer feasible given the parameters of risk and return that they have determined for themselves. According to the findings, a portfolio that takes into account ANNs semi variance approach generates greater returns than semi variance models that are kept straightforward.

Figure 4: Pakistan: Portfolio weights based on target risk and return

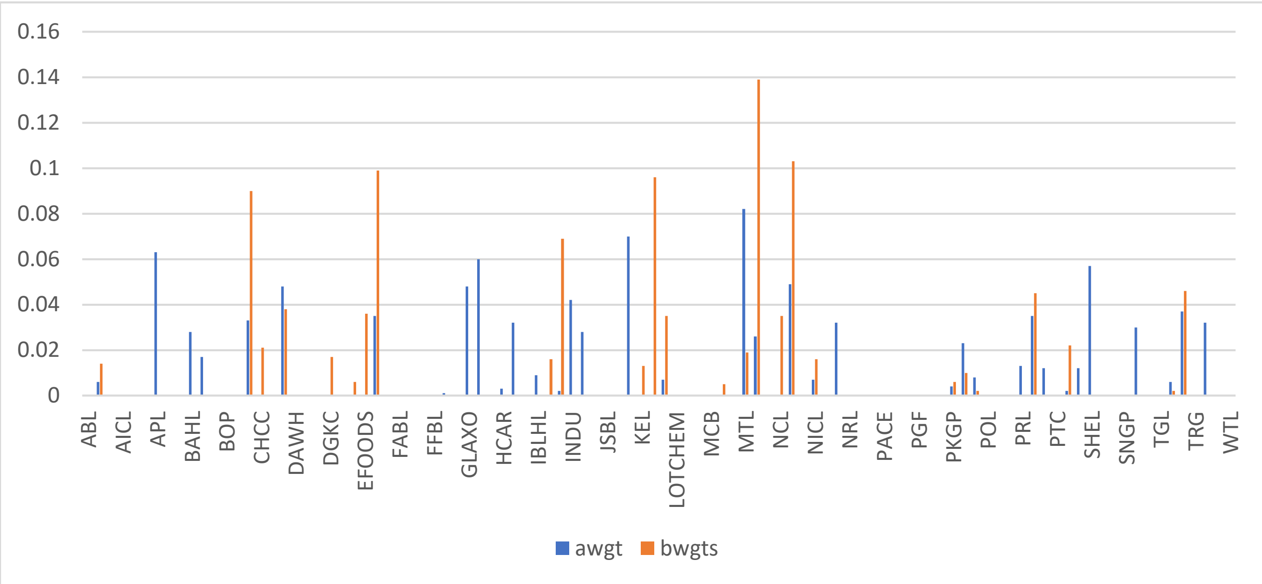


Figure 5: Sri Lanka: Portfolio weights based on target risk and return

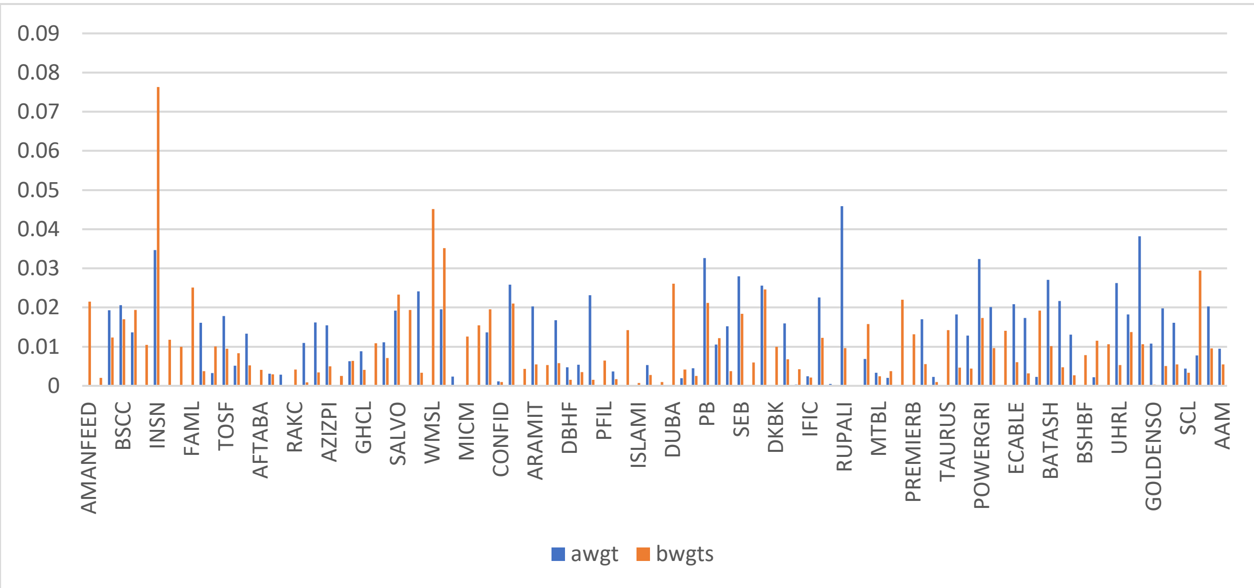


Figure 6: India: Portfolio weights based on target risk and return

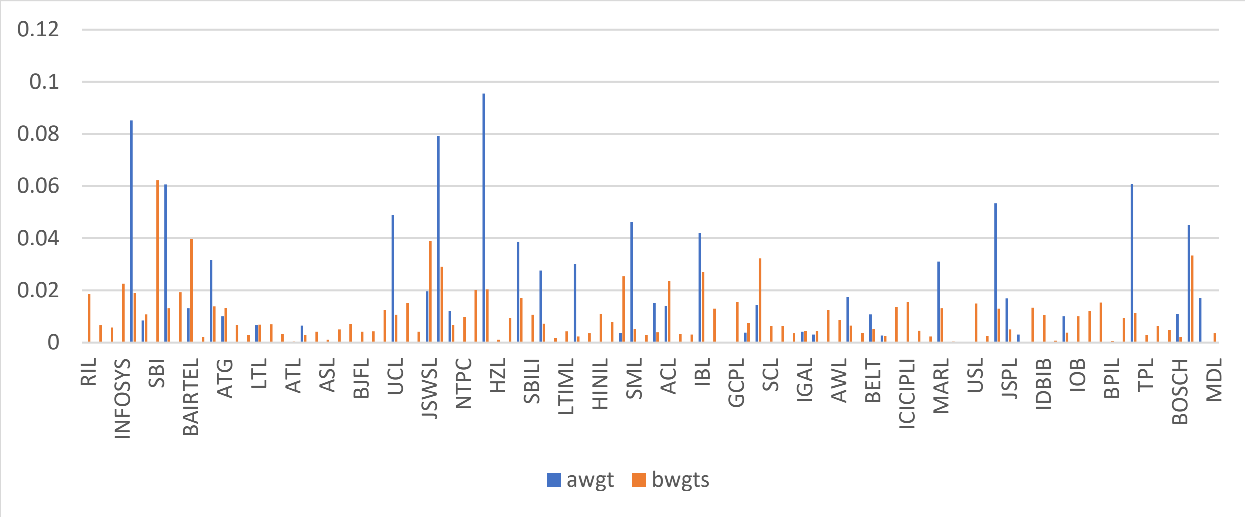


Figure 7: Nepal: Portfolio weights based on target risk and return

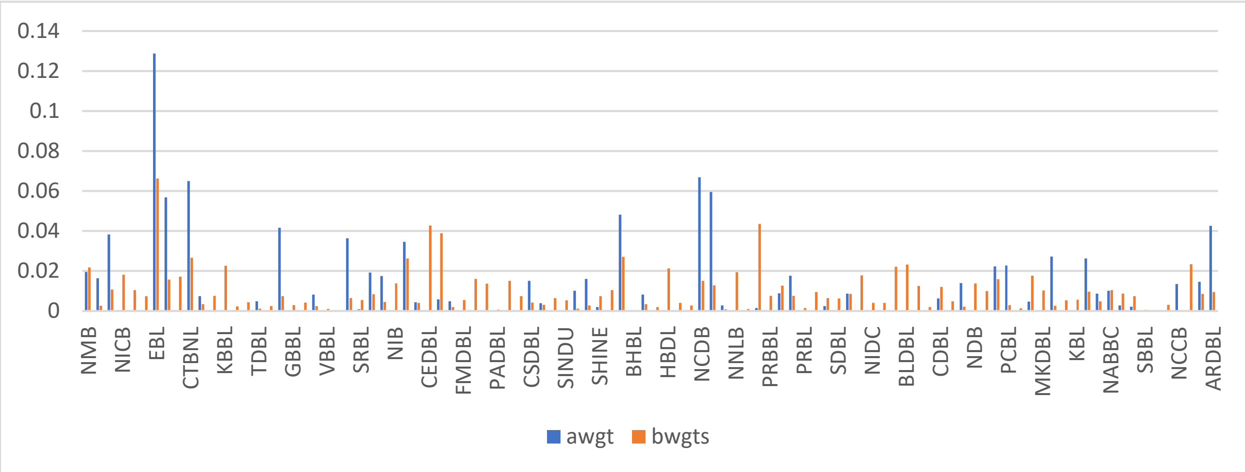
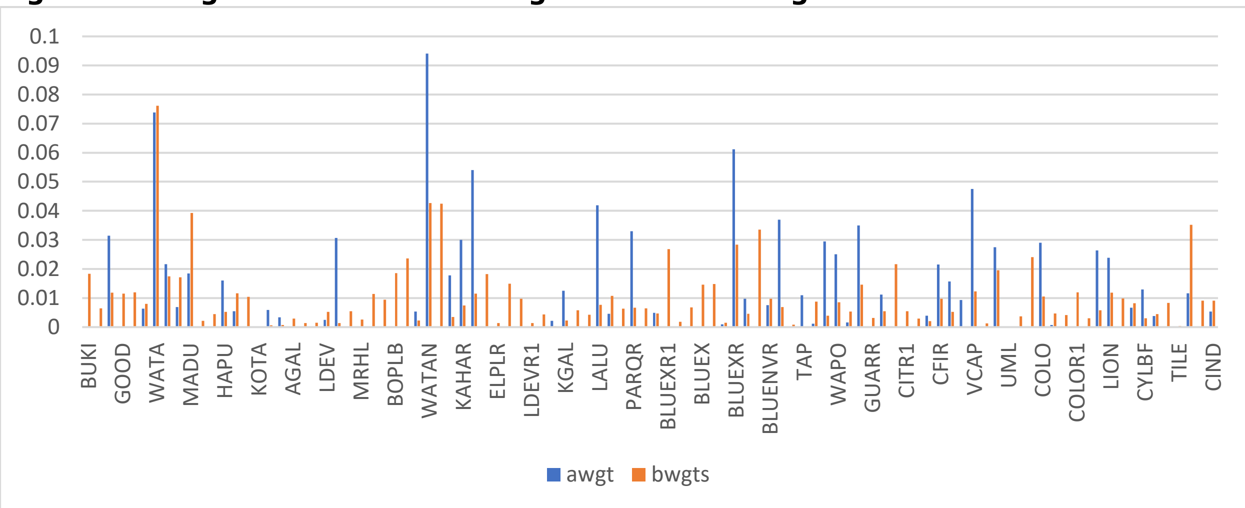


Figure 8: Bangladesh: Portfolio weights based on target risk and return



4.2.4. Results of hypothesis 4

"When compared to a standard mean-semi variance model, the use of Neural Networks with Transaction Cost Constraints results in a considerable boost in portfolio returns."

We found that the difference between the gross and net efficient frontiers is considerable for mean-semi variance returns (0.15) but small for ANNs price returns (0.10). The market is less efficient if transaction costs can be calculated consistently. Thus, mean-semi variance returns are less efficient than ANN price returns.

Table 4: Transaction cost-based Portfolio Risks and Returns

Country	Removing Transaction costs			Applying Transaction costs		
		MSV	ANNs		MSV	ANNs
Pakistan	prsk	0.1618	0.189	Qrsk	0.114	0.171
	pret	0.822	0.626	Qret	0.618	0.607
India	prsk	0.1668	0.184	Qrsk	0.109	0.166
	pret	0.917	0.621	Qret	0.613	0.602
Bangladesh	prsk	0.1568	0.184	Qrsk	0.109	0.166
	pret	0.817	0.621	Qret	0.613	0.602
Nepal	prsk	0.1518	0.179	Qrsk	0.104	0.161
	pret	0.812	0.616	Qret	0.608	0.597
Sri Lanka	prsk	0.1448	0.172	Qrsk	0.097	0.154
	pret	0.805	0.609	Qret	0.601	0.59

Our findings suggest that portfolio returns shift dramatically in terms of simple MV, but less so for ANNs when transaction costs are taken into account. Portfolio returns rise significantly more for simple MSV (0.161) than for ANNs (0.189) for Pakistan, and 0.166 and 0.184 for India. Since no market is 100% efficient, introducing transaction costs increases its value to 0.172 and 0.607 for Pakistan and decreases it to 0.166 and 0.162 for India.

4.2.5. Results of Hypothesis 5

"Portfolio Returns rise considerably using Neural Networks with Turnover restrictions compared to mean-semi variance model."

The turnover constraint is the portfolio sale or buy proportion. We set it to 0.20, 20%. Trading cycles may drive our starting portfolio to an independent efficient frontier. ANNs outperformed the mean-semi variance model when turnover is limited. The table shows unconstrained 'p' values and restricted 'q' values. ANNs have a higher Qret value than the MSV model, even with turnover constraints of 0.20. This proves our theory.

Table 5: Portfolio returns and risk with or without turnover constraint

Country	Unconstrained		Constrained with 20% turnover	
Pakistan	Pret(MSV)	0.001 to 0.0037	Qret(MSV)	0.001 to 0.0048
	Pret(ANNs)	0.0001 to 0.0036	Qret(ANNs)	0.00002 to 0.0060
	Prsk(MSV)	0.001 to 0.0038	Qrsk(MSV)	0.001 to 0.0049
	Prsk(ANNs)	0.0001 to 0.0037	Qrsk(ANNs)	0.00002 to 0.0061
India	Pret(MSV)	0.001 to 0.0043	Qret (MSV)	0.001 to 0.0054
	Pret(ANNs)	0.0001 to 0.0042	Qret(ANNs)	0.00002 to 0.0066
	Prsk (MSV)	0.001 to 0.0044	Qrsk (MSV)	0.001 to 0.0055
	Prsk(ANNs)	0.0001 to 0.0043	Qrsk(ANNs)	0.00002 to 0.0067
Bangladesh	Pret (MSV)	0.001 to 0.0041	Qret (MSV)	0.001 to 0.0052
	Pret(ANNs)	0.0001 to 0.0040	Qret(ANNs)	0.00002 to 0.0064
	Prsk (MSV)	0.001 to 0.0042	Qrsk (MSV)	0.001 to 0.0053
	Prsk(ANNs)	0.0001 to 0.0041	Qrsk(ANNs)	0.00002 to 0.0065
Nepal	Pret(MSV)	0.001 to 0.0039	Qret (MSV)	0.001 to 0.0050
	Pret(ANNs)	0.0001 to 0.0038	Qret(ANNs)	0.00002 to 0.0062
	Prsk (MSV)	0.001 to 0.0040	Qrsk (MSV)	0.001 to 0.0051
	Prsk(ANNs)	0.0001 to 0.0039	Qrsk(ANNs)	0.00002 to 0.0063
Sri Lanka	Pret (MSV)	0.001 to 0.0035	Qret (MSV)	0.001 to 0.0046
	Pret(ANNs)	0.0001 to 0.0034	Qret(ANNs)	0.00002 to 0.0058
	Prsk(MSV)	0.001 to 0.0036	Qrsk (MSV)	0.001 to 0.0047
	Prsk(ANNs)	0.0001 to 0.0035	Qrsk(ANNs)	0.00002 to 0.0059

4.2.5. Results of Hypothesis 6

"Compared to mean-semi variance model, Neural Networks with Sharpe Ratio increase portfolio returns significantly."

Portfolio analysis relies on the Sharpe ratio, an absolute return-to-risk metric. The Sharpe ratio depicts considerably extra portfolio returns per unit of risk (Sharpe, 1994). This ratio plays a vital role in the analysis of portfolios.

Table 6: Portfolio returns and risks with or without Sharpe ratio

Country	Simple MSV Returns Portfolio			With Maximum Sharpe Ratio		
		MSV	ANNs		MSV	ANNs
Pakistan	Prsk	0.1618	0.189	srsk	0.164	0.221
	Pret	0.822	0.626	sret	0.668	0.657
India	Prsk	0.1668	0.184	srsk	0.159	0.216
	Pret	0.917	0.621	sret	0.663	0.652
Bangladesh	Prsk	0.1568	0.184	srsk	0.159	0.216
	Pret	0.817	0.621	sret	0.663	0.652
Nepal	Prsk	0.1518	0.179	srsk	0.154	0.211
	Pret	0.812	0.616	sret	0.658	0.647
Sri Lanka	Prsk	0.1448	0.172	srsk	0.147	0.204
	Pret	0.805	0.609	sret	0.651	0.64

4.2.6. Results of Hypothesis 7

"Compared to simple mean-semi variance model, Neural Networks with Information ratio increase portfolio returns significantly.

Our research shows that MSV closing prices yield lower returns than relative returns and portfolios with the highest Sharpe ratio (see table below). ANNs outperform closing prices return because their Rret is 1.5% compared to 0.76%. Using the information ratio, sretinfo is 0.12% and ANNs are 0.17%, both better than the MSV (closing price returns).

Table 7: Application of relative returns constraints for portfolio optimization

Country	relative returns constraints		Information Ratio	
Pakistan	Rret (MSV)	0.00757	sretinfo (MSV)	0.00124
	Rret (ANN)	0.01522	sretinfo (ANN)	0.00176
	Rrsk (MSV)	0.00106	srskinfo (MSV)	0.00682
	Rrsk (ANN)	0.00071	srskinfo (ANN)	0.01992
India	Rret (MSV)	0.002545	sretinfo (MSV)	0.05271
	Rret (ANN)	0.006019	sretinfo (ANN)	0.05882
	Rrsk (MSV)	0.009493	srskinfo (MSV)	0.03493
	Rrsk (ANN)	0.012967	srskinfo (ANN)	0.04104
Bangladesh	Rret (MSV)	0.016441	sretinfo (MSV)	0.04715
	Rret (ANN)	0.019915	sretinfo (ANN)	0.05326
	Rrsk (MSV)	0.023389	srskinfo (MSV)	0.05937
	Rrsk (ANN)	0.026863	srskinfo (ANN)	0.06548
Nepal	Rret (MSV)	0.030337	sretinfo (MSV)	0.07159
	Rret (ANN)	0.033811	sretinfo (ANN)	0.0777
	Rrsk (MSV)	0.037285	srskinfo (MSV)	0.08381
	Rrsk (ANN)	0.040759	srskinfo (ANN)	0.08992
Sri Lanka	Rret (MSV)	0.044233	sretinfo (MSV)	0.09603
	Rret (ANN)	0.047707	sretinfo (ANN)	0.10214
	Rrsk (MSV)	0.051181	srskinfo (MSV)	0.10825
	Rrsk (ANN)	0.054655	srskinfo (ANN)	0.11436

$1 invested in the Indian BSX portfolio might provide $2.55 in MSV (closing price returns) and $5.88 in ANNs projected returns. Our hypothesis is valid since ANNs mean-semi variance strategy boosts portfolio returns more than closing price returns.

4.2.7. Results of Hypothesis 8

"The Neural Networks and Simple mean-semi variance model portfolio is highly feasible for 130/30 investment."

Our investigation found that south Asian portfolios meet 130/30 standards for long and short positions, making them investable. The fact that an evenly weighted portfolio has lower returns than a portfolio with a weighting ratio of 130/30 shows that our portfolios are substantial and investable and that ANNs are more accurate than a mean-semi variance model. Our ANN model improves portfolio returns by 3.9%. Our theory is right.

Table 8: Portfolio risk and returns by applying 130/30 fund structure

Country	Without 130/30 Structure			130/30 Structure		
		MSV	ANNs		MSV	ANNs
Pakistan	Prsk.	0.1738	0.201	qrsk	0.2031	0.2444
	pret	0.834	0.638	qret	1.0276	1.0625
India	prsk	0.1668	0.184	srsk	0.2031	0.2444
	pret	0.917	0.621	sret	1.0276	1.0625
Bangladesh	prsk	0.1568	0.184	srsk	0.2031	0.2444
	pret	0.817	0.621	sret	1.0276	1.0625
Nepal	prsk	0.1518	0.179	srsk	0.2031	0.2444
	pret	0.812	0.616	sret	1.0276	1.0625
Sri Lanka	prsk	0.1448	0.172	srsk	0.2031	0.2444
	pret	0.805	0.609	sret	1.0276	1.0625

5. Conclusion and Recommendations

In portfolio management and asset allocation, Markowitz's mean-semi variance model has been widely used. However, its stringent mathematical assumption that portfolio asset returns follow a normal distribution has drawn criticism. This assumption underlies most of its criticism. The mean-semivariance model may provide investors with an asset allocation approach that minimizes asset allocation in assets with higher variance. The plan would minimize the share of assets allocated to assets with higher variance and semivariance.

Our semivariance model findings have practical implications for investors, both individual and institutional, for asset allocation and portfolio optimization while limiting downside risk. Individual and institutional investors are affected. Both options could have these effects. It is most relevant to the banking and insurance industries, which have a higher risk aversion for bad outcomes. Insurance firms and commercial banks in developed and developing countries must maintain a certain level of capital based on the risk of their investments. This requirement safeguards these institutions' finances. This applies to industrialized and developing nations. Insurance companies and banks want to minimize risk while maintaining a targeted return on investment.

This result was obtained despite both sectors' efforts to cut capital requirements to the lowest possible level. The mean-semivariance approach could help these organisations manage risk. The mean-semivariance approach also lets portfolio managers accurately define risk based on the investment portfolio's goals and limits. Follow-up measurements for this research include: More study is needed into more complex optimization methods that account for investor behaviours such fear of loss, overconfidence bias, and self-attribution bias. Future study should include return vector estimators like the black-litterman (BL) model, ARIMA model, etc. Future study should focus on improving portfolio optimization methods. Optimization determines if a portfolio is optimal. Research should find better covariance estimators. These matrices can increase portfolio performance and financial efficiency. Future portfolio construction research should employ cutting-edge studies.

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