Stationary Bootstrap to Determine the Optimal Portfolio Weights and Obtain the Value at Risk

SC/2021/12450
SC/2021/12482
SC/2021/12508

Group 01
Supervisor : Prof. Leslie Jayasekara
Department of Mathematics
Faculty of Science
University of Ruhuna

Contents

Introduction

Background of the Study

- Asset diversification reduces risk by spreading investments across different assets, ensuring a more stable return.
- With growing uncertainty in the financial markets, investors are becoming increasingly concerned about the future of their investments.
- It is difficult for investors to identify an optimal portfolio by balancing both return and loss.
- Analysts use techniques to gain confidence in the future behavior of investments.

Aim and Objectives

Aim :

Apply the stationary bootstrap method to generate the re-samples and determine the optimal portfolio weights that minimize risk while effectively maximize return using Value at Risk (VaR).

Objectives :

1. Evaluating the optimal portfolio weights under uncertain circumstances and calculating the portfolio future risk.

2. Create the application for any stock market portfolio and determine the optimal weight and risk then help to the investors decision.

Research Problem

The Colombo Stock Exchange has 284 listed companies. Investors seek to know which stocks to purchase based on technical and fundamental analysis ?

Significance Of the Study

- Obtain an accurate approach using stationary bootstrap to portfolio optimization by accounting for market uncertainties and volatility.
- Examines Value at Risk (VaR) estimation using different portfolio weights and confidence intervals.
- Investors can get an idea of how to allocate their capital between different companies.
- Gain a better understanding of how to choose which stocks to purchase.

Literature Review

Literature Review

- Kunsch (1989) and Liu and Singh (1988) have independently introduced nonparametric versions of the bootstrap and jackknife that are applicable to weakly dependent stationary observations.
- Rockafellar and Uryasev (2000), Bengtsson and Olsbo (2003), and Pritsker provide an overview of the standard tools used for measuring financial risk as VaR.
- A bootstrap-based approach explored using leveraging Michaud's (1999) re-sampled efficiency method, which reduces reliance on excessive constraints and uncertain information. The study compares block bootstrap optimization models with the traditional Markowitz model using frequently traded stocks on the BSE.

Materials and Methods

1) Identifying Key Variables:

- Daily stock price data from the Colombo Stock Exchange was gathered for two selected companies covering the period from January 2016 to June 2020.
- The data set was sourced from the Kaggle website.

Company Name	**Symbol**	**Data Type**
LOLC Holdings PLC	LOLC	Float
United Motors Lanka PLC	UM	Float

2) Data Preparation:

1. Calculate the **monthly average stock prices** using daily data.
2. Then calculate the **monthly return** values for the each stock prices.

$$\text{Stock Return} = \frac{\text{Ending Price} - \text{Beginning Price}}{\text{Beginning Price}} \times 100\%$$

3. Calculate the **portfolio returns** according to the various weights.

$$\text{Portfolio Return} = \sum_{i=1}^{n} w_i R_i$$

Data Preparation Cont...

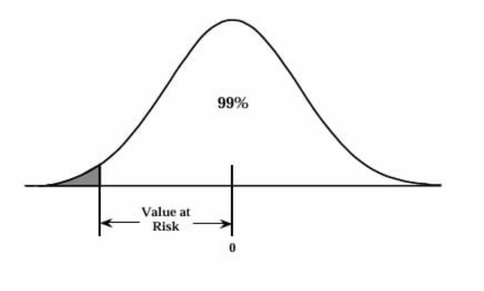
1. Use the **non-parametric** method for analysis

- It is difficult to individually check the normality assumption for each portfolio return weights because it involves a 100 number of portfolios.
- Then can be select the bootstrap method to generate samples.
- Stationary bootstrap method was used to dataset because of stock prices depend on time under different market conditions.

3) Analytical Methods

1. **Value at Risk (VaR)**

   Use historical portfolio returns values in 99% confidence level for calculate the VaR value.



Analytical Methods Cont...

1. **Stationary Bootstrap**

   This is **resampling technique** to obtain samples and also this method considers **data dependency** between data. Resample B datasets

   $X_1^*, X_2^*, \ldots, X_B^*$ of size n with replacement from the original dataset X.

   For each bootstrap sample X_b^*, calculate the bootstrap statistic:

   $$\theta_b^* = t(X_b^*), \quad b = 1, 2, \ldots, B.$$

   The bias of the statistic θ can be estimated as:

   $$\text{Bias}(\hat{\theta}) = E[\theta^*] - \hat{\theta},$$

   where:

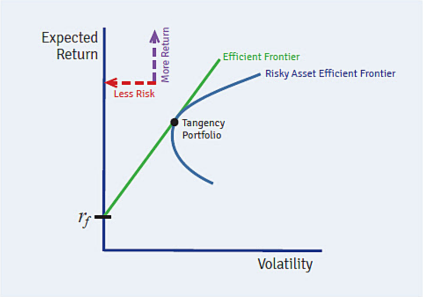
   $$E[\theta^*] \approx \frac{1}{B}\bar{\theta}^* = \frac{1}{B}\sum_{b=1}^{B} \theta_b^*.$$

Analytical Methods Cont...

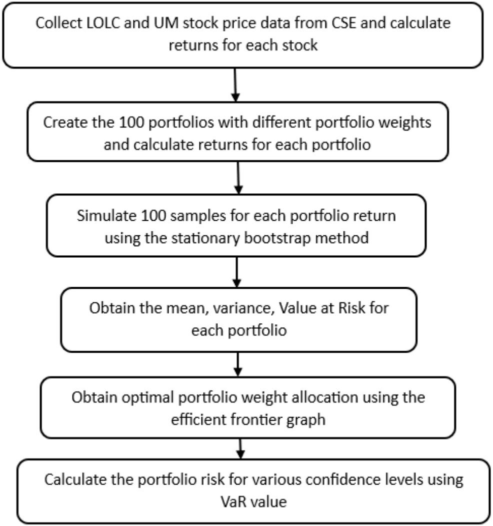
1. **Sharpe Ratio**

   This ratio is used to calculate the **optimal portfolio weights**.

$$\text{Sharpe Ratio} = \frac{\text{Expected Return} - \text{Risk Free Return}}{\text{Standard Deviation of Return}}$$



4) Conceptual Framework



Results

Portfolio Weight Allocation

- This table shows the head of the **portfolio weight allocations**.
- Generate 100 portfolios according to the uniform distribution and all portfolio weights are **greater than 10%**.

Portfolio	LOLC	UM
1	0.4380039	0.5619961
2	0.4015565	0.5984435
3	0.2365534	0.7634466
4	0.5776600	0.4223400
5	0.8106526	0.1893474
6	0.5243222	0.4756778

Bootstrap Simulation

- This plot shows the bootstrap 100 samples for the equal weight portfolio. Some samples are highly volatile, rather than the original values.

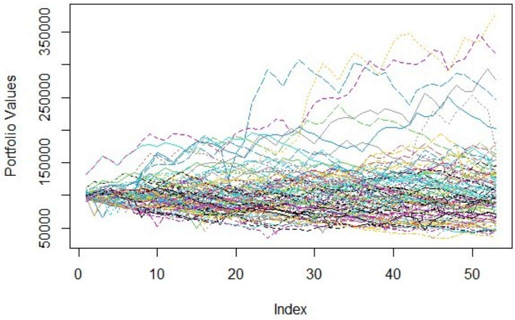


Figure: Bootstrap simulation of equal returns portfolio

Efficient Frontier

- This graph shows the returns and standard deviation values for **100 portfolios**. Then calculate the sharp ratio value for every point.
- Use **maximum sharp (0.1718)** ratio for obtain the optimal portfolio weights. **(LOLC:61.71% and UM:38.29%)**

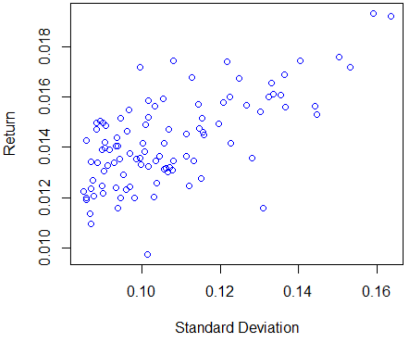


Figure: Efficient frontier of investment portfolio

Optimal Portfolio VaR for Various Confidence Level

- This plot shows the VaR values for each confidence level. According to the graph, as the confidence level increases, the VaR value also increases.
- 99% confidence level = 19.13%
  95% confidence level = 7.93%

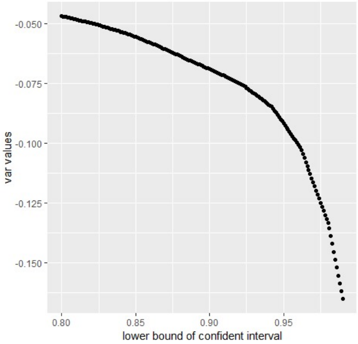


Figure: Optimal portfolio VaR values

VaR Values of Optimal Portfolio

- This table shows the VaR values for each confidence level.
- Select the confidence level which has maximum VaR value. Because it has the highest loss with comparing other confidence levels.
- The chosen confidence level depends on the preferences of the investor or entity.

Confidence Level	VaR value
99%	-0.1913 (19.13%)
98%	-0.1443 (14.43%)
95%	-0.0793 (7.93%)
90%	-0.0580 (5.80%)
85%	-0.0483 (4.83%)
80%	-0.0414 (4.14%)

Table: VaR values of optimal portfolio

Selecting Optimal Portfolio Weights

- This pie chart shows the optimal portfolio and its 99% confidence level VaR value is 19.13%.

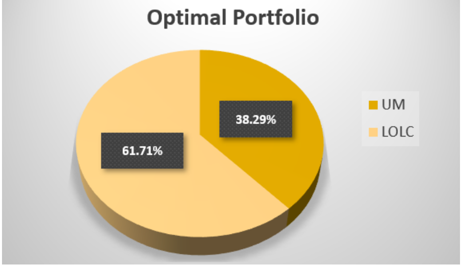


Figure: Optimal portfolio allocation

Discussion

Discussion

- Assume investor select three companies (LOLC/UM/Sampath Bank) according to the fundamental and technical analysis then can be make four different portfolios.

  Portfolio 1 : LOLC, UM and Sampath Bank
  Portfolio 2 : LOLC and UM
  Portfolio 3 : LOLC and Sampath Bank
  Portfolio 4 : UM and Sampath Bank

- Using this model can be obtain the **VaR values** for this four porfolios then **choose minimum risk and invest according to the its optimal weights**.

Discussion Cont...

	LOLC	**UM**	**Sampath**	**VaR**
Portfolio 1	13.67%	61.61%	24.70%	-19.13%
Portfolio 2	61.71%	38.29%	-	-28.04%
Portfolio 3	80.50%	-	19.50%	**-16.35%**
Portfolio 4	-	76.69%	23.30%	-39.94%

Table: Optimal portfolio

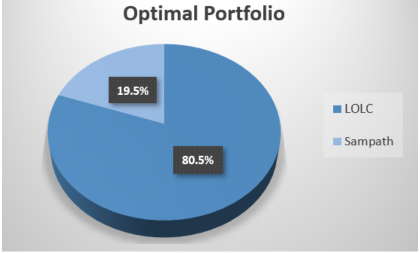
This table shows optimal portfolio weights in 99% confidence level for the above four portfolios. Among them, Portfolio 3 is selected for investment as it has the minimum Value at Risk (VaR) and it is -16.35%.

Conclusion

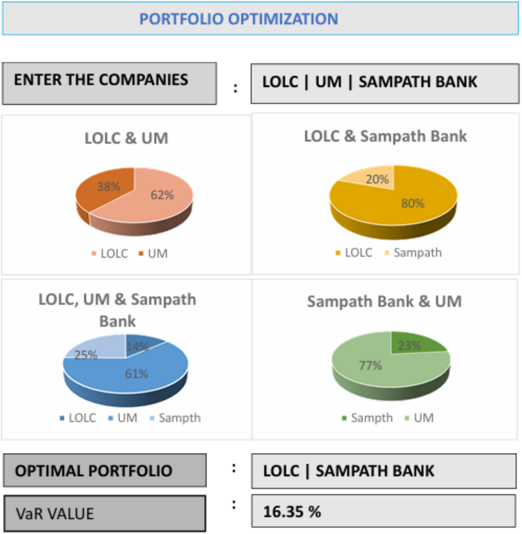
Conclusion

Key Findings :

- According to this application among the **LOLC,UM and Sampath Bank** companies, best optimal portfolio is 80.5% LOLC and 19.5% for Sampath Bank and its VaR value is 16.35% at 99% confidence level.
- When increasing confidence level then VaR value is increasing.



Portfolio Optimization Interface



Conclusion Cont..

Limitation of the Model :

- Investors can use this model for get the future decisions but in future volatility is more impact to the model accuracy.

Future Research Directions :

- Therefore, it is more accurate to recommend a combination of bootstrap plus any machine learning forecasting technique for future prediction.

References

References

- Dimitris N Politis and Joseph P Romano. The stationary bootstrap. Journal of the American Statistical association, 89(428):1303–1313, 1994
- Jos´ e Jim´enez-Moscoso and Viswanathan Arunachalam. Using tukey's g and h family of distributions to calculate value-at-risk and conditional value-at-risk. Journal of Risk, 13:95–116, 06 2011
- Pin-Huang Chou andGuofuZhou. Usingbootstrap to test portfolio efficiency. Annals of Economics Finance, 7(2), 2006

Thank You