Modern Portfolio Theory and Application in Australia

Yanjie Cui and Chulong Cheng

Abstract—**International financial markets are facing unprecedented challenges due to the impact of COVID-19. This paper aims to test whether the modern portfolio theory (MPT) is still applicable as an efficient tool for evaluating stock returns and excess returns under volatile markets. It includes an evaluation of prior works that first started out the MPT and those who furthered Markowitz's innovative algorithms. Basically, this theorem aims at helping investors make investment decisions by lowering investment risk to the minimum and at the same time reaching a maximum payoff. The methodology of testing is implying a trading algorithm based on the MPT in a set of R scripts. The algorithm generates an optimized portfolio from the six biggest stocks traded on the Australian Securities Exchange and the 30-day bank bill swap rate from the Reserve Bank of Australia. It uses the training data to calculate the returns and standard deviations of the portfolio and uses the held back data to examine. Evaluation of the algorithm is carried out using a portfolio that has an initial value of $10,000,000. The result shows that a simulated 99th percentile of the portfolio value distribution at the 10 days' time-horizon is $531,805,142, indicating that the portfolio will not incur a huge gain or loss. Therefore, the trading algorithm performs relatively well in a volatile international financial situation, and the modern portfolio theory still has reference value and guidance for the future development of financial markets.**

Index Terms—**Modern portfolio theory, stock returns, algorithm efficiency, COVID-19.**

I. Introduction

A. Research Background and Motivation

The outbreak of the new crown pneumonia epidemic in 2019 has brought a huge impact on the development of the world society and economy, and the development of financial markets has also been greatly affected, and the volatility of stocks is more significant than in previous years, which is a greater challenge for both investors and financial market managers, and how to regulate the development of stock markets and guide investors to participate rationally in market investment activities has become an urgent need to be solved at this stage One of the issues that needs to be addressed at this stage. However, due to the inherent uncertainty of financial markets, it is difficult to have a uniform evaluation algorithm for different stocks, and an effective evaluation model for stock markets is needed to achieve better investments. As mentioned by Nobel Prize winner Harry Markowitz in his Modern Portfolio Theory (Markowitz, 1952), it is possible to generate relatively better returns than speculating on only one asset by evaluating the portfolio as a whole and by applying a good diversification strategy [1].

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B. Literature Review

Markowitz's Modern Portfolio Theorem (MPT) is surrounding important points like helping investors maximize their returns under a certain level of risk and helping investors reduce their risk by diversification (i.e., choosing different products to spread investors' risk) (Markowitz, 1952) [1]. With this assumption that we believe investors are rational, or even risk-averse, saying they would purchase the portfolios that are less risky along with less return. Why is this the case? let's simply put that MPT gives us the suggestion that when investors are rational, and they are more likely to choose the portfolio with the least volatility. However, MPT shows that using the principle of expected variance, it is possible to hedge the risk posed by individual stocks by selecting stocks with minimized risk (Markowitz, 1952) [1]. In other words, the total risk of a portfolio is lower than that of the individual assets themselves. For the MPT to work, there are some other assumptions that we need to hold. For example, the variance between periods is independent of each other, but in reality, it is a hard job to find two assets that are totally independent of each other (Elton & Gruber, 1997) [2]. In addition, the MPT also brings up the Efficient Surfaces (Markowitz, 1952) [1]. In this concept, this article obtain a graph that gives us different combinations of possible stocks that can provide a decent level of return at a certain risk level. Those that are outside the graph are the ones that bear too low in return or too high in risk.

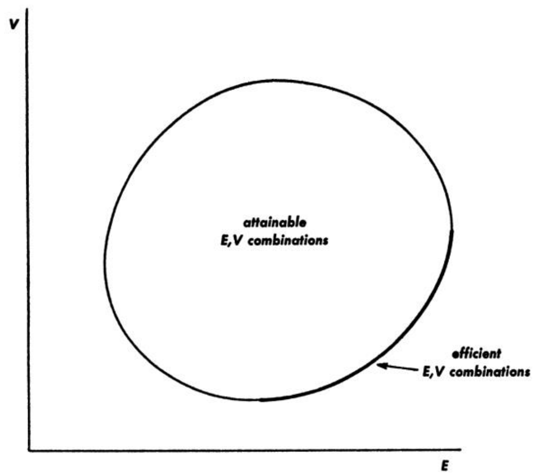

Fig. 1. Efficient Surfaces [1].

However, what is the important factors to focus on when we apply the theory in real life? According to Shipway's research (Shipway, 2009), the three main factors include the annual expected return of holding an investment, the risk of each component of the portfolio, and the way the assets interact with each other [3]. A scenario is given in the

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Shipway, 2009 study to demonstrate the problem of how assets interact with each other. This is shown in the Fig. 2 below.

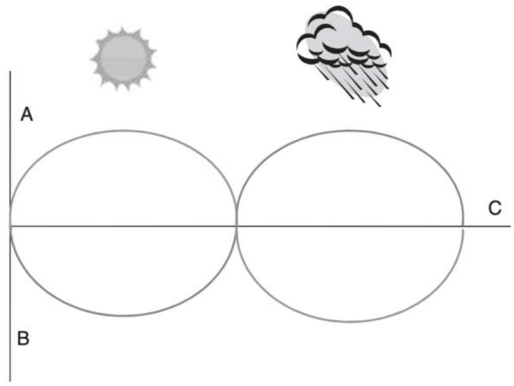

Fig. 2. Diagram of how different assets interact with each other [3].

Those discussed are the fundamentals of the Modern Portfolio theory. There are also some later works that bring up the potential problems that go with the theory and some even come with possible improvements. Scholars (Fabozzi, Gupta, & Markowitz, 2002) suggested that MPT is a normative theory, that someone should do to build an optimal portfolio, other than something we should always follow [4]. Therefore, policy-wise, when we put our portfolio under specific economic conditions, we need to account for the economic stability as well as the political stability of the economy instead of only looking at historical data like most applications are doing. From a corporate diversification perspective, it might be a different story that MPT might not fitfully apply (Lubatkin & Chatterjee, 1994) [5]. There are two types of risks we need to consider Unsystematic risk, risks that are particular to the firm not to the market, fire, CEO death etc. and systematic risk involving all firms in the market, like government policies etc. It might be confusing, but how to tell apart systematic risk and firm-specific risk is hard. Those two kinds of risks are intrinsically correlated to each other making the way of corporate diversification inconsistent with the MPT. Some further analysis applies the MPT to other disciplines but discovered possible shortcomings of the theory. From Curtis (Curtis, 2004)'s research about MPT and behavioral Finance, Curtis pointed out the "descriptive" nature of the MPT other than "prescriptive", which is like what (Fabozzi, Gupta, & Markowitz, 2002) mentioned that no one has to follow the MPT suggestion [4], [6]. In other words, it is likely that human behaves irrationally, but with the new study in behavioral science, it is possible to fill up the hole left by the MPT theory. Other than stock portfolio selection or other businesses application, it is also possible to apply the MPT in other areas such as on how E&P companies (upstream exploration and production companies for search, exploration, drilling, and extraction phases) select projects that minimize their risk (Orman & Duggan, 1999), or in an energy planning and electricity production situation (deLlano-Paz, Calvo-Silvosa, Soares, & Antelo, 2017) [7], [8].

C. Research Contents

This paper attempts to analyze the effectiveness of modern portfolio theory based on economic trends from 2000 to 2020, with sample data spanning 20 years and covering the major events of the 2008 financial crisis and the 2019 New Crown Pneumonia epidemic. The research framework of this paper is as follows; the first part is the introduction, which includes an introduction to the paper and a review of the literature, the second part is the methodology, which includes the specific expressions of the trading algorithm, the data sources of this paper and the analysis of the properties of the stock market in the sample time span, the third part is the results and discussion, and finally the conclusion.

II. Methodology

A. The Trading Algorithm

Professor Geoffrey Shuetrim of the University of Sydney, who wrote the original trading algorithm for his ECMT 2130 Financial Econometrics course in the second semester of 2020, derives optimized portfolios based on Markowitz's modern portfolio theory. It has the following properties. The algorithm is implied in a set of R scripts with the training data. It assumes a transaction cost associated with trading risky assets, a trade of $1 risky asset will incur 0.1% of the trade amount transaction costs, which are too small to account into the portfolio optimisation process. Thus, the weight on the risk-free asset was adjusted to account for it. There are two constraints on the portfolio. One is that the algorithm rebalances the weights monthly on a selection of equities to form a fully invested portfolio, which restricts the portfolio weights. The other is only long action is permitted, so weights of the risky assets must be nonnegative. It computes the capital allocation line (CAL) using the expected return and standard deviations of return of fully invested portfolios, as well as the risk-free rate, then derives the negative Sharpe Ratio (slope of the CAL). The resulting portfolio should be on the CAL. It generates the efficient frontier and defines the tangency portfolio (updated monthly). Then the algorithm adjusts weights on the tendency portfolio (i.e., optimal risky portfolio) and the risk-free asset to reach the 2% target return. Weights on the optimal risky portfolio cannot be more than 150% of the initial invested amount. The performance of the algorithm is evaluated using a portfolio that has an initial value of $10,000,000. Eventually, the algorithm iterates the weights of each asset in the targeting portfolio and reports the result graphically.

B. Source of Data

For the evaluation of the current trading algorithm, we take the data of the six biggest stocks traded on the Australian Securities Exchange (ASX) in accordance with their market capitalisation (Australia blue chips, n.d.) [9]. These stocks are BHP.AX, CBA.AX, TLS.AX, RIO.AX, NAB.AX, ANZ.AX. All the stock data, including the closed price and adjusted price, is retrieved from Yahoo Finance from 2000/11/01 to 2020/06/30 on a daily frequency (Yahoo Finance, n.d.) [10]. To be specific, the period of the Global Financial Crisis and the beginning period of COVID-19 is also included to test that if the trading algorithm is robust to such great shocks in financial markets under a turbulent international situation. For data of the risk-free rate of return, the trading algorithm takes the 30-day bank bill swap rate as the risk-free rate which is a combination of older 30-day bank bill rates from 1976 to 2010 with more recent data from the

Reserve Bank of Australia (RBA). All missing risk-free rate values are replaced with the value from the preceding day. Note that they are annualized risk-free rate and thus each of them should be de-annualized using the formula $\frac{rf}{12}$.

C. Analysis of Stock Properties in Training Time Span

Since the data is split into a training set and a held back set, we set the time span of training from 2000.12.01 to 2010.12.31. The simple monthly price returns of stocks (in percentage) are computed as the following in the algorithm.

$$Monthly\ Returns = 100 * \frac{StockPriceChangesData}{StockPriceLagData} \quad (1)$$

Theoretically, the excess return can be expressed as,

$$Excess\ Return = stock\ return - risk\ free\ rate \quad (2)$$

The rank of average monthly excess returns and average monthly excess return standard deviations of each stock is presented below respectively. For missing values in stock price returns, the algorithm removes that observation from the dataset.

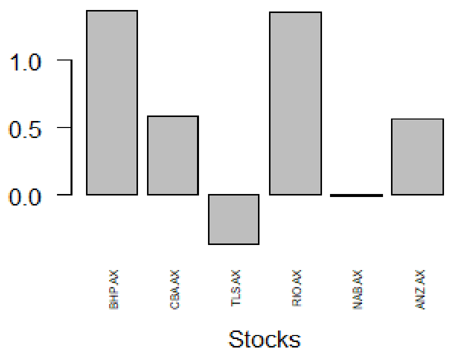

Fig. 3. Rank of average monthly excess returns.

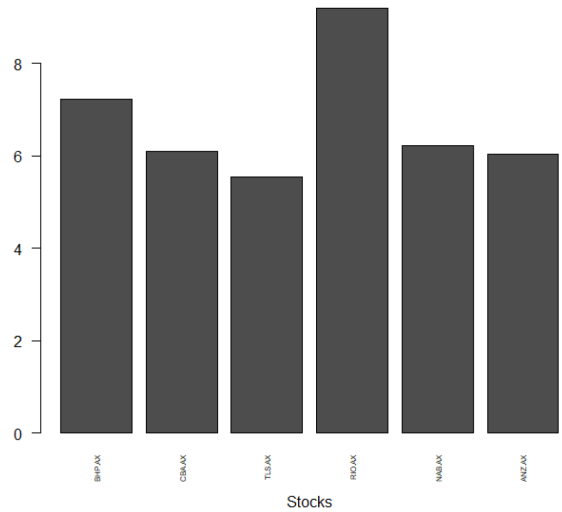

Fig. 4. Average monthly excess return standard deviations.

This paper uses the Sharpe Ratio to measure the ratio of a portfolio's risk premium to its standard deviation (Brealey, Myers, & Allen, 2017) [11]. The formula is

$$Sharpe\ Ratio = \frac{Average\ monthly\ stock\ returns - Average\ risk\ free\ rate}{Average\ monthly\ stock\ return\ standard\ deviation} \quad (3)$$

The rank of Sharpe ratios of each individual stock and correlations between the excess returns on the stocks are presented below respectively.

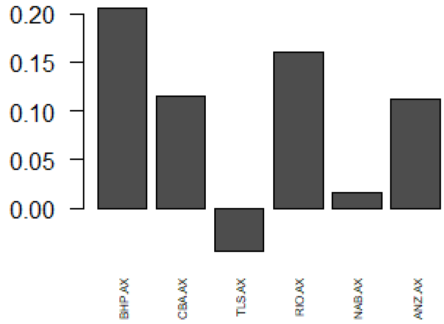

Fig. 5. Rank of Sharpe ratios.

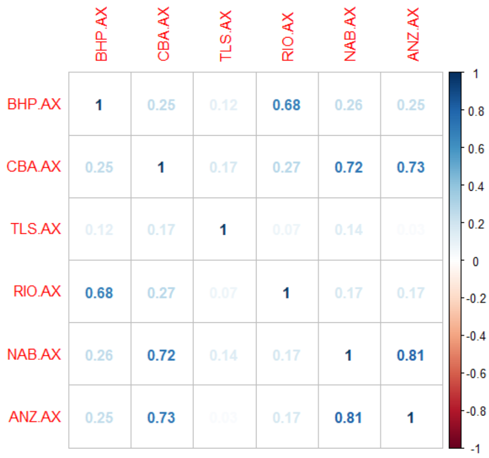

Fig. 6. Correlations between the excess returns.

To check the distribution of excess returns, we conduct the Shapiro-Wilk normality test and get a p-value=0.4409, which is statistically insignificant at any usual level of significance. Thus, we do not reject the null hypothesis that excess returns are normally distributed. Extreme outliers of the simple returns of each stock are presented in Table I (in percentage):

TABLE I: EXTREME OUTLIERS OF THE SIMPLE RETURNS

BHP.AX	CBA.AX	TLS.AX	RIO.AX	NAB.AX	ANZ.AX
-24.2019	-24.4069	-16.3297	-39.9485	-33.5458	-31.6955

III. RESULTS AND DISCUSSION

A. Evaluation of the Trading Algorithm

After iterating the weights of each asset in the targeting portfolio, the result is presented in the following Fig. 7.

In the training data, the algorithm with leverage=-0.5 shows the average monthly return on portfolio and portfolio standard deviation, which is 0.8805% and 6.1080% respectively. After putting it in the held back data, it generates the average monthly return of 1.1006% and portfolio standard deviation of 5.8598%. Therefore, the average monthly return is 25.00% higher, and its standard deviation is 4.06% lower from the held back calculation. This is too good to be true as it achieves a higher return with a small decrease in the risk. Therefore, the characteristics that may affect the informativeness of the trading algorithm performance assessment are including, first, the leverage ratio equal to -0.5, which is low, and second, the algorithm fits better in a relatively good 10-year market.

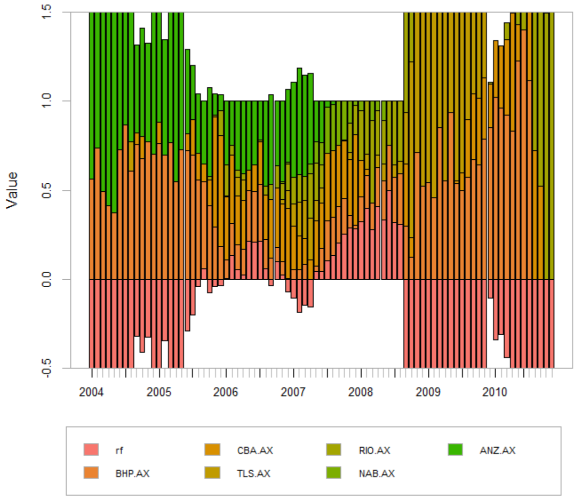

Fig. 7. Weights of each asset in the portfolio.

B. *Evaluation of the Performance Assessment for the Trading Algorithm*

The mean and standard deviation of portfolio returns (in percentage) in held back data are presented in the following Table II (from 2010-2015 and 2016-2019, respectively). The portfolio return distribution is likely to be stable into the future as the standard deviation decreases. The algorithm is not robust to such changes as it adjusts weights significantly (presented in Fig. 8, Fig. 9 below).

TABLE II: MEAN AND STANDARD DEVIATION OF PORTFOLIO RETURNS

	2010-2015	2016-2019
Mean	1.2825	0.8198
Standard Deviation	5.6683	6.0976

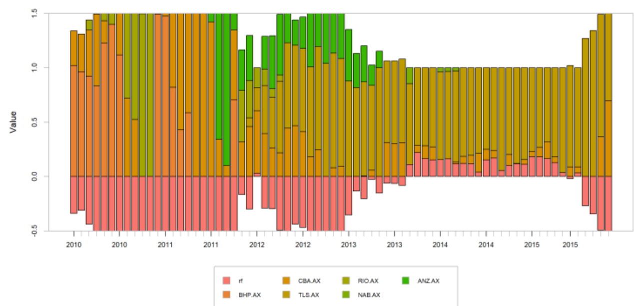

Fig. 8. Weights of each asset in the portfolio from 2010-2015.

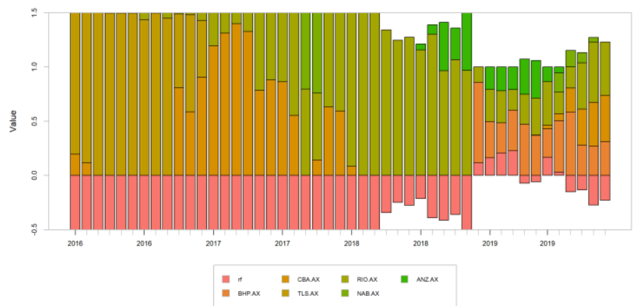

Fig. 9. Weights of each asset in the portfolio from 2016-2019.

Besides, in a bull market (2005-2006) and bear market (2008-2009), the algorithm does not perform in the same way. The result it generates corresponds to the bull and bear market. Therefore, it would be informative about performance into the future.

TABLE III: MEAN AND STANDARD DEVIATION OF PORTFOLIO RETURNS IN BULL AND BEAR MARKET

	2005-2006	2008-2009
Mean	2.5304	-1.4122
Standard Deviation	5.6176	7.1157

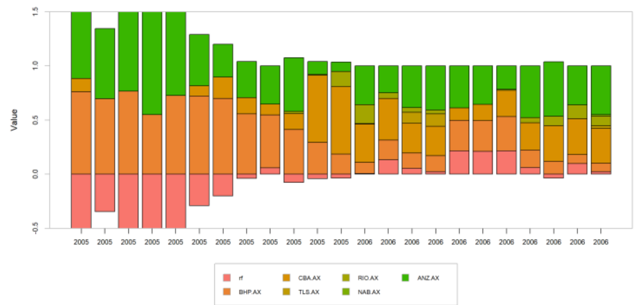

Fig. 10. Weights of each asset in the portfolio from 2005-2006.

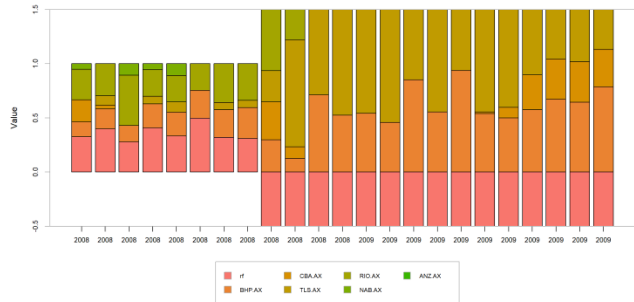

Fig. 11. Weights of each asset in the portfolio from 2008-2009.

Since the excess returns are normally distributed, we assume history will repeat itself (from a risk perspective) and apply the historical simulation to measure a 1-month-ahead 99th percentile Value-at-Risk (VaR) for the portfolio. The timespan is from 2010/01/01 to 2020/06/30, which is consistent with and a little longer than that of held back data. This assures the VaR analysis includes 2020 data as COVID-19 have affected the financial market greatly at the beginning of 2020. Starting with a $10000000 investment, we do 20000 historical simulations and set the holding period 10 days. One of the simulated VaR is $531,805,142. It indicates the algorithm has a quite good performance as a 99th percentile of the portfolio value distribution at the 10 days' time-horizon is $531,805,142.

IV. CONCLUSION

To sum up, the trading algorithm generates a portfolio that has a relatively higher average monthly return (25% higher) and relatively lower standard deviation (4.06% lower) in the held back data from 2011 to 2020 compared to the portfolio generated using training data from 2000 to 2010. It might be the reason that the chosen stocks had a good performance during the held back period. Besides, the trading algorithm can rebalance the weights in the portfolio automatically given different years and different markets. Based on the assumption that history will repeat itself, a 99th percentile of the portfolio value distribution at the 10 days' time-horizon is $531,805,142, indicating that the portfolio will not incur a huge gain or loss. Given the analysis above, this trading algorithm has a relatively good performance. Moreover, it can be further improved in the following aspects: The way of handling absent values in the dataset, as eliminating the rows of missing returns may distort the calculation results; For professional users, the dataset like Yahoo Finance lakes precision, it may not update the data timely. Besides, the risk-free rate may not be so representative of today's financial situation, especially during the COVID-19 period, as it consists of data from the past. In addition, users can also modify the trading algorithm based on his/her preference. For example, increasing the leverage (in absolute value) if the user has a high risk tolerance, or allowing short-selling of the risky assets. There may not exist an algorithm that can predict everything, but there can exist an algorithm that corresponds to an investor's appetite. Overall speaking, the trading algorithm performs relatively well during the past 2 decades. Therefore, it can infer that the modern portfolio theory is still informative and instructive for today's financial market.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Yanjie Cui mainly collected the data, improved and ran the code using R studio for analysis for the portfolio selection. Yanjie also drafted the portfolio selection analysis and formatted the graphs into the paper. Chulong Cheng made the contribution through the exposition of the basic theorem and introduced the literature before this paper. Chulong also ensured the formatting of the bibliography as well as the overall structure of the paper. All authors had approved the final edition.

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