OPTIMAL OPTION PORTFOLIO STRATEGIES: EVIDENCE FROM THAILAND

BY

MR. MATAS VATTANALOUVIT

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL
FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF SCIENCE
PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)
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THAMMASAT UNIVERSITY
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ENTITLED

OPTIMAL OPTION PORTFOLIO STRATEGIES:
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was approved as partial fulfillment of the requirements for
the degree of Master of Science (Finance)

on 0 1 MAY 2017

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Independent Study Title	OPTIMAL OPTION PORTFOLIO STRATEGIES: EVIDENCE FROM THAILAND
Author	Mr. Matas Vattanalouvit
Degree	Master of Science (Finance)
Major Field/Faculty/University	Master of Science Program in Finance (International Program) Faculty of Commerce and Accountancy Thammasat University
Independent Study Advisor	Associate Professor Chaiyuth Punyasavatsut, Ph.D.
Academic Year	2016

ABSTRACT

Current practises of asset allocation (such as modern portfolio theory – mean variance optimisation) are not suitable for optimisation of portfolios that contain options due to return distribution not being normal with short-life and high-dimensional covariance matrix problem. This is due to there being many options that have the same underlying asset. This study followed the option portfolio optimisation approach using a myopic objective function with options in the Thailand Futures Exchange, which has lower liquidity and more transaction costs compared to options in more developed countries.

The study showed that, even with lower liquidity and higher transaction costs, this strategy still achieved a better Sharpe ratio at 1.63 with positive skewness. Such performance was uncorrelated with market return without putting more risk in the portfolio.

Keywords: Option, Portfolio Allocation, Optimisation

ACKNOWLEDGEMENTS

My gratitude and appreciation go to my advisor Associate Professor Chaiyuth Punyasavatsut, Ph.D., who have been my instructor for this study. I would like to thank for all the supports and comments received to complete this independent study.

A special thanks to all my MIF17, PwC, and MTL colleges who always provide support. This independent study would not be completed if there were no supports from all of you.

Mr. Matas Vattanalouvit

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CHAPTER 1
INTRODUCTION

The Stock Exchange of Thailand has allowed individual investors to fund derivatives such as options. Derivatives can be used for hedging purposes, risk management or speculation on underlying asset prices, but are rarely used in investment portfolios except for hedge funds and some types of mutual funds (such as long-short strategies).

Compared to investment in underlying assets, derivatives such as options can provide similar return payoffs with less capital required. Also, an investor needs to have collateral pledged to short-sell in a derivatives market, so an investor can use the option to simulate similar return patterns by using options on underlying assets that offer a similar payoff as that of short-selling assets with less capital required.

Investment portfolios, which contain derivatives without underlying assets, can provide a similar return to an assets portfolio using various return payoffs from different kinds of derivatives, but with less capital required. This result adds additional exposure to new kinds of risk-return given the same level of capital. However, this model portfolio can eliminate investor limitations such as short-selling the underlying asset in a traditional portfolio.

Due to the short life of derivatives instruments and the historical data in Thailand, there is not enough data series for estimation of the distribution function for mean-variance return. Also, there are many derivatives that may be exposed to the same underlying asset, which means it runs into a high-dimensional covariance matrix in estimation. Therefore, a traditional model such as Markowitz mean-variance cannot be applied to construct an optimal portfolio[1].

The author proposes a simple approach to the portfolio allocation method – optimal option portfolio strategies (OOPS) instead of mean-variance. This OOPS approach uses the maximisation of expected utility. For the short-life instrument

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[1] Faias, José and Santa-Clara, Pedro, Optimal Option Portfolio Strategies: Deepening the Puzzle of Index Option Mispricing, Journal of Financial and Quantitative Analysis, forthcoming

problem, which is the characteristic of option[2], the historical data of the underlying assets is used instead to simulate the underlying asset payoff then corresponding option returns. The simulation approach uses simple bootstrapping to fit the return distribution of underlying assets. Given the option return in the portfolio, the expected utility can be averaged and maximised to get the optimal weight of each option.

The study is conducted with historical data from the Stock Exchange of Thailand (SET), which contains options such as index options (both call and put) and single stock options (warrant and derivative warrant). Also, the authors applied the price of underlying stock and index for simulation purposes in order to estimate the expected return of those options for optimal weighted allocation.

The author applied out-of-sample testing for this OOPS approach from January 2012 to March 2017. The results showed annualised return of 28.3% with annualised standard deviation of 14.71% and a Sharpe ratio of 1.63. The results also better than buy-and-hold strategy for underlying assets (SET50 Index) gave only 5.64% annualised return with annualised standard deviation of 13.71% and a Sharpe ratio of 0.42.

The OOPS provides positive skewness, leap kurtosis and has low exposure to the market. Also, OOPS cumulative return is a monotonic increase over time with regard to market returns.

The rest of this paper consists of the following sections: A literature review on the study of modelling for derivative portfolios in the past; the research methodology section, which provides the model used in this study; the data selection for each instrument and the results and conclusions of the study.

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[2] 12. Buraschi A., and J.Jackworth, 2001, The Price of a Smile: Hedging and Spanning in Option Markets. Review of Financial Studies, Vol. 14, 495-527.

CHAPTER 2
REVIEW OF LITERATURE AND CONCEPTUAL FRAMEWORK

2.1 Review of Literature

There exist many studies on option trading and portfolio allocation for options which can be separated into 2 main groups: First are studies that aim to construct option portfolios, and second are studies that aim to put options into existing portfolios.

For the studies that aim to construct the option portfolios, Faias and Santa-Clara (2011) tried to optimise the option portfolio numerically with a portfolio containing only index options and risk-free assets using a simulation technique to generate return on underlying assets and corresponding option returns based on historical data (S&P 500). Then, they generated the distribution using the simulated return to optimise the portfolio via utility function. This method is interesting since it requires less option information, only needing the underlying asset return for simulation purposes. Also, Eraker (2013) focused on the difference between the market efficient of stocks and options, say that options were not efficient in the market due to there being no "true model". A portfolio is constructed with allocation between stocks and options, as well as allocated with respect to the difference between model option price and real price. However, this approach requires rebalancing, which is not suitable for a market which has high transaction costs.

Unlike the utility maximisation of Faias and Santa-Clara (2011), Malamud (2014) models the portfolio with a variety of options. His approach focuses more on minimum risk based on options greeks in many moments. This results in optimal sensitivity compared to the traditional mean-variance asset approach.

Other groups of study that aimed to put options into portfolios include Liu and Pan (2003), who expanded the optimal portfolio of stocks by adding the derivative and focusing on stochastic volatility. They used an analytical approach to optimise the portfolio with options included, which they need to specify the dynamic of stock price and estimate the parameter. They focused on how derivatives affect the existing portfolio and how to rebalance the portfolio to obtain the optimal point that cannot extend to a stand-alone option portfolio. However, this study is based on pure derivative and the estimated distribution of returns for underlying assets. Also, Sawitree (2012) constructed a portfolio which consisted of stocks, bonds and risk-free assets using the traditional mean-variance method, then tested whether future contracts could improve the performance of portfolio using the utility maximisation to obtain the weight. The results found that, if an investor's utility is mean-variance, there is no significant benefit. However, if the investor's utility is not mean-variance, adding SET50 futures can improve the performance of the portfolio.

There are some studies that have shown that option portfolios cannot be optimal without short-allow. Driessen and Maenhout (2007) constructed a portfolio by maximising the utility based on return parameters. The portfolio consisted of stocks and index options (S&P500 index option). The results showed that an optimal portfolio with long puts option cannot be optimal, which suggest that constructing the portfolio that shorts the out-of-the-money puts and at-the-money straddles give superior risk-return compared to a traditional portfolio.

There are many pieces of literature that follow the concept of using CRRA for investor consumption choice. Chiappori (2013) and Christina (1993) found that households have CRRA preference with no significant difference within the Thai economy. Supanee (2014) studied two types of assets pricing models, namely CAPM and CCAPM, using CRRA and found that the coefficient of risk aversion for Thailand investors is 22.94. However, Faias and Santa-Clara (forthcoming) optimised the portfolio with CRRA utility function using a difference of γ and found similar performance.

2.2 Theoretical Framework

Since the study is proposing the optimal portfolio strategy, modern portfolio theory, is applied in essence so that the portfolio is constructed based on a basket of assets. The expected return of portfolio is maximised given the level of risk desired by using the mathematical framework:

$$E(R_p) = \sum_i w_i * E(R_i),$$

where R_p = Portfolio return,

w_i = weight of security *i*,

R_i = Return of security *i*.

The risk in MPT is represented by the variance which will be optimal based on the correlation between assets in the portfolio:

$$\sigma_p^2 = \sum_i w_i^2 \sigma_i^2 + \sum_i \sum_{j \neq i} w_i w_j \sigma_i \sigma_j \rho_{ij},$$

where σ_p^2 = Portfolio variance,

w_i = weight of security *i*,

σ_i = variance of security *i*,

ρ_{ij} = correlation coefficient between the returns on assets *i* and *j*.

As the portfolio contains more than one asset in which those assets are not perfectly positive correlate, the constructed portfolio will reduce the individual risk of each asset when combined together as a portfolio.

2.3 Power utility function

From preliminary assumption that investor is risk-averse, we use the isoelastic utility function, or power utility function which mainly used for consumption choice problem. This power utility function which has constant relative risk aversion (CRRA) are present by:

$$U(C) = \begin{cases} \frac{1}{1-\gamma} C^{1-\gamma}, & \gamma \neq 1 \\ \ln(C) \quad , & \gamma = 1 \end{cases}$$

where γ = Coefficient of relative risk aversion,

C = Consumption,

$U(C)$ = Associated utility.

Constant relative risk aversion means that $\frac{-C* U"(C)}{U\prime(C)} = \gamma$ which is constant and also represents measurement of risk aversion. Moreover, the CRRA is appropriate for this study due to its property that consumption choice is independence of the initial level of wealth.

2.4 Higher moments of distribution

According to MPT, investor optimized the consumption choice consider only mean and variance of return which supposed to be normal distributed. Also, investor ignore the higher moment when optimize the allocation. However, as the option return are not normal distributed, ignoring the higher moment can lead to over value which result in underestimated the risk in portfolio. The higher moments related to this study is third and fourth moment, Skewness and Kurtosis, describe as follow:

Third moment (known as Skewness) is an asymmetry measurement of the distribution which can be describe into positive skewness, negative skewness and zero skewness (normal distribution). Skewness can be defined as:

$$Skewness = E\left[(\frac{X_t - \mu}{\sigma^3})^3\right],$$

where X_t = Return of any securities at time *t*,

μ = Mean of returns,

σ = Standard deviation of returns.

Normally, investor preference are positive skewness. The positive skewness for asset return means that positive outcome has higher change of occurred and expected the low tail-risk, or the tail on the right side is longer or fatter than the left side.

Fourth moment (known as Kurtosis) is a degree measurement of the distribution which can be defined as:

$$\text{Kurtosis} = E\left[(\frac{X_t - \mu}{\sigma^4})^4\right],$$

where X_t = Return of any securities at time *t*,

μ = Mean of returns,

σ = Standard deviation of returns.

The excess kurtosis is defined as kurtosis minus 3. Normally, investor preference are platykurtic (negative excess kurtosis). The negative excess kurtosis mean that the return distribution is less fat tail than normal distribution which result in less chance of extreme case to be occurred for both side of distribution.

CHAPTER 3
RESEARCH METHODOLOGY

This chapter explain approach to the portfolio allocation method – optimal option portfolio strategies (OOPS). Portfolio allocation start with return simulation, utility optimization and the out-of-sample testing. This method follows the approach taken by Faias and Santa-Clara (2011).

Time is discrete and contains intervals for rebalance monthly as represented by *t*. The author performs optimisation of the portfolio allocation, which consists of risk-free assets and options that have one period of maturity, by simulating the underlying asset return from *t* to *t+1* and computing the option return based on those simulated underlying asset values. Computing the portfolio return depends on the weight of each option. The portfolio returns are computed by simulating return of the *t+1* wealth, which will be used as wealth to calculate the weight of each security by maximising the investor expected utility. After obtaining the weight from the optimisation process, using the weight obtained from the optimisation process in the out-of-sample is done to determine the actual return and actual wealth for time *t+1*. The process is repeated for the next period. An example of the methodology is illustrated in Appendix A.

The formula and model in the detail will be described as follows.

3.1 Portfolio Optimisation method

1. Simulation of the underlying asset log-return r

$$r_{t+1,s}^{n}, n = 1, \ldots, N,$$

where n = simulation path.

The return from this simulation is based on historical return and variance data, as described in a subsequent section. The simulation method is described in the next section.

2. From the return simulation, the underlying asset value can be obtained at time *t+1* using these formulas:

$$S^n_{t+1|t} = S^n_t * e^{r^n_{t+1}},$$

where $S^n_{t+1|t}$ = Underlying asset at time *t+1*,
S^n_t = Underlying asset at time *t*.

3. As we know the underlying asset value in the next period, $S^n_{t+1|t}$, we also know the price of each derivative at time *t+1*. We can also simulate derivative payoff at the maturity in time *t+1*.

3.1) Call option return

$$C^n_{t+1|t,c} = \max(S^n_{t+1|t} - K_{t,c}, 0),$$

3.2) Put option return

$$P^n_{t+1|t,p} = \max(K_{t,p} - S^n_{t+1|t}, 0),$$

where $C^n_{t+1|t,c}$= Call Option price at time *t+1*
$P^n_{t+1|t,p}$= Put Option price at time *t+1*
K_t = Strike price of each option

From the payoff as calculated, derivative return *r* can be computed as follows:

$$r^n_{t+1|t,c} = \frac{C^n_{t+1|t,c}}{C^n_{t,c}} - 1 \ and \ r^n_{t+1|t,p} = \frac{P^n_{t+1|t,p}}{P^n_{t,p}} - 1 ,$$

where $C^n_{t,c}$ = Call Option price at time *t*
$P^n_{t,p}$ = Put Option price at time *t*

4. After obtaining the return from the simulation, we can construct the portfolio and portfolio return as follows:

$$rp^n_{t+1|t} = rf_t + \sum_{c=1}^{C} w_{t,c} \left(r^n_{t+1|t,c} - rf_t\right) + \sum_{p=1}^{P} w_{t,p} \left(r^n_{t+1|t,p} - rf_t\right),$$

where $rp^{n}_{t+1|t}$ = Portfolio return from time *t* to *t+1*,

$w_{t,c}$ = Weight of each call option

$w_{t,p}$ = Weight of each put option

rf_t = Risk-free interest rate from time *t* to *t+1*

5. To obtain the weight of each derivative w_t, calculate the weight by maximising the expected utility given wealth at time *t+1* from the portfolio return

$$\max_{w} E[U(W_{t+1})],$$

subject to wealth constraint $W_{t+1} = W_t[1 + rp^{n}_{t+1|t}]$,

where W_{t+1} = Investor wealth at time *t+1*

W_t = Investor wealth at time *t*

Using the constant relative risk aversion utility function (CRRA), the power utility function can be formed as follows:

$$U(W) = \begin{cases} \dfrac{1}{1-\gamma} W^{1-\gamma}, & \gamma \neq 1 \\ \ln(W) \quad , & \gamma = 1 \end{cases},$$

where γ = Coefficient of relative risk aversion.

So, with the utility function as above, the utility function is formulated subject for maximisation as follows:

$$\max_{w} E[U(W_t[1 + rp^{n}_{t+1|t}])] \approx \max_{w} \frac{1}{N} \sum_{n=1}^{N} U(W_t[1 + rp^{n}_{t+1|t}]),$$

which will obtain the weight for each derivative, $w_{t,c}$ *and* $w_{t,p}$ as a result of this optimisation process.

6. From the weight obtained in 5, out-of-sample testing is performed by using the optimised weight with option price at time *t+1*.

$$r^{n}_{t+1|t,c} = \frac{C^{n}_{t+1|t,c}}{C^{n}_{t,c}} - 1 \ amd \ r^{n}_{t+1|t,p} = \frac{P^{n}_{t+1|t,p}}{P^{n}_{t,p}} - 1 \ ,$$

where $C^{n}_{t+1|t,c}$ = Out-of-Sample Call Option price at time *t+1*,

$P^{n}_{t+1|t,p}$ = Out-of-Sample Put Option price at time *t+1*,

with option return, we can determine the portfolio return:

$$rp^{n}_{t+1|t} = rf_t + \sum_{c=1}^{C} w_{t,c}\left(r^{n}_{t+1|t,c} - rf_t\right) + \sum_{p=1}^{P} w_{t,p}\left(r^{n}_{t+1|t,p} - rf_t\right),$$

where $w_{t,p}$ = Weight of each put option from optimisation process,

$w_{t,c}$ = Weight of each call option from optimisation process.

Lastly, the portfolio returns from time *t* to *t+1* will determine wealth for time *t+1*. The process is then performed again for rebalancing of the portfolio for the next discrete time, which is monthly data until covering all data.

Alternatively, if the underlying stock is included in the model, the process is similar when we include the return and the weight of the underlying assets into the optimisation process.

3.2 Return Simulation

From the methodology, the weight of each option is calculated based on the simulation path of underlying asset returns. From the raw data in this study, SET50 index, it was found that the distribution of return for the index itself was left-skewed and presented ARCH effects, as shown in Table 3.1. In order to simulate the distribution of underlying asset returns, the standardised return *(sr)* is constructed, which consists of raw return *(rr)* and its standard deviation as follows:

$$sr^{n}_{t+1} = \frac{rr^{n}_{t+1}}{stdev_{t+1}} \ where \ n = 1, \dots, N.$$

From the constructed standardised return, it was found that the return distribution was closer to normal distribution with no significant ARCH effect, even left-skewed.

So, the standardised return was simulated for each path by the bootstrap method (Efron and Tibshirani (1993)), which was then multiplied by the volatility to get the simulated return as follows:

$$r_{t+1}^{n} = sr_{t+1}^{n} \times \ stdev_{t+1} \, where \, n = 1, \dots, N.$$

Estimated volatility is described in the next section.

Table 3.1. SET50 Index Returns – Summary statistics

	Raw Return			Standardised returns		
	1995-2012	2012-2017Q1	1995-2017Q1	1995-2012	2012-2017Q1	1995-2017Q1
Obs	196	63	259	196	63	259
Skew	0.57	-0.47	0.60	-0.01	-0.54	-0.11
Exc Kurt	3.00	-0.36	4.28	0.21	-0.56	0.07
Arch (1)	Significant ARCH effect			No Significant ARCH effect		

3.3 Volatility Estimator

As mentioned in the section concerning return simulation, the calculation of underlying asset returns required current realised volatility. Thus, the previous data from last d trading days was used (which was conducted at 1, 5, 10, 20, 30 days and selected the one that maximised utility at that month) and scale by 21, which is average trading day per month, to get the estimation of volatility.

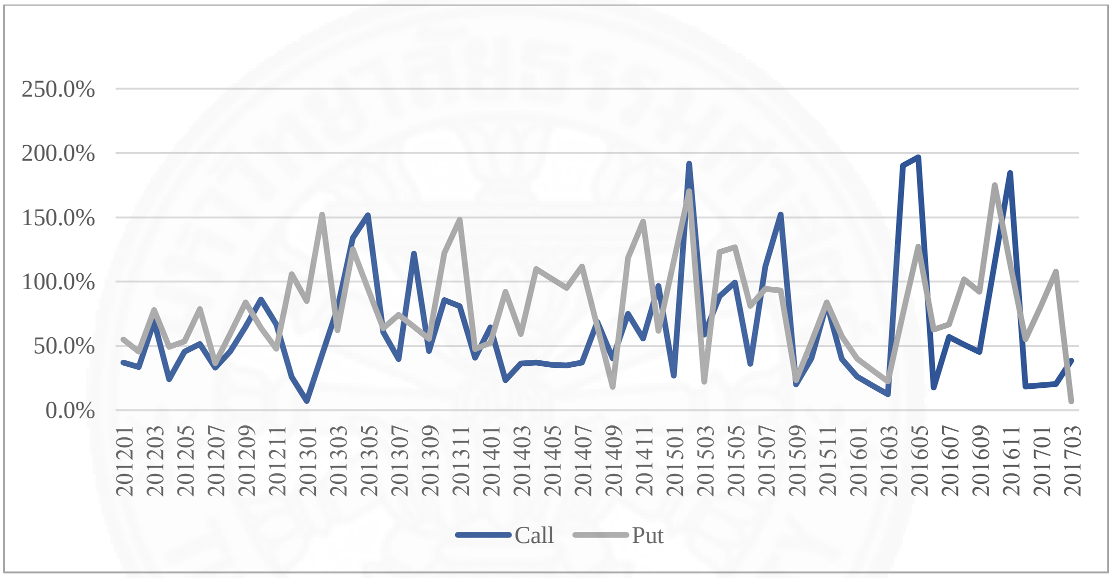
Also, as the alternatives, we will use the implied volatility from the market value of options itself by average the implied volatility calculated from available options to compare with volatility calculated from the last trading day for the optimal method.

3.4 Transaction Cost

Due to the existence of the bid-ask spread in the actual market, it implies that there is transaction cost. This study included the transaction cost into optimisation by separating each option into two securities: a “Bid price” for the short position and “Ask price” for the long position. For other types of transaction costs like brokerage fees, they will be ignored due to the fixed amount which has limited impact on the optimisation process in this study.

Figure 3.1 shows the monthly bid-ask spread ratio (calculated from absolute bid-ask spread divide by mid-price) from January 2012 to March 2017, averaged by each type of option: Call option and Put option. This relative high figure compared to Faias and Santa-Clara (2011), which reported a bid-ask spread ratio of around 0%-40%.

Figure 3.1: Bid-Ask Spread ratio



This high bid-ask spread ratio means that the transaction cost might be high. This can lead to a problem when performing portfolio optimisation due to incorporation of the transaction cost into the return calculation. Thus, another analysis is performed on transaction cost, as shown in Figure 3.2.

Figure 3.2: Bid-Ask Spread ratio (compared to index price)

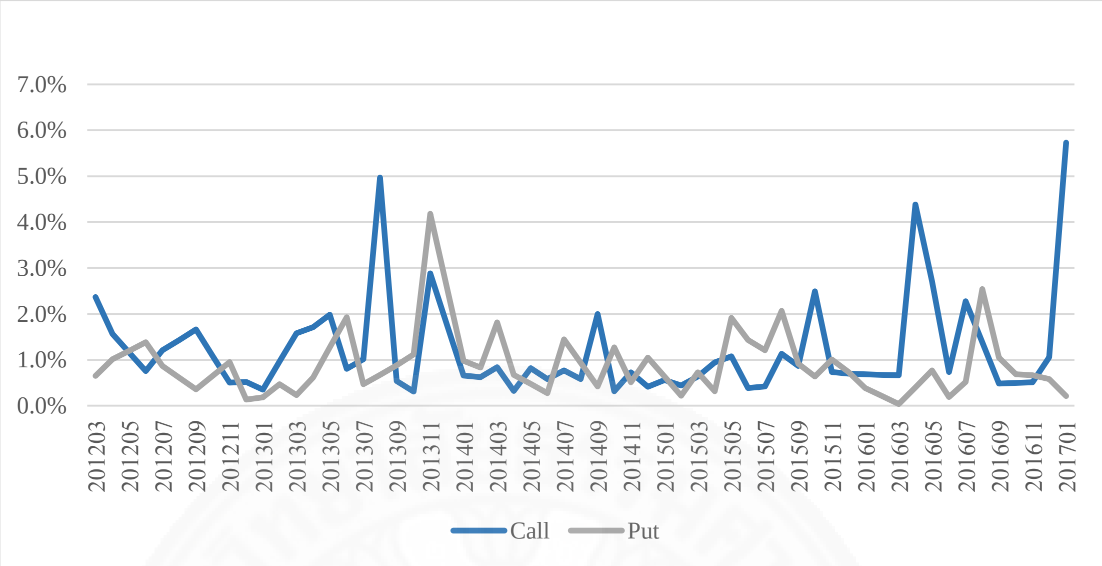


Figure 3.2 shows the monthly bid-ask spread compared to the underlying asset price. From the chart, the bid-ask spread ratio compared to the underlying asset price is relatively low (around 0%-7%) compared to the bid-ask spread ratio with a mid-price. This is also consistent with Faias and Santa-Clara (2011), who reported a bid-ask spread ratio of around 0%-40%. Therefore, the high bid-ask spread ratio mainly came from the relatively low price of the option and not the significantly high transaction cost.

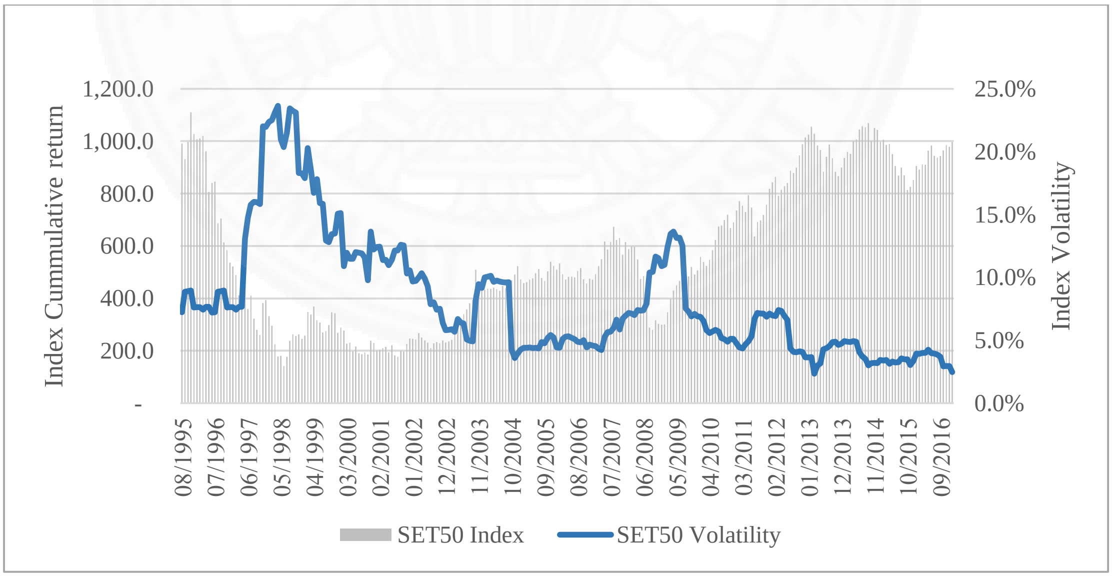
CHAPTER 4
DATA SECTION

4.1 Securities as underlying assets for optimisation

From the methodology section, portfolio optimisation in this study is performed based on the simulation of the return for underlying assets to optimise for the weight of each derivative instrument. So, the optimisation process requires two main sets of data: Securities returns and Risk-interest rate.

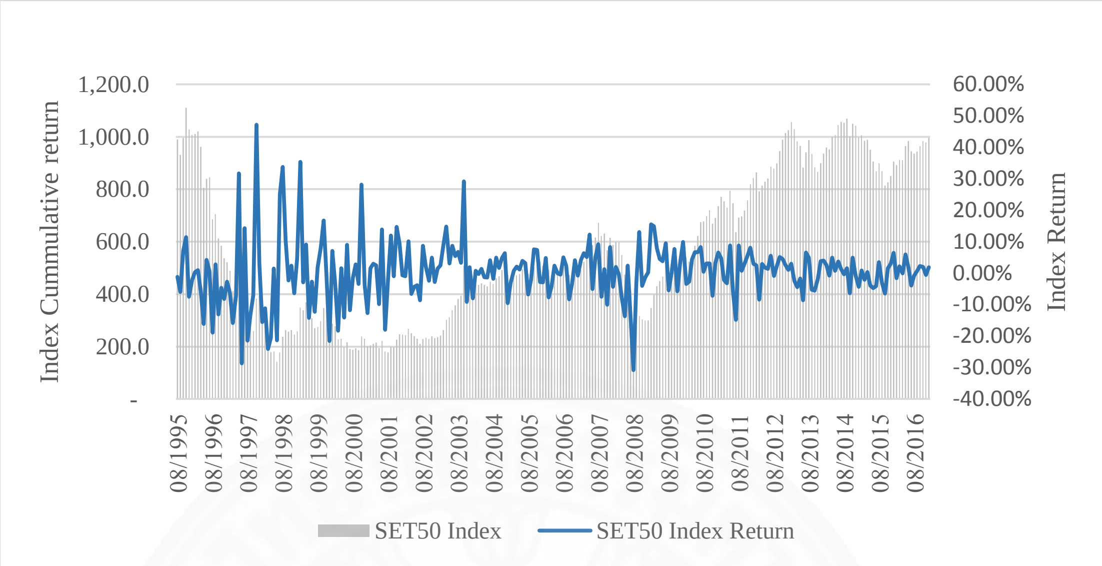
The securities data will be the SET50 index and underlying assets, which have options available, including price returns. We use log return of the securities, as mentioned from Aug 1995 to June 2016 in Bloomberg, as data for the simulation process. Figure 4.1 represents the monthly observation of SET50 index return, cumulative return (left axis) compared with its volatility (right axis) from August 1995 to March 2017.

Figure 4.1: SET50 Index Cumulative return and Volatility



This period is appropriate in terms of comprising both bull, bear and crisis market conditions. The data type will be the last price of each month ending from the period as above. From those periods as described, the total of 251 observations for the SET50 index is obtained.

Figure 4.2: SET50 Index Cumulative return and Snapshot return



Also, as mentioned in the Volatility Estimator and Return Simulation section, the log-return simulated using the bootstrap method also required the latest volatility data. Thus, the daily data of SET50 Index was needed in order to have the current realised volatility. The daily data of SET50 index can also be obtained from Bloomberg with last price of each day from Aug 1995 to June 2016.

The risk-free interest rate used in this study is separated due to the limitation of data. Most will be a proxy from one-month T-Bill, whose maturity matches with the simulation horizon. The series of this one-month T-Bill (one-month yield interpolations) is obtained from Thai BMA, which provides historical data from March 2001 to June 2016. The remaining risk-free rate before March 2001 is proxy by saving rate obtained from the Bank of Thailand, which has been available since Jan 1978.

4.2 Options

In the process of this study, the option price was needed for the optimisation process and for out-of-sample testing. For the optimisation process, the option value of the current period was needed to determine the simulated return for optimisation purposes. After the simulation, the weight for each derivative was obtained with the actual option price for out-of-sample test to get the actual portfolio return.

For the option data, the option price from Bloomberg database for SET50 was used in addition to the underlying stock option trade on the Stock Exchange of Thailand.

The data obtained consists of Bid, Ask, Last price and Volume trade of each day for the period between Oct 2007 and June 2016. From the data extract, this study eliminated the pricing data from the day that has no volume to ensure the reliable of the dataset due.

Since the process consists of optimisation and out-of-sample testing, the optimisation uses the option price from first trading of the month (which will have the option that expired at the end of the month available) and the option price at the end of month as value for out-of-sample testing. This selection of data makes the rebalancing period and time interval for optimisation match at one month.

The options selection to portfolio consists of both ATM and OTM options, with time to maturity at one month, which is the simulation horizon in this study. This one-month horizon came from most of the option series that liquid trade is one month to maturity series.

As show in Figure 4.3 and 4.4, the distribution of option returns are not normal with negative tail risk (max loss 100%).

Figure 4.3 Call Option return distribution

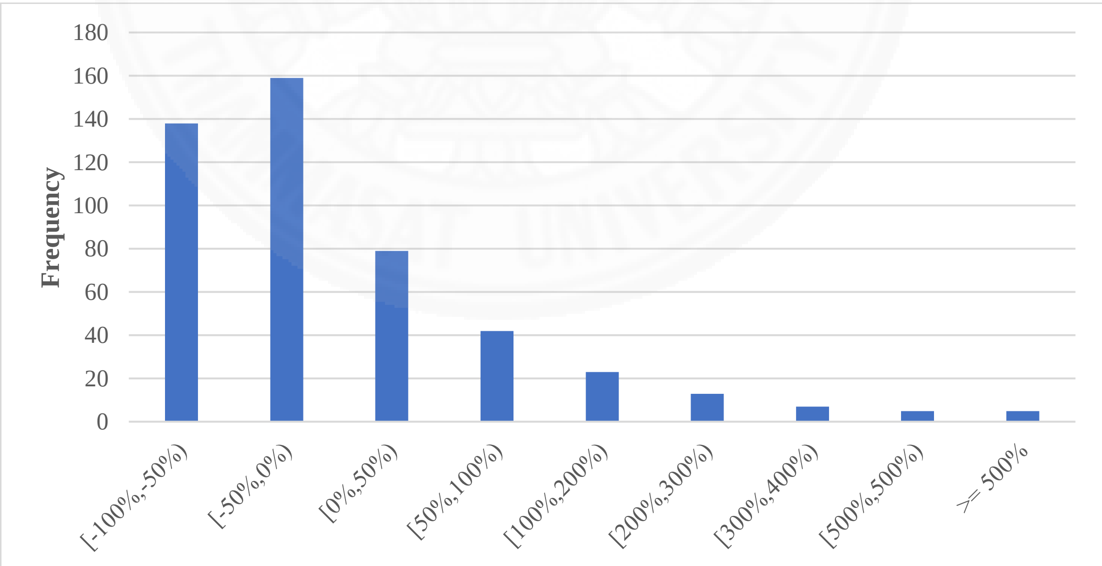
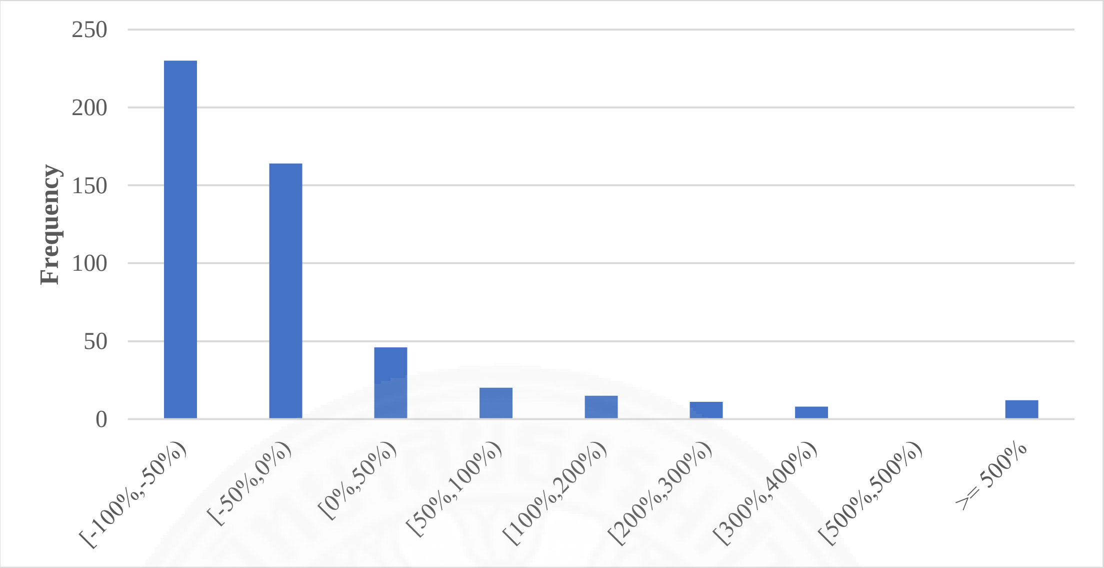


Figure 4.4 Put Option return distribution



CHAPTER 5
RESULTS

5.1 Out-of-sample returns

The author applied out-of-sample testing for this OOPS approach from January 2012 to March 2017. Figure 5.1 shows the distribution of OOPS out-sample monthly return. The OOPS return is closer to normal asset return than options or derivatives. Its distribution is closer to normal distribution with low tail risk.

Figure 5.1: Optimal Option Portfolio Strategy - Return Distribution

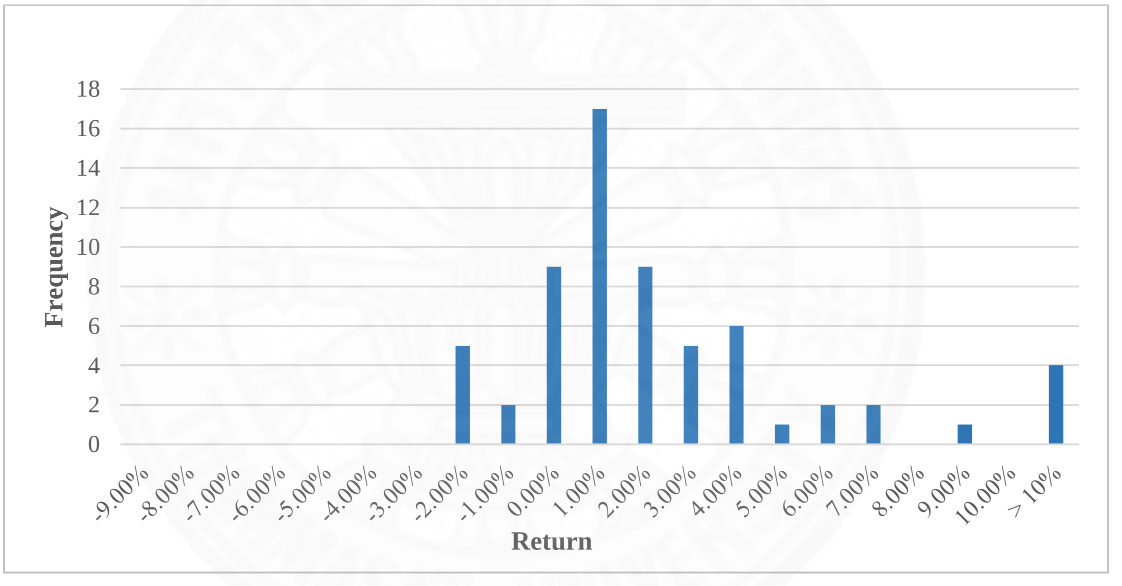


Figure 5.1 represents monthly return of optimal option portfolio strategy return, which incorporates transaction costs from January 2012 to March 2017

For more statistic information regarding OOPS return, Table 5.1 shows the summary statistic of OOPS return compared with SET50 index return from January 2012 to March 2017, which is the out-of-sample testing period for this study. Shown in Table 5.1 is the comparison between cumulative return of SET50 index (Buy and Hold), OOPS Strategy and Risk-free cumulative return between January 2012 to March 2017. Optimal option portfolio strategy gives an annualised return of 28.3% with annualised standard deviation of 14.71%, which already incorporates transaction costs. This result is significantly different when compared to SET50 index, which gives only 5.64%

annualised return with annualised standard deviation of 13.36%. Thus, OOPS consequently gives the annualised Sharpe ratio of 1.63 and SET50 index of 0.42 in terms of risk-adjusted return measurement as Sharpe ratio.

However, this study also measures the return using gain to pain ratio, which ignores the risk as long as a portfolio can generate return since Sharpe ratio penalised the return for upside volatility (even though the volatility of OOPS and SET50 Index is the same level). OOPS has impressive GPR at 8.56 compare to SET50 index at only 1.45

Also, OOPS has positive skewness and low kurtosis for the higher moment when compared to SET50 index in the same period, which results in OOPS with a minimum return of -2.8% and a maximum return of 20.1% compared to SET50 Index, which has a minimum return of -8.6% and maximum return of 8.1%.

Table 5.1. Out-of-Sample Return summary statistics

	SET50 Index	OOP-Strategy
Total Return (2012-2017Q1)	131.6%	347.7%
Average Monthly Return	0.59%	2.13%
Average Monthly S.D.	3.86%	4.25%
Annualised Return	5.64%	28.30%
Annualised S.D.	13.36%	14.71%
Sharp Ratio	0.4186	1.6338
Min	-8.6%	-2.8%
Max	8.1%	20.1%
Skew	(0.46)	2.33
Exc Kurt	(0.36)	6.36
GPR	1.45	8.56

For the cumulative returns shown in Figure 5.2, OOPS shows a monotonic increase in return. The last value of cumulative return for OOPS is more than three times compared to the initial amount and almost two times compared to SET50 index return. Moreover, the drawdown on OOPS is significantly lower than SET50 index, as previously mentioned. The largest loss of OOPS in May 2012 was only -2.8% compared to SET50 index, which had the largest loss of -8.6% in Aug 2013.

Figure 5.2: Optimal Option Portfolio Strategy - Cumulative return

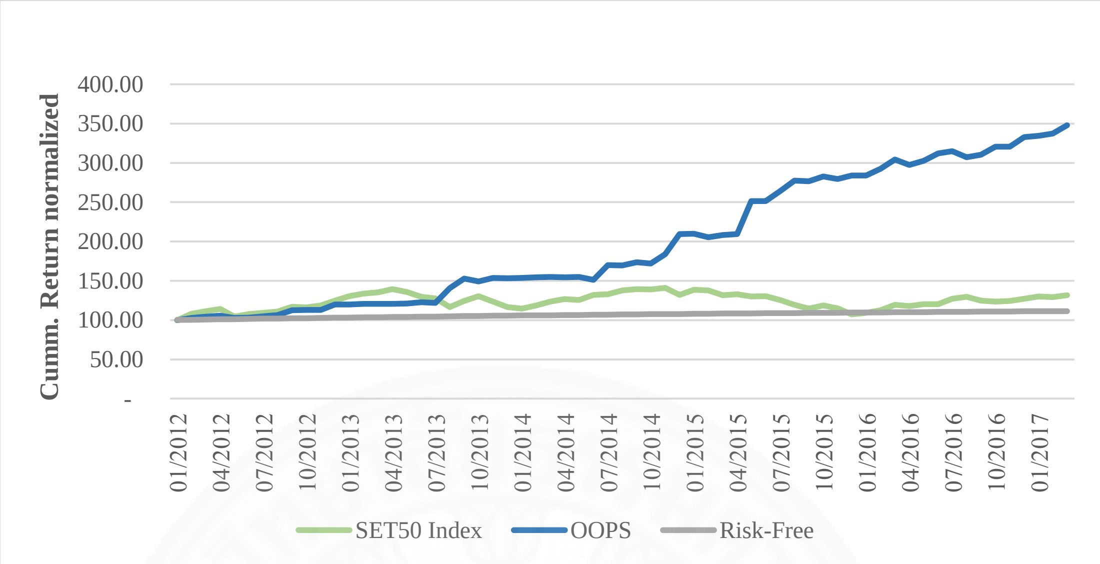


Figure 5.2 - Cumulative return: Optimal option portfolio strategy and SET50 Index return from January 2012 to March 2017 (Normalised base to 100 in January 2012)

For the portfolio allocation, Figure 5.3 to 5.6 shows the weight of each security over time (Call option, Put option and Risk-free securities). From Figure 5.3 to 5.5, the weight of options has no pattern over time and there is no overweight in either call or put option.

However, the average weight of Risk-free is more than 100% and 80% of observation beyond 100%, which means that OOPS mostly takes a net short option. Even when OOPS mostly takes a net short position, it will not have only one side short, but mostly will offer the position with other options.

Figure 5.3: Oprion weight over time (Call Option)

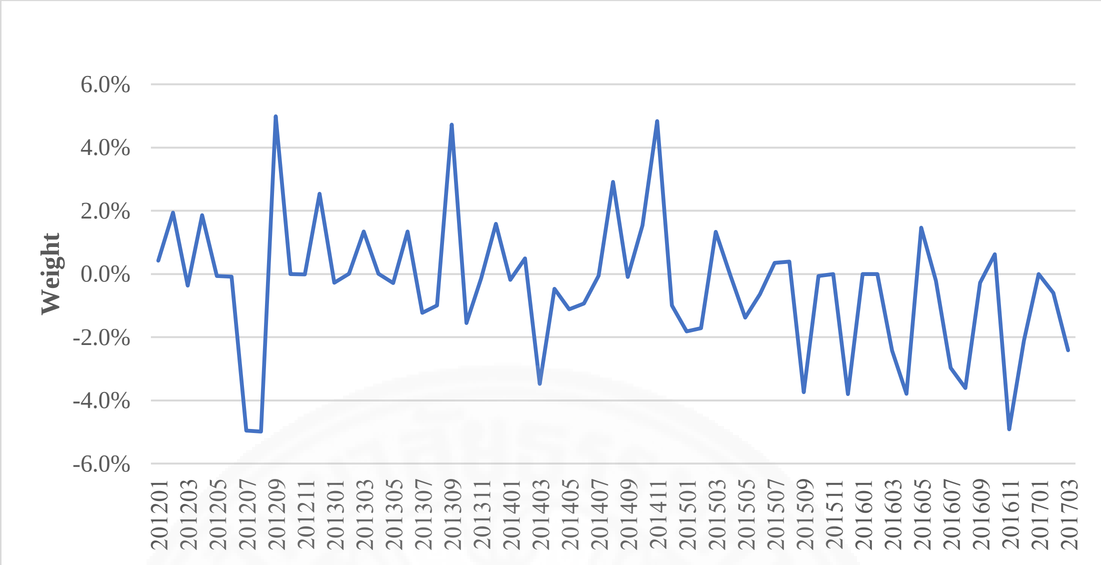


Figure 5.3 – Monthly weight of Call option in OOPS from January 2012 to March 2017 (Positive % means long position, while negative % means short position)

Figure 5.4: Option weight over time (Put Option)

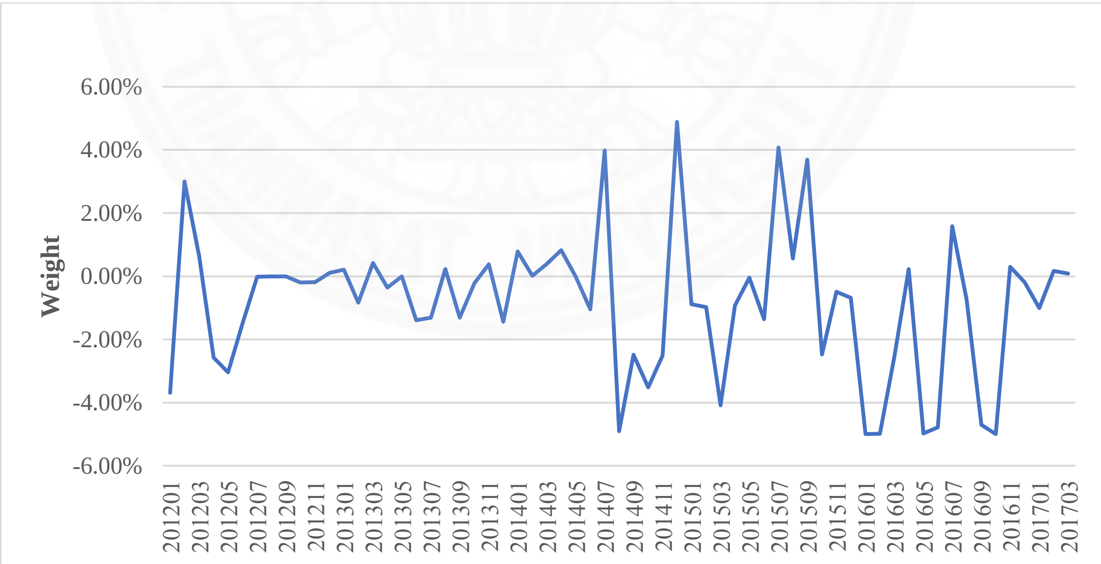


Figure 5.4 – Monthly weight of Put option in OOPS from January 2012 to March 2017 (Positive % means long position, while negative % means short position)

Figure 5.5: Option Weight over time

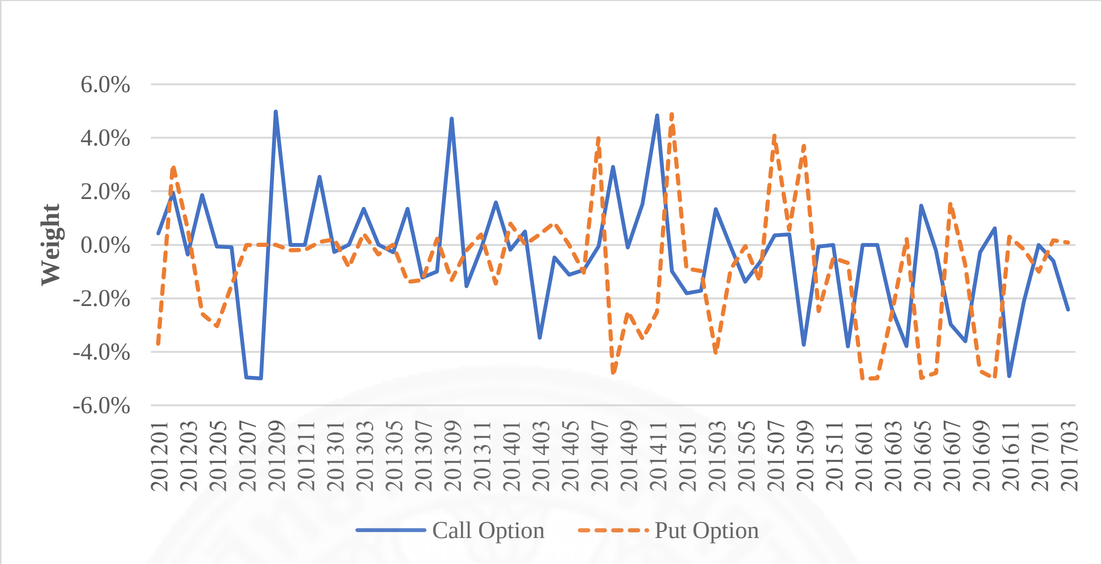


Figure 5.5 – Monthly weight of Option in OOPS from January 2012 to March 2017 (Positive % means long position, while negative % means short position)

Figure 5.6: Weight over time (Risk-Free)

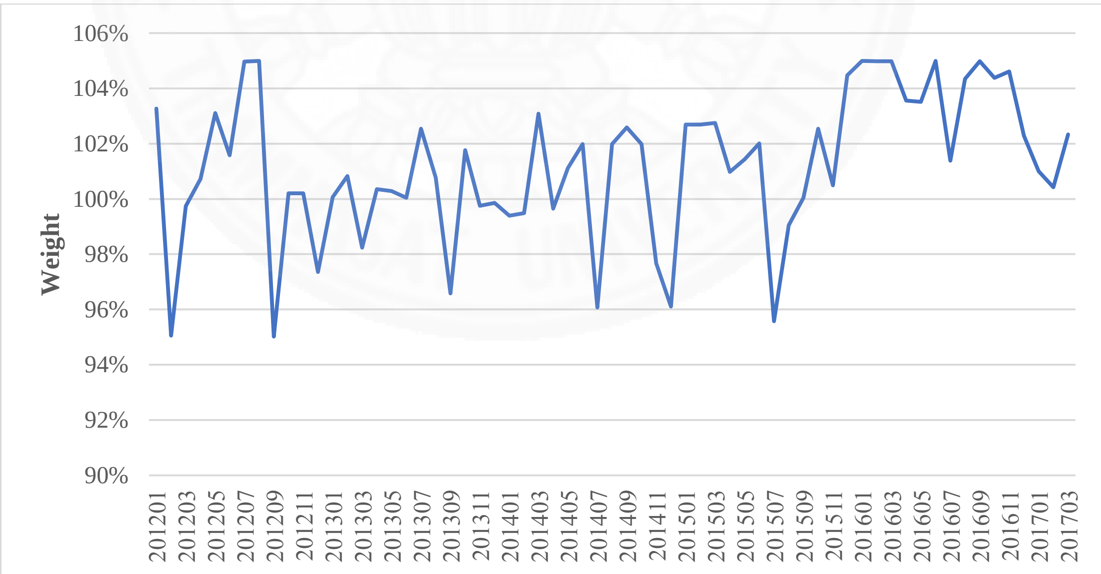


Figure 5.6 – Monthly weight of Risk-free security in OOPS from January 2012 to March 2017 (Positive % means long position, while negative % means short position)

5.2 Risk or mispricing?

There are two main reasons behind the result of OOPS. First, OOPS has more risk than the underlying asset due to leveraging. Second, there exist the option mispricing. We compare the risk of OOPS to SET50 index, the risk (in terms of standard deviation is close). So, there is no risk loading into OOPS to get the superior return.

Then, we find that OOPS also have low exposure to other risk factor. We use simple linear regression to identify whether the OOPS return has correlated with other factor. Figure 5.7 shows the relationship between OOPS return and SET50 index return

Figure 5.7: OOPS Return plot with SET50 index return

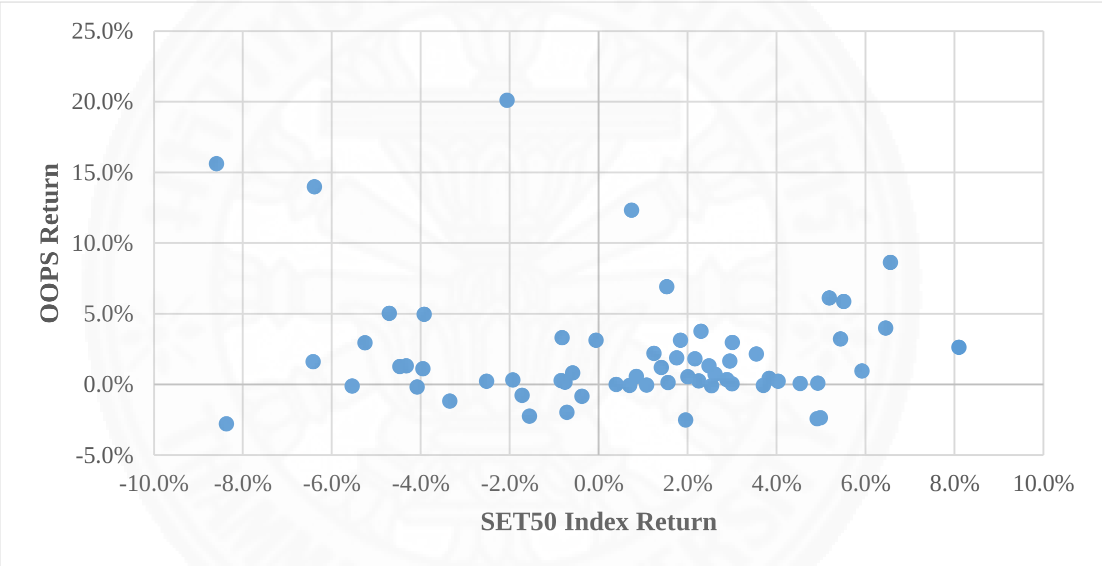


Figure 5.7 shows that there is no significant relationship between SET50 Index return and OOPS return with low correlation (Regression table in Appendix B) the correlation between SET50 Index return and OOPS return is only -15%.

Figures 5.8 to 5.10 shows the example of payoff pattern depend on change in SET50 index value. The OOPS payoff is evolution over time but most of payoff is little exposed to market. On average, OOPS was net short position with tail risk in upside increase in SET50 index.

Figure 5.8: Payoff Profile - March 2016

Figure 5.8 – OOPS payoff profile on March 2016 which has exposed to right tail risk.

Figure 5.9: Payoff profile - September 2016

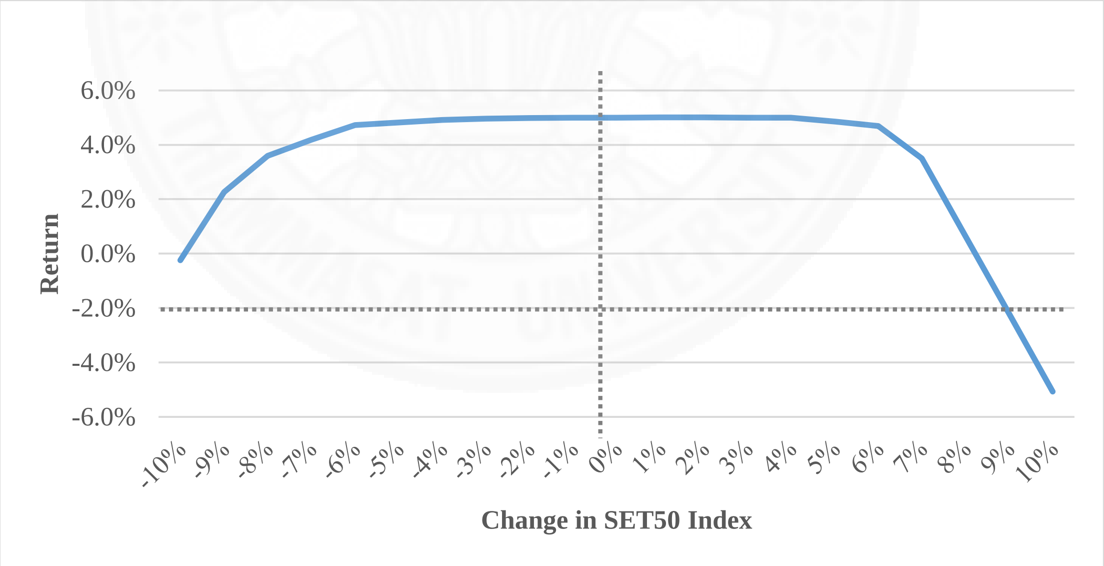


Figure 5.9 – OOPS payoff profile on September 2016 which has exposed to right tail risk.

Figure 5.10: Payoff profile - August 2015

Figure 5.10 – OOPS payoff profile on August 2015 which has no exposed to tail risk.

Moreover, since the OOPS input is underlying asset volatility, we use Vega as a measurement of exposure to volatility risk to return. In average, OOPS Vega is 3.52%, means that if volatility increase by 1%, portfolio return will increase by 0.03%. So, the exposure of return to volatility is quite low.

So, we can conclude that the return from OOP has low exposure to market risk such as current volatility or market return. Also, the superior return itself aren't from loading more risk into portfolio. The OOPS cumulative return is intuitive and increase over time.

CHAPTER 6
CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The objectives of this research endeavour are to propose the simple and practical approach to do the portfolio optimization with options which require minimum forward-looking. The optimization approach solves the problem of distribution of options by using only observed historical price. Performance evaluation is done by out-of-sample testing as well as the comparison of the result of underlying asset performance.

In terms of out-of-sample test, the proposed optimization approach provides interesting performance in every aspect. Return distribution from the portfolio is more like normal distribution which is totally different from individual options. This approach can provide better annualized return to underlying asset and also better GPR. Even risk-adjusted return measurement as Sharpe ratio, the optimization approach can also provide high Sharpe ratio. Moreover, this impressive result is little exposed to market as the correlation with market return is limited.

This result is also consistent with Faias and Santa-Clara (2011), who achieve average annualized return of 16.1% with annualized Sharpe ratio of 0.82 from U.S. market, compared to this study average annualized return of 28.3% with annualized Sharpe ratio of 1.63.

Another conclusion is to whether those proposed methodologies are still practical with relatively low liquidity, fewer option choices and higher transaction cost than developed market. This study shows that for our observation, which is SET50 index and its option, the result is still significant even though the market has fewer choices of liquid.

6.2 Recommendations

This study focuses on simple method to construct the option portfolio which has limitations and constraints, only options and risk-free securities are included in portfolio. These constraints are to eliminate the distribution of option problem by putting into portfolio, optimize to get the weight and more return distribution than normal distribution. Therefore, only options and risk-free which has no correlation are includes in the portfolio. Therefore, the principal goal of this study is to incorporate the options into multi-asset portfolio using simple approach.

As our study focuses on options, in general, Thailand Exchange market practice, investors should post the cash as collateral for writing the options. This will result in additional cost which is not included in our study.

Also, as the comparison of this strategy is to buy and hold the underlying asset, which might not be exactly a benchmark since the proposed method has monthly rebalancing the portfolio which is more similar to dynamic trading strategy on the Index itself.

Moreover, as the study reveals that the strategy has low exposure to the market and the superior result do not come from loading more risk into the portfolio. The real factor contributed to return can be further discussed and studied to calibrate the model for better capture of the trends of those factors.

Lastly, this study is conducted base on option trade in TFEX which does not include the 'Derivative warrant' trade in SET. Derivative warrant itself is an option on the index future which might be suitable to include into OOPS as well. However, due to the similarity between derivative warrant from each issuer and historical data availability, this study does not incorporate the derivative warrant into optimization process.

REFERENCES

1. Constantinides, G. M.; J. C. Jackwerth; and A. Z. Savov. “The Puzzle of Index Option Returns.” The Review of Asset Pricing Studies 3 (2013), 1–29.

2. Driessen, J., and P. Maenhout. “An Empirical Portfolio Perspective on Option Pricing Anomalies.” Review of Finance 11 (2007), 561–603.

3. Eraker, B. “The Performance of Model Based Option Trading Strategies.” Review of Derivatives Research 16 (2013), 1–23.

4. Faias, José and Santa-Clara, Pedro, Optimal Option Portfolio Strategies: Deepening the Puzzle of Index Option Mispricing, Journal of Financial and Quantitative Analysis, forthcoming

5. Jones, C. “A Nonlinear Factor Analysis of S&P 500 Index Option Returns.” Journal of Finance 61 (2006), 2325–2363.

6. Liu, Jun, and Jun Pan, 2003, Dynamic derivative strategies, Journal of Financial Economics 69, 401–430.

7. Malamud, S. “Portfolio Selection with Options and Transaction Costs.” Swiss Finance Institute Research Paper (2014) No. 14-08.

8. Surayut Nathaphan, advisor, & Sawitree Pongkawong. (2012). Do futures improve risk-return portfolio?: evidence in Thailand market. Thammasat University.

9. Chiappori, P; et al. Portfolio choices and risk preferences in village economies. Minneapolis, Minn., 2013.

10. Paxson, Christina H. "Consumption And Income Seasonality In Thailand." Journal Of Political Economy 101.1 (1993): 39.

11. Supanee Harnphattananusorn, “Asset Pricing in CAPM and CCAPM: Thailand Case Study” Proceedings of 52nd Kasetsart University Annual Conference: Education, Economics and Business Administration, Humanities and Social Sciences., 201

12. Buraschi A., and J.Jackwerth, 2001, The Price of a Smile: Hedging and Spanning in Option Markets. Review of Financial Studies, Vol. 14, 495-527.

APPENDICES

APPENDIX A
EXAMPLE OF METHODOLOGY

Appendix A illustrated the process of construction for the optimal portfolio as explained in the Research Methodology section. For the proposed example, the assumption is made as follows:

1) Only 2 periods of time are assumed, $t = 0$ and $t = 1$, which use the actual from February 2016 as period 0 and March 2016 as period 1. So, the underlying assets and derivatives prices are as follows:

	Unit: THB	
	Feb-16	Mar-16
Underlying Asset (SET50)	851.02	908.79
S50H16C850 (C_1)	27.20	63.60
S50H16C875 (C_2)	15.00	39.40
S50H16C900 (C_3)	7.60	4.50
S50H16P825 (P_1)	8.50	0.10
S50H16P850 (P_2)	14.70	0.10
S50H16P875 (P_3)	27.70	0.20

For the option symbol, S50 means option on SET50 Index, while H16 means maturity in the next month. C/P describes the type of option (Call, Put) and later value states the strike price. For example, S50H16C850 means call option on SET50 index, maturity at end of March 2016 at strike price 850. Also, this study assumes the risk-free rate to be 1.5% per annum (0.125% per month).

2) For the example purpose, the study simulates return on only 7 paths and uses the volatility from the last 21 trading days to scale up monthly volatility. Also, we assume coefficient of relative risk aversion (γ) equal to 10 for the utility optimisation process, resulting in the weight of each option.

3) For simulated return from 2), the study computes the next-period underlying asset value and corresponding option return based on underlying asset value. Then, the portfolio is formulated consist with those options whose returns are based on the weight of each option. Then, the study maximises the expected utility function on wealth to get the weight of each option.

4) Using weight from 3) to the out-of-sample test, the result in portfolio return is 7.12%.

The table below shows an example of portfolio optimisation in two periods with 7 paths simulated (two periods are in the example from Feb 2016 to March 2016).

1.) Simulate the underlying asset log-return in the next period using standardised return and current realised volatility, which is calculated from the last 21 trading days scaled up to monthly volatility						
$r_2^1 = 0.76\%$	$r_2^2 = 0.48\%$	$r_2^3 = 2.23\%$	$r_2^4 = 3.46\%$	$r_2^5 = 2.34\%$	$r_2^6 = -0.02\%$	$r_2^7 = -0.82\%$

2.) Find the next-period underlying asset value (At time t=0, S=851.02)						
$S_2^1 = 857.46$	$S_2^2 = 855.09$	$S_2^3 = 870.85$	$S_2^4 = 880.48$	$S_2^5 = 870.90$	$S_2^6 = 850.87$	$S_2^7 = 844.06$

3.) Determine the option payoff for each path simulated						
$C_{2\|C_1}^1 = 7.46$	$C_{2\|C_1}^2 = 5.09$	$C_{2\|C_1}^3 = 20.9$	$C_{2\|C_1}^4 = 30.5$	$C_{2\|C_1}^5 = 20.9$	$C_{2\|C_1}^6 = 0.87$	$C_{2\|C_1}^7 = 0.00$
$C_{2\|C_2}^1 = 0.00$	$C_{2\|C_2}^2 = 0.00$	$C_{2\|C_2}^3 = 0.00$	$C_{2\|C_2}^4 = 5.49$	$C_{2\|C_2}^5 = 0.00$	$C_{2\|C_2}^6 = 0.00$	$C_{2\|C_2}^7 = 0.00$
$C_{2\|C_3}^1 = 0.00$	$C_{2\|C_3}^2 = 0.00$	$C_{2\|C_3}^3 = 0.00$	$C_{2\|C_3}^4 = 0.00$	$C_{2\|C_3}^5 = 0.00$	$C_{2\|C_3}^6 = 0.00$	$C_{2\|C_3}^7 = 0.00$
$P_{2\|P_1}^1 = 0.00$	$P_{2\|P_1}^2 = 0.00$	$P_{2\|P_1}^3 = 0.00$	$P_{2\|P_1}^4 = 0.00$	$P_{2\|P_1}^5 = 0.00$	$P_{2\|P_1}^6 = 0.00$	$P_{2\|P_1}^7 = 0.00$
$P_{2\|P_2}^1 = 0.00$	$P_{2\|P_2}^2 = 0.00$	$P_{2\|P_2}^3 = 0.00$	$P_{2\|P_2}^4 = 0.00$	$P_{2\|P_2}^5 = 0.00$	$P_{2\|P_2}^6 = 0.00$	$P_{2\|P_2}^7 = 5.93$
$P_{2\|P_3}^1 = 17.5$	$P_{2\|P_3}^2 = 19.9$	$P_{2\|P_3}^3 = 4.15$	$P_{2\|P_3}^4 = 0.00$	$P_{2\|P_3}^5 = 4.10$	$P_{2\|P_3}^6 = 24.13$	$P_{2\|P_3}^7 = 30.9$

4.) Corresponding options return						
$r_{2\|C_1}^1 = -0.73$	$r_{2\|C_1}^2 = -0.81$	$r_{2\|C_1}^3 = -0.23$	$r_{2\|C_1}^4 = 0.12$	$r_{2\|C_1}^5 = -0.23$	$r_{2\|C_1}^6 = -0.97$	$r_{2\|C_1}^7 = -1.00$
$r_{2\|C_2}^1 = -1.00$	$r_{2\|C_2}^2 = -1.00$	$r_{2\|C_2}^3 = -1.00$	$r_{2\|C_2}^4 = -0.63$	$r_{2\|C_2}^5 = -1.00$	$r_{2\|C_2}^6 = -1.00$	$r_{2\|C_2}^7 = -1.00$
$r_{2\|C_3}^1 = -1.00$	$r_{2\|C_3}^2 = -1.00$	$r_{2\|C_3}^3 = -1.00$	$r_{2\|C_3}^4 = -1.00$	$r_{2\|C_3}^5 = -1.00$	$r_{2\|C_3}^6 = -1.00$	$r_{2\|C_3}^7 = -1.00$
$r_{2\|P_1}^1 = -1.00$	$r_{2\|P_1}^2 = -1.00$	$r_{2\|P_1}^3 = -1.00$	$r_{2\|P_1}^4 = -1.00$	$r_{2\|P_1}^5 = -1.00$	$r_{2\|P_1}^6 = -1.00$	$r_{2\|P_1}^7 = -1.00$
$r_{2\|P_2}^1 = -1.00$	$r_{2\|P_2}^2 = -1.00$	$r_{2\|P_2}^3 = -1.00$	$r_{2\|P_2}^4 = -1.00$	$r_{2\|P_2}^5 = -1.00$	$r_{2\|P_2}^6 = -1.00$	$r_{2\|P_2}^7 = -0.60$
$r_{2\|P_3}^1 = -0.37$	$r_{2\|P_3}^2 = -0.28$	$r_{2\|P_3}^3 = -0.85$	$r_{2\|P_3}^4 = -1.00$	$r_{2\|P_3}^5 = -0.85$	$r_{2\|P_3}^6 = -0.13$	$r_{2\|P_3}^7 = 0.12$

5.) Construct the simulated portfolio return based on each path
$Path\ 1: rp_{2\|1}^{1} = 0.00125 + w_{1,C_1}(-0.74) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-0.38)$
$Path\ 2: rp_{2\|1}^{2} = 0.00125 + w_{1,C_1}(-0.83) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-0.29)$
$Path\ 3: rp_{2\|1}^{3} = 0.00125 + w_{1,C_1}(-0.25) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-0.86)$
$Path\ 4: rp_{2\|1}^{4} = 0.00125 + w_{1,C_1}(0.11) + w_{1,C_2}(-0.65) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-1.01)$
$Path\ 5: rp_{2\|1}^{5} = 0.00125 + w_{1,C_1}(-0.24) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-0.86)$
$Path\ 6: rp_{2\|1}^{6} = 0.00125 + w_{1,C_1}(-0.98) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-1.0) + w_{1,P_3}(-0.14)$
$Path\ 7: rp_{2\|1}^{7} = 0.00125 + w_{1,C_1}(-1.01) + w_{1,C_2}(-1.01) + w_{1,C_3}(-1.01) + w_{1,P_1}(-1.01) + w_{1,P_2}(-0.61) + w_{1,P_3}(0.10)$

6.) Find the weight of each option by maximising the expected utility over simulated portfolio returns; $\frac{1}{7}\sum_{n=1}^{7}\frac{(1+rp_{2\|1}^{n})^{1-10}}{1-10}$, resulting in the weight of each option.					
$w_{1,C_1} = 0.00$	$w_{1,C_2} = 0.00$	$w_{1,C_3} = -0.05$	$w_{1,P_1} = -0.05$	$w_{1,P_2} = 0.00$	$w_{1,P_3} = 0.00$
E(U) = -0.046					

7.) Use the weight from 6) to compute the actual payoff and actual return at time t=1

Options	t=0	t=1	Return for each option
S50H16C850 (C_1)	27.20	63.60	$r_{2\|C_1}^{1} = 1.34$
S50H16C875 (C_2)	15.00	39.40	$r_{2\|C_2}^{1} = 1.63$
S50H16C900 (C_3)	7.60	4.50	$r_{2\|C_3}^{1} = -0.41$
S50H16P825 (P_1)	8.50	0.10	$r_{2\|P_1}^{1} = -1.00$
S50H16P850 (P_2)	14.70	0.10	$r_{2\|P_2}^{1} = -1.00$
S50H16P875 (P_3)	27.70	0.20	$r_{2\|P_3}^{1} = -1.00$

8.) Lastly, get the out-of-sample portfolio return
$rp_2 = 0.00125 + (0\%)(1.34) + (0\%)(1.63) + (-5\%)(-0.41) + (0\%)(-1) + (0\%)(-1) + (-5\%)(-1)$
$rp_2 = 7.12\%$

APPENDIX B
REGRESSION RESULT

Appendix B show the result of linear regression between SET50 index return and OOPS return in out-of-sample testing period from January 2012 to March 2017.

SUMMARY OUTPUT

Regression Statistics	
Multiple R	0.157
R Square	0.025
Adjusted R Square	0.009
Standard Error	0.038
Observations	63

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.002	0.002	1.536	0.220
Residual	61	0.090	0.001		
Total	62	0.092			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	0.009	0.005	1.656	0.103
X Variable 1	(0.142)	0.115	(1.239)	0.220

	Lower 95%	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	(0.002)	0.020	(0.002)	0.020
X Variable 1	(0.372)	0.087	(0.372)	0.087

BIOGRAPHY

Name	Mr. Matas Vattanalouvit
Date of Birth	August 21, 1991
Educational Attainment	2009: Bachelor of Accounting
	Thammasat University
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