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A COMBINATION OF ACTIVE BUY-WRITE STRATEGIES

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ABSTRACT

The purpose of this study is to examine active buy-write strategies and whether a dynamic strike price strategy, a volatility risk premium estimation utilizing strategy and a combination of those active strategies can improve the performance of a vanilla buy-write strategy. Buy-write strategy's popularity among investors and an increasing amount of strategy indices and exchange-traded funds are the motivation for this thesis.

The buy-write strategy is an investment strategy that includes having a long position on a stock and a short position on a call option on the stock. A short call option obligates its holder to sell the underlying stock at a predetermined strike price at a predetermined time. As the buy-write strategy is entered, the investor creates instantly a positive cash-flow from selling (shorting) the call option but also caps the return of the stock, since if the stock price rises above the strike price the stock has to be sold to the holder of the other end of the option contract. The dynamic strategy tries to improve the vanilla buy-write strategy by using the exercise probability of the option as the criteria which options to sell. The volatility risk premium strategy adds another criterion. It estimates whether the option's price is artificially high or not. These concepts and theories are explained more thoroughly in theory and methodology sections of this study.

The combine strategy uses both of the aforementioned criteria to construct an active buy-write strategy. The combine strategy is able to improve the performance of the vanilla buy-write strategy. Also, the dynamic and volatility risk premium strategies alone are able to improve the performance. These and some other results and findings are presented and discussed in detail in the last two sections before references.

KEY WORDS: buy-write strategy, dynamic strike price, volatility risk premium, Heston model, options

1. INTRODUCTION

Options, as derivatives, have existed circa 2300 years. Options on olive presses were traded in the ancient Greece around 300 BC. In 1630's, option and futures were used in speculation of tulip prices during the Tulip Mania, which almost crashed the Dutch economy. Around 340 years later, the first exchange for listed options, Chicago Board Options Exchange, opened. (Markham 2002: 5-6; CBOE 2017a.) Since the opening of the CBOE, the buy-write, or covered call strategy has been the most popular option investment strategy (Lakonishok, Lee, Pearson & Poteshman 2007).

Today, CBOE only offers ten different buy-write strategy benchmark indices, ranging from the vanilla buy-write on S&P 500 and Dow Jones Industrial Average indices to more complex 30-Delta BuyWrite index (CBOE 2017b). There are 25 different covered call Exchange Traded Funds (ETFs) available for investors, investing in different asset classes and regions (ETF Insights 2018). Interest towards the buy-write strategy is high among investors and institutions, as indicated by the increasing number of buy-write products.

The research on the buy-write strategy started four decades ago. Among the first, Merton, Scholes & Gladstein (1978) presented their paper focusing on the risk and return characteristics of the covered call strategy. Since then, the focus of the covered call research has ranged from company cash management properties (see Brown & Lummer 1984) to constructing of a benchmark index for the strategy (Whaley 2002). The two most recent, and essential, studies from the point of this thesis have tested a dynamic buy-write strategy (see Che & Fung 2011) and an estimation model to time the strategy according to market movements (Simon 2014). Both Che & Fung (2011) and Simon (2014) show promising results in their respective studies.

This thesis combines a dynamic buy-write strategy with market movements predicting model to construct an active buy-write strategy superior to either strategy alone and superior to a passive benchmark index. The dynamic buy-write strategy is at its best when the markets are volatile, and the forecasting model is designed to predict when the markets are optimal for the strategy.

1.1 What are an option and a buy-write strategy?

An option is a derivative security, meaning that its value depends on the value of some other asset, known as the underlying asset. A stock option's value is dependent of the value of the underlying stock. Other than the value, an option gives its holder a right, not obligation, to buy or sell the underlying asset. A *call* option gives its holder a right to buy the underlying asset and a *put* option gives the holder a right to sell the underlying asset. A stock option can be a call or a put, but it can be also either *European, American, Asian* or *Bermudian* (the last two are inessential in this case). A European option can be exercised only at the expiration date of the option and an American option can be exercised whenever during the maturity. When a European option expires, and it is beneficially for the holder to exercise it, the predefined *strike price* or exercise price defines the price at which the holder can buy or sell the underlying stock. (Hull 2015: 1, 213.)

There are four different positions one can have on an option. A long call and a long put positions are already explained above. The other two positions are a short call and a short put, which obligates the holder to buy or sell the underlying asset. The seller or writer of an option has always a short position in an option and the buyer or holder has a long position. (Hull 2015: 216-217.)

A buy-write or covered call strategy is an option trading strategy which involves taking a position in both the underlying stock and a call option. This means buying a stock and selling (taking a short position) a call option on that stock. As mentioned above, selling an option obligates the seller to sell or buy the underlying asset, in this case, buying the underlying stock. Since the investor has both the stock and a short call position on the stock, it means that investor's short position is covered. In this example, the option is a European option, meaning that it can be exercised only at the expiration date (Hull 2015: 256-257.) From now on unless otherwise mentioned, all options are considered as European options.

1.2 Hypothesis and the purpose of the study

The purpose of this study is to analyze the buy-write strategy and to examine the effects of combining a dynamic strike price method (as in Hill, Balasubramanian, Gregory & Tierens 2006; Che & Fung 2011; Hsieh, Lin & Chen 2014) and an ex-ante volatility risk premium estimation model constructing out-of-sample fitted implied volatility values (as in Simon 2014) on the buy-write strategy. Both dynamic strike price method and volatility risk premium estimation have showed some promising results in their respective studies (see Hill et al. 2006; Che & Fung 2011; Hsieh et al. 2014; Simon 2014).

In short, the dynamic strike price method means that rather than choosing the option according to the strike price, it is chosen according to its exercise probability (Hill et al. 2006; Che & Fung 2011; Hsieh et al. 2014). The exercise probability can be derived from the Heston option pricing model (see Heston 1993).

The ex-ante volatility risk premium is calculated as the difference between the actual implied volatility and the out-of-sample fitted implied volatility. The VIX index (CBOE Volatility Index, see Chicago Board Options Exchange 2014) is used as a proxy for the actual implied volatility and the out-of-sample fitted implied volatility is estimated with an estimation model as in Simon (2014).

The first hypothesis states that a combination of attributes exists (maturity and strike price), that offers best performance to a buy-write strategy. Intuitively there must be one combination better than the others, but the goal is to find a performance-wise distinctive combination.

H1: *The performance of a buy-write strategy can be improved by altering the fundamentals of the strategy.*

Previous studies (see e.g. Whaley 2002; Feldman & Roy 2005; Figelman 2008) suggest that utilizing call options with shorter maturities (one month) are more preferable than options with longer maturities. Considering these findings, the first hypothesis is tested only with different strike prices, keeping the maturity at one month.

The second hypothesis states that the best practices found in the first hypothesis can be improved further, performance wise, by entering the buy-write strategy when the ex-ante volatility risk premium is at optimal level. Volatility risk premium is calculated as the difference between the actual and estimated implied volatility of the option. This hypothesis is parallel with the research problem in Simon (2014).

H2: *The performance of the vanilla buy-write strategy can be improved by timing the implementation of the strategy based on ex-ante volatility risk premium.*

The third hypothesis states that utilizing a dynamic price method improves the performance of the buy-write strategy. The third hypothesis is similar to the research problems in Hill et al. (2006), Che & Fung (2011) and Hsieh et al. (2014).

H3: *The performance of the vanilla buy-write strategy can be improved by utilizing the dynamic strike price method.*

The fourth hypothesis elaborates on the second and third hypotheses by stating that employing both dynamic strike price method and ex-ante volatility risk premium on buy-write strategy improves its performance even further.

H4: *The performance of the vanilla buy-write strategy can be improved further by timing the implementation of the strategy based on ex-ante volatility risk premium and utilizing the dynamic strike price method.*

The performance measurements which are used to test all of the hypotheses are presented in 4th main section.

1.3 Intended contribution and limitations of the study

The intended contribution is to take the research on buy-write strategies further by demonstrating that it is beneficiary, risk-return wise, to utilize dynamic pricing method and ex-ante volatility risk premium estimation in a buy-write strategy. Put in short, this paper tries to demonstrate that an active buy-write strategy is more beneficial than a passive buy-write strategy.

The limitations of this study may have some effect on this study and its results. One limitation is the time period of the data, which ranges from January 2004 to January 2018. Considering the financial crisis started in 2008, it leaves less than 8 years (ca 96 monthly observations) post-crisis examination period. Also, this study does not consider for example trading costs nor inflation. Other limitations are for example in the volatility premium estimation model, which is parsimonious comparing to, for example a recent study of Psaradellis & Sermpinis (2016) examining a promising volatility estimation model combining a heterogeneous autoregressive process and a genetic algorithm-support vector regression.

1.4 Structure of the study

This thesis has seven main sections as a whole. First section is the introduction and the rest of this thesis is divided as follows. The second section introduces the previous studies focusing on the buy-write strategy. The literature review starts from the 1970s and ends in 2016, covering the essential papers on this topic.

The third section covers the options theory, starting from basic terminology and ending to option risk management measures known as the Greeks. This section covers also option valuation and pricing with Black-Scholes-Merton and Heston option pricing models.

The fourth section presents the performance measurements, which are used in the comparison of the different buy-write strategies. This section starts from the construction of Capital Asset Pricing Model (CAPM) and presents several different performance measurements.

The fifth section presents the methodology and the data used in this study. The methodology follows mostly the methodology of previous studies. This section describes in detail how the buy-write returns, volatility risk premium estimates and dynamic strategy returns are calculated.

The sixth section presents the results of this study and discusses these results and findings in detail. First, the results on all of the hypothesis testing are examined in own sections and then the results summarized in last section.

The last section concludes this study and discusses the results and proposals for future research topics.

Appendices includes figures and tables visualizing the results as a whole.

2. LITERATURE REVIEW

This literature review starts from 1978, when Merton, Scholes and Gladstein (1978) published their paper on covered call strategy and ends in 2016 to the paper of Diaz and Kwon (2016). The literature review is not an exhaustive review of all the studies published on the strategy, but it tries to give a coherent picture of the history and topics already covered of the buy-write strategy.

This section is divided in subsections by topic, to make it easier to the reader to perceive the different research directions of the study of buy-write strategy. The first subsection presents the previous main studies, which have highest importance to this paper. The second covers the risk and return characteristics of the strategy, including an own section for risk-adjusted return. The third section covers the creation of a benchmark index for passive covered call strategies, the BXM (the CBOE S&P 500 BuyWrite Index). The fourth section explains how market conditions affects the returns of the strategy.

2.1 Previous main studies

The previous main studies for this thesis are the studies of Hill et al. (2006), Che & Fung (2011) and Simon (2014). These studies are essential to this study, since much of the methodology of this thesis is motivated by these three studies.

Hill et al. (2006) examines active covered call strategies in their study, which are fixed and flexible (also known as dynamic) strike price strategies. They use the CBOE S&P 500 BuyWrite index as the benchmark index and finds that both active strategies offer higher risk-adjusted returns than the benchmark. The fixed strike price strategy has been examined before in the studies mentioned in the next section, but the dynamic strike price strategy has had minimum to none coverage in studies previous to Hill et al. (2006). They construct the covered call portfolios of at-the-money, 2% out-of-the-money and 5% out-of-the-money call options on the S&P 500 index with maturity of one-month (they also examine calls with three-month maturity, but this part is not presented). They account only return and standard deviation in the performance comparison. This may affect the results of the study, since several studies before have demonstrated that the returns of covered call strategy are non-normally distributed, which is why semi-standard deviation, or some other non-normality considering measure, is suggested as the risk measure of the strategy (see e.g. Board, Sutcliffe & Patrinos 2000; Whaley 2002; Feldman & Roy 2005; Figelman 2008).

Hill et al. (2006) results shows that the dynamic strike price strategy offers higher returns with lower volatility than the underlying S&P 500 index and that in some cases the dynamic strategy offers higher return than the fixed strike price strategy. The dynamic strategy allows the strike price to adapt to the changes of volatility, which may be the reason for the higher performance. Also, they find that the strategy with one-month maturity calls outperforms the strategy with longer maturity calls. (Hill et al. 2006.)

Che & Fung (2011) does a similar study to Hill et al (2006) by testing the fixed strike price and dynamic strike price covered call strategies. They find that both buy-write strategies outperform the stock index with statistically significant positive alphas and, that in some cases the dynamic strike price strategy outperforms the fixed strike price strategy. Overall, only the near at-the-money dynamic strike price strategy outperforms with a higher Sortino ratio the other strategy. When accounting for different market and volatility conditions, the dynamic strategy outperforms the fixed strategy during sharply rising market and moderately volatile market. The time period is divided to four volatility conditions and four market conditions. Che & Fung (2011) uses Hang Seng Index as the underlying and they substitute the cash leg (the stock index) of the strategy with futures. They reason using futures instead of direct long position on the underlying index, because futures have smaller bid-ask spreads than the index and it allows avoiding the transaction costs.

Hsieh, Lin & Chen (2014) continues the study of Che & Fung (2011) by examining three different covered call strategies, one fixed strike price and two dynamic strike price strategies. The other dynamic strategy is similar to the dynamic strategies examined in Hill et al. (2006) and in Che & Fung (2011), but the other dynamic strategy uses Heston model (see Heston 1993) instead of Black-Scholes-Merton model (BSM-model) (see Black & Scholes 1973; Merton 1973) to implement the dynamic strategy. The Heston model assumes that volatility is a stochastic process and it changes over time, whereas the BSM-model assumes that volatility is a constant (the models are discussed further in the theory section of this study). They conduct their study in Taiwan, using Taiwan index options on futures contracts in Taiwan stock markets, similarly to the study of Che & Fung (2011).

Hsieh et al. (2014) finds that overall the dynamic strategy using the Heston model has higher risk-adjusted return (higher Sortino ratio) than the dynamic strategy using BSM-model. The Heston dynamic strategy outperforms also the future-only strategy when the exercise probability is 20% or 17%.

Che & Fung (2011) also estimates the volatility risk premium (the difference between implied and realized volatility) with an error correction model following the studies of Christensen & Prabhala (1998) and Fung (2007). The results of their forecasting model are congruent to previous studies, demonstrating that there is a positive relationship between volatility premium and buy-write strategy returns (Che & Fung 2011).

Simon (2014) also does a study utilizing ex-ante volatility risk premium estimation, finding that utilizing the estimation increased both pure returns and risk-adjusted returns. The model differs from the model of Che & Fung (2011), since the former is a GARCH -like (generalized autoregressive conditional heteroscedasticity) model and the latter is an AR-like (autoregressive) model. Simon (2014) tests the model on Nasdaq 100 ETF (QQQ) and constructs an implied volatility index of the QQQ -ETF, following the methodology of VIX -index (see Chicago Board Options Exchange 2014). The model is then used to estimate the out-of-sample implied volatility and compare it to the actual volatility. This difference (ex-ante or conditional volatility premium) between the implied and actual volatility is used as a gauge for expensiveness of the option (the higher the difference, the more expensive is the option). Intuitively, it is more profitable to sell at higher price, meaning that the buy-write strategy is implemented when the ex-ante volatility risk premium is high. (Simon 2014.)

Simon (2014) also constructs a framework for an active buy-write strategy, by separating the buy-write position to a delta neutral short call and a long stock position. With this framework the strategy can be actively rebalanced to maintain delta-neutrality (delta means options sensitivity to changes in the price of the underlying and it is one of the Greeks discussed thoroughly later; see Neftci 2008: 228). The results show that rebalancing delta-neutrality leads to higher buy-write strategy risk-adjusted returns. (Simon 2014.)

2.2 Risk and return characteristics

Merton, Scholes and Gladstein (1978) published their paper on covered call strategy five years after the opening of the first options exchange CBOE. They examine the risk and return characteristics of the covered call strategy by using two groups of stocks, 30 Dow Jones Industrial Average stocks and 136 stocks (all of the stocks which were currently available as underlying in option exchange) as underlying. Since the option market data was not available for enough long period, they calculated the option prices with BSM –model. This may affect the results because it has shown that the returns of a covered call strategy using option prices calculated with the BSM –model differs from covered call returns calculated with real market data (see McIntyre & Jackson 2007). They use fully covered positions (i.e. the same number of stocks and options) with call option maturities of 6 months and with four different variation of 'moneyness', 10% in-the-money, at-the-money, 10% out-of-the-money and 20% out-of-the-money, and they assume that the positions are held until maturity. Their results demonstrate that the covered call strategy offers better risk-return combination than the underlying stock or a portfolio of stocks and fixed-income products. They also find that the 10% ITM portfolio offers best risk-return combination. (Merton, Scholes & Gladstein 1978.)

Zivney & Alderson (1986) studies on companies' cash management and how it could be enhanced with dividend capturing strategies. They construct a hedge portfolio that captures dividends by using covered call strategy. The data consists of the S&P 100 stock index and call options on that index with maturity of one month. The moneyness of the options is slightly in-the-money or at-the-money. The data period consists of the year 1984. They make several findings on systematic risk, total risk and return of the strategy. Having a stock index as the underlying on the covered call strategy lowers the systematic risk (market beta) and the overall risk (standard deviation). Also, they compared their results on Brown & Lummer's (1984) similar study, which found that covered call strategy reduces portfolio's systematic and overall risk but doesn't increase annualized return. In contrast, Zivney & Alderson (1986) demonstrates that covered index writing results in both reduced systematic and overall risk, but also higher annualized return. (Zivney & Alderson 1986.)

Board, Sutcliffe & Patrinos (2000) focuses on the return distribution of the covered call strategy in their study. They argue that variance is not a suitable risk measure for the strategy since its returns are not normally distributed, because the covered call returns have a cap and because of the returns are negatively skewed. The data consists of FTSE-

100 index (as the underlying) and call options on the index and it ranges from 1992 to 1995. Their results show that the returns are negatively skewed, which means that semi-variance is a more correct risk measurement than the simple variance, because semi-variance counts only the downside risk. Although, they conclude that the covered call strategy is beneficial for an investor, their results are contrary with Isakov & Morard's (2001) study. Isakov & Morard (2001) finds that the returns of the covered call portfolio are normally distributed, which is in contrast with the findings of Board et al (2000). The reason may be in the different time period and different data, but it could also be because Isakov & Morard (2001) used a minimum-variance algorithm in their strategy construction.

Figelman (2008) presents a theoretical framework for calculating the expected return of the covered call strategy. With this framework, the historical returns of covered call can be divided into three components: risk-free rate, equity risk premium (ERP) and implied-realized volatility spread. The framework also suggests using short dated calls in the strategy. The framework is tested with the S&P 500 stock index and CBOE BXM index (discussed more thoroughly in next section). The results show again that the covered call strategy returns are non-normally distributed because of the negative skewness, which suggests using semi-standard deviation instead of standard deviation as a risk measure. Also, the results show that the higher the spread between implied and realized volatility, the beneficiary the strategy. This relation between implied and realized volatility is discussed further in Figelman (2009). (Figelman 2008.)

Diaz & Kwon (2016) also constructs a theoretical framework for calculating the expected return of covered call strategy, but it also allows to calculate the optimal strike price and write-buy ratio (the ratio of number of short calls and underlying stocks, i.e. ratio of 1 means a fully covered position) risk-return wise. They also consider covered call positions combining calls with different strikes and use value-at-risk (VAR) and conditional-value-at-risk (CVAR) in addition to traditional risk measures variance and semi-variance. The data consist of S&P 500 (as the underlying) and an own version of the CBOE BXM index, which are then simulated. Diaz & Kwon's (2016) results shows that it is often optimal to sell several calls with different strike prices risk-return wise (e.g. their optimal portfolio contained short calls with 5 different strikes prices). This is due to the negative relationship between the call risk premium (CRP, which is the difference between call's value and price) and covered call return.

The studies above have found several characteristics of the buy-write strategy. Zivney & Alderson (1986) finds that when using buy-write strategy, it is more profitable to write call options on a stock index instead of individual stocks. Board, Sutcliffe & Patrinos (2000) demonstrates that the buy-write strategy returns are not normally distributed, which is why variance or standard deviation are not suitable risk measures for the strategy. They argue that semi-variance describes more correctly the risk of the strategy. Figelman (2008) demonstrates that volatility spread (difference between implied and realized volatility) is one of the key components of the buy-write strategy returns. Figelman (2008) also finds that, because of the negative relationship between call risk premium (CRP) and buy-write returns, it is preferable to use short-dated options.

2.2.1 Risk-adjusted return

Several studies have found that the traditional volatility measure, standard deviation, does not capture well the risk of the buy-write strategy, since the strategy returns are negatively skewed. This negative skewness can be accounted by measuring semi-standard deviation that accounts for the non-normality by measuring only the downside deviation of the returns. (Whaley 2002; Feldman & Roy 2005; Figelman 2008.)

Whaley (2002) and later Figelman (2008) calculates the risk-adjusted return of the strategy by calculating the risk as semi-standard deviation. They measure the semi-standard deviation as downside deviation from the risk-free rate, and the positive deviations as zero. This measure differs slightly form the method used in Che & Fung (2011) and Simon (2014). They measure the risk with Sortino ratio, which measures the risk as downside deviations from the mean return (instead of the risk-free return) (Sortino 1994). Kapadia & Szado (2007) and Figelman (2008) calculates the risk-adjusted return with Stutzer Index, that employs an information statistic whether the return is above a reference level. The Stutzer Index returns the same value as the Sharpe ratio, if the returns are normally distributed (Stutzer 2000).

These three non-normality accounting risk-adjusted return measurements presented above are considered in the performance comparison of the buy-write strategies examined and they are discussed further later in this paper.

2.3 CBOE S&P 500 BuyWrite -index

In 2002, CBOE presented the CBOE S&P 500 BuyWrite Index (BXM), which is a buy-write strategy index using the S&P 500 -index as underlying and it was developed with the help of Robert E. Whaley (Whaley 2002). BXM is presented in its own subsection, because it is used as a benchmark index for a passive buy-write strategy in this thesis.

BXM is constructed to follow a buy-write strategy, writing almost at-the-money call options on the S&P 500 -index. 'Almost' meaning that the call option written is chose so, that it has the strike price closest to the underlying, but still out-of-the-money (i.e. the strike price is higher than the price of the underlying). The strategy writes call options with a maturity of one month and the strategy rolls every month's third Friday (with some exceptions), when the option expires. (Whaley 2002.)

Whaley (2002) and later Feldman & Roy (2005) studies the risk-return characteristics of the strategy, and the latter study also concentrates on the strategy's investment properties. Both find that the benefit of the strategy is in its better risk-adjusted return than the underlying's. Measuring only return, the strategy returns follows the underlying's returns, but the strategy returns have lower standard deviation than the underlying. This finding is supported by the strategy's property to generate constant cash flows from writing the options. (Whaley 2002; Feldman & Roy 2005.)

The performance measurements are done using semi-standard deviation (as described in the previous section). Whaley (2002) suggests using a version of semi-standard deviation, which considers only downside deviations from the risk-free rate, in the calculation of total risk, and a version considering downside deviations from excess returns when calculating systematic risk. Feldman & Roy (2005) uses instead Stutzer ratio (see previous section) and Leland´s alpha (i.e. abnormal return), which uses systematic risk that considers non-normality of returns (Leland's beta) (Leland 1999). These performance measurements are discussed more thoroughly later under an own heading. (Whaley 2002; Feldman & Roy 2005.)

2.4 Market conditions

Previous studies have found that market, and furthermore volatility conditions, affects the buy-write strategy returns. Figelman (2008) constructed an expected return framework for the strategy and demonstrated that the implied-realized volatility spread is in positive relationship with the spread between buy-write's and its underlying's returns. Later, Hill et al. (2006) demonstrated that only during the highest volatility-regimes the volatility spread is turned negative (i.e. realized volatility is higher than the implied volatility). This connection between volatility regimes and buy-write strategy returns is discussed below.

Che & Fung (2011) demonstrates that the buy-write strategy has higher absolute return than the underlying when the market volatility higher than its lowest quartile level. Similarly, Kapadia & Szado (2012) found that the buy-write strategy returns were almost twice the underlying's returns when the implied-realized volatility spread was highly positive, and the market volatility was relatively high.

Intuitively, when the market (the underlying) are in an upward trend, the call option is exercised with higher probability, leading to lower buy-write returns. Feldman & Roy (2005) found that during a bull market the S&P 500 return were higher than the buy-write return and vice versa during bear market. Likewise, Hill et al. (2006) and Che & Fung (2011) demonstrates that during bull markets the buy-write strategy has lower absolute return than the underlying stock index, and during bear markets the strategy outperforms the underlying return wise. Even though the strategy demonstrates lower returns than the underlying e.g. during bull market, the risk-adjusted performance still supports the dominance of the strategy over the underlying stock index (Feldman & Roy 2005; Hill et al. 2006; Che & Fung 2011; Kapadia & Szado 2012).

3. OPTIONS THEORY

This section introduces the theory behind options, starting from basic terminology and ending with the Greeks. The theory is divided into subsections as follows. First, the terminology in presented. Some of it is discussed already in the first section of this thesis, but here it is in more detail. Second, conversion and put-call parity are presented. In 1969, Stoll (1969) presented the put-call parity, which later became a fundamental part of option pricing and valuation. Third comes Black-Scholes-Merton and Heston option pricing models. These two pricing models were presented in 1970s and 1990s, respectively, and are a part of the methodology of this study. Last part of this section are the Greeks, which represents options' sensitivities to changes.

3.1 Introduction of options and the buy-write strategy

The introduction section of this study already introduced the reader to some concepts of option. To summarize the introduction, an option is a derivative, meaning that its value is derived from the value of its *underlying* asset. An option gives its holder a right to buy the underlying asset if it is a *call* option. If it is a *put* option, it gives its holder a right to sell the underlying asset. Whether it is a call or a put, transaction of the underlying is executed at a predetermined *strike price* either at a predetermined maturity date, or *expiration date*, or any time before a predetermined date, depending whether the option is a *European* or an *American* option, respectively. These properties apply only for exchange traded options, which are regulated and available for investors. There are also OTC (over-the-counter) traded options, which are tailored for the needs of the trade counterparts. (The Options Clearing Corporation 1994: 1-22, 49-53; Hull 2015: 1, 213.) As mentioned in the introduction, this study assumes that every option is a European stock option unless otherwise mentioned.

The four option positions are long call, long put, short call and short put. The buyer has always a long position and the seller, or writer, has short position on the option. A long position gives a right to execute the option and a short position obligates the holder to act accordingly, either sell or buy the underlying. Values of the positions on call options can be demonstrated with the following formulas (Hull 2015: 215-217):

(1) $$Long\ call = max(S_T - K, 0)$$

(2) $Short\ call = min(S_T - K, 0)$

Where S_T is price of the underlying stock at expiration and K is the strike price. If the stock price is higher than the strike price at expiration date, it is beneficiary for the holder to exercise the call option and buy the underlying stock at price K and sell it immediately at price S_T and receive a payoff equal to $S_T - K$ minus the premium paid of the option. The payoff for the option writer is the opposite: $K - S_T$ plus the premium received from the option (Hull 2015: 215-217). Values of put options are as follows (Hull 2015:217):

(3) $Long\ put = max(K - S_T, 0)$

(4) $Short\ put = min(K - S_T, 0)$

Where the variables are the same. Now, if the stock price is lower than the strike price at expiration date, the holder of put option buys the stock from markets at price S_T, exercises right to sell the stock to the option writer at price K. The payoff from long position is $K - S_T$ minus the option premium and the payoff from short position is $K - S_T$ plus the premium. Again, the win from the long position is unlimited and the loss from the short position unlimited. In an opposite scenario, the short position payoff would be limited to the premium received and the long position loss would be limited to the premium paid of the option. (Hull 2015: 216-217.)

If the strike price of a call option is lower than the stock price (the option produces positive cash-flow), it is in-the-money (ITM), if it is equal to the stock price, it is at-the-money (ATM) and if it is higher than the stock price, it is out-of-the-money (OTM). In the same fashion, if a put option generates positive cash-flow to the holder, it is ITM, if it generates no cash-flow, it is ATM and if it generates negative cash-flow, it is OTM (Bodie, Kane & Marcus 2014: 680; Hull 2015: 220.)

The buy-write strategy is an option strategy that has a long position on a stock and a short call position on the stock. The strategy generates a positive cash-flow when the call option is written and the long position on the underlying stock covers the short call position, which is why the strategy is also known as covered call strategy. The formula for calculating return of buy-write strategy is presented in the methodology part of this study, but the payoff from the strategy is presented in the figure below. (Hull 2015: 256-257.)

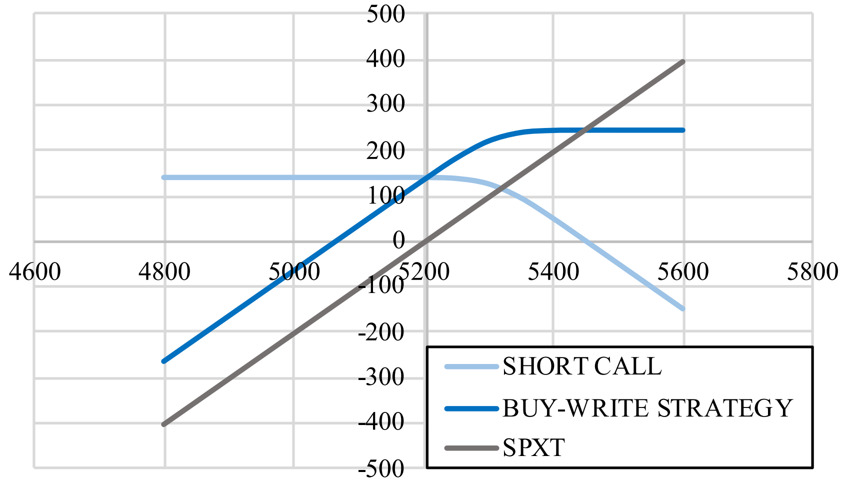

Figure 1. The payoff from buy-write strategy. The underlying SPXT is S&P 500 Total Return index as of 27.3.2018. The price S is 5206 and the option is 2% out-of-the-money. Data source: Bloomberg Terminal.

The figure above demonstrates the option premium as the distance between the SPXT and buy-write strategy lines. As can be seen, the returns from buy-write strategy are capped, because as the underlying price increases above the strike price, the option is executed by its holder and the underlying stock is sold to the holder at the strike price (Hull 2015: 256-257.)

3.2 Conversion and put-call parity

Conversion and put-call parity are mechanisms that explain interrelationships between European call and put options and their underlying stocks. The relationship between call and put option prices can be demonstrated with the lower and upper bounds of option prices presented in the section above and these two mechanisms together if the markets are efficient. (Stoll 1969; Klemkosky & Resnick 1979; Hull 2015: 241-244.)

In the 1960s, Stoll (1969) presented an arbitrage mechanism, known as *put-call parity*, to explain the parity between call and put option prices. He starts by demonstrating that through a mechanism called *conversion*, there is two ways to enter a position on an option. The first is to buy the option and the second is to create the option synthetically (Stoll 1969.) Conversion is demonstrated with vector notation, as follows:

$$(5)\qquad \underset{\text{Long}}{\begin{bmatrix}+1\\-1\end{bmatrix}} + \underset{\text{Buy put}}{\begin{bmatrix}0\\+1\end{bmatrix}} = \underset{\text{Buy call}}{\begin{bmatrix}+1\\0\end{bmatrix}}$$

$$(6)\qquad \underset{\text{Short}}{\begin{bmatrix}-1\\+1\end{bmatrix}} + \underset{\text{Buy call}}{\begin{bmatrix}+1\\0\end{bmatrix}} = \underset{\text{Buy put}}{\begin{bmatrix}0\\+1\end{bmatrix}}$$

Where *Long* and *Short* are long and short positions on the underlying stock and the upper number demonstrates payoff when the price of underlying increases and the lower number demonstrates payoff when the price of underlying decreases. Formulas 5 and 6 shows how a call option can be created synthetically by taking a long position in a stock and buying a put option on it. The same way a put option can be created by short-selling a stock and buying a call. Also, short positions in options can be created in the same fashion, but by taking the opposite positions to the formulas presented above. (Stoll 1969.)

Motivation to create synthetically an option could be that a contract is mispriced. For example, if an investor believes that the price of a call is artificially high, she could write the mispriced call (take a short position on it), create a synthetic call and end up with no position and arbitrage profit equal the difference between the 'real' call and synthetic call.

Assuming that there are no transaction costs, the stock does not pay dividend, investing and borrowing money is done at a risk-free rate without any risk and that the put and call options have the same time to maturity and strike price, the example above can be presented in a form of a formula is as follows (Klemkosky & Resnick 1979; Hull 2015: 241:242):

$$(7)\qquad c - p - S + Ke^{-rT} = A$$

Where *c* is the price of a call, *p* is the price of a put, *S* is stock price, *K* is strike price, *r* is risk-free rate, *T* is time to maturity and *A* is arbitrage profit. Similarly, assuming that the price of a put option is artificially high, an investor could make arbitrage profit by short-selling the put option and creating a synthetic put through the conversion mechanism, as demonstrated with the following formula (Klemkosky & Resnick 1979; Hull 2015: 241-242):

$$(8)\qquad p - c + S - Ke^{-rT} = A$$

Where variables are the same as in formula 7. Stoll (1969) proposes a parity between call and put option prices, basing it on the conversion mechanism, the formulas 7 and 8. Assuming, that if there exist arbitrage possibilities (A>0), investors will exploit these arbitrage possibilities until A is zero. This leads to the put-call parity by combining the formulas 7 and 8 (Stoll 1969; Hull 2015: 242):

(9) $$c + Ke^{-rT} = p + S$$

The put-call parity demonstrates how the price of a European call option can be derived from a European put option and vice versa.

3.3 Black-Scholes-Merton option pricing model

In 1970s, Black & Scholes (1973) and Merton (1973) presented their new option pricing model (BSM-model) to the public. The model was a breakthrough, which led to Nobel prizes for Merton and Scholes in 1997. Black & Scholes (1973) approach the option pricing model with Capital Asset Pricing Model (CAPM, which is introduced in section 4.1), by explaining the connection between stock and option expected returns with beta (see section 4.1). Merton's (1973) has a more general approach where a fully hedged portfolio of an option and the underlying stock is assumed risk-free during a short period of time. These approaches were better to explain the correct discount rate, which earlier attempts failed to explain (Jarrow 1999; Hull 2015: 321.)

The modern option pricing theory started 1900 from Bachelier's (1900) work on option speculation. Among others, Itō's (1951) work on stochastic calculus and Samuelson's (1965) work on warrant (an OTC traded option) pricing influenced the work of Black & Scholes (1973) and Merton (1973). (Jarrow 1999; Hull 2015: 321.)

The examination of BSM-model starts with presenting variables and assumptions, as follows (Black & Scholes 1973; Kosowski & Neftci 2015: 290):

1. Lending and borrowing is possible at a risk-free rate *r*.
2. The option is considered as European, it has a strike price *K* and it expires at time *T*-*t*, where *t* is current time.
3. The underlying stock price follows a stochastic process in continuous time (stochastic differential equation, SDE, below) and it pays no dividends.

4. There are no transaction costs.

The SDE as follows (Kosowski & Neftci 2015: 290):

(10) $$dS_t = \mu(S_t)S_t\, dt + \sigma S_t\, dW_t, \;\; t \in [0, \infty]$$

Where μ and σ are drift and volatility of stock *S*, respectively, and W_t is a Wiener process. A Wiener process (also known as Brownian motion) is a Markov process, with mean equal zero and variance equal to one (Föllmer & Schied 2011: 314-315; Hull 2015: 303-305.)

Black & Scholes (1973) presents a partial differential equation (PDE), which has a closed-form solution known as the Black-Scholes-Merton option pricing model and from the Greeks (presented further) can be derived. The PDE can be also derived, for example to price stock paying dividends, which are presented in detail in e.g. Chin, Nel & Ólafsson (2017: 89-190). The Black-Scholes PDE as follows (Black & Scholes 1973; Lee, Lee & Lee 2010: 502; Hull 2015: 332):

(11) $$\frac{\partial \Pi}{\partial t} + rS\frac{\partial \Pi}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 \Pi}{\partial S^2} - r\Pi = 0,$$

Where,

(12) $$\Pi_{call} = \max(\mathrm{S} - \mathrm{K}, 0)$$

$$\Pi_{put} = \max(K - S, 0)$$

Where Π is value of the option on stock *S*, *r* is risk-free rate and σ is stock price volatility. The Black-Scholes-Merton option pricing model is a closed-form solution of the Black-Scholes PDE, under the assumptions and with the variables and parameters presented above. The BSM-model as follows (Black & Scholes 1973; Kosowski & Neftci 2015: 290-291):

(13) $$C(t) = S_t N(d_1) - Ke^{-r(T-t)}N(d_2)$$

Where,

(14) $d_1 = \frac{\ln\frac{S_t}{K}+\left(r+\frac{\sigma^2}{2}\right)*(T-t)}{\sigma\sqrt{T-t}}$, $d_2 = \frac{\ln\frac{S_t}{K}+\left(r-\frac{\sigma^2}{2}\right)*(T-t)}{\sigma\sqrt{T-t}}$

Where *C* is the price of a call option, *N()* is a standard normal cumulative density function (cdf) (see e.g. equation 9.55 in Kosowski & Neftci 2015: 291) and the other variables and parameters are defined above. The price for a put option can be calculated with the same formula but rearranging the terms (see put option boundary eq. 3) and changing the normal cdf loadings as negative (Hull 2015: 335-336).

The terms $N(d_1)$ and $N(d_2)$ from formula 13 can be interpreted also other way than just as normal cumulative density functions. The $N(d_1)$ is also known as option *delta* (one of the Greeks) and in a risk neutral-world, $S_tN(d_1)$ equals the expected price of stock *S* at time *t* assuming stock prices lower than *S* equal to zero. The term $N(d_2)$ demonstrates the probability that the option C will be exercised in a risk-neutral world. (Hull 2015: 337; Kosowski & Neftci 2015: 297-298.)

This section describes the option pricing model developed by Black, Scholes and Merton. The equations above represent only a fraction of the full derivation of the model to give enough detail to the reader to comprehend the logic behind the model. For a full and detailed derivation of the BSM-model and its extensions (e.g. models allowing dividends), please see the original papers of Black & Scholes (1973) and Merton (1973), and e.g. Chin et al. (2017: 89-190).

3.4 Heston option pricing model

In 1993, Steven L. Heston (1993) presented a closed-form solution on a European option pricing model (such as the BSM-model), but that allows the underlying asset to have stochastic volatility. Heston (1993) argues that the BSM-model, under its assumptions, is not suitable for pricing bond and currency options, which is why he proposes a new model. The new model is suitable for pricing bond and currency options, in addition to European options since it allows the use of stochastic interest rates (Heston 1993).

Whereas the BSM-model assumes that the price of the underlying stock follows a stochastic differential equation (SDE) but the volatility is constant, the Heston model assumes that both stock price and volatility follow a stochastic process (Heston 1993; Lee et al. 2010: 1165). SDE's for the underlying stock and its variance (volatility squared) as follows (Heston 1993; Lee et al. 2010: 1165-1166):

(15) $$dS_t = rS_t dt + S_t\sqrt{V_t}dW_S(t)$$

And

(16) $$dV_t = \kappa(\theta - V_t)dt + \sigma_V\sqrt{V_t}dW_V(t)$$

Where *r* is the risk-free rate, S is the stock price and *V* is the variance at time *t*, κ (kappa) is the mean reversion speed, θ (theta) is long-run mean variance, σ_V is the volatility of the variance and W_S and W_V are Wiener processes (see the explanations of formula 10) with a correlation equal to ρ (rho). The reader can see the resemblance between formulas 15 and 10. Then, Heston partial differential equation (PDE) can be formulated as follows (Heston 1993; Lee et al. 2010: 1166):

(17) $$\frac{\partial C}{\partial t} + \frac{VS^2}{2}\frac{\partial^2 C}{\partial S^2} + \sigma_V \rho SV\frac{\partial^2 C}{\partial S \partial V} + \frac{\sigma_V^2 V}{2}\frac{\partial C}{\partial V^2} + rS\frac{\partial C}{\partial S} + \kappa(\theta - V)\frac{\partial C}{\partial V} - rC = 0$$

Where the variables are the same as in the SDEs above. The PDE is then solved to form the characteristic function. Similarly, as in the BSM-model, let's assume that a European call option price is as follows (Heston 1993):

(18) $$C(s, v, t) = SP_1 - KP(t,T)P_2$$

Where, SP_1 is the presents value of the underlying stock at optimal exercise and $KP(t,T)P_2$ is the present value of the strike price. Defining *x=ln(S)*, the probabilities P_1 and P_2 can be calculated as follows (Heston 1993):

(19) $$P_j(x, v, T; \ln[K]) = \frac{1}{2} + \frac{1}{\pi}\int_0^\infty Re\left[\frac{e^{-i\phi \ln[K]} f_j}{i\phi}\right] d\phi$$

Where

(20) $$f_j(x, v, t;\ \phi) = e^{C(T-t;\phi)+D(T-t;\phi)+i\phi x}$$

The formula 20 is the characteristic function solution, which satisfies the Heston PDE. The terms of the characteristic function are as follows (Heston 1993):

$$(21) \quad C_j(T;\phi) = r\phi iT + \frac{a}{\sigma^2}\left\{(b_j - \rho\sigma\phi i + d_j)T - 2\ln\left[\frac{1-g_j e^{d_j T}}{1-g_j}\right]\right\}$$

And

$$(22) \quad D_j(T;\phi) = \frac{b_j-\rho\sigma\phi i+d_j}{\sigma^2}\left[\frac{1-e^{d_j T}}{1-g_j e^{d_j T}}\right]$$

Where

$$(23) \quad g_j = \frac{b_j-\rho\sigma\phi i+d_j}{b_j-\rho\sigma\phi i-d_j}, \qquad d_j = \sqrt{(\rho\sigma\phi i - b_j)^2 - \sigma^2(2\mu_j\phi i - \phi^2)},$$

$$\mu_1 = \frac{1}{2}, \qquad \mu_2 = -\frac{1}{2}, \qquad \alpha = \kappa\theta, \qquad b_1 = K + \lambda - \rho\sigma,$$

$$b_2 = K + \lambda$$

Where λ is the market price of volatility risk as a function of the stock price, its volatility and time. The other variables are explained above. (Heston 1993.)

The formulas above do not present every part of the derivation of the Heston model. This section is designed to give a coherent picture of the Heston model with only the minimum amount of equations and derivations necessary. For the full derivation of the model (and e.g. the partial differential equation), please see the original research of Heston (1993) and e.g. Chin et al. (2017: 753-769) and Lee et al. 2010: 487-489).

In 2007, Lord & Kahl (2007), in collaboration with Kahl & Jäckel (2006), presents their extension on the Heston model. The Heston model is found to have issues on continuity on pricing options with short maturities or strike prices deep-in-the-money or deep-out-of-the-money (see e.g. Lee et al. 2010: 1167-1168). Lord & Kahl (2007) argue, that their model is capable of robust pricing of European options with large scale of levels of maturities and strikes with an optimal Fourier inversion. They suggest that finding the optimal level of α is the key in the pricing process. α is the damping parameter and ensuring the optimal level enables the Fourier transform of it (Lord & Kahl 2007). The methodology of this study uses the Kahl & Jäckel (2006) and Lord & Kahl (2007) extension on the Heston model, because of its argued capability of higher robustness in pricing of short maturity European options.

3.5 The Greeks

The Greeks describes options' sensitivities to changes, for example in the price of the underlying stock and risk-free rate. Sensitivities to the two mentioned changes are called *delta* and *rho*, respectively. The other 3 Greeks are *gamma, theta* and *vega*. These all are first order derivatives except gamma, which is a second order derivative. There are also other second order, third and even higher order Greeks, but these are left out of examination in this study (for the higher order Greeks see e.g. Ederington & Guan 2007). These Greeks are used in risk management, for example to create delta or gamma hedge, but they also have a theoretical aspect because they explain the mechanics behind option pricing and Black-Scholes-Merton model. (Ederington & Guan 2007; Kosowski & Neftci 2015: 297, 305-506.)

This section introduces the Greeks of call option only. Put options are left out of examination because of two reasons. First, put options are trivial for this study since they are not used in the methodology of this study. Second, put options are left out to focus on the essentials and to keep this theory section brief. The theory part is designed to be detailed enough to give the reader necessary theoretical background to help comprehend the rest of this study.

3.5.1 Delta

Let's start by examining again the Black-Scholes PDE and rewriting it (Lee et al. 2010: 502):

$$(24) \quad \frac{\partial \Pi}{\partial t} + rS\frac{\partial \Pi}{\partial S} + \frac{1}{2}\sigma^2 S^2 \frac{\partial^2 \Pi}{\partial S^2} - r\Pi = 0$$

$$\Theta + rS\Delta + \frac{1}{2}\sigma^2 S^2 \Gamma - r\Pi = 0$$

Where Π is value of the option on stock *S*, *r* is risk-free rate and *σ* is stock price volatility and *t* is time to maturity (as in formula 11). Now part of the second term from left is substituted with Δ, or *delta*. (Lee et al. 2010: 502.)

As mentioned, delta represents sensitivity of the option's price to changes in the price of the underlying stock. For example, the price of a call option with a delta of 0,2 changes 20 percent of the underlying stock's price change. If a portfolio has a delta equal to zero, it is immune to price changes in the underlying stock, i.e. it is delta-neutral. A delta-neutral position can be created by delta-hedging, but as the delta changes over time, the delta-hedge must be rebalanced periodically to uphold delta-neutrality (Deacon & Faseruk 2000.)

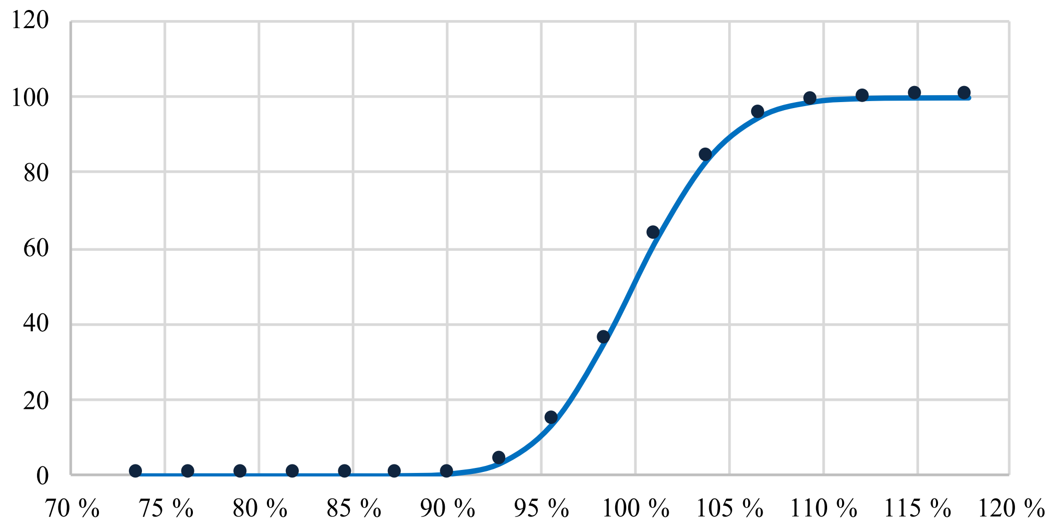

Figure 2. SPX call option delta for different SPX prices. X-axis is moneyness and Y-axis is delta. Strike price is SPX closing price as of 21st March 2018. Data source: Bloomberg Terminal.

The figure 2 demonstrates the s-shape curve of the option delta. As can be seen, the deeper the option is in-the-money, the lower the delta is and vice versa for out-of-the-money options. Delta changes fastest when the option is near at-the-money and beyond the delta curve starts turning horizontal. *Gamma* measures the sensitivity of delta, which is examined next. (Deacon & Faseruk 2000; Kosowski & Neftci 2015: 297-299.)

3.5.2 Gamma

Gamma, Γ in the formula 24, demonstrates the option's sensitivity to changes in the delta in relation to the price of the underlying stock. Gamma is a second order derivative of the BSM-model. Unlike delta, gamma is always positive, and it reaches the maximum value when the option is near or at-the-money and it approaches zero when the option is deep-out-of-the-money or deep-in-the-money. (Deacon & Faseruk 2000; Ederington & Guan 2007; Kosowski & Neftci 2015: 300-303.)

Gamma's importance in risk management is highlighted since it can be used in explaining option price changes and to measure the cost of adjusting delta. Achieving gamma-neutrality decreases the necessity of continuous delta adjustments and minimizes the risks of larger changes in the underlying stock price. (Deacon & Faseruk 2000; Ederington & Guan 2007; Papahristodoulou 2004; Kosowski & Neftci 2015: 300-303.)

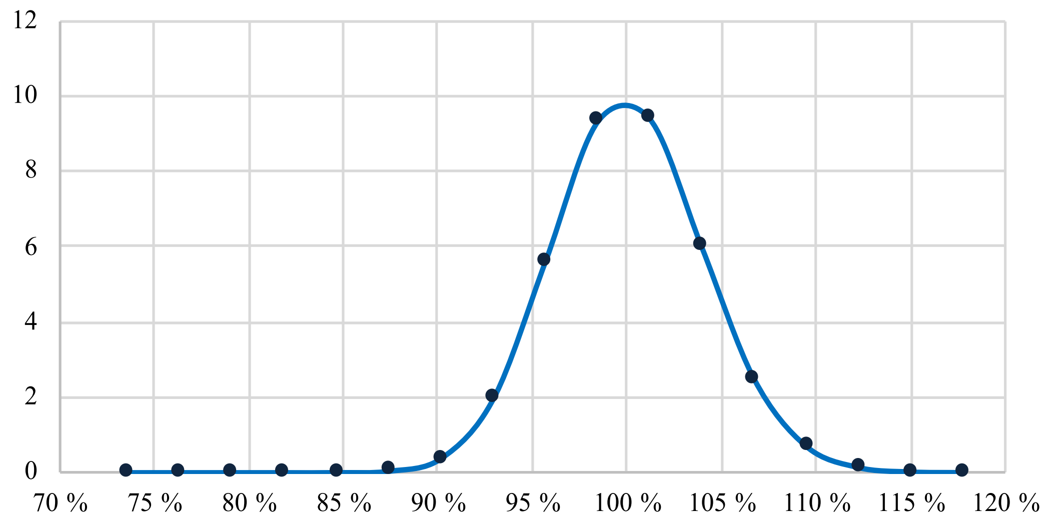

Figure 3. SPX call option gamma for different SPX prices. X-axis is moneyness and Y-axis is gamma. Strike price is SPX closing price as of 21st March 2018. Data source: Bloomberg Terminal.

The figure 3 demonstrates the gamma in relation to the underlying stock price. As mentioned above, the delta is most sensitive when the option strike is near the stock price, which is demonstrated as the bell-shaped curve of the gamma.

3.5.3 Theta

Theta, Θ in the formula 24, measures the option's sensitivity to time decay. Theta demonstrates how much the time value of the option changes when the option approaches its maturity. The time value decreases as the time to maturity decreases and vice versa for the put option, which is supported by the logic that when the maturity approaches, the underlying stock has less time to progress above the strike price (and the opposite for put options). (Kosowski & Neftci 2015: 305-306.)

Emery, Guo & Su (2008) finds the lower and upper bounds for values of theta and that option theta is at maximum level when the option is slightly in-the-money. The lower bound for call option theta is zero when the stock price approaches zero, and the upper bound is rKe^{-rT}(the present value of strike price multiplied by the risk-free rate) when the stock price approaches infinity. (Emery et al. 2008.)

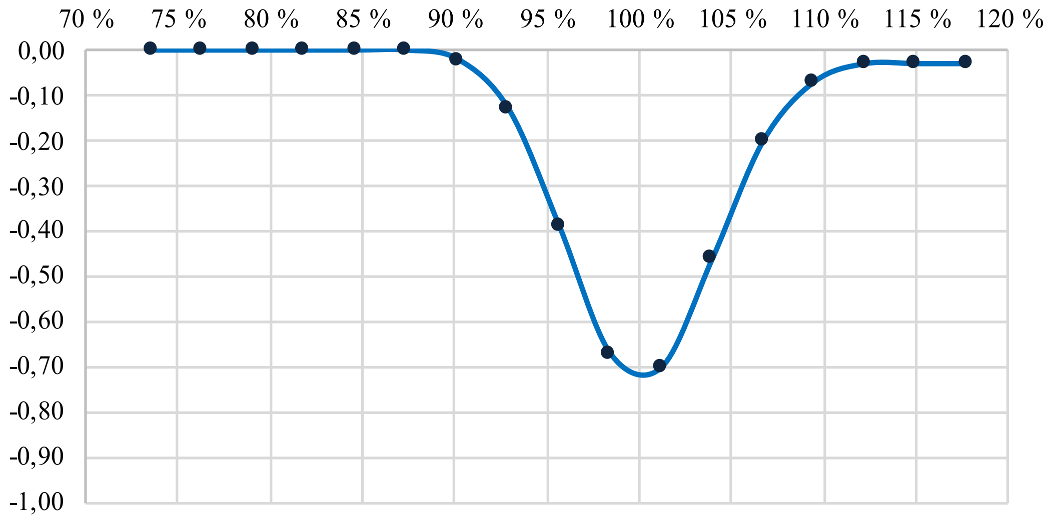

Figure 4. SPX call option theta for different SPX prices. X-axis is moneyness and Y-axis is theta. Strike price is SPX closing price as of 21st March 2018. Data source: Bloomberg Terminal.

The figure 4 demonstrates the call option theta in relation to underlying stock prices. The figure demonstrates the findings of Emery et al. (2008) that the theta reaches its maximum when the option is slightly in-the-money.

3.5.4 Vega

Vega, sometimes referred by kappa (κ) or lambda (λ), (see Deacon & Faseruk 2000; Gao 2009) measures option's sensitivity to changes in the option's value in respect to changes in its volatility (Kosowski & Neftci 2015: 303, 305). The sensitivity can be calculated with the following formula (Gao 2009):

(25) $$vega = \frac{\partial c}{\partial \sigma} = S\sqrt{T}N(d_1)$$

Where the variables are familiar from the BSM-model (see section 3.3). The formula shows that an increase in volatility grows the value of the option, and that high absolute value of vega implies that the option is sensitive to changes in volatility (Chance 1994).

The figure 5 demonstrates vega in relation to its underlying and shows the resemblance between vega and gamma. Vega has the highest value when the option is near or at-the-money and it approaches zero when option is deep-out-of-the-money or deep-in-the-money, similarly as gamma. Regardless the similarity between those two, vega-neutrality does not imply gamma-neutrality. (Ederington & Guan 2007; Hull 2015: 415; Kosowski & Neftci 2015: 303-305.)

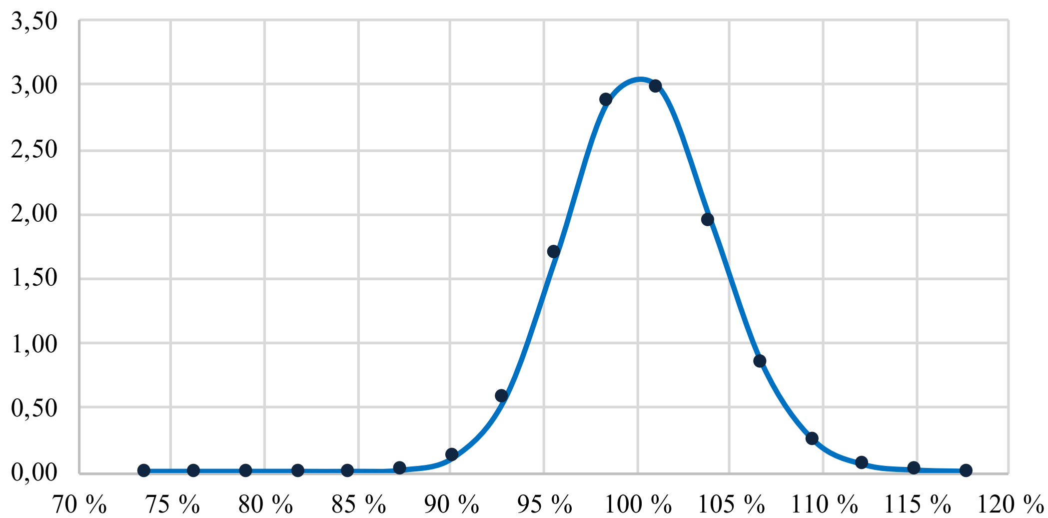

Figure 5. SPX call option vega for different SPX prices. X-axis is moneyness and Y-axis is vega. Strike price is SPX closing price as of 21st March 2018. Data source: Bloomberg Terminal.

3.5.5 Rho

Rho, Greek letter ρ, measures the sensitivity of an option to changes in risk-free interest rate. Rho should be always positive for a call option, since increasing interest rates lowers the strike price of the option through the discount factor, which increases the option's price (Lee et al. 2010; 500). The formula for calculating rho as follows (Chance 1994):

$$(26) \qquad \rho_c = \frac{\partial c}{\partial r} = TKe^{-rt}N(d_2) > 0$$

Where the variables are the same as in BSM-model presented in section 3.3. Figure 6 shows that rho is most sensitive to interest rate changes when the option is near or at-the-money. The call option rho approaches zero when the option becomes deep-out-of-the-money and rho approaches the approximate value of *T*K* when the option becomes deep-in-the-money (Deacon & Faseruk 2000).

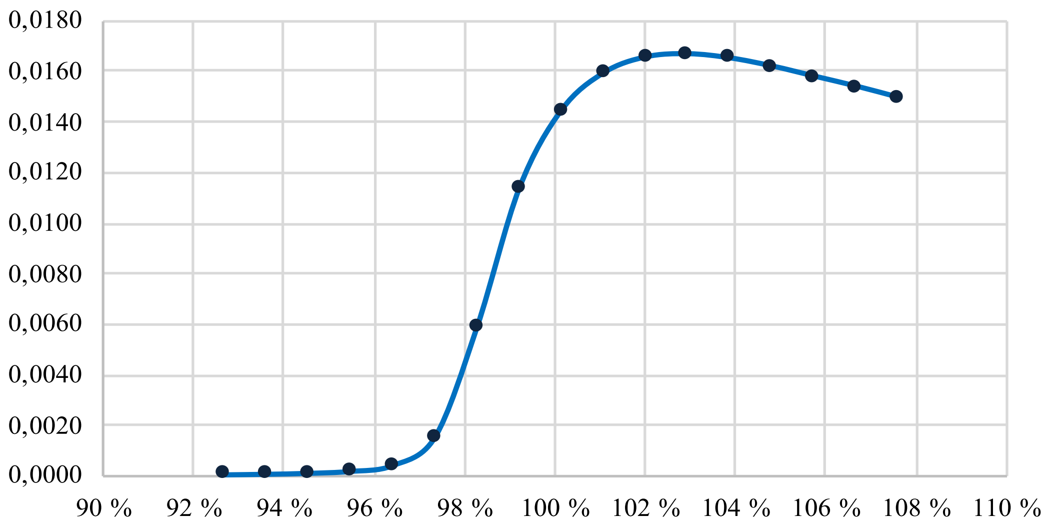

Figure 6. SPX call option rho for different SPX prices. X-axis is moneyness and Y-axis is rho. Strike price is SPX closing price as of 21st March 2018. Data source: Bloomberg Terminal.

4. PERFORMANCE MEASUREMENTS

This section introduces the performance measurements used in the evaluation of the buy-write strategies. First, the Capital Asset Pricing Model is presented to establish the framework for performance measurements as Sharpe ratio and Jensen's alpha. Although, these measurements alone are not enough to describe the relationship between risk and return as suggested by earlier studies (see e.g. Lien 2002; Eling & Schuhmacher 2007). Following the previous studies examining buy-write strategy (see e.g. Feldman & Roy 2005; Kapadia & Szado 2012), this study also measures Leland's alpha and beta, Sortino ratio and Stutzer index.

4.1 Capital Asset Pricing Model

In 1960s, the studies of Sharpe (1964), Lintner (1965) and Mossin (1966) led to a pricing model known as the Capital Asset Pricing Model (CAPM). The model assumes that the total risk of an asset is a sum of systematic risk and unsystematic risk, and the return of the asset is a sum of systematic return and unsystematic return. (Lee et al. 2010: 10-11; Bodie, Kane & Marcus 2014: 291-292.)

The Capital Asset Pricing Model assumes that markets only explain the systematic risk of the asset. The rest of the risk, unsystematic risk, is asset specific risk which can be minimized by diversification. The systematic risk, also known as *beta*, is the slope coefficient of the linear regression of the asset excess return, as follows: (Lee et al. 2010: 11; Bodie et al. 2014: 302)

(27) $$R_i = \alpha_i + \beta_i R_M + u_i$$

Where R_i is excess return of a stock (calculated as the difference between stock return and risk-free rate), α_i is the intercept (alpha), β_i is the slope coefficient (beta), R_M is the market excess return (market factor) and u_i is the residual. Beta demonstrates the systematic risk of the stock and the residual demonstrates the unsystematic risk, and combined, beta and residual equals total risk of the stock. As mentioned earlier, the unsystematic risk can be minimized by diversification, since its mean is assumed zero and it is uncorrelated with the market factor. As CAPM assumes, investor is a rational actor and minimizes unsystematic risk, all the risk left is explainable by market factor, which magnitude is represented with the slope coefficient beta (Lee et al. 2010: 11; Bodie et al. 2014: 301-303.)

As the investor has diversified all the unsystematic risk, all the risk left is beta. Assuming CAPM with its underlying assumptions holds, beta represents the measurable risk, which can be used when comparing assets, for example, the riskiness of stocks. As the beta represents the risk of a stock, alpha represents the abnormal return of a stock, which is discussed further in the section below (Lee et al. 2010: 11; Bodie et al. 2014: 301-303.)

4.2 Jensen's alpha

In 1968, Jensen (1968) presented his study on the performance of mutual funds, where he compared performances of the mutual funds with a measure, currently known as Jensen's alpha. The measure, Jensen's alpha, is derived from the Capital Asset Pricing Model (presented above) and it describes the abnormal return of an asset. The alpha is calculated as follows, and for the full derivation of the measure, see the original study (Jensen 1968; Bodie et al. 2014: 840.)

(28) $$\alpha_P = \bar{r}_P - [\bar{r}_f + \beta_P(\bar{r}_M - \bar{r}_f)]$$

Where α_P is the abnormal return (Jensen's alpha), $\bar{r}_P$ is the asset return, $\bar{r}_f$ is the risk-free rate, β_P is beta and $\bar{r}_M$ is the return of market portfolio. A positive value of alpha means that the realized excess return of the asset is higher than the excess return expected by the CAPM, indicating that the asset has performed well. As described in Bodie et al. (2014: 840), Jensen's alpha can be also calculated with other models than CAPM, for example with factor models (see e.g. Fama & French 2015). In general, Jensen's alpha indicates whether an asset provides higher return than expected by a certain pricing model, and it can be also used to measure whether a portfolio benefits from active management. (Lee at al. 2010: 275; Bodie et al. 2014: 840.)

4.3 Sharpe ratio

In addition to his contribution to the Capital Asset Pricing Model, Sharpe (1964) studied the performance of mutual funds and presented a performance measure, later known as the Sharpe ratio. This ratio divides asset's excess return with its total risk, as follows (Sharpe 1966):

$$(29) \quad Sharpe\ ratio = \frac{\bar{r}_p - \bar{r}_f}{\sigma_p}$$

Where $\bar{r}_p$ is the mean portfolio return, $\bar{r}_f$ is the risk-free rate and σ_p is the portfolio volatility (Bodie et al. 2014: 840). Since the ratio considers total risk, it can be interpreted as how efficiently a portfolio is diversified compared to other portfolios with similar contents. Even though Sharpe ratio is the most popular performance measurement, it is criticized because it assumes portfolio returns to be normally distributed (Eling & Schuhmacher 2007; Lee et al. 2010: 274-275).

4.4 Leland's alpha and beta

Leland (1999) argues that CAPM and its risk measurement, beta, and Jensen's Alpha are invalid, because of CAPM's assumption of normally and symmetrically distributed returns. Leland (1999) proposes his risk measurement and alpha in a power utility model which is based on Rubinstein's (1976) constant relative risk aversion model. Although, one could argue that the underlying assumptions of Leland's model are also suspect. The model assumes that the market portfolio is independently and identically distributed (IID) and that the markets are perfect. (Goyal & Saretto 2009.)

Leland's model is similar to CAPM, but it considers skewness and kurtosis, which are present in portfolios containing derivatives (and especially in portfolios with buy-write positions, see the appendix 2). With the same data and with an additional variable to the CAPM, the Leland's alpha and beta is calculated as follows (Leland 1999):

$$(30) \quad E(r_P) = r_f + B_P\left[E(r_M) - r_f\right]$$

Where $E(r_P)$ is the expected return of a portfolio, r_f is risk-free rate, r_M is the return of market portfolio and B_P is Leland's beta, which is calculated as follows:

$$(31) \quad B_P = \frac{cov\left[r_P, -(1+r_M)^{-b}\right]}{cov\left[r_M, -(1+r_M)^{-b}\right]}$$

Where the other coefficients are the same, but b is calculated as follows:

$$(32) \qquad b = \frac{ln[E(1+r_M)] - ln(1+r_f)}{var[ln(1+r_M)]}$$

The Leland alpha can be derived from the equation 30, as follows (Leland 1999):

$$(33) \qquad A_P = E(r_P) - B_P[E(r_M) - r_f] - r_f$$

Where A_P is the Leland's alpha and the other terms are explained above. Leland's alpha and beta are interpreted in the same fashion as Jensen's alpha and CAPM beta. Particularly to this study, Leland's alpha is in focus, since it is used as a gauge whether an investor can benefit from active buy-write strategies, compared to passive strategies.

4.5 Sortino ratio

Downside deviation, lower partial standard deviation or semi-standard deviation is a risk measurement, which considers only downside deviations from a reference level (Bodie et al. 2014: 140). The reference level is user defined and as in Whaley (2002) and Bodie et al. (2014), this thesis uses risk-free rate as the reference level. This means that when calculating the semi-standard deviation, only negative values of excess returns are considered. The semi-standard deviation is calculated as in Whaley (2002):

$$(34) \qquad Semi - standard\ deviation = \sqrt{\frac{\sum_{t=1}^{T} min\,(R_{i,t} - R_{f,t}, 0)^2}{T}}$$

Where $R_{i,t}$ is the return of portfolio *i* at time *t* and $R_{f,t}$ is the risk-free rate. In 1994, Sortino & Price (1994) presented their modified version of Sharpe ratio, which divides the portfolio excess return with semi-standard deviation, instead of standard deviation (volatility). (Sortino & Price 1994.)

$$(35) \qquad Sortino\ ratio = \frac{R_{i,t} - R_{f,t}}{DD}$$

Where the numerator is excess return of portfolio i at time t and the denominator is downside deviation. Sortino ratio is suitable for measuring risk-adjusted returns of normally and non-normally distributed returns since it considers only downside deviations and this way takes skewness into account. Lien (2002) shows that Sortino ratio is an increasing function of Sharpe ratio, whether the returns are normally distributed or not (see section 2.2.1; Sortino & Price 1994; Whaley 2002).

4.6 Stutzer index

In 2000, Stutzer (2000) presented his performance index for measuring portfolios' risk-adjusted returns. He argues that lacking the capability of considering skewness or kurtosis, Sharpe ratio is not suitable for evaluating portfolios with return non-normalities ensued from, for example the use of options. Basing his model on large deviation theory, the Stutzer index as follows (Stutzer 2000; Feldman & Roy 2005):

(36) $$I_P = \max_{\theta}\left\{- \log\left(\frac{1}{T}\sum_{i=1}^{T} e^{\theta r_i}\right)\right\}$$

Where I_P is Stutzer information statistic, which is maximized by adjusting the value of theta. The Stutzer index is then calculated with the following formula (Stutzer 2000; Feldman & Roy 2005):

(37) $$Stutzer\ index = \left(\overline{r_i - r_f}\right)\sqrt{2I_P}$$

Where the difference inside parentheses is the mean excess return of portfolio *i* over risk-free rate and I_P is the information statistic from formula 36. When the returns are normally distributed, Stutzer index equals Sharpe ratio. Stutzer index can be interpreted as a rate of decay at which, the probability that the portfolio *i* underperforms its benchmark. The higher value of Stutzer index, the higher is the decay and the faster the probability of portfolio underperformance approaches zero. The probability can be estimated with the following formula (Stutzer 2000):

(38) $$P\left(\left(\overline{r_i - r_f}\right) \leq 0\right) \approx \frac{c}{\sqrt{T}} e^{-I_P T}$$

Where the left-hand side is the probability of the portfolio's underperformance, which approaches zero at rate I_P as *T* approaches infinity. *c* is a constant related to the return distribution. (Stutzer 2000; Feldman & Roy 2005.)

5. DATA AND METHODOLOGY

This section presents the data and methodology used in this study. It starts with short introduction to the whole examination period of this study. The data part describes in detail what data this study uses and where it is from, in an own section. The methodology part is divided in three. The first part presents the buy-write return calculation method. The second part presents the methodology behind the volatility risk premium estimation and the buy-write strategy utilizing it. The third part describes how the Heston model is employed to the dynamic strike price strategy.

In 2002, Chicago Board Options Exchange (CBOE) introduced a benchmark index for passive covered call strategies, the BXM (the CBOE S&P 500 BuyWrite Index). As covered call strategies, the BXM is constructed by taking a long position in the S&P 500 and taking a short position in call options on the S&P 500 (Whaley 2002). Since then, several studies demonstrate that the BXM has higher risk-adjusted returns than the S&P 500 (see e.g. Whaley 2002, Feldman & Roy 2005, Hill et al. 2006, Figelman 2008).

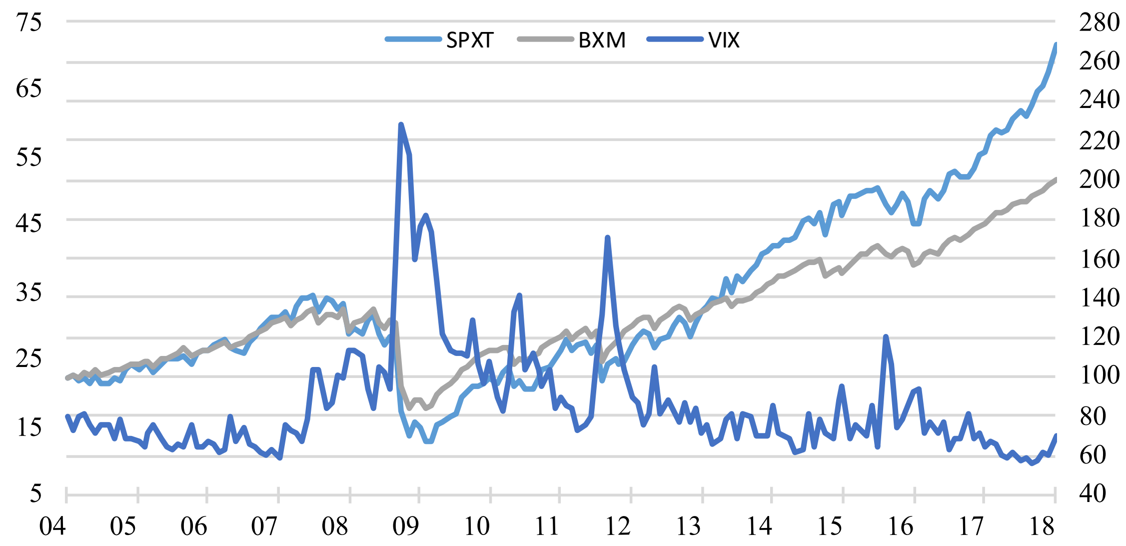

Figure 7. Return of the BXM, S&P 500 Total Return and VIX indices. From January 2004 to January 2018. Normalized on 100 as per January 2004. LHS = VIX, RHS = SPX and BXM.

The figure 7 graphs the BXM, S&P 500 Total Return (SPXT) and VIX indices for the whole observation time period. The BXM and SPXT indices are on right-hand side (RHS) and the VIX index is on left-hand side (LHS). The figure demonstrates the return of a 100 dollars investment on both BXM and SPXT indices. The time period before financial crisis (in 2008) is a market uptrend period with low volatility from 2004 to end of 2006 and from 2006 market volatility expectations (VIX) starts to increase. During the financial crisis in 2008, SPXT and BXM falls sharply and VIX rises above 60. From January 2009, both BXM and SPXT have rose ever since, except in 2011 and 2012 because of the European debt crisis and in 2015. The volatility index has lowered since the debt crisis except the spike in 2015.

This thesis aims to examine if the use of active covered call strategies by benchmarking them against the underlying stock index and a passive covered call strategy is justified. It seems like an obvious choice to use the BXM as a proxy for the passive covered call strategy, since its performance is demonstrated in several studies, as mentioned above. The next section describes the data used in this paper, followed by the methodology part.

5.1 Data

The option data is downloaded from CBOE Datashop's server. The option data consists of quote and expiration dates, strike prices, underlying (S&P 500 index) prices, bid 1545 prices (bid price 15 minutes before the closing time of the exchange) and value-weighted average prices (VWAP). The VWAP prices were used if there were not bid 1545 prices or the bid 1545 price were zero.

The data for BXM, SPXT and VIX were downloaded from Bloomberg Terminal software as daily prices, which were then transformed to correct monthly values according to the option quote and expiration dates. The US Government Treasury 1-Month Treasury Constant Maturity Rate (later 1M T-Bill or T-Bill) is used as a proxy for one-month risk-free rate. The T-Bill data was downloaded from FRED, Federal Reserve Bank of St. Louis.

The table 1 presents the descriptive statistics of the BXM, SPXT and VIX indices. BXM offers lower mean return than SPX or SPX, but also lower volatility, which is in line with the previous studies (see e.g. Whaley 2002). Also, the table shows that the BXM returns are negatively skewed and highly leptokurtic, meaning that the returns are not normally distributed. SPXT and SPX have also high positive kurtosis, but less negatively skewed returns.

Table 1. Descriptive statistics of the SPXT, SPX, BXM and VIX indices.

	SPXT	SPX	BXM	VIX
Observations	169	169	169	169
Mean	0,71 %	0,54 %	0,47 %	18,61
Annualized mean	8,82 %	6,61 %	5,80 %	
Lowest return	-3,49 %	-3,92 %	-2,01 %	12,08
Highest return	12,52 %	12,60 %	5,74 %	59,89
Standard deviation	4,70 %	4,76 %	3,28 %	
Kurtosis	9,84	8,41	21,96	6,12
Skewness	-2,02	-1,89	-3,74	2,22

5.2 Methodology

The progress of the empirical part of this study is as follows. First, the optimal combination of fundamentals of the options used in the buy-write strategy examined by comparing the returns of different strategies. Next, the volatility risk premium estimation model is presented and last the dynamic strike price model. MATLAB is used as the primary calculation software and Excel is used in some simple calculations.

The only variable in the fundamentals is option strike price, since previous studies (e.g. Hill et al. 2006; Figelman 2008) suggests that it is preferable to use short-dated options, which are in this case call options with maturity of one month. More precisely, *moneyness* is the only variable in the fundamentals of the compared strategies. Moneyness is calculated by dividing the strike price with the SPX price (S/K) and it is presented as percentage and if it is in or out of the money (ITM or OTM), e.g. 2%-OTM.

5.2.1 Buy-write strategy return

The hypothesis one (H1) states that the buy-write strategy returns can be improved by altering the fundamentals (in this case, the strike price) of the strategy. This is done by comparing the risk-adjusted returns of different strategies, which are calculated with the following formula (following Whaley 2002 and Hill et al. 2006):

(39) $R_{t-1,t} = \frac{S_t - S_{t-1} + D_t}{S_{t-1}} + \frac{C_{t-1}}{S_{t-1}} - \frac{C_t}{S_{t-1}}$

Where,

(40) $C_t = max(S_t - K, 0)$

Where $R_{t-1,t}$ is the return of the strategy, S_t is the SPX price at time *t*, *D* is dividend, *K* is the strike price, C_{t-1} is price of the call option when it is written and $C_t$is value of the call at expiration date. The dividend factor is omitted from the formula since the S&P 500 Total Return index already includes dividends.

5.2.2 Volatility risk premium estimation model

The next step is to examine the methodology for the ex-ante volatility risk premium estimation model. The ex-ante volatility risk premium is calculated as the difference between actual implied volatility and estimated out-of-sample fitted implied volatility. The VIX index is used as a proxy for actual implied volatility and the estimated out-of-sample fitted implied volatility is calculated with the following model (as in Simon 2014):

(41) $VIX_t = \beta_0 + \beta_1 * VIX_{t-1} + \beta_2 * R^+ + \beta_3 * R^- + u_t$

Where VIX_t is the value of VIX at time *t*; β_0, β_1, β_2 and β_3 are coefficients and u_t is residual term. R^+ is a variable that gets the value of 0 when return of SPXT (S&P 500 Total Return index) is negative, otherwise it gets the value of the positive return of the SPXT. R^- is an opposite variable to R^+, which gets the value of 0 when return of the underlying is positive, otherwise it gets the value of the negative return of the SPXT.

The model is operated as follows. First, the model needs a learning period to calculate the coefficients. The learning period starts from January 2002 and ends in December 2003. The coefficients (β_0, β_1, β_2 and β_3) are estimated with Ordinary Least Squares (OLS) method. The model is then assessed with coefficient of determination (R-squared, Rsqr or R^2) and adjusted coefficient of determination (adjusted R-squared, ARsqr of AR^2), Student's t-statistic (t-statistic or t-stat), Durbin-Watson statistic (DW) and Ljung-Box (LB) statistic. The last two statistics are measured to test whether there is autocorrelation between residual terms over time.

Then, with these coefficients calculated with the learning period, the model is used to estimate monthly fitted values for 2004. In January 2005, the model is re-calibrated with 2004 in the learning period and then used to estimate monthly fitted values for 2005. This operation is rolled from January 2004 to January 2018 to obtain monthly fitted for the whole period.

Table 2. The volatility risk premium estimation model coefficients and test statistics. ** means p-value <0,05 and *** p-value<0,01. LP is the learning period from Jan 2002 to Dec 2003 and the last period includes year 2017 and Jan 2018. Ljung-Box (LB) and Durbin-Watson (DW) test p-values only are presented.

Period	β_0	β_1	β_2	β_3	AR^2	LB	DW
LP	0,0402**	0,8369***	-0,7050***	-0,6544***	0,90	0,90	0,74
2004	0,0252**	0,8829***	-0,6729***	-0,6753***	0,93	0,88	0,53
2005	0,0209***	0,9020***	-0,7438***	-0,6953***	0,94	0,99	0,38
2006	0,0233***	0,8890***	-0,7599***	-0,7166***	0,94	0,95	0,29
2007	0,0325***	0,8328***	-0,7730***	-0,8884***	0,91	0,79	0,55
2008	0,0466***	0,7162***	-0,6563***	-1,2576***	0,94	0,85	0,09
2009	0,0414***	0,7601***	-0,5957***	-1,1966***	0,94	0,37	0,13
2010	0,0456***	0,7328***	-0,5436***	-1,2754***	0,92	0,52	0,37
2011	0,0472***	0,7256***	-0,5322***	-1,3107***	0,92	0,88	0,44
2012	0,0464***	0,7239***	-0,4954***	-1,3067***	0,92	0,77	0,50
2013	0,0459***	0,7271***	-0,5182***	-1,3013***	0,92	0,72	0,66
2014	0,0456***	0,7295***	-0,5420***	-1,2984***	0,92	0,69	0,68
2015	0,0449***	0,7287***	-0,5315***	-1,3106***	0,92	0,58	0,73
2016	0,0445***	0,7292***	-0,5399***	-1,3080***	0,92	0,61	0,84
2017→	0,0441***	0,7289***	-0,5351***	-1,3147***	0,92	0,51	0,92

Table 2 presents the VRP estimation model coefficients and the test statistics. All of the betas have p-values below 1% (except β_0 during the learning period and year 2004), meaning that they are statistically significant. The model variations explain above 90% of the VIX variations according to the adjusted R-squared (AR^2). Ljung-Box (with 12-month lag) and Durbin-Watson test p-values indicates that in any calibration neither of the tests' null hypothesis cannot be rejected (in both tests the null hypothesis states that the model residuals are not correlated). However, there is a drop in the p-values (DW p-value drops from 0,55 to 0,09 between 2007 and 2008) during the financial crisis, implying that the model's estimation capability may have weakened, since the probability of autocorrelation increases. This is only logical, since during the years of financial crisis, the VIX increased more than six-fold and then dropped more than 50% (see figure 7).

Appendix 4 plots the actual VIX, estimated VIX and the volatility risk premium (VRP) for the whole period. VRP is below its average until the financial crisis, increases during the crisis and then stays at higher level than post-crisis. This could indicate, that even though the VIX decreased after the crisis to pre-crisis levels it stayed and continued being at artificial high level, according to the VRP.

The first two coefficient estimates (β_0 and β_1) are in line with Simon (2014), meaning that a 1% change in the previous period VIX translates on average to 0,77 percentage change in the following period VIX. The differences in β_2 and β_3 are higher between this study and Simon (2014). On average, a 1% increase in SPXT translates to a 0,61-percentage decrease in VIX (ca. 0,12 percentage decrease in Simon 2014) and a 1% decrease in SPXT translates to 1,1 percentage increase in VIX (ca. 0,95 percentage decrease in Simon 2014). The magnitude of the positive impact of negative returns of the SPXT on VIX increases and in contrast, the negative impact of positive SPXT returns on VIX decreases during the period. The reason behind this could be in the investors' sentiment, that when the VIX decreases and is low, negative news have greater increasing impact than positive news has decreasing impact on the VIX.

In an attempt to improve the forecasting ability of the model, a modified version of the model was also tested. In the modified version the calibration was done in monthly basis after the learning period to result in more accurate estimates of the coefficients. However, the differences in the results and statistical tests (Rsqr, DW and LB) between the modified and unmodified models were insignificant, which is why the modified version of the model was not examined further.

The ex-ante volatility risk premium (VRP) is then calculated as the difference between actual implied volatility (VIX) and out-of-sample fitted values, which is used as a gauge for call option expensiveness. The buy-write position is then entered when the VRP is above its average level (also 50% and 75% median classes are tested) and the call option is sold when its price is at artificially high level, according to the VRP estimation model.

The table 3 shows the statistics of the three different volatility risk premium calculation methods. During 66 of the 169 months the VRP is above the average level and during 84 and 42 months the VRP is above the median and median 75% levels respectively. The other statistics of the mean method are also between the two median classes. The appendix 4 plots the actual VIX, estimated VIX and volatility risk premiums (only for mean method).

Table 3. Statistics of the three different call option expensiveness (VRP) calculation methods.

Sort	Mean	Median 50%	Median 75%
Count of VRPs > 0	66	84	42
Average VRP	6,28	5,76	7,33
Min VRP	4,08	3,67	4,91
Max VRP	13,82	13,82	13,82

5.2.3 Dynamic strike price strategy

Call options are chosen according to options' exercise probability for the dynamic strategy, instead of strike price (as for the vanilla buy-write strategy). The dynamic strategy is designed to better adapt to changes in the market conditions, since the exercise probability is not fixed in a certain moneyness (the ratio of strike price and the price of underlying) level. Previous studies show that the dynamic strategy outperforms the fixed strike price strategy only when the markets are sharply rising or highly volatile (see Hill et al. 2006; Che & Fung 2011), if the exercise probability is estimated with Black-Scholes-Merton model. Hsieh et al. (2014) estimates the exercise probability with Heston model, which outperforms the BSM-model based dynamic strategy and fixed strike price strategy, despite the market condition. Motivated by this finding of Hsieh et al. (2014), this study uses also Heston model in the estimation of exercise probability.

The estimation of exercise probabilities with the Heston model starts with calibrating the model to acquire the five unknown parameters: theta (θ), sigma (σ), rho (ρ), kappa (κ) and the initial variance (v_0). The calibration is done as a least squares optimization problem with a non-linear least-squares solver (MATLAB-function *lsqnonlin*), where the difference between real market prices of options and the model prices is minimized by finding the optimal values for the five unknown parameters (explained below). This study uses a semi-analytical extension of Heston model presented by Kahl, Jäckel and Lord (Kahl & Jäckel 2006; Lord & Kahl 2007). The calibration process is executed as follows:

1. The least-square solver needs an initial guess for the parameters where to start the optimization and upper and lower bounds for the values. The lower bounds are [0, 0, -1, 0, 0] and the upper bounds are [∞, ∞, 1, ∞, ∞]. Rho is bound between -1 and 1, and the other parameters can have any positive value.

2. The solver is run with limit on maximum 600 evaluations and 400 iterations. If the solver is stuck in local minimum, it is run again with the local minimum parameter values as the starting values.

3. When the solver is done, the parameter values are used in the next step, and if the solver was run twice, the parameters that resulted in lower root-mean-square-error (RMSE) are chosen.

Next, the model prices for all of the call options are calculated with the calibrated model, as follows (for the complete version of the formula see section 3.4; Heston 1993; Lord & Kahl 2007):

(42) $$C(S,K,T,r) = S_0\Pi_1 - Ke^{-rT}\Pi_2$$

Where *C* is the price of call option, *S* is price of the underlying, *K* is the strike price, *T* is time to maturity, *r* is risk-free rate, Π_1 (P1) is option delta and Π_2 (P2) is the exercise probability. The formula 42 is a simplified description of the Heston model for option pricing but gives enough detail to comprehend how the exercise probability is estimated.

The exercise probability P2 is solved with the calibrated model and model prices. In a similar fashion as the calibration, the P2s are solved as a least-squares optimization problem, which is solved with the same MATLAB function. The solver is programmed to minimize the difference between actual option prices and the model prices by adjusting the P2 (Π_2) of the pricing model. The P2 is estimated for 23130 call options (all of the call options with maturity of one month). Then the calls are rounded to nearest 10% multiple and sorted to groups accordingly. Since the probabilities are clustered to above 90% and below 10%, there are additional groups, 95% and 5%. These two groups are formed with closest probabilities that are over 95% in 95%-group and lower than 5% in 5%-group.

The table 4 shows average exercise probability and moneyness of the eleven dynamic strategies and statistics of Heston model pricing. The average exercise probabilities tend to cluster in the both sides of the probability scale, as can be seen from the longer distance between the rounding points and group averages. Also, the moneyness jumps when approaching either the D95% or D5% groups. The model P2 and the percentage of options executed shows deviation between the groups. In the 95% group the model P2 is closer to the realized exercise probability, compared to the same difference in group D10%

where the difference is highest (0,06% and -40% respectively). Also, there are some differences in exercise probability and moneyness pairs between this study and previous studies. Hill et al. (2006) associates e.g. 20% probability with 3,81% out-of-the-money (OTM), compared to the corresponding figures in this study, 20% and 1%. Che & Fung (2011) associates 42% probability to 1,1% OTM and 20% probability to 5,6% OTM, compared to the table above: 40% probability with 0,3% OTM and 20% probability with 1% OTM. Although, these differences could be explained with the different pricing models between the studies.

Table 4. Dynamic strategy sorts and Heston model statistics. P2 is exercise probability. Model and actual prices are averages. MAD is median absolute deviation, AAE is average absolute error and RMSE is root mean square error.

	Avg. P2	Pct. Executed	Avg. Moneyness	Model price	Actual price	MAD	AAE	RMSE
D95%	98,4 %	98,2 %	89,1 %	167,60	168,03	1,94	3,26	5,13
D90%	94,4 %	94,0 %	93,8 %	99,41	99,45	2,24	4,56	7,11
D80%	80,0 %	72,6 %	98,9 %	35,94	34,79	3,10	6,83	10,21
D70%	69,6 %	71,4 %	99,3 %	32,23	31,03	3,22	6,94	10,33
D60%	59,2 %	69,6 %	99,7 %	28,95	27,73	3,23	6,96	10,38
D50%	49,4 %	67,3 %	100,0 %	26,15	24,94	3,46	6,97	10,40
D40%	39,7 %	62,5 %	100,3 %	23,42	22,16	3,33	6,95	10,40
D30%	29,7 %	58,9 %	100,6 %	20,80	19,53	3,26	6,91	10,34
D20%	20,1 %	53,6 %	101,0 %	18,28	17,00	3,26	6,75	10,19
D10%	11,2 %	51,2 %	101,3 %	15,81	14,56	3,07	6,57	9,98
D5%	2,8 %	6,5 %	105,6 %	2,87	2,63	0,52	2,52	5,24

The pricing accuracy of the Heston model is highest in groups D95% and D5% and when measured with MAD. This is logical, since the other two measurements gives higher weight on the maximum deviations. The accuracy is relatively even between groups from D70% to D20%. Groups D80% and D10% have accuracy below the most accurate groups (D95% and D5%). Similarly, to the moneyness also the group average prices jumps when approaching either extremity of the exercise probabilities. This jump is clearer near the high exercise probability groups than the other end groups.

6. RESULTS

This section presents the results of this study in five subsections. The first section examines the vanilla buy-write strategy, finds the strike price that leads to highest strategy performance and tests the hypothesis one. The second section examines the volatility risk premium estimation strategy, shows that applying VRP estimation to buy-write strategy increases its performance and tests the second hypothesis. The third section examines the dynamic strike price strategy and its performance and tests the third hypothesis. The fourth section examines buy-write strategies combining both volatility risk premium estimation and dynamic strike price method, shows that the combine strategy leads to highest performance and tests the fourth hypothesis. The last section discussed some findings further and summarizes the results of this study.

6.1 Vanilla buy-write strategy

The first research problem is to find optimal combination of buy-write strategy parameters, as the first hypothesis states below. Motivated by earlier studies, this study considers only call options with maturity of one month. This leaves the strike price of the option as the only variable. As the table 5 shows, eight different buy-write strategies are compared. Two of the strategies writes in-the-money (ITM) calls, one writes at-the-money (ATM) calls and 5 strategies writes out-of-the-money (OTM) calls. These eight strategies are then compared against each other and against the benchmark index SPXT (S&P 500 Total Return index).

Table 5 shows the performance measurements, Leland alpha and beta, Sharpe and Sortino ratios and Stutzer index, of the benchmark indices and the buy-write strategies. Appendix 2 panel B shows the return and risk characteristics of the strategies and benchmarks. As can be seen, the OTM-4% buy-write strategy performs the best of the buy-write strategies, considering the return non-normality capturing performance measurements (Leland alpha, Sortino ratio and Stutzer index). OTM-4% strategy offers highest risk-adjusted return, according to the Sortino ratio and Stutzer index values. In addition, OTM-4% strategy offers 0,26% statistically significant Leland alpha, indicating that the strategy is capable of making both economically and statistically significant abnormal return. The OTM-4% strategy outperforms also both SPXT and BXM indices, supporting the hypothesis 1, which is as follows:

H1: *The performance of a buy-write strategy can be improved by altering the fundamentals of the strategy.*

Considering the performance of the OTM-4% buy-write strategy, the implied null hypothesis, that the risk-adjusted return of buy-write strategy *cannot* be improved by altering the fundamentals of the strategy, is rejected.

Table 5. Performance measurements of the vanilla buy-write strategies and benchmarks. The whole estimation period from January 2004 to January 2018. 169 monthly observations. * is p-value <0,1, ** is p-value<0,05 and *** is p<0,01.

	Leland alpha	*p-value*	Leland beta	Sharpe ratio	Sortino ratio	Stutzer index
SPXT				0,1302	0,1693	
BXM	0,08 %	*0,4099*	0,67	0,1144	0,1331	0,0748
ITM-5%	-0,05 %	*0,7330*	0,36	0,0529	0,0560	0,0000
ITM-2%	0,01 %	*0,8816*	0,50	0,0883	0,0965	0,0000
ATM	0,11 %	*0,3472*	0,67	0,1198	0,1377	0,0778
OTM-1%	0,16 %	*0,1463*	0,73	0,1333	0,1572	0,1401
OTM-2%	0,21%**	*0,0408*	0,79	0,1441	0,1742	0,1913
OTM-3%	0,26%***	*0,0069*	0,84	0,1534	0,1903	0,2308
OTM-4%	0,26%***	*0,0022*	0,88	0,1527	0,1925	0,2332
OTM-5%	0,25%***	*0,0012*	0,90	0,1495	0,1902	0,2254

The table 5 and appendix 1 shows that the trade-off between mean monthly returns and semi-standard deviations changes somewhat linearly as the moneyness grows (assuming that ITM is lower than OTM in moneyness). Also, the Leland beta follows the same pattern, being lowest when the option is furthest ITM and highest when the option is furthest OTM. As can be seen from the table, all of the buy-write returns are non-normally distributed, where the 5%-ITM strategy demonstrates lowest skewness and highest kurtosis. Due to this non-normality, the value of Stutzer index is zero for 5%-ITM and 2%-ITM strategies.

Comparing the appendix 1 with figure 7 in Hill et al. (2006) shows that the risk and return are positively correlated when the moneyness grows. Though, the figure 7 in Hill et al. (2006) shows more clearly the shift in the correlation, when the moneyness grows past 2%-OTM, compared to appendix 1 where the correlation has smaller shift and does not change to negative. Although, as this study does not consider higher moneyness than 5%-

OTM, the shift to negative correlation could occur with higher moneyness. Otherwise, the results in the table 5 are in line with the findings of previous studies. Leland's alphas and betas are close to corresponding measures in Kapadia & Szado (2012). Both studies show that the alphas and betas grow as the moneyness grows.

The appendix 3 demonstrates the cumulative returns of each buy-write strategy. It can be imagined demonstrating the development of a 100-dollar investment in each of the strategies for the whole period. The best yielding vanilla buy-write strategy is the OTM-4% strategy and the worst is ITM-5% strategy. The OTM-4% has also higher cumulative return than the benchmarks. One interesting finding is the smooth plot of ITM-5% strategy, since its volatility less than half compared to SPXT or OTM-4%. Also, the ITM-5% has third lowest mean return of all of the strategies, but it could be suitable for a risk averse investor.

6.2 Volatility risk premium strategy

The second hypothesis states that the performance of buy-write strategies can be improved by utilizing the estimation of volatility risk premium (VRP). This estimation is done with a model (see section 5.2.2) which calculates out-of-sample fitted values for the VIX and then measuring the difference between the actual values of VIX with the estimated VIX. This difference, VRP, is the estimate whether the actual implied volatility (VIX) is at an artificially high level. When VRP is above its average, the buy-write position is entered and when it is below, only the stock position is entered. As mentioned in section 5.2.2. 50% and 75% median levels were also used as the expensiveness thresholds, but these two methods do not lead to as good performance as the mean method. To save space, the results for these two methods are not shown in this paper.

Table 6 shows the performance measurements of the VRP enhanced buy-write strategies (VRP strategies). ITM-5% VRP strategy outperforms the other VRP strategies with every performance measurement and has *also* the lowest systematic (Leland beta) and total risk (volatility, see appendix 2 panel D). The ITM-5% VRP strategy has 0,53% (6,55% as annualized) statistically significant Leland alpha, highest Sortino ratio at 0,3334, highest Stutzer index at 0,1233 and highest Sharpe ratio 0,2472 (the last measurement has least weight since it does not capture non-normality of the returns).

Comparing the VRP strategy to the vanilla buy-write strategy shows that the ITM VRP strategies outperforms with every performance measurement and the OTM VRP strategies outperforms with Leland alpha, Sortino ratio and Sharpe ratio the respective vanilla buy-write strategies. OTM Vanilla buy-write strategies outperforms the respective VRP strategies with the Stutzer index, even though the vanilla OTMs have lower skewness and higher kurtosis. The second hypothesis is as follows:

H2: *The performance of a buy-write strategy can be improved by timing the implementation of the strategy based on ex-ante volatility risk premium.*

Considering the findings discussed above, the implied null hypothesis that the performance of a buy-write strategy *cannot* be improved by timing the implementation of the strategy based on ex-ante volatility risk premium, is rejected.

Table 6. Performance measurements of the volatility risk premium strategies and benchmarks. The whole estimation period from January 2004 to January 2018. 169 monthly observations. * is p-value <0,1, ** is p-value<0,05 and *** is p<0,01.

	Leland alpha	*p-value*	Leland beta	Sharpe ratio	Sortino ratio	Stutzer index
SPXT				0,1302	0,1693	
BXM	0,08 %	*0,4099*	0,67	0,1144	0,1331	0,0748
ITM-5%	0,53%***	*0,0002*	0,57	0,2472	0,3334	0,1233
ITM-2%	0,47%***	*0,0002*	0,68	0,2201	0,2867	0,1180
ATM	0,38%***	*0,0009*	0,78	0,1845	0,2369	0,1125
OTM-1%	0,36%***	*0,0009*	0,82	0,1768	0,2269	0,1204
OTM-2%	0,33%***	*0,0008*	0,85	0,1681	0,2155	0,1111
OTM-3%	0,32%***	*0,0004*	0,88	0,1648	0,2121	0,1165
OTM-4%	0,30%***	*0,0003*	0,90	0,1586	0,2045	0,1041
OTM-5%	0,26%***	*0,0005*	0,91	0,1513	0,1949	0,0782

Examining the VRP strategy's properties further reveals that it differs risk-return wise from the vanilla buy-write strategy, or to be more precise, it is the opposite. The figure in appendix 1 shows that applying the VRP estimation method to the vanilla buy-write strategy turns the correlation between mean return and semi-standard deviation from positive to negative and closer to horizontal. This finding suggests that it would be beneficial to choose even deeper ITM options to write, than the 5%-ITM options written.

On the OTM side of moneyness the choice between vanilla buy-write and VRP strategies seem indifferent, considering only the payoff between risk and return.

The outperformance of ITM-5% strategy has also other interpretations. Let's start from the logic behind the VRP strategy. The logic is to estimate when the VIX is at artificially high level and write the call options only then, because then the options prices also are artificially high. Option price and implied volatility are positively correlated through the exercise probability, since when the volatility is high the underlying's price has higher change of deviating above the strike price. The VRP estimation model is then used to reflect the correct level of implied volatility and abnormalities in VIX. This leads us to the interpretations. Either: the SPX options are repeatedly overpriced; the SPX options are overpriced and the VIX is abnormally high repeatedly; or the markets tend to overestimate the SPX performance.

Previous studies (see e.g. Feldman & Roy 2005) supports the interpretation that the SPX options are overpriced, and it seems also the simplest explanation. But, considering that the VIX is calculated of options written on the SPX (see the VIX white paper: Chicago Board Options Exchange 2014) and assuming that the SPX options are overpriced it leads to the deduction that also the VIX has to be overpriced or at an artificially high level. The third interpretation relies on an assumption that the model is able to anticipate when the SPX is at artificially high level. The second and third interpretation are not mutually exclusive, but it would need further research to reject or confirm the third interpretation. No matter of the correct interpretation, the performance of ITM-5% VRP strategy and the statistics in table 2 (in section 5.2.2) suggests that the estimation model is capable of out-of-the-sample estimation of the VIX.

Also, the figure in appendix 3 demonstrates the benefits of the VRP strategy. The ITM-5% buy write strategy offers a cumulative return equal to ca. 100% for the whole period, but when the VRP estimation model is utilized, the ITM-5% (VITM-5% in the figure) strategy offers ca. 300% cumulative return for the whole period. The appendix 2 panel D shows that the VRP ITM-5% strategy has also highest mean monthly return, which is 11,09% as annualized return.

This study finds greater difference between VRP and vanilla buy-write strategies than the original study does. Simon (2014) finds that utilizing VRP (or conditional volatility premium, CVP, as he defines it) increases performance of the strategy, but not as significantly as this study finds. Also, the risk-return payoff is an increasing function of the strategy returns in whether the VRP estimation is employed or not. Though, it should be noted that Simon (2014) constructs his own volatility index for the underlying exchange-traded fund, which may not capture the same characteristics or interdependence with the underlying as VIX may have with its underlying (SPX).

6.3 Dynamic strike price strategy

The third research problem focuses on the dynamic strike price strategy, which writes call options based on their exercise probability instead of moneyness. These exercise probabilities are calculated for call options on the SPX with Heston option pricing model and then the options are sorted to 11 groups by their exercise probabilities. The 11 groups are then used to form 11 dynamic strike price strategies. Statistics for each group are found in table 4 in section 5.2.3.

Table 7 shows the performance measurements of these 11 dynamic strategies and benchmarks. D5% is the best performing dynamic strategy with the only statistically significant Leland alpha, the highest Sortino ratio at 0,1952 and the highest Stutzer index value of 0,1130. The D5% strategy writes call options with average moneyness of 5,6% OTM.

Comparing the best dynamic strategy with the best vanilla buy-write strategy shows that the D5% dynamic strategy outperforms the OTM-4% vanilla strategy and both BXM and SPXT benchmark indices. Also, the D5% strategy outperforms its closest equivalent OTM-5% vanilla strategy. Otherwise, the dynamic strategy underperforms the vanilla buy-write strategy. The groups above D20% have Stutzer index value of zero, because the Stutzer index penalizes skewness and kurtosis which the groups have highest among all strategies (see appendix 2, panel C). Also, the Sortino ratio is below the vanilla strategies and D95% is the only of all the strategies that has a negative Sortino ratio.

Considering the results presented in the table above and the third hypothesis:

H3: *The performance of the vanilla buy-write strategy can be improved by utilizing the dynamic strike price method.*

The implied null hypothesis, that the performance of the vanilla buy-write strategy cannot be improved by utilizing the dynamic strike price method, is rejected. Although, on average level the dynamic strategy does not improve the performance of the vanilla strategy, but the best version of dynamic strategy does, and this is what the third hypothesis is stating.

Table 7. Performance measurements of the dynamic strike price strategies and benchmarks. The whole estimation period from January 2004 to January 2018. 169 monthly observations. * is p-value <0,1, ** is p-value<0,05 and *** is p<0,01. K/S (strike price/stock price) is average moneyness.

	K/S	Leland alpha	*p-value*	Leland beta	Sharpe ratio	Sortino ratio	Stutzer index
SPXT					0,1302	0,1693	
BXM		0,08 %	*0,4099*	0,67	0,1144	0,1331	0,0748
D95%	89,1 %	-0,14 %	*0,1552*	0,20	-0,0331	-0,0344	0,0000
D90%	93,8 %	-0,06 %	*0,5812*	0,32	0,0391	0,0412	0,0000
D80%	98,9 %	0,04 %	*0,7223*	0,58	0,1002	0,1118	0,0000
D70%	99,3 %	0,05 %	*0,6605*	0,60	0,1036	0,1164	0,0000
D60%	99,7 %	0,07 %	*0,5283*	0,62	0,1106	0,1253	0,0000
D50%	100,0 %	0,09 %	*0,4278*	0,64	0,1162	0,1327	0,0000
D40%	100,3 %	0,10 %	*0,3868*	0,67	0,1182	0,1357	0,0000
D30%	100,6 %	0,12 %	*0,2880*	0,68	0,1239	0,1437	0,0000
D20%	101,0 %	0,15 %	*0,1851*	0,71	0,1314	0,1541	0,0052
D10%	101,3 %	0,17 %	*0,1305*	0,73	0,1359	0,1608	0,0279
D5%	105,6 %	0,27%***	*0,0003*	0,91	0,1527	0,1952	0,1130

The appendix 1 shows that the dynamic strike price strategy and the vanilla buy-write strategy have similar risk-return payoff patterns (the reader can notice that the D95% is not plotted). Both strategies are somewhat linear functions of the risk-return payoff, so it would appear that it is indifferent which strategy to choose and the only difference is which moneyness or exercise probability to choose. The dynamic strategy maintains its linearity with higher risk-return combinations, compared to the vanilla strategy which starts turning horizontal. Assuming that this linearity would hold with higher risk-return pairs, it would be an attractive quality for an investor with higher risk-taking capacity, since the performance (Leland alpha, Sortino ratio and Stutzer index) is also increasing.

The figure in appendix 3 shows that the D5% dynamic strategy offers third highest cumulative return (ca. 202%) and the D95% offers the lowest cumulative return (ca. 6%), of all of the strategies. The cumulative return of D95% is even lower than the corresponding return of the risk-free rate (T-Bill), which is ca. 17%. This indicates that the risk-free rate is a better investment than the D95% strategy.

Comparing the dynamic strategy with the VRP strategy shows that the best dynamic strategy (D5%) is able to outperform only the worst performing VRP strategy (OTM-5%). D5% Leland alpha, Stutzer index and Sortino ratio values are 0,27%, 0,1130 and 0,1952 respectively and the corresponding values for OTM-5% strategy are 0,26%, 0,0782 and 0,1949. The systematic risk (Leland beta) and total risk (semi-standard deviation, see appendix 2 panel C and D) are the same for both strategies. This difference between the D5% and the OTM-5% strategies is marginal, compared to the difference between the D5% and the best VRP strategy ITM-5%. With lower systematic and total risk, the ITM-5% is able to offer ca. twice as high Leland alpha, higher Stutzer index and higher Sortino ratio.

Hill et al. (2006), Che & Fung (2011) and Hsieh et al. (2014) examines the dynamic strike price strategy in their studies. All of the studies are conducted in different markets with different time periods, which may be the reason to somewhat different results between their studies and this study. Table 3 in Che & Fung (2011) shows that the Sortino ratio is highest (0,219) for the 49% probability group and lowest (0,167) for the 17% probability group. Hsieh et al. (2014) (tables 2 and 3) shows that the Sortino ratio is at highest in 17% group (0,066 and 0,1062) and lowest in 49% group (0,0159 and 0,0307) calculated with BSM and Heston models, respectively. Hill et al. (2006) does not report any performance measures for the strategies.

Both Hsieh et al. (2014) and this study suggest a lower exercise probability dynamic strategy, in contrast to findings of Che & Fung (2011) which suggests a higher exercise probability dynamic strategy. The difference could be explained with different probability calculating methods, but Hsieh et al. (2014) uses both BSM and Heston models which both contradicts the findings of Che & Fung (2011).

6.4 The combine strategy

The combine strategy is a buy-write strategy that combines the volatility risk premium estimation (VRP) strategy and the dynamic strike price strategy. This strategy uses the VRP estimation model to time when to enter the dynamic strike price strategy and when to hold just the underlying stock (SPXT index in this case). The methodology for both strategies is explained in previous sections.

The table 8 presents the performance metrics for the 11 combine strategies. The 10,9%-ITM strategy performs the best of the all combine strategies with every performance measurement. It offers statistically significant 0,58% Leland alpha, 0,1463 Stutzer index and 0,4088 Sortino ratio. The Leland alpha and Sortino ratios are the highest among all of the strategies examined in this study.

The fourth research problem focuses on the performance of the combine strategy. Comparing the best combine strategy (10,9%-ITM) to other buy-write strategies, shows that the 10,9%-ITM strategy outperforms every other buy-write strategy with every performance measurement, except with Stutzer index the vanilla OTM-2%-OTM5% strategies. The 10,9%-ITM offers fourth highest mean monthly return with fourth lowest systematic risk (Leland beta) and third lowest total risk (semi-volatility) among all buy-write strategies (see appendix 2 panel E). The fourth hypothesis is as follows:

H4: *The performance of the vanilla buy-write strategy can be improved further by timing the implementation of the strategy based on ex-ante volatility risk premium and utilizing the dynamic strike price method.*

Considering the performance of the 10,9%-ITM combine strategy, the implied null hypothesis to the H4, that the performance of the vanilla buy-write strategy *cannot* be improved further by utilizing the VRP and dynamic strategies, is rejected.

The figure in appendix 1 demonstrates the effect applying VRP estimation to the dynamic strategy has. Comparing the 6,2%-ITM (second triangle from the left) to D90% shows that, applying VRP estimation to the D90% strategy (closest to the origin) increases semi-standard deviation 38 basis points (bp) but increases mean return 70 bp. Or comparing the best VRP strategy with the worst dynamic strategy shows that the change in risk-return payoff is 47 bp increase in risk and 81 bp increase in mean return. In relative terms the change is equal to 33% increase in risk and 1620% increase in mean return. Only the best dynamic strategy (D5%) is able to offer better risk-return payoff than the worst combine strategy (5,6%-OTM). Mean returns are equal but the semi-standard deviation of D5% strategy is 1 bp lower.

Table 8. Performance measurements of the combine strategies and benchmarks. The whole estimation period from January 2004 to January 2018. 169 monthly observations. * is p-value <0,1, ** is p-value<0,05 and *** is p<0,01. P2 Group is the exercise probability group.

	P2 Group	Leland alpha	*p-value*	Leland beta	Sharpe ratio	Sortino ratio	Stutzer index
SPXT					0,1302	0,1693	
BXM		0,08 %	*0,4099*	0,67	0,1144	0,1331	0,0748
10,9%-ITM	D95%	0,58%***	*0,0002*	0,43	0,2744	0,1463	0,4088
6.2%-ITM	D90%	0,54%***	*0,0003*	0,53	0,2522	0,1170	0,3470
1,1%-ITM	D80%	0,43%***	*0,0004*	0,73	0,2035	0,1135	0,2628
0,7%-ITM	D70%	0,41%***	*0,0005*	0,74	0,1974	0,1075	0,2544
0,3%-ITM	D60%	0,40%***	*0,0005*	0,76	0,1939	0,1113	0,2496
0,0%-ATM	D50%	0,40%***	*0,0005*	0,77	0,1918	0,1207	0,2470
0,3%-OTM	D40%	0,38%***	*0,0008*	0,78	0,1847	0,1099	0,2370
0,6%-OTM	D30%	0,37%***	*0,0007*	0,79	0,1833	0,1162	0,2355
1,0%-OTM	D20%	0,36%***	*0,0008*	0,81	0,1802	0,1187	0,2314
1,3%-OTM	D10%	0,36%***	*0,0008*	0,82	0,1778	0,1216	0,2282
5,6%-OTM	D5%	0,26%***	*0,0003*	0,92	0,1497	0,0755	0,1931

Also, the VRP strategy benefits from combining with the dynamic strategy. Comparing ITM-5% VRP strategy to its closest equal 6,2-ITM strategy shows that the change from fixed strike price to dynamic strike price decreases mean return 1 basis point but decreases semi-standard deviation 12 bp. Or comparing ATMs (0,0%-ATM and ATM) shows that the change from VRP to combine strategy leads to 2 bp increase in mean return and 5 bp decrease in risk. Similarly to the dynamic strategy, the VRP strategy benefits less from the combining the further the options are out-of-the-money. OTM-1% VRP strategy and 1,0%-OTM combine strategy have equal mean returns and 4 bp difference in semi-standard deviation, in favor for 1,0%-OTM strategy. The difference decreases when moving further away from the money. At ca. 5% out-of-the-money, 5,6%-OTM combine strategy and OTM-5% VRP strategy have 1 bp difference in risk, the mean returns being equal.

The table 9 demonstrates the effect of combining the strategies to the dynamic strategies cash-flows from option writing. The D5% strategy is the only with positive mean cash-flow. D95% strategy has a mean of -10,49 and nearly twice as many negative cash-flow months than positive.

Table 9. The effect of combining to dynamic strategy option premiums.

	D95%	D90%	D10%	D5%
Panel A: Without VRP				
Mean	-10,49	-8,51	-2,30	0,62
Median	-18,65	-14,89	6,31	0,50
Max	164,70	130,94	58,10	36,00
Min	-172,19	-163,69	-124,89	-66,54
No. Pos	60	66	105	157
No. Neg	108	102	63	11
Panel B: With VRP				
Mean	3,72	3,86	1,74	0,69
Median	0	0	0	0
Max	164,70	130,94	58,10	36,00
Min	-95,85	-87,65	-64,92	-44,42
No. Pos	32	34	47	61
No. Neg	34	32	19	5

After combining the strategies, the median of all strategies turns to zero, since the VRP is below its mean most of the months (see appendix 4). The effect of combining is more dramatic on the ITM side than the OTM side of the strategies. For the D95% strategy, the mean monthly cash-flow turns positive by increasing from -10,49 to 3,72, the lowest cash-flows grows from -172,19 to -95,85 and the number of positive cash-flows months increases from ca. 36% to 48%. The table 9 supports the VRP models capability and combining of the dynamic and VRP strategies.

Appendix 2 shows that the combine strategy is able to combine strengths from both dynamic and VRP strategies, lower semi-volatility from dynamic strategy and higher mean return from VRP strategy. This effect is strongest when options are deep-in-the-money and weakest when options are deep-out-of-the-money. Combining affects also skewness and kurtosis of the returns, as can be seen from the figure 8 below. The D95% dynamic strategy skewness and kurtosis decreases in absolute terms from -10,58 and 125,67 to -1,63 and 10,93 after combination, respectively. Also, the VRP strategy return distribution changes to more normally distributed after combining. The ITM-5% VRP strategy skewness and kurtosis decreases in absolute value from -2,58 and 16,69 to -1,63 and 10,93 after combining, respectively. The kurtosis of buy-write strategies is high compared to the excess return distribution of SPXT.

Appendix 3 shows that the 10,9%-ITM combine strategy offers the second highest cumulative return for the whole period. The difference between the first (ITM-5% VRP strategy) and the second is relatively small, only 1,66 index points (399,10 vs. 397,44). The worst combine strategy offers higher cumulative return than the best vanilla strategy (OTM-4%), SPXT or BXM indices. Also, the figure shows that the financial crisis has the least effect on 10,9%-ITM strategy from all of the strategies. This is examined further in the next section.

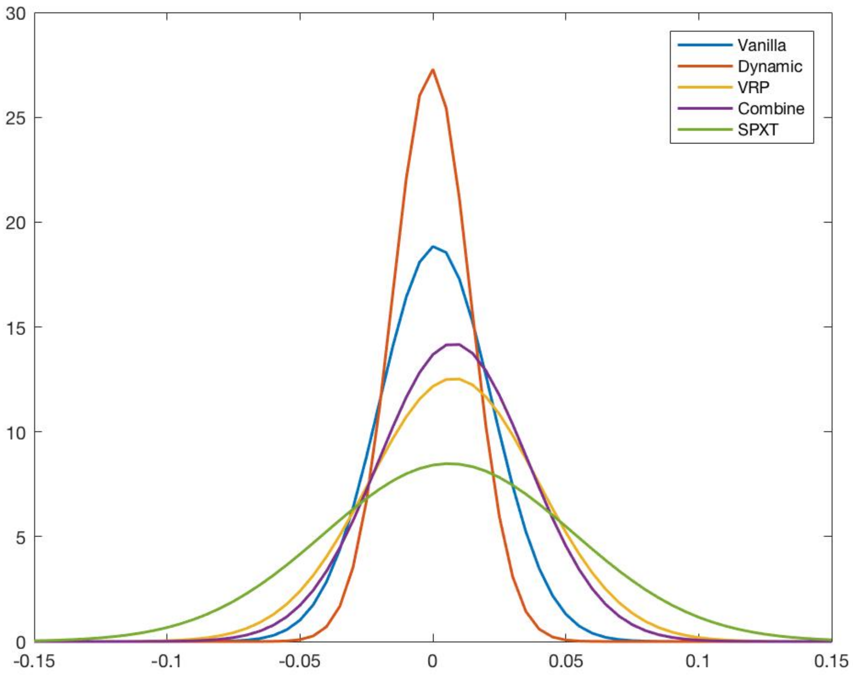

Figure 8. Excess return probability distribution function. Strategies plotted: vanilla, dynamic, VRP and combine buy-write strategies and S&P 500 Total Return (SPXT) index of the whole period.

6.5 Further discussion and summary

The table 10 summarizes the best and worst performers of all of the buy-write strategies. The 10,9%-ITM combine strategy performs the best with statistically significant Leland alpha more than twice higher than the OTM-4% and D5% offers, lowest Leland beta of the top performers, highest Sharpe and Sortino ratios and second highest Stutzer index. The VRP strategy comes second, dynamic strategy third and the vanilla buy-write strategy last, although the OTM-4% vanilla buy-write strategy has highest Stutzer index value of the strategies. Appendix 2 shows that the 10,9%-ITM strategy offers fourth highest mean monthly return (0,86%), which is 10,89% mean annualized return with third lowest semi-volatility. The ITM-5% VRP strategy has the highest mean monthly return (0,88%), which is 11,09% annualized. All of the top performers outperform the benchmark indices (SPXT and BXM) with every performance measurement and even the worst performers of combine and VRP strategies outperforms the benchmark indices. These results support the intended contribution of this study, that is to demonstrate that active buy-write strategies outperform the passive strategies.

Table 10. The best and worst performers of all buy-write strategies. V in the strategy name indicates that it is VRP strategy.

	Leland alpha	*p-value*	Leland beta	Sharpe ratio	Sortino ratio	Stutzer index
SPXT				0,1302	0,1693	
BXM	0,08 %	*0,4099*	0,67	0,1144	0,1331	0,0748
Panel A: Top performers						
10,9%-ITM	0,58%***	*0,0002*	0,43	0,2744	0,4088	0,1463
VITM-5%	0,53%***	*0,0002*	0,57	0,2472	0,3334	0,1233
D5%	0,27%***	*0,0003*	0,91	0,1527	0,1952	0,1130
OTM-4%	0,26%***	*0,0022*	0,88	0,1527	0,1925	0,2332
Panel B: Worst performers						
VOTM-5%	0,26%***	*0,0005*	0,91	0,1513	0,1949	0,0782
5,6%-OTM	0,26%***	*0,0003*	0,92	0,1497	0,1931	0,0755
ITM-5%	-0,05 %	*0,7330*	0,36	0,0529	0,0560	0,0000
D95%	-0,14 %	*0,1552*	0,20	-0,0331	-0,0344	0,0000

Examining the appendix 3 shows that the ITM-5% VRP strategy (VITM-5%) demonstrates highest cumulative return for the whole period, the 10,9%-ITM combine strategy less than two index points behind. D95% dynamic strategy has lowest cumulative return, below the cumulative return of risk-free rate (ca. 6% vs. 17%). The figure in appendix 3 also demonstrates how the strategies react to market disturbances. The table 11 shows how much the top and worst performers and the benchmark indices draw down during the financial crisis.

Table 11. The effect of financial crisis on top and worst performers and benchmarks. Calculated from period between 21.9.2017-20.2.2009, when the SPXT started to decline until it started to incline again.

	SPXT	BXM	ITM-5%	OTM-4%	D95%
Drawdown	-52 %	-36 %	-25 %	-45 %	-15 %
	D5%	VITM-5%	VOTM-5%	10,9%-ITM	5,6%-OTM
Drawdown	-47 %	-29 %	-48 %	-21 %	-48 %

The S&P 500 Total Return index decreases 52% and the BXM decreases 36% during the 17-month period. The OTM-5% VRP and the 5,6%-OTM combine strategies both decreases 48%, which is the highest drawdown of the buy-write strategies. The financial crisis has least effect on the worst performer D95% dynamic strategy, which decreases 15%. The best performer 10,9%-ITM combine strategy has the second least effect, a drawdown of 21%. The figure in appendix 3 shows that also in 2015 when other strategies occurs some market turbulence, the 10,9%-ITM manages to increase, but at a more flattish rate. Also, the ITM-5% VRP strategy seems more immune to spikes in market volatility (compare appendix 3 and the actual VIX in appendix 4). This finding could mean that in addition to the benefits in performance, applying the VRP estimation to a buy-write strategy increases its immunity against market fluctuations. Examination of this possible property of the combine strategy is left at a speculative level and should be tested with proper statistical analysis, but since it is out of this study's scope it is left to future research to be conducted.

The appendix 1 shows that the vanilla and dynamic buy-write strategies are approximately increasing linear functions of the risk-return payoff, meaning that the higher return an investor wants, the higher risk she has to bear and the deeper-out-of-the-money options she has to write. But if the VRP estimation is applied to the buy-write strategy, the risk-return payoff turns to a decreasing function, where out-of-moneyness leads to lower return and higher risk. This finding indicates that writing deeper in-the-money options would minimize the risk. The return would be approximately unchanged, as the both VRP estimation utilizing strategies' risk-return payoff curves turns horizontal with deep-in-the-money options.

The figure 9 demonstrates also other characteristics of the buy-write strategies. All of the strategies approach the same relatively small area in the risk-return space as the out-of-moneyness grows. The deepest out-of-the-money version of each strategy are within a 3 basis point range, measured with both mean monthly return and semi-standard deviation.

Considering that in the in-the-money-side of the strategies the differences in returns and semi-volatilities are nearly 90 basis points at highest, signifying the close range of the deep-out-of-the-money strategy risk-return characteristics.

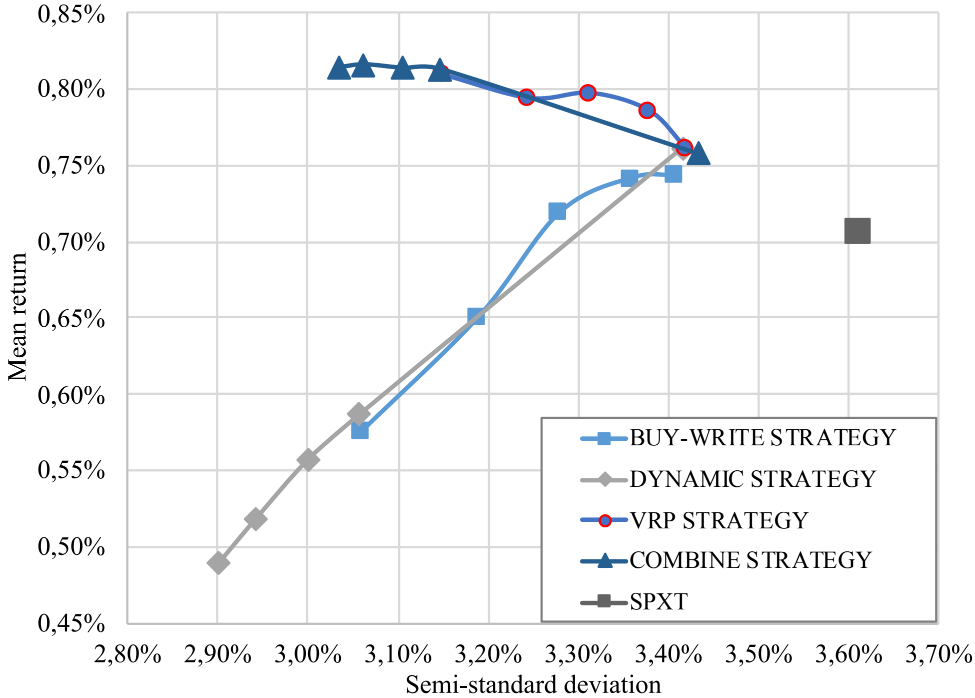

Figure 9. The risk-return characteristics of out-of-the-money buy-write strategies.

The explanation for this out-of-the-moneyness cluster is that as the buy-write strategy writes deeper OTM options, the cash-flows generated from the option writing approaches zero, since as the strike price grows (out-of-moneyness deepens) the more likely it is that the option expires worthless. And as the cash-flows decreases, the buy-write returns approaches its underlying's returns (the individual data point, SPXT, in figure above). This finding leads to two deductions, as follows.

The first is, that if an investor plans to use buy-write strategy as a passive investment strategy he should write approximately 4-5% OTM options (assuming that pure buy-write strategy can be considered as a passive strategy). As the table shows, all of the 4-5% OTM strategies offers the same risk-return payoff inside a 3 basis point range, despite the buy-write strategy. Also, the OTM-4% vanilla buy-write strategy offers highest Stutzer index among OTM strategies.

The second deduction is, that if an investor plans to use buy-write strategy as an active investment strategy, she should write ITM options and choose the buy-write strategy carefully. Compared to the OTM strategies, the differences between buy-write strategies in the ITM side of the risk-return space are greater in significance, as can be seen from the figure 9. The dynamic and vanilla buy-write strategies start approaching the origin from the OTM cluster, where both risk and return is lower, whereas VRP and combine strategies start approaching the opposite direction (return increases, but risk decreases). As the appendix 1 demonstrates, VRP and combine buy-write strategies offers more attractive risk-return payoffs than dynamic and vanilla buy-write strategies.

7. CONCLUSIONS

The buy-write strategy has been the most popular option strategy, at least until the recent decade. The growing amount of exchange-traded funds and strategy indices employing this strategy, in addition to its popularity, are the motivation for this study. The purpose of this study is to examine buy-write strategies and whether the active strategies outperform the passive strategies. These active strategies are the dynamic strike price, the volatility risk premium and the combine strategy.

The history of studies examining the buy-write strategy starts from the 1970s, the same decade the first option exchange, Chicago Board Options Exchange, opened. The five decades of research is divided into four groups according to their direction of research and importance to this study.

The first group presents the previous main studies to this study. Hill et al (2006) and Che & Fung (2011) examines the dynamic strike price strategy in their respective studies and finds that the dynamic strategy is a beneficial strategy during highly volatile markets conditions, since it offers higher risk-adjusted return than the vanilla fixed trike price strategy. Hsieh et al (2014) examines the dynamic strategies further and argues that a dynamic strategy using the Heston option pricing model instead of Black-Scholes-Merton model performs better. Simon (2014) presents a model to estimate the volatility risk premium of call options, which is based on the ability to predict when the implied volatility is artificially high. The buy-write position is then entered when the volatility risk premium is above its average level, leading to an increase in strategy performance. Motivated by these studies, this study examines a combine strategy, that according to its name, combines the dynamic strike price strategy and the volatility risk premium strategy.

The second group of studies focuses on the risk-return characteristics of the buy-write strategy. Brown & Lummer (1984) and Zivney & Alderson (1986) finds that writing options on a stock index instead of individual stocks leads to higher strategy performance. Later studies find that returns of a buy-write strategy are non-normally distributed, which is why the more traditional performance measurements as Jensen alpha and Sharpe ratio do not capture the performance of the strategy well (see e.g. Board et al. 200 and Figelman 2008). These traditional performance measures are then substituted with non-normality considering Leland alpha and beta, Sortino ratio and Stutzer index.

The third and fourth group focuses on the construction of the CBOE S&P 500 BuyWrite Index (BXM) and the effect of market conditions in buy-write returns. The BXM is a buy-write strategy index writing options on the S&P 500 stock index and is used as a benchmark index for the buy-write strategies in this study. The effect of market conditions and especially volatility conditions in buy-write returns is demonstrated in several studies (see e.g. Feldman & Roy 2005 and Kapadia & Szado 2012). These studies show that the strategy outperforms the underlying stock index during market downturn and vice versa during market upturn.

The theory part of this study is divided in half, the first part focusing on the options theory and the second part focusing on the performance measurements used in evaluation of the different buy-write strategies in the research part of this study. The options theory starts from the basic terminology, explains the valuation and boundaries of option prices and ends with Black-Scholes-Merton and Heston option pricing models and risk management measures known as the Greeks. The performance measurement section presents the traditional CAPM based measurement and also non-normality capturing Leland alpha and beta, Sortino ratio and Stutzer index.

The data and methodology part disclose the data sources, presents some descriptive statistics of the data and explains in detail how the empirical part of this study is conducted. The option data is acquired from CBOE Datashop and all the rest of data is downloaded from Bloomberg Terminal, except the proxy for risk-free rate, US 1-month Treasury Bill, which is downloaded from Federal Reserve Bank of St. Louis. The methodology part presents first the calculation method for the buy-write strategy return and the proceeds to more complex methods used in the dynamic strategy and the volatility risk premium (VRP) strategy. The dynamic strategy writes call options based on their exercise probability, which is derived from the Heston option pricing model. The VRP strategy uses a model to estimate the difference between actual and out-of-sample fitted values of implied volatility and then times the strategy when the difference (volatility risk premium) is at optimal level. The combine strategy combines these two active strategies and tries to exploit the strengths of both strategies.

The sixth section of this study presents the results of this study and discussed the interpretations of these results and findings. Results of each of the hypotheses are presented and discussed in own subsections and the last subsection discusses the interpretations of these findings in more general level.

The results of the performance of the vanilla buy-write strategies are examined in the first subsection. The results presented and discussed demonstrates that the OTM-4% buy-write strategy performs the best of the 8 vanilla buy-write strategies. The OTM-4% has highest performance measures (Leland alpha, Stutzer index and Sortino ratio), second highest mean return and second highest systematic and total risk of the vanilla strategies. These findings support the first hypothesis and are in line with previous studies, e.g. Hill et al. (2006) and Kapadia & Szado (2012).

The second subsection presents the results of the volatility risk premium estimation strategies and discusses the findings. The deepest in-the-money ITM-5% volatility risk premium strategy performs the best of the VRP strategies with every performance measurement. It outperforms also the vanilla buy-write strategies which supports the second hypothesis and rejects the implied null hypothesis. An interesting result is that the ITM-5% strategy has also the lowest systematic and total risk of the VRP strategies. The results show that as the moneyness changes from ITM to OTM, mean returns decrease but semi-standard deviations increase. The appendix 1 shows that the VRP strategy's risk-return payoff curve is almost perpendicular to the corresponding curve of the vanilla buy-write strategy, although the VRP starts turning horizontal as it approaches Y-axis (as the semi-standard deviation decreases). This finding is not examined in this study but would be an interesting question to answer in future research.

The inverted risk-return payoff curve and the performance of ITM strategies demonstrates that the volatility risk premium estimation model is capable of estimating the VIX correctly. The best performance of 10,9%-ITM strategy supports the logic that when the implied volatility (as considered the option price) is artificially high, the price is high because the probability of exercising is thought to be high. And as the most ITM strategy performs the best, it indicates that implied volatility truly was artificially high. The appendix 4 shows that the volatility risk premium is below its average level the time before the financial crisis, is above during the crisis and periodically roses above the average after the crisis. This study does not examine why the volatility risk premium stays at higher level after the crisis and periodically rises above its average, even though the underlying S&P 500 index has been rising since the crisis (see figure 7 in section 5, but notice that the SPXT is just directive since it includes dividends).

The third subsection presents and discusses the results of the dynamic strike price strategy. From 11 dynamic strategies the D5% strategy (writing on average 5,6% OTM options) performs the best. It is the only dynamic strategy with both economically and statistically significant Leland alpha and it also outperforms the other strategies with every performance measurement. The D95% (writing 10,9% ITM options) is the worst performing dynamic strategy of all of the buy-write strategies in this study, for example it offers lower total period cumulative return than the risk-free rate (1-month T-Bill). The D5% strategy outperforms vanilla buy-write strategies supporting the third hypothesis and rejecting the implied null hypothesis.

The findings of both Hsieh et al. (2014) and this study on dynamic strategy suggests writing lower exercise probability option in contrast to Che & Fung (2011) suggesting writing higher exercise probability options. This difference in results may be explained by the different exercise probability calculating methods, but Hsieh et al. (2014) uses both BSM and Heston model which both contradicts with Che & Fung (2011) who uses BSM model.

The fourth subsection examines the results of the combine strategy, which utilizes both dynamic strike price and VRP strategies. The deepest in-the-money combine strategy performs the best. The 10,9%-ITM strategy has the highest statistically significant Leland alpha and highest Sortino ratio of all of the buy-write strategies. Except vanilla OTM-2%-OTM-5% strategies, the combine strategy outperforms every other buy-write strategy with every performance measurement. These results support the fourth hypothesis and rejects the implied null hypothesis. The 10,9%-ITM strategy offers also the second highest cumulative return for the whole observation period (297,44 %). Examining the appendix 3 further also shows that the 10,9%-ITM strategy is less sensitive to market disturbances compared to other strategies.

The appendix 1 shows the effect on the dynamic strategy when it is combined with the VRP strategy. The D95% dynamic strategy is so close to the origin that it is not plotted in the figure, but when it is enhanced with the VRP estimation method, its risk-return payoff moves to the leftmost triangle marker (the 10,9% ITM combine strategy). The change is equal to 81 basis points increase in mean return but 47 basis point increase in semi-standard deviation.

The last subsection summarizes the results of this study and discusses some findings further, for example the clustering of OTM strategies' risk-return payoffs and the immunity of strategies against fluctuations in markets. Last, the section discusses the preferable buy-write strategies for active and passive investors.

The purpose of this study (see section 1.2) is to analyze the buy-write strategy and to examine the effects on strategy performance when combining a dynamic strike price method and a volatility risk premium estimation model. Each of the four hypotheses (see section 1.2) focuses on a different buy-write strategy examined in this study. All of the implied null hypotheses were rejected, supporting the four hypotheses and the intended contribution of this study, which is to demonstrate that the active buy-write strategy outperforms the passive buy-write strategy. This study found some interesting topics or at least questions to answer for future research. The first is to examine further the contributing factors behind the VRP strategy's ability to invert the risk-return payoff curve of the vanilla buy-write strategy, could this ability be enhanced by utilizing a more sophisticated volatility estimation model and how to choose the optimal threshold for VRP expensiveness (this study tested mean, median and median 75% and found mean the best). The second is to use robust methods and test whether the combine strategy has some immunity against market fluctuations and what are reasons behind it

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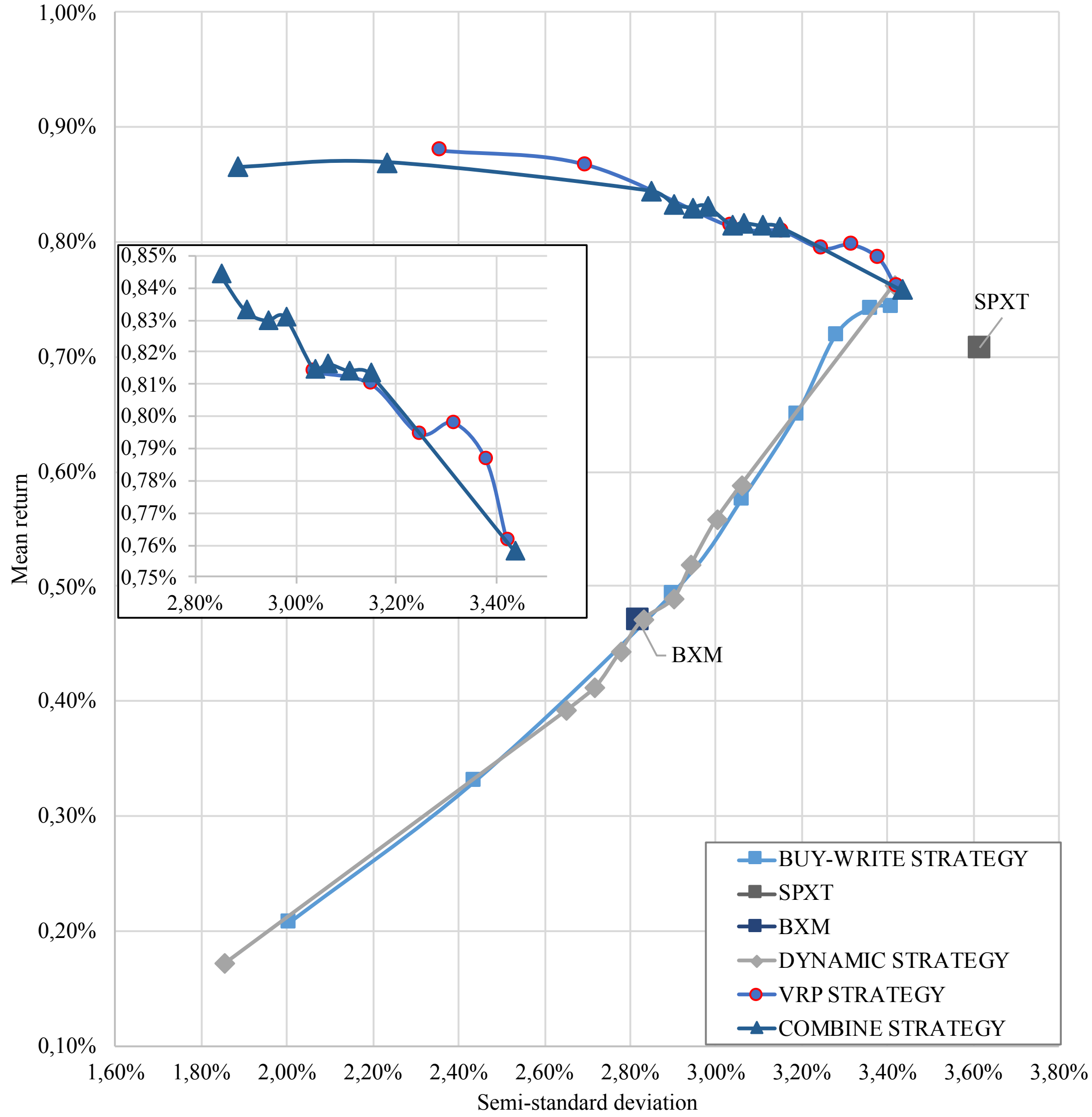
APPENDIX 1. Tradeoff between risk and return.

Tradeoff between mean return and semi-standard deviation of the strategies. Smaller plot is a zoomed plot of the cluster. D95% (1,41%; 0,05%) is not plotted to compress the figure size.



APPENDIX 2. Return and risk statistics of the strategies.

This table contains return and risk measurements and statistics of all of the strategies. Skewness and kurtosis are calculated of excess returns.

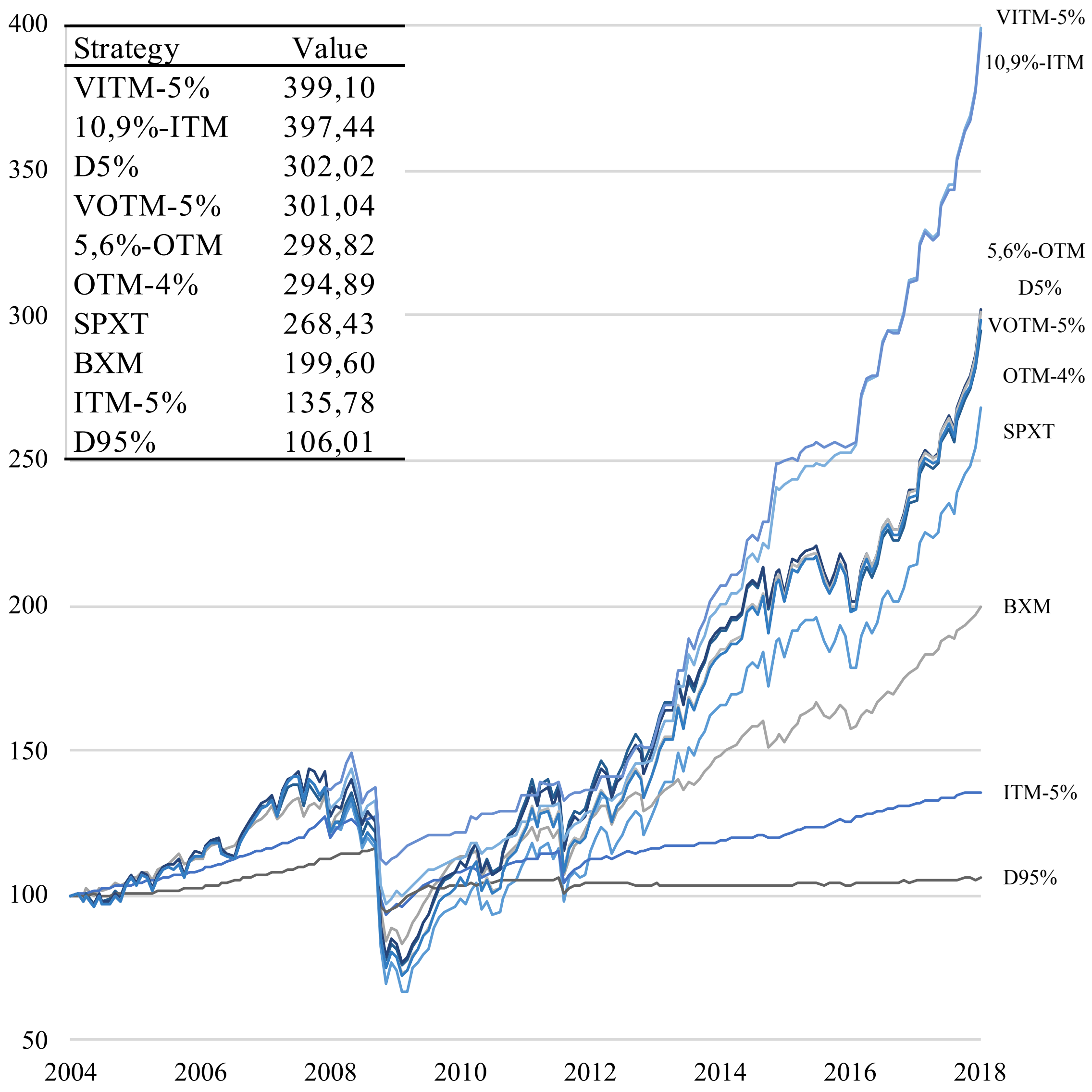
	Mean Return	Annualized Mean Return	Volatility	Semi-Volatility	Skewness	Kurtosis
Panel A: Benchmark indices.						
SPXT	0,71 %	8,82 %	4,70 %	3,61 %	-1,86	8,28
BXM	0,47 %	5,80 %	3,28 %	2,82 %	-3,69	21,62
Panel B: Vanilla buy-write strategies						
ITM-5%	0,21 %	2,52 %	2,12 %	2,00 %	-8,04	78,66
ITM-2%	0,33 %	4,04 %	2,66 %	2,44 %	-5,83	46,32
ATM	0,49 %	6,10 %	3,33 %	2,90 %	-4,06	25,28
OTM-1%	0,58 %	7,14 %	3,61 %	3,06 %	-3,50	19,68
OTM-2%	0,65 %	8,10 %	3,86 %	3,19 %	-3,11	16,28
OTM-3%	0,72 %	8,98 %	4,07 %	3,28 %	-2,78	13,66
OTM-4%	0,74 %	9,28 %	4,23 %	3,36 %	-2,56	12,28
OTM-5%	0,74 %	9,30 %	4,33 %	3,41 %	-2,42	11,44
Panel C: Dynamic strike price strategies						
D95%	0,05 %	0,56 %	1,47 %	1,41 %	-10,58	125,67
D90%	0,17 %	2,08 %	1,95 %	1,85 %	-8,51	86,39
D80%	0,39 %	4,80 %	2,96 %	2,65 %	-4,91	34,88
D70%	0,41 %	5,05 %	3,05 %	2,72 %	-4,65	31,90
D60%	0,44 %	5,45 %	3,15 %	2,78 %	-4,44	29,51
D50%	0,47 %	5,80 %	3,23 %	2,83 %	-4,19	26,62
D40%	0,49 %	6,03 %	3,33 %	2,90 %	-4,06	25,34
D30%	0,52 %	6,40 %	3,41 %	2,94 %	-3,85	23,13
D20%	0,56 %	6,90 %	3,52 %	3,00 %	-3,63	21,07
D10%	0,59 %	7,28 %	3,62 %	3,06 %	-3,48	19,52
D5%	0,76 %	9,54 %	4,37 %	3,42 %	-2,39	11,30

This table continues in the next page.

	Mean Return	Annualized Mean Return	Volatility	Semi-Volatility	Skewness	Kurtosis
Panel D: Volatility risk premium strategies						
ITM-5%	0,88 %	11,09 %	3,17 %	2,35 %	-2,58	16,69
ITM-2%	0,87 %	10,93 %	3,51 %	2,69 %	-2,71	15,90
ATM	0,81 %	10,22 %	3,89 %	3,03 %	-2,58	13,55
OTM-1%	0,81 %	10,17 %	4,04 %	3,15 %	-2,49	12,43
OTM-2%	0,79 %	9,96 %	4,16 %	3,25 %	-2,44	11,93
OTM-3%	0,80 %	10,01 %	4,26 %	3,31 %	-2,36	11,24
OTM-4%	0,79 %	9,86 %	4,36 %	3,38 %	-2,30	10,92
OTM-5%	0,76 %	9,53 %	4,40 %	3,42 %	-2,27	10,72
Panel E: Combine strategies						
10,9%-ITM	0,86 %	10,89 %	2,80 %	1,88 %	-1,63	10,93
6.2%-ITM	0,87 %	10,94 %	3,07 %	2,23 %	-2,35	15,21
1,1%-ITM	0,84 %	10,61 %	3,68 %	2,85 %	-2,66	14,84
0,7%-ITM	0,83 %	10,47 %	3,74 %	2,90 %	-2,64	14,45
0,3%-ITM	0,83 %	10,43 %	3,79 %	2,94 %	-2,62	14,19
0,0%-ATM	0,83 %	10,44 %	3,83 %	2,98 %	-2,57	13,51
0,3%-OTM	0,81 %	10,23 %	3,89 %	3,04 %	-2,58	13,56
0,6%-OTM	0,82 %	10,25 %	3,93 %	3,06 %	-2,53	13,02
1,0%-OTM	0,81 %	10,22 %	3,99 %	3,11 %	-2,51	12,72
1,3%-OTM	0,81 %	10,21 %	4,04 %	3,15 %	-2,50	12,48
5,6%-OTM	0,76 %	9,49 %	4,43 %	3,43 %	-2,24	10,61

APPENDIX 3. Cumulative returns of different strategies.

Cumulative returns of best and worst version of each strategy. Indexed to value of 100 as of 16.1.2004. A strategy starting with: a V is a volatility risk premium strategy, with a one decimal percentage is a combine strategy, with a D is dynamic strategy and with ITM or OTM is vanilla buy-write strategy. The observation period is 16.1.2004-18.1.2018.



Strategy	Value
VITM-5%	399,10
10,9%-ITM	397,44
D5%	302,02
VOTM-5%	301,04
5,6%-OTM	298,82
OTM-4%	294,89
SPXT	268,43
BXM	199,60
ITM-5%	135,78
D95%	106,01

APPENDIX 4. Actual and estimated VIX.

Actual and estimated VIX from 2004 to 2018. VRP stands for volatility risk premium.