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THE PROFITABILITY OF VOLATILITY SPREAD TRADING ON EUROPEAN EQUITY OPTIONS

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ABSTRACT

Volatility is mean-reverting by nature. A large divergence between option implied volatility and long-run historical volatility is a potential signal of option mispricing. Goyal and Saretto (2009) propose an option trading strategy relying on this signal. Their findings are later verified by Do, Foster and Gray (2016) who on the other hand question the authenticity of the returns due to transaction costs. The purpose of this study is to verify the U.S. and Australian findings in the European setting examining options on the most liquid stocks in the European market. Transaction costs in the form of bid-ask spreads are lower for liquid options.

This thesis employs data on European equity options during 2014–2018. The options' underlying stocks are required to be a member of the EURO STOXX 50 Index to ensure liquidity. The final sample consist of 1 794 matched pairs of call and put options that are at-the-money and have one month to maturity. Each month the options are sorted into tertile, quintile and sign difference portfolios by the volatility spread. Within each portfolio, option straddles of the call-put pairs are established, and the cross-sectional returns are calculated. A panel regression is run to examine the reasons for the volatility spread. Also, the straddle returns are regressed on explanatory variables to examine whether they are attributed to the volatility spread.

The results of this study show that a negative spread between the historical volatility and the implied volatility indicates overpricing of an option. By shorting straddles on overpriced options, statistically significant returns are attainable. Depending on the way the options are sorted, the average monthly returns vary from 4.96% to 9.26%. The reason for the volatility spread is that traders may overemphasize the recent behavior of the underlying stock. Despite the promising returns from the short straddles, the returns are not significantly related to the spread. The reason for it is likely explained by the composition of the sample that includes a period in which the volatility spreads are unevenly distributed, making the sorting of the options difficult.

KEY WORDS: Volatility spread trading, option trading strategy, option

1. INTRODUCTION

Forecasting volatility is a daunting task. As volatility in the option pricing equation is the only variable that cannot be directly observed from the markets, it is potentially the source of option mispricing. Goyal and Saretto (2009) study the U.S. equity option markets during 1996–2006 and find that when the implied volatility (IV) diverges from the historical volatility (HV), the option becomes mispriced. The volatility of the underlying asset has a direct relationship with the option price. When IV is low compared to HV, the option is underpriced; when IV is high compared to HV, the option is overpriced. The authors derive their logic from the mean-reverting nature of volatility. They study the cross-section of option returns and find that when taking a long position on the portfolio of underpriced options and simultaneously shorting the portfolio of overpriced options, the returns are both economically and statistically significant: 22.7% per month at the highest. The reasons for the mispricing may be that traders overweight the recent extreme behavior of the underlying asset and underestimate the mean reversion of volatility.

Do, Foster and Gray (2016) question the authenticity of the returns found by Goyal and Saretto (2009). By examining the Australian option market during 2000–2012 using tick data, they find that the returns are largely reduced when transaction costs are taken into account. They also state that the returns to short option positions should be scaled by the initial margin to provide a more realistic view on the profits. However, reasonable monthly returns are still attainable if a trader manages to achieve effective spreads that are smaller than the quoted spreads. Also, if the trades are timed when the quoted spreads are smaller than what they have been in their history, the returns are larger.

The purpose of this study to examine whether volatility spread trading profits exist in the European market when trading options on the most liquid blue-chip stocks. To my knowledge, the eligibility of such volatility spread trading strategy has not been examined in the European market before. The profits attainable from the strategy are astonishing when compared to the profits from famous stock market anomalies. The option trading strategy that exploits option mispricing signaled by the volatility spread is overall very interesting.

Both Goyal and Saretto (2009) and Do et al. (2016) find that transaction costs in the form of bid-ask spreads, that are particularly large in option markets, vastly erode the high profits of the volatility spread trading strategy. Do et al. (2016) investigate the relationship between the volatility spread and the bid-ask spread. They find that there is no evidence to support the claim that the volatility spreads are only a false artifact of bid-ask spreads. However, the findings of Do et al. (2016) suggest that high illiquidity may be an explanation for the volatility spread. The authors refer to Chordia, Roll and Subrahmanyam (2000) as they state that low bid-ask spreads are a common proxy for liquidity. They also refer to Cao and Wei (2000) according to whom option trading volume is another proxy for liquidity in the option market. In the regression results of Do et al. (2016), high bid-ask spreads and low trading volume (i.e. high illiquidity) are associated with wider volatility spreads. Thus, the implication is that trading volatility spread is more profitable for illiquid options when measured in raw returns.

Goyal and Saretto (2009) also acknowledge the above-mentioned issue prior to the investigations of Do et al. (2016). They address the issue by dividing their sample into two different liquidity groups. They find that although the raw returns are higher for illiquid options, the transaction costs are relatively higher for them, too. Consequently, when taking the transaction costs into account, the profits from the strategy are significantly higher for more liquid options.

Do et al. (2016) state that for traders to earn significant profits with the strategy, they need to achieve effective spreads within 75% of the quoted spreads. Goyal and Saretto (2009) refer to De Fontnouvelle, Fisher, and Harris (2003) and Mayhew (2002) whose findings show that typically the ratio of effective to quoted spread is less than 0.5. On the other hand, they also refer to Battalio, Hatch, and Jennings (2004) who find that for a small sample of large stocks the ratio of effective spread to quoted spread is from 0.8 to 1. As the transaction costs are lower for more liquid options, and the ratio of effective spread to quoted spread is only rarely 1, the implication is that volatility spread trading profits are eligible for the sample of liquid options on the largest blue-chip stocks in Europe.

The data in this thesis comprises the options on the most liquid stocks in Europe. The underlying stocks are required to be a member of the EURO STOXX 50 Index. The EURO STOXX 50 Index, "Europe's leading blue-chip index for the Eurozone, provides a blue-chip representation of supersector leaders in the region" (STOXX Limited 2018). Blue-chip companies are considered large and well-established, and their stocks are highly liquid. The options on these stocks are sorted into tertile, quintile and sign difference portfolios based on the spread in this study. Assumedly the quintile portfolios generate the highest returns as they contain the options with more extreme levels of spreads.

1.1. Purpose of the study

The purpose of this study to examine whether volatility spread trading profits exist in the European market. The study closely follows the empirical methods of Goyal and Saretto (2009) and Do et al. (2016) who conducted their studies by examining the U.S. and Australian option markets, respectively. The European market differs from the U.S. and Australian markets in many respects. The objective of this study is to verify the U.S. and Australian findings in the European setting examining options on the most liquid stocks in the European market.

1.2. Research hypotheses

The hypotheses of this study revolve around the issue of whether volatility spread trading profits exist in the European option market. Goyal and Saretto (2009) and Do et al. (2016) find that a trading strategy that enters long positions on options with a large positive volatility spread, and at the same time enters short positions on options with a large negative volatility spread generates great risk-adjusted returns. Their findings suggest that traders do not anticipate the mean reversion in volatility and overweight the stocks' recent behavior in their implied volatilities which leads to option mispricing. Thus, the hypotheses are following:

H_0: Volatility spread trading profits do not exist in the European market.

H_1: Volatility spread trading profits do exist in the European market.

In case the null hypothesis is rejected and H_1 is accepted, additional hypotheses can be drawn:

H_2: Overemphasizing of both recent stock returns and recent volatility causes IV to diverge from HV.

H_3: Straddle returns are attributed to volatility spreads.

1.3. Structure of the thesis

The thesis is structured as follows. The second chapter focuses on the option pricing theory by describing the pricing of both European and American options, volatility, and option markets in general. The third chapter reviews previous literature on the volatility spread trading strategy and the key characteristics of option trading that affect the profitability of the strategy. The fourth chapter presents the data and methodology that are used in the empirical examinations. The fifth chapter presents the empirical results and discusses them from the hypotheses' point of view. Finally, the sixth chapter concludes the paper by summarizing the main results and providing suggestions for future research.

2. OPTION THEORY AND THE MARKETS

Although this thesis focuses on the volatility spread trading strategy and its profitability and does not exactly take a stand on the validity of the option pricing models, it is beneficial to understand the fundamentals of options in general, the option pricing models, and the markets. This chapter also introduces the concept of volatility from the point of view that is relevant to this thesis.

2.1. European options

Based on the most famous option pricing model by Black and Scholes (1973), the price of an option is a function of the price of the underlying asset, the strike price, the continuously compounded risk-free interest rate, the asset price volatility, and the time to maturity of the option. The pricing formulas for European call and put options are following:

(1) $$c = S_0 N(d_1) - Ke^{-rT} N(d_2)$$

(2) $$p = Ke^{-rT} N(-d_2) - S_0 N(-d_1)$$

where

(3) $$d_1 = \frac{\ln(S_0/K) + (r + \sigma^2/2)T}{\sigma\sqrt{T}}$$

(4) $$d_2 = \frac{\ln(S_0/K) + (r - \sigma^2/2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T}.$$

In equations 1–4,

c = the price of a European call option

p = the price of a European put option

S_0 = the stock price at time zero

K = the strike price

r = the continuously compounded interest rate

σ = the stock price volatility

T = the option's time to maturity

$N(x)$ = is the cumulative probability distribution function for a standardized normal distribution. (Hull 2012: 313-314.)

Variable	*European call*	*European put*	*American call*	*American put*
Current stock price	+	−	+	−
Strike price	−	+	−	+
Time to expiration	?	?	+	+
Volatility	+	+	+	+
Risk-free rate	+	−	+	−
Amount of future dividends	−	+	−	+

* + indicates that an increase in the variable causes the option price to increase;
− indicates that an increase in the variable causes the option price to decrease;
? indicates that the relationship is uncertain.

Figure 1. Variables affecting the price of an option (Hull 2012: 215).

Figure 1 shows the effect on the price of an option when increasing one variable while keeping all other variables fixed. As can be seen from the table, volatility of the underlying asset has a direct relationship with the option price: when the volatility increases, the option price increases. This holds true for both call and put options.

2.2. American options

American options differ from European options. Whereas European options can be exercised only on the expiration date, American options can be exercised at any time before the expiration date. Options that are traded on exchanges are mostly American. (Hull 2012: 7.)

The option pricing model by Black, Scholes, and Merton is not suitable for pricing American options as one of the inputs in the equation is the option's time to maturity. The model does not allow for an early exercise. A binomial tree procedure is more suitable for valuing American options and it is widely used in the industry. The model was first proposed by Cox, Ross and Rubinstein (1979). It is a diagram that represents different possible paths that the stock price could follow during the life of an option. The procedure begins by reducing the possible changes in next period's stock price to two: an "up" move and a "down" move. The assumption that there are only two possible outcomes for a stock is clearly not realistic. However, the idea is to take shorter and shorter intervals where each step shows two possible paths. When the pricing method is used in practice, the life of the option is usually divided into at least 30 time steps. Thus, the selection of different prices becomes large. As the periods are chopped into shorter and shorter ones, eventually a situation is reached where the stock price is changing continuously. In fact, it can be shown that when the time steps become smaller, the European option price calculated using the binomial tree model converges to the price given by Black-Scholes-Merton model (Brealey, Stewart & Allen 2011: 530; Hull 2012: 253-268).

The following formulas enable an option to be priced when there are only two possible outcomes for a stock price:

(5) $$f = e^{-rT}[pf_u + (1-p)f_d]$$

(6) $$p = \frac{e^{rT}-d}{u-d}.$$

In the equations 5 and 6,

f = the option price

r = the risk-free interest rate

T = the option's time to maturity

p = probability of an up movement for the stock price

f_u = the payoff from the option if the stock price moves up

f_p = the payoff from the option if the stock price moves down

d = the new level for the stock price after a down movement

u = the new level for the stock price after an up movement. (Hull 2012: 256.)

The same logic applies when the time steps become smaller and when there are more possible paths for the stock price. As the length of the time step is Δt instead of T, the equations (5) and (6) become

(7) $$f = e^{-r\Delta t}[pf_u + (1-p)f_d]$$

and

(8) $$p = \frac{e^{r\Delta t} - d}{u - d}.$$

The equation (7) is applied repeatedly at each node of the binomial tree. For example, when there are two steps in a binomial tree, the value of the option is given by the equation

(9) $$f = e^{-2r\Delta t}[p^2 f_{uu} + 2p(1-p)f_{ud} + (1-p)^2 f_{dd}]$$

The two-step binomial tree is illustrated in Figure 2. S_0 stands for stock price. (Hull 2012: 261.)

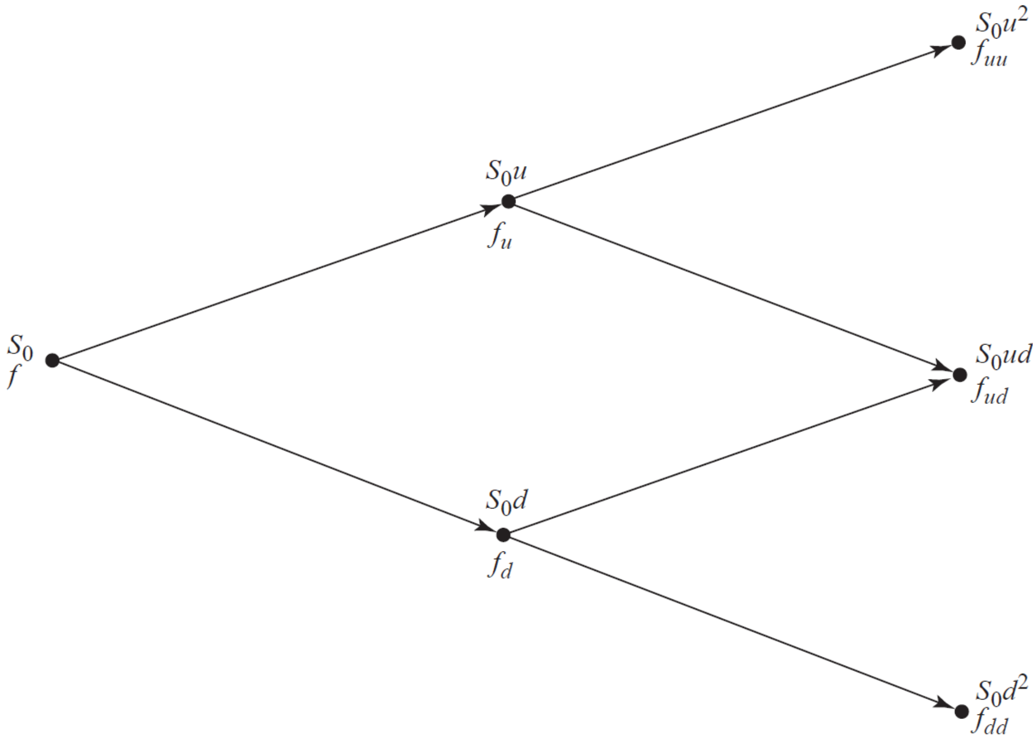

Figure 2. A two-step binomial tree (Hull 2012: 262).

The objective is to find the option price at the initial node of the tree. The option prices at the final nodes are easily calculated as they are the payoffs from the option. The value of the option at the final nodes is the same for European and American options as the option's time to maturity is reached at that point. The procedure is to work back from the end of the option's life to the beginning to find the value of the option. Each binomial step is treated separately. As American options can be exercised early, it is tested at each node whether an early exercise is optimal. If an early exercise is optimal, the value of the option is the payoff from the early exercise. The payoff is greater than the value given by the equation (7). If an early exercise is not optimal, the value of the option is the one given by the equation (7). (Hull 2012: 263.)

Two important principles are related to valuing options. First, there are no arbitrage opportunities. Second, it can be assumed that the world is risk-neutral: riskless portfolios must earn the risk-free interest rate. Even though the real world is not risk-neutral, assuming the world is risk-neutral gives the correct option price for both a risk-neutral and the real world. As an option is priced in terms of the price of the underlying stock, risk preferences do not matter. Hull (2012: 253-259) proves the validity of these assumptions using numerical examples.

The volatility of the stock price can be matched with the parameters u and d. Hull (2012: 265) shows that it does not matter whether the volatility is matched in the real world or the risk-neutral world. Thus, the following is explained using the notation in the real world. The expected stock price at the end of a step Δt is $S_0 e^{\mu \Delta t}$, where μ stands for the expected return. When the expected return on the stock is matched with the binomial tree's parameters, we have:

(10) $p = \frac{e^{\mu\Delta t} - d}{u - d}.$

The volatility σ of a stock price is defined so that $\sigma\sqrt{\Delta t}$ is the standard deviation of the stock return in Δt. When the stock price volatility is matched with the tree's parameters, we have:

(11) $pu^2 + (1-p)d^2 - [pu + (1-p)d]^2 = \sigma^2\sqrt{\Delta t}.$

Thus,

(12) $e^{\mu\Delta t}(u+d) - ud - e^{2\mu\Delta t} = \sigma^2\sqrt{\Delta t}.$

When the terms in Δt^2 and higher powers of Δt are ignored, the solution by Cox, Ross and Rubinstein (1979) to this equation is

(13) $u = e^{\sigma\sqrt{\Delta t}}$

and

(14) $d = e^{-\sigma\sqrt{\Delta t}}.$

When moving from the real world to the risk-neutral world, the expected return on the stock changes. However, the volatility remains the same, at least in the limit Δt moves to zero. This is an illustration of a general result called Girsanov's theorem. (Hull 2012: 265-267.)

2.3. Option markets

Option markets are divided into exchange-traded markets and over-the-counter markets (OTC). In derivatives exchanges individuals trade standardized contracts that are defined by the exchange. Derivatives exchanges have existed for quite a long time, although option trading did not formally start until the 1970s. The Chicago Board of Trade (CBOT) was founded in 1848 for farmers and merchants. Within a few years the first futures-type contract was established. A rival futures exchange Chicago Mercantile Exchange (CME) was established in 1919. CBOT and CME later merged to form the CME Group, which also includes the New York Mercantile Exchange.

The Chicago Board Options Exchange (CBOE) was a pioneer in creating an organized option market with well-defined contracts in 1973 (Hull 2012: 2). Nowadays many other exchanges around the world trade options. When measured by volume, CME Group is clearly the largest exchange as approximately 4.09 billion contracts were traded there in 2017 (Statista 2017). Many exchanges have consolidated over the years. Euronext and the NYSE merged to form NYSE Euronext in 2007. (Hull 2012: 817.) NYSE Euronext was then acquired by the IntercontinentalExchange (ICE) in 2013 (ICE 2012). In 2014, however, Euronext detached itself from ICE and the NYSE. Thus, Euronext and the NYSE are now separate exchanges. (Bloomberg 2014.) Eurex, which is operated by Deutsche Borse AG, acquired the International Securities Exchange (ISE) in 2007 (CNBC 2007), but sold it to Nasdaq in 2016 (Nasdaq 2016). These are just a few examples among the many consolidations. As in mergers and acquisitions in other fields, the consolidations have most likely been driven by economies of scale.

In the OTC market trades are usually done between two financial institutions or between a financial institution and its client. The terms of a contract do not have to be standardized or specified by the exchange. Financial institutions often act as market makers, meaning that they are prepared to quote both a bid and an ask price. Trades in the OTC market are usually larger than those in the exchange-traded markets. (Hull 2012: 3.) As shown in Figure 3, the vast majority of the derivatives traded in the OTC market are interest rate derivatives. The second biggest groups are credit default swaps and foreign exchange derivatives.

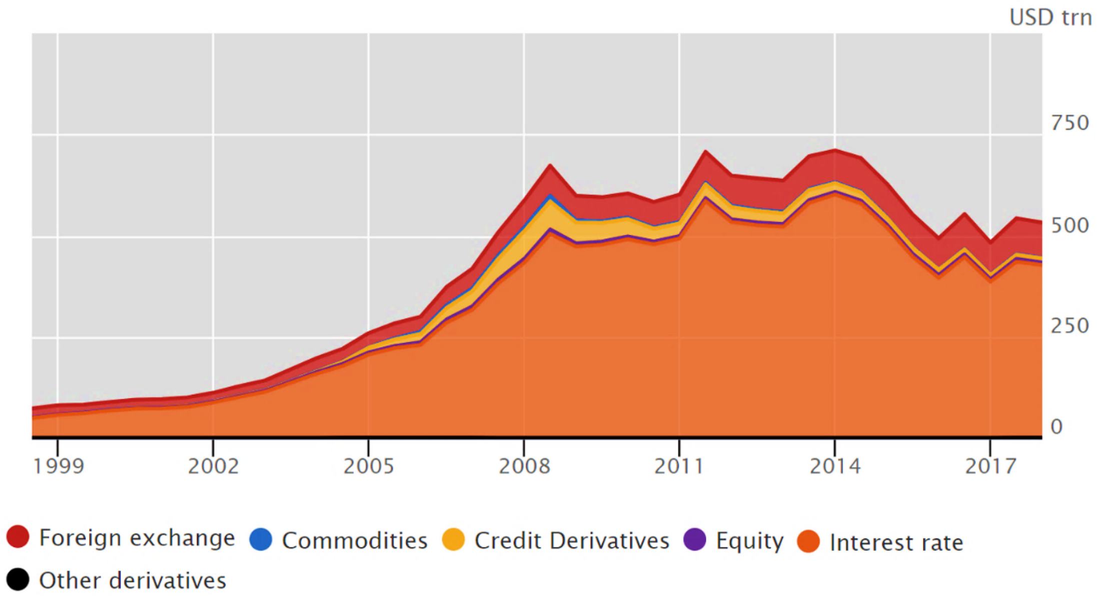

Figure 3. Global OTC derivatives outstanding (Bank for International Settlements 2018b).

Even though the statistics concerning the OTC and the exchange-traded markets are not exactly comparable, it is clear the OTC market is much larger. The notional amount of the outstanding OTC derivatives contracts has fluctuated between $480 trillion and $550 trillion since 2015. In contrast, the notional amount of exchange-traded futures and options as measured by open interest was $81 trillion in 2017. (Bank for International Settlements 2018a, 2018c.) However, one should be careful when interpreting these numbers. The principal underlying the transaction is not the same as its value. When measured in the gross terms, the market value of the outstanding OTC derivatives was \$11 trillion at the end of 2017 (Bank for International Settlements 2018a) which is quite modest when compared to the notional value.

2.4. Volatility

The volatility, σ, of a stock measures the uncertainty of the stock returns. The stock volatility is typically between 15% and 60%. The volatility of a stock price can be defined as the standard deviation of the stock return. (Hull 2012: 303.)

The volatility of the stock price is the only parameter that cannot be directly observed from the markets. Although volatility can be estimated from the historical stock prices, in practice traders use volatilities implied by option prices in the market. (Hull 2012: 318.) To say it in other words, practitioners use iterative search procedures to find σ when they know the price of the option and all the other variables that are plugged into the option pricing equation. Implied volatilities are forward looking, whereas past volatilities of a stock are backward looking. Since the volatility and the price of an option are correlated, practitioners often quote the implied volatility of an option rather than its price. (Hull 2012: 319.)

Implied volatilities are used to monitor the market's sentiment about the volatility of a certain stock. There are also many indices of implied volatility. The most famous one is the VIX index published by the CBOE. It is an index of the implied volatility of 30-day options on the S&P 500 index. The VIX is considered as the "investor fear gauge" (Whaley 2000) as high levels of the VIX occur simultaneously with market turmoil. Also, it has been shown by for example Giot (2005) and Banerjee, Doran and Peterson (2007) that high levels of the VIX predict high future stock returns. The VIX is highly mean-reverting which means that it will return to its long-run average after being high. Since the VIX and the S&P 500 have a negative relationship, it means that when the high VIX eventually mean reverts, the S&P 500 increases. The same logic works the other way around, too. Low levels of the VIX predict negative future returns (Giot 2005).

Poon and Granger (2003) study 93 published and working papers in their article “Forecasting Volatility in Financial Markets: A Review” and write about the collective findings. There are important features documented about financial time series and financial market volatility. In addition to central features such as volatility clustering and asymmetry, mean reversion is often documented. Figure 4 shows that the VIX is highly mean reverting. The graph also illustrates the above-mentioned negative relationship between the VIX and the S&P 500. The data for the graph is obtained from CBOE (2018).

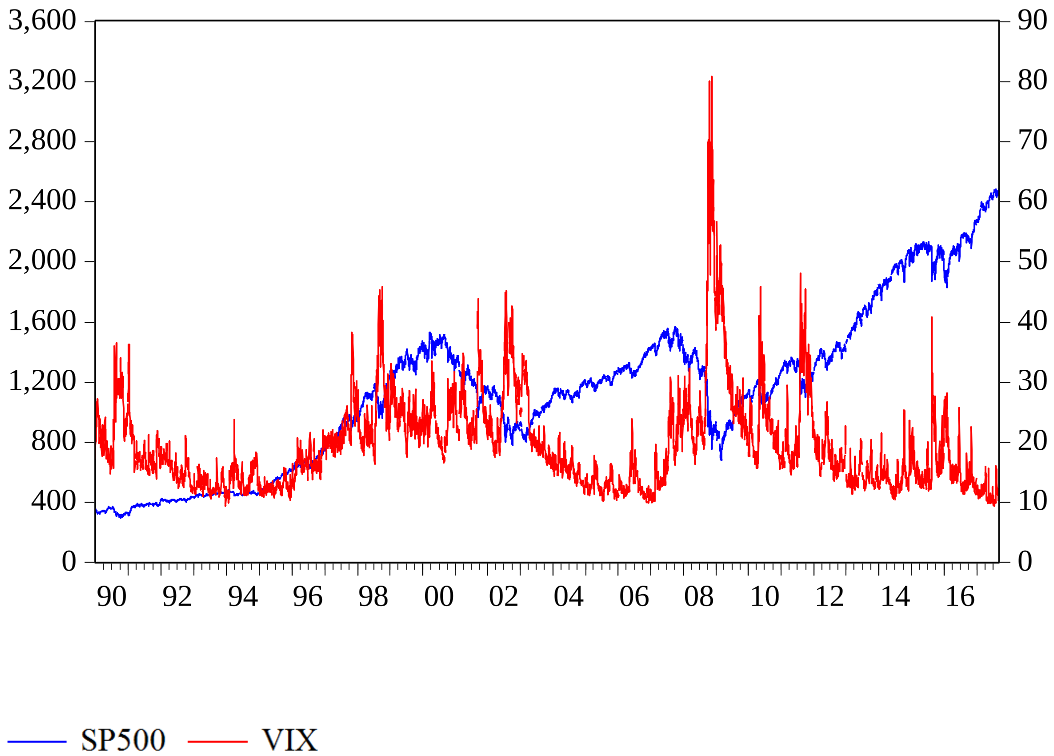

Figure 4. Negative relationship between the S&P500 and VIX.

3. VOLATILITY SPREAD TRADING

This chapter describes the volatility spread trading strategy. The literature regarding volatility forecasting is rather extensive. However, only two articles could be found concerning a trading strategy that exploits the option mispricing arising from the difference between the historical volatility and the implied volatility. Goyal and Saretto (2009) were assumedly the first to study the economic impact of such strategy. Do et al. (2016) re-examined he strategy in the Australian setting. The following sections discuss these two articles in detail, describing the methods and findings of the studies as well as the reasons that possibly deteriorate the profits from the strategy.

3.1. The strategy

"Options allow an investor to trade on a view about the underlying security price and volatility. A successful option trading strategy must rely on a signal about at least one of these inputs. In the vernacular of option traders, at the heart of every volatility trade lies the trader's conviction that the market expectation about future volatility, which is implied by the option price, is somehow not correct." (Goyal and Saretto 2009.)

Goyal and Saretto (2009) document the profitability of trading volatility spread. The volatility spread, in this context, means the difference between the historical volatility (HV) and the option implied volatility (IV). The authors state that when the option implied volatility deviates from the long-run historical volatility levels, the option is mispriced. They derive their logic from the mean-reverting nature of volatility. The forecasted volatility may not be the same as the historical volatility. However, the IV of an option should reflect the fact that the future volatility will, on average, be closer to its equilibrium level than to its current volatility. Goyal and Saretto (2009) state that when IV of an option is too low in relation to HV, the spread is positive and indicates underpricing of the option. The logic works the other way around, too. When the IV is too high in relation to HV, the spread is negative and indicates overpricing.

Goyal and Saretto (2009) examine the profitability of volatility spread trading by studying the cross-section of stock option returns during the period from 1996 to 2006 in the U.S. They sort stocks into 10 deciles based on the difference between HV and IV. The first decile consists of stocks with the lowest negative spread while the tenth decile consists of stocks with the highest positive spread. The authors also sort the stocks into two groups depending on the sign of the spread, so that the group labeled P contains the stocks with positive spreads and the group labeled N contains the stocks with negative spreads. The authors use the most recent 12 months' volatility of the stocks as the HV, and as the IV, they use the average of IVs of the calls and puts which are closest to at the money (ATM) and have one month to maturity. An option is referred to as "at the money" when the stock price equals the strike price (Hull 2012: 201). These option characteristics ensure the liquidity of the contracts.

As Goyal and Saretto (2009) are interested in the option returns only based on their volatilities, they aim to neutralize the effect of movements in the underlying stocks. Thus, they form delta-hedged call portfolios and straddle portfolios. Delta of an option defines the rate of change of the option price in relation to the price of the underlying stock (Hull 2012: 380). For example, if the delta of a call option on a stock is 0.4, it means that when the stock price changes by certain amount, the option price changes by 40% of that amount. The authors obtain delta-hedged call positions by buying one call contract and short-selling delta shares of the stock. The gain or loss on the stock position offsets the loss or gain, respectively, on the option position. Straddles, then again, are formed by the combination of one put and one call with the same underlying stock, strike price and maturity. Figure 2 shows the profit pattern of a bought straddle. The figure of shorted straddle looks similar, except it is upside down.

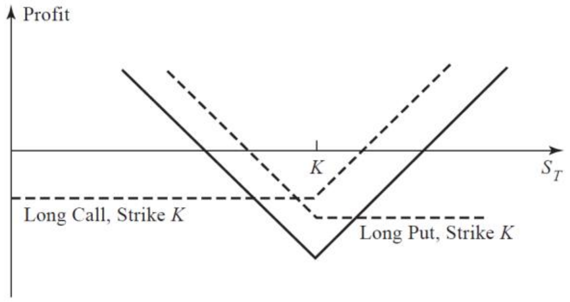

Figure 5. Profit pattern of a bought straddle (Hull 2012: 246).

Goyal and Saretto (2009) find great profit opportunities that deploy the mispricing of the options. When looking at the returns of the decile portfolios, the results are consistent with the authors' hypotheses. The average return for the straddle portfolios in the first decile is -12.8% whereas the average return for the straddle portfolios in the tenth decile is 9.9%. When taking a long position in an option portfolio of stocks with a large positive spread and at the same time taking a short position in an option portfolio of stocks with a large negative spread, the returns generated are as high as 22.7%. The monthly Sharpe ratio of this strategy is 0.90 which indicates that trading the volatility spread generates great risk-adjusted returns. The returns for the delta-hedged calls are not as striking as those for the straddles. The average return of the delta-hedged 10-1 portfolio is only 2.7%. The authors state that one of the reasons for it is that straddles benefit from mispricing of both puts and calls, whereas delta-hedged calls benefit only from mispricing of calls. As a conclusion, when aiming to profit from the volatility spread, one should trade the straddle portfolios. Also, the returns from 10-1 portfolio are better than those from the P-N portfolio. Therefore, one should trade portfolios that comprises options with more extreme levels of the spread, instead of portfolios sorted based only on the sign of the spread.

3.2. Reasons for the option mispricing

Goyal and Saretto (2009) derive the reason for the abnormal returns from the behavioral model by Barberis and Huang (2001). According to the model, recent large positive returns might make traders think that the stock is less risky than it actually is, whereas recent large negative returns might make traders become too pessimistic about the future riskiness of the stock. In other words, when the traders are too optimistic about the future riskiness of the stock, they price the option too low, and when they are too pessimistic, they price to the option excessively high. Do et al. (2016) find mixed results concerning this conjecture. When it comes to stocks in the portfolio with a large positive spread, they find that the recent one-month returns have been higher than the average monthly returns over the previous year. However, when it comes to stocks in the portfolio with a large negative spread, the difference between the past one-month and the past one-year returns is not statistically significant.

Due to the mixed results, Do et al. (2016) suggest an alternative explanation for the abnormal returns. They refer to the findings of Stein (1989) and Poteshman (2001) when they state that traders put too much weight on the volatility in the recent past. Due to the mean-reverting nature of volatility, traders should place more emphasis on the historical levels of volatility. Do et al. (2016) first examine the volatility characteristics and find that in the portfolio with a large positive spread, the one-month volatility prior to the formation of the portfolio has been low compared to the historical volatility. This makes the traders estimate the current volatility too low, and thus underprice the option. The same logic works the other way around, too. Do et al. (2016) find that when it comes to the portfolio with a large negative spread, the prior one-month volatility has been high compared to the historical volatility. The recent high volatility makes the traders estimate the current volatility high as well, which leads to overpricing of the option. This is all due to the mean reversion of the volatility. Eventually, volatility will revert to its equilibrium level.

To support the anecdotal evidence about the volatility characteristics, Do et al. (2016) run a two-step multivariate regression. They first regress the volatility spread (HV-IV) on the difference between stock returns over the prior month (R1) and the preceding year (R12), the difference between historical volatility (HV) and the prior one-month volatility (HV1), and control variables. The regression results suggest that the option mispricing is partly due to the prior one-month behavior in the underlying stock. In the second step, Do et al. (2016) examine how the straddle returns are explained by these variables. They use four different models. In the third model, in which the spread (HV-IV) variable is excluded, the coefficient for the difference between historical volatility and the prior one-month volatility is significant and positive. This again supports the evidence that the recent behavior of the underlying stock affects the mispricing of the option. However, in the fourth model, in which the authors include all the variables, the only the coefficient that remains significant is the spread between historical volatility and implied volatility. The implication is that although the recent volatility in relation to historical volatility seems to affect straddle returns, its impact is not significant when the spread (HV-IV) is controlled for.

3.3. The authenticity of the volatility spread returns

Do et al. (2016) question the authenticity of the volatility spread returns found by Goyal and Saretto (2009). They begin their research by using a similar methodology to Goyal and Saretto (2009), but instead of examining the U.S. markets, they examine the profitability of spread trading on the Australian Securities Exchange (ASX) over the period 2000–2012. Do et al. (2016) then extend the study by Goyal and Saretto (2009) by taking the real-world settings into account. Although the authors also find that straddle strategies exploiting the option mispricing generate seemingly high returns, they state that the profits are largely reduced by of the bid-ask spreads. Also, they state that the way the profits are scaled overestimates the actual returns.

Goyal and Saretto (2009) acknowledge the deterioration of performance of the volatility spread trading strategy when transaction costs are taken into consideration. Due to the lack of transaction data, they rely on the trading day’s closing quotes. However, the bid-ask spreads likely vary throughout the day, and therefore the closing quote is not an accurate representative of the spreads possible throughout the day. Do et al. (2016) use tick data to examine the impact of the bid-ask spreads on the profitability of the volatility spread trading more accurately. They have 4 514 matched of call-put pairs in their analysis for which they have the complete tick history. By exploiting the tick data, the authors are able to examine intraday changes in the bid-ask spreads.

3.3.1. Bid-ask spreads and the volatility spread

Ask price is the price a trader pays for an instrument, whereas bid price is a lower price a trader receives when he sells an instrument to a dealer. Bid-ask spread is the difference between these prices and it is also the source of profit for the dealer. (Bodie, Kane & Marcus 2014: 29.) Bid-ask spreads in the derivatives markets are larger than those in the underlying asset markets (Fleming, Ostdiek & Whaley 1996). Do et al. (2016) reason that bid-ask spreads not only decrease the profitability of trading volatility spreads, but they can also affect the call and put components of the straddles. The authors state that bid-ask spreads may even partly cause the large differences between HV and IV. As stated before, the option price and the implied volatility are correlated, and practitioners often refer to the implied volatility of the option instead of its price. If the true option price (true IV) lies somewhere between the bid and ask prices, a volatility that is implied from the ask price will appear too high. Similarly, a volatility that is implied from the bid price will appear too low. If the bid-ask quote is very wide, meaning that the difference between the bid and ask prices is large, traders may think that there is option mispricing even when such does not exist. Thus, wide bid-ask spreads may give false signals of option mispricing.

Do et al. (2016) examine whether bid-ask spreads impact the HV-IV spread by studying the distribution of buyer- and seller-initiated trades in their sample. They state that if the mispricing signals of HV-IV are only an artifact of bid-ask spreads, it is more likely that the IV of overpriced (underpriced) options were derived from a buyer (seller) -initiated trade. Do et al. (2016) follow Flint, Lepone and Yang (2014) and use the quote rule by Savickas and Wilson (2003) to determine the direction of each trade. Do et al. (2016) find that nearly 45% of the trades are seller-initiated. Thus, they conclude that mispricing signals cannot be attributed only to bid-ask spreads.

Bid-ask spreads are considered a proxy for liquidity (Chordia et al. 2000). Do et al. (2016) examine whether the divergence of IV from HV is attributable to illiquidity by regressing the HV-IV spread on the percentage effective spread (PES), trading volume and control variables. Their regression results show that large bid-ask spreads and low trading volume, that is a proxy for high illiquidity, are related to the HV-IV spread. Although the results are only modestly significant, they suggest that the option mispricing is partly attributable to illiquidity.

3.3.2. The impact of bid-ask spreads on profits

Do et al. (2016) use the PES and the percentage quoted spread (PQS) as transaction cost metrics. The authors define the PES and PQS as follows:

(15) $$PES = 200\% \times \left|\frac{Trade - Midpoint}{Midpoint}\right|$$

(16) $$PQS = \frac{Ask - Bid}{Midpoint}$$

The average PES on calls and puts are 8.47% and 9.13%, respectively. The PQS are marginally higher: 10.45% for calls and 11.65% for puts. Do et al. find that the opening and closing quoted spreads are remarkably higher. The implication of this is that the size of these spreads has a significant impact on trading profits if the straddles are entered at the opening or closing of trade. However, spreads narrow considerably between the opening of the market and the first option trade. The PES on first trade on trading day is 8.04% for calls and 9.54% for puts. Thus, the correct timing of the option trade is important if a trader wishes to profit from trading volatility spreads.

Do et al. (2016) examine different trading scenarios to further study the impact of bid-ask spreads on trading profits. If option positions are entered at the high opening quotes, average returns to straddle portfolios are remarkably reduced. In fact, when taking a long position on the portfolio with positive volatility spreads, and at the same time taking a short position on the portfolio with negative volatility spreads, the profits are completely eroded: long-short portfolio returns are -7.76%. When considering more typical levels of the bid-ask spreads, the average returns to long-short strategy generates 4.49% per month, yet it is statistically insignificant. However, when compared to the raw returns of the strategy, that is 15.71%, the drop is remarkable. The implication is that the seemingly high profits from the volatility spread trading are vastly eroded when taking the existence of transaction costs into account.

If a trader manages to achieve an effective spread that is narrower than the quoted spread, the long-short volatility spread portfolio can still produce reasonable profits. For example, if a trader achieves an effective spread that is 75% of the quoted spread, the returns from long-short portfolio are 6.84% per month. The narrower the effective spread is compared to the quoted spread, the bigger the returns are. For example, if the effective spread is 25% of the quoted spread, the returns grow to 11.54% per month. Another alternative is to delay the trade until the quoted spreads are smaller than what they have been on average. For example, if a trader waits until the quoted spread is below the 25th percentile of its historical distribution, the returns increase to 8.02% per month. If the trader waits until the quoted spread falls more, the returns become even higher. (Do et al. 2016.) As a conclusion, Do et al. 2016 find that the volatility spread trading profits are clearly not as high as suggested by Goyal and Saretto (2009). However, if a trader times the trades conveniently and manages to achieve sufficiently narrow effective spreads, reasonable profits are still possible.

3.3.3. The impact of initial margins on profits

When taking a long option position, the possible loss is limited to the paid premium whereas when shorting an option, the possible loss is unlimited. Because of the risk of remarkable losses on short positions, investors are required to lodge cash margins to cover these possible losses (Do et al. 2016). Although asset returns are generally estimated by scaling the realized returns by the initial price, Murray (2013) suggests scaling the returns to short option positions by the initial margins. If initial margins are ignored, the returns to short option positions are overestimated.

Do et al. (2016) examine the impact of initial margins on volatility spread trading profits. When they scale the returns to long option positions by their initial margin, the profits are naturally the same since the margin in the case of long options is the paid premium. When it comes to short option positions, the margins required very likely exceed the premiums.

When returns are scaled by a larger denominator, the profits are naturally reduced. When Do et al. (2016) scale the returns to short option positions by the initial margin, the profits are vastly reduced in each scenario. For example, if a trader manages to achieve an effective spread that is 50% of the quoted spread, and trades the long-short portfolio, the price-based returns are 9.2% whereas the margin-based returns are 3.81%. As another example, if a trader waits until the quoted spread is below the 25th percentile of its historical distribution, the price-based returns are 8.02% whereas the margin-based returns are modest 2.14%. As a conclusion, the returns to short option positions are exaggerated if not scaled by their initial margin. However, these are monthly returns: when annualizing the returns, they are high even if the returns from short positions are scaled by the initial margin.

4. DATA AND METHODOLOGY

The purpose of this study is to examine whether volatility spread trading profits exist in European markets when trading options on most liquid and well-established stocks. Suitable data and methods are chosen to achieve this goal. A detailed description of the data and the methodology is provided in the following subchapters.

4.1. Data

The data on equity options and stock returns are obtained from the Datastream database. The data contain information on American ATM put and call option prices, their implied volatilities, and the underlying stock prices. The data includes daily closing prices for both options and stocks. The daily settlement prices for options are determined through the binomial model according to Cox, Ross and Rubinstein (1979). The underlying stocks are required to be a member of the EURO STOXX 50 Index to ensure liquidity. The options have a variety of exercise prices, and the contracts cover a quantity of 100 shares. Most options on the data are traded at Eurex, expect two companies whose options are traded at Euronext. The data spans from December 2014 to October 2018.

In addition to the data on options, book-to-market ratios and market values of the underlying stocks are collected. They are used as control variables when further examining the reasons for the spread and the straddle returns. The data on them are also collected from the Datastream database.

In order to have a balanced panel data in which information for all the variables is available, the original data is filtered. Consequently, the final sample comprises data on 39 unique companies. For each stock, the matched pair of put and call options is identified. The strike price, that is the one closest to ATM in this case, is the same for both options. As it is not always possible to select ATM options whose ratio of strike price to stock price is exactly equal to one, the options whose moneyness is between 0.95 and 1.05 are included in the sample. The reason to choose ATM options is that they are the most liquid ones.

To have a continuous time-series data with constant maturity, only those options that expire in approximately one month are considered. The options expire on the third Friday of each month. Thus, the portfolio formation date, *t*, is the first trading day (Monday) immediately following the expiration Friday. As the data comprises altogether 46 months and 39 unique companies, the final sample consist of 1 794 matched pairs of call and put options.

The country and sector distribution of the sample companies are shown in Figures 6 and 7, respectively. The sector classification is obtained from STOXX Limited (2018). Figure 6 shows that most of the sample companies are from France and Germany which is natural as they are the biggest economies in the Euro Area. Altogether there are 7 countries represented in the sample. The industries which the companies operate in are more widely dispersed. Altogether there are 16 sectors represented in the sample, and the distribution is rather even. The data is not too clustered at least when it comes to industries. All the companies operate internationally which also mitigates the regional concentration.

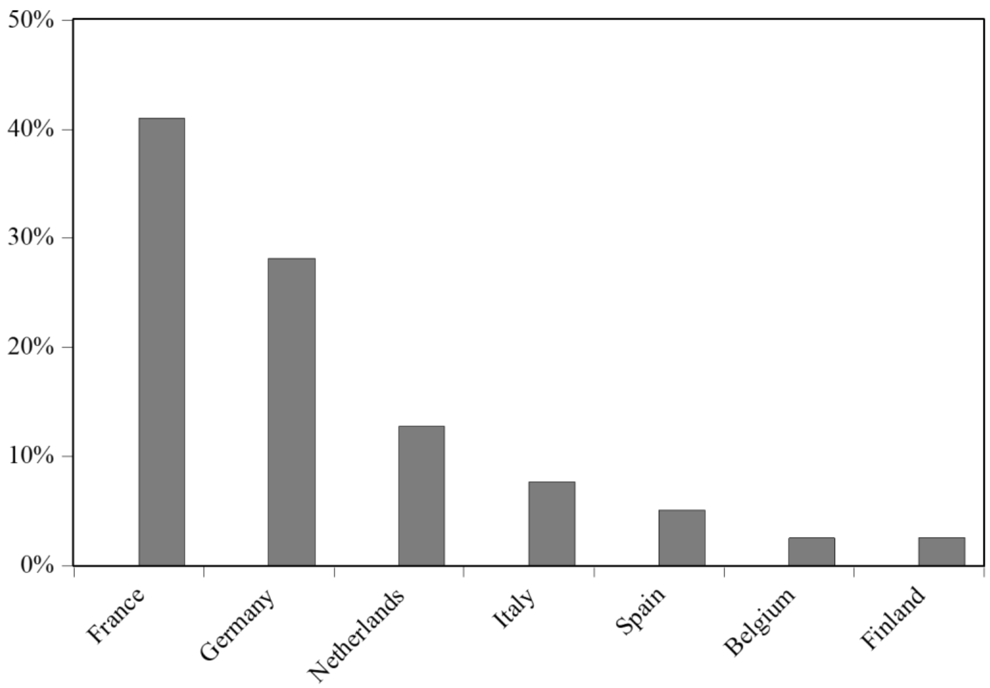

Figure 6. Data distribution among countries.

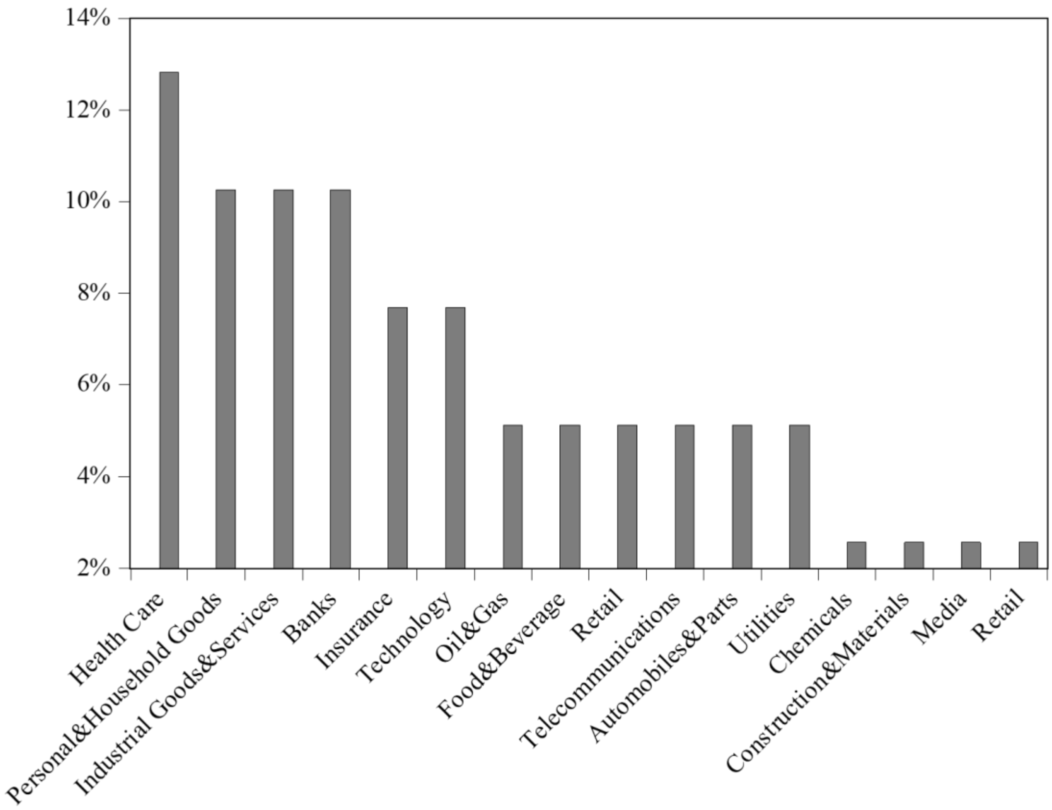

Figure 7. Data distribution among sectors.

Table 1 presents summary statistics for the sample of matched pairs of call and put options. HV is calculated using the standard deviation of daily stock returns over the previous year. IV is calculated by taking the average of the ATM call and put implied volatilities. RV is the future realized volatility over the remaining life of the option. The reported statistics are obtained by first calculating the time-series averages for each stock and then calculating the cross-sectional averages of the time-series averages.

Table 1. Summary statistics of the volatility characteristics.

	Mean	StDev	Min	Median	Max	Skew	Kurt
IV	0.2339	0.0623	0.1357	0.2283	0.4264	0.9855	4.3508
HV	0.2386	0.0487	0.1628	0.2381	0.3157	0.0017	1.7822
RV	0.2263	0.0863	0.0970	0.2133	0.4935	0.9746	4.2688

The volatility estimates are noticeably low compared to those obtained by Goyal and Saretto (2009), who report average volatilities around 50%. Do et al. (2016) report average volatilities around 30%. As Do et al. (2016) state, the composition of the sample affects the results. The data employed by Do et al. (2016) comprises equity options within the top 100 ASX stocks whereas Goyal and Saretto (2009) have data on the entire U.S. equity option market. Driessen, Maenhout and Vilkov (2009) focus on S&P100 stocks and report average volatilities around 40%. The volatility estimates around low-to-mid 20% reported in Table 2 are in line with the view that larger companies are less volatile. The options' underlying stocks reside in the EURO STOXX 50 that are considered as well-established and stable companies. The average volatilities are very close to each other. HV has the highest average volatility whereas RV has the lowest. Do et al. (2016) and Goyal and Saretto (2009) report similar differences between average volatilities. IV and RV are both positively skewed.

Volatility correlations are reported in Table 2. The three metrics strongly correlate as expected. The highest correlation can be found between RV and IV, whereas RV and HV have the most modest correlation. Again, the pattern is similar to the trend observed by Do et al. (2016).

Table 2. Volatility correlations.

	IV	HV	RV
IV	1		
HV	0.63	1	
RV	0.69	0.42	1

The volatility spread distribution is shown in Figure 8. The spreads are normally distributed while the distribution is slightly negatively skewed. Descriptive statistics of the volatility spreads are reported in Table 3. The mean spread is 0.0044 whereas the median is 0.0079. Cumulative statistics on the volatility spread distribution are reported in Table 4. Out of the total 1 794 volatility spread observations, 57.5% are positive. Most of the positive spreads, 94.96%, lie between 0 and 0.10. The negative spreads are more widely dispersed as 90.56% of them lie between 0 and -0.10, and the rest lie between -0.10 and -0.25.

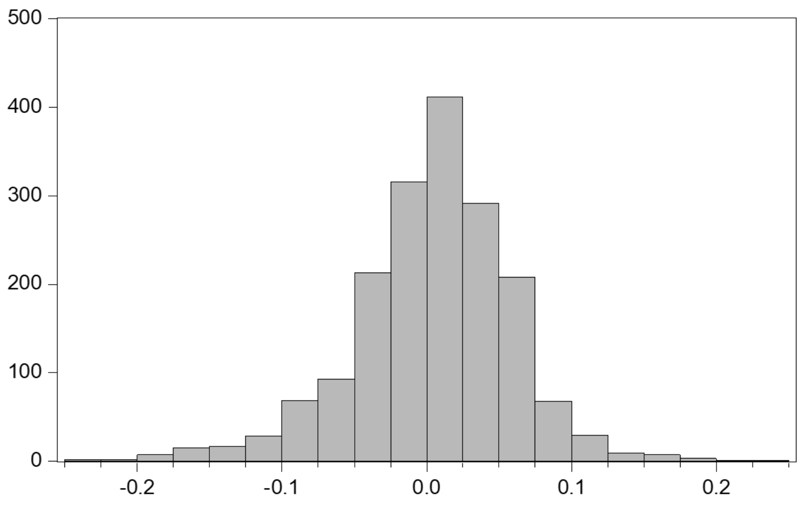

Figure 8. Volatility spread distribution.

Table 3. Descriptive statistics of the volatility spreads.

	HV-IV
Mean	0.0044
Median	0.0079
Max	0.2251
Min	-0.2322
StDev	0.0545
Skew	-0.4944
Kurt	4.6287

Table 4. Cumulative statistics on the volatility spread distribution.

Value	Count	%	Cumulative Count	Cumulative %
[-0.25, -0.2]	4	0.52	4	0.52
[-0.2, -0.15]	22	2.88	26	3.40
[-0.15, -0.1]	46	6.03	72	9.43
[-0.1, -0.05]	162	21.23	234	30.66
[-0.05, 0]	529	69.33	763	100.00
[0, 0.05]	703	68.19	703	68.19
[0.05, 0.1]	276	26.77	979	94.96
[0.1, 0.15]	40	3.88	1019	98.84
[0.15, 0.2]	10	0.97	1029	99.81
[0.2, 0.25]	2	0.19	1031	100.00
Total	1794	200.00	1794	200.00
Negative	763			
Positive	1031			

4.2. Methodology

The methodology employed in this thesis closely follows the procedure used by Do et al. (2016) and Goyal and Saretto (2016). The authors investigate American and Australian option markets, respectively. The idea in this thesis is to test the same option trading strategy in European option markets – especially examining the options on underlying stocks that are well-established, the most liquid blue-chip stocks in Europe. Do et al. (2016) find that the strategy is more profitable for illiquid options. Thus, it is interesting to see whether volatility spread trading profits exist for options on European blue-chip stocks at all.

Before examining the profitability of volatility spread trading, the potential of IV and HV for predicting future realized volatility (RV) is investigated. The hypothesis is that both IV and HV contain unique information about RV. Neither IV or HV should subsume each other as the idea that the volatility spread indicates mispricing relies on both components. Following Christensen and Prabhala (1998), the following regressions are conducted. These models are later denoted as Models A, B, and C, respectively.

(18) $$\ln\left(RV_{t,t+\tau}^{i}\right) = \alpha + \beta_1 \ln\left(IV_t^i\right) + \varepsilon_{t,t+\tau}^{i}$$

(19) $$\ln\left(RV_{t,t+\tau}^{i}\right) = \alpha + \beta_1 \ln\left(HV_t^i\right) + \varepsilon_{t,t+\tau}^{i}$$

(20) $$\ln\left(RV_{t,t+\tau}^{i}\right) = \alpha + \beta_1 \ln\left(IV_t^i\right) + \beta_2 \ln(HV_t^i) + \varepsilon_{t,t+\tau}^{i}$$

In the equations above, $RV_{t,t+\tau}^{i}$ is the future realized volatility over the remaining life of the option, and HV_t^i and IV_t^i are time-t estimates of historical and implied volatility, respectively. The logs of each variable are used to mitigate the impact of outliers. Standard errors are corrected for heteroskedasticity and cross-sectional correlation (White 1980). The method has an equation for each cross-section and computes robust standard errors for the system of equations. The procedure is similar to Do et al. (2016) and Goyal and Saretto (2009) who run the regression each month and calculate the time-series average of each OLS estimator together with their standard errors.

When conducting estimations using panel data, random or fixed effects can be used in the equation – depending on the type of data. A key assumption in random effects estimation is that the random effects do not correlate with the explanatory variables. To determine whether to use a random or fixed effects model in panel estimations, the Hausman test (Hausman 1978) is performed. The Hausman statistic for an explanatory factor is

$$(21) \qquad Hausman\ test = \frac{(\hat{\beta}_{FE}^{*} - \hat{\beta}_{RE}^{*})^2}{Var(\hat{\beta}_{FE}) - Var(\hat{\beta}_{RE})}.$$

When performing the Hausman test, the null hypothesis is that the random effects model is the efficient model that should be used. If the p-value is less than 0.05, the null hypothesis is rejected. In case the null hypothesis is rejected, the fixed effects model is more suitable for the estimation. Following Do et al. (2016), it is examined whether a potential time trend in realized volatility affects the information content in IV and HV. Table 5 shows the Hausman test scores for the three volatility estimation models. For Models A and B, the p-value is more than 0.05 meaning that the null hypothesis is not rejected. For Model C, in contrast, the p-value is less than 0.05. In this case, the null hypothesis is rejected, and the alternative hypothesis is accepted. Thus, the time fixed effects are added to Model C. This way the influence of aggregate time-series trends is captured.

Table 5. The Hausman test scores for the volatility estimation models.

Model	Chi-Sq.	p-value
A	2.92	0.08
B	0.09	0.77
C	7.55	0.02

The volatility spread trading strategy is tested using straddles of call-put pairs. First, the historical volatility is estimated from the standard deviation of the underlying stock returns over the prior year. As previously stated, the prices used for calculating the stock returns are the daily closing quotes. The IV of each call and put option is obtained from the options' closing prices on the portfolio-formation date. The IV of the call and put are averaged for reducing possible measurement error. The volatility spread is calculated as the difference between the log transformations of HV and IV. (Goyal and Saretto 2009; Do et al. 2016.) Log transformations of variables are commonly used to mitigate the impact of outliers.

In each month, the observations are sorted by their volatility spread. According to the hypotheses, negative spreads where IV is higher than HV indicate overpricing whereas large positive spreads indicate underpricing. The strategy is tested using three different ways to sort the option pairs by the spread. First the option pairs are sorted into tertile portfolios. The lowest one-third of observations is placed in Portfolio 1, whereas the highest one-third is placed in Portfolio 3. If the strategy works and the hypothesized mispricing is corrected, Portfolio 1 generates negative return while Portfolio 3 generates positive return. Similarly, the observations are sorted by their spread into quintile portfolios. Again, the lowest one-fifth of observations is placed in Portfolio 1 and the highest one-fifth in Portfolio 5. Portfolio 1 (5) of quintile portfolios assumedly generates more negative (positive) return than Portfolio 1 (3) of tertile portfolios as it comprises more extreme observations. The observations are also sorted by their sign into portfolios of negative and positive spreads. The returns generated by the sign difference portfolios are assumedly more modest as the observations are mixed with non-extreme levels of spread.

Within each portfolio, option straddles of the call-put pairs are established. Straddles are used because the interest is in option returns based on the volatility characteristics only. Thus, the movement of the underlying stock is neutralized. Straddle portfolio returns are calculated as follows:

$$(22) \qquad SPR_{t,t+\tau} = \frac{1}{n} \Sigma_{i=1}^{n} \left[\frac{C_{t+\tau}^{i} + P_{t+\tau}^{i}}{C_{t}^{i} + P_{t}^{i}} - 1 \right]$$

In equation 22, $C_{t+\tau}^{i} = max\ (0, S_{t+\tau}^{i} - K^{i})$ is the payoff on expiry day $t + \tau$ for a call option on a stock i with strike price K^{i}, $P_{t+\tau}^{i} = max\ (0, K^{i} - S_{t+\tau}^{i})$ is the payoff for a put option with the same terms, $S_{t+\tau}^{i}$ is the price of a stock i on expiry day $t + \tau$, C_{t}^{i} and P_{t}^{i} are the option prices to enter the straddle on day t, and n stands for the number of straddles. Following Goyal and Saretto (2009) and Do et al. (2016), the portfolios are formed on the first trading day, but the strategies are initiated on the second trading day. This method is used to reduce microstructure bias.

There are two main proposals to what might cause IV to diverge from HV. Barberis and Huang (2001) present a theory according to which recent extreme stock returns, either poor or strong, may lead the traders on to think that the stocks are more or less risky, respectively, than they actually are. Goyal and Saretto (2009) conclude that their results are consistent with the model. Do et al. (2016) present an alternative explanation drawing on the overreaction theories of Stein (1989) and Poteshman (2001). According to those theories, the excessive emphasizing of recent volatility can make IV to diverge from long-run HV. After the stock and volatility characteristics are studied along with the straddle returns, a panel regression, following Do et al. (2016), is run to confirm the findings:

(23) $$(HV - IV)_{t}^{i} = \alpha + \beta_{1}(R1 - R12)_{t}^{i} + \beta_{2}(HV - HV1)_{t}^{i} + \beta_{3}\ln(size_{t}^{i}) + \beta_{4}\ln(BTM_{t}^{i}) + \varepsilon_{t}^{i}.$$

In the equation above, $HV - IV$ is the volatility spread, $R1 - R12$ is the difference between stock returns over the prior month and the preceding year and $HV - HV1$ is the difference between long-run historical volatility and prior one-month volatility. The natural logs of book-to-market ratio and size, as measured by market capitalization, serve as control variables in the equation. Time fixed effect is again included in the equation as suggested by the Hausman test. Standard errors are corrected for heteroskedasticity and cross-sectional correlation (White 1980).

Following Do et al. (2016), the extent to which the variables above explain the straddle returns is examined. Regression of straddle returns on explanatory variables is run in four models as follows:

(24) $$SPR_{t,t+\tau} = \alpha + \beta_1(HV - IV)_t^i + \beta_2 \ln(size_t^i) + \beta_3 \ln(BTM_t^i) + \varepsilon_t^i.$$

(25) $$SPR_{t,t+\tau} = \alpha + \beta_1(R1 - R12)_t^i + \beta_2 \ln(size_t^i) + \beta_3 \ln(BTM_t^i) + \varepsilon_t^i$$

(26) $$SPR_{t,t+\tau} = \alpha + \beta_1(HV - HV1)_t^i + \beta_2 \ln(size_t^i) + \beta_3 \ln(BTM_t^i) + \varepsilon_t^i$$

(27) $$SPR_{t,t+\tau} = \alpha + \beta_1(HV - IV)_t^i + \beta_2(R1 - R12)_t^i + \beta_3(HV - HV1)_t^i + \beta_4 \ln(size_t^i) + \beta_5 \ln(BTM_t^i) + \varepsilon_t^i$$

The models are later denoted as Models 1, 2, 3, and 4, respectively. The notation in the equations above is the same as for equation 23. Time fixed effects are included in the models and standard errors are corrected for heteroskedasticity and cross-sectional correlation (White 1980). The regressions are run not only to support the findings of equation 23, but also to examine whether the volatility spread is positively and statistically significantly related to the straddle portfolio returns after the effect of other variables is controlled for.

5. EMPIRICAL ANALYSIS

The results of the empirical analysis are reported in this section. First, the capability of IV and HV for predicting future realized volatility is examined. After that, the volatility spread trading strategy is tested using different ways to sort the option pairs based on the spread. The risk-return trade-off is assessed by calculating the Sharpe ratios. A regression of the spread on explanatory variables is run to examine the reasons for the spread. Regressions of straddle returns on explanatory variables are run to further examine what constitutes the profitability of the strategy. Finally, the effect of transaction costs on profits is discussed.

5.1. Forecasting power of implied and historical volatility

Table 4 shows the results of regressing realized volatility on implied and historical volatilities. T-statistics of statistical significance for each coefficient are shown in brackets: they report whether the coefficient is statistically different from zero. The results for Model A show that IV strongly, both statistically and economically, forecasts RV. The question of whether IV is an unbiased estimator of HV arises. If IV can alone predict RV, the coefficient for IV in Model A is one. Following Do et al. (2016), the Wald test is employed. The t-statistic (un-tabulated) for the hypothesis that β_1 equals one is -4.43. Thus, the null is rejected meaning that IV does not alone predict RV. This is further confirmed by F-statistic for Model A in which the hypothesis for the Wald test is that α equals zero and β_1 equals one. The null is again rejected as the p-value is less than 0.05.

The results for Model B in Table 4 show that also HV predicts RV. However, the prediction power is not economically as strong as that of IV. Also, the goodness of fit, indicated by adjusted R^2, is clearly weaker. The Wald test hypothesizing that β_1 equals one is employed. The null is again rejected as the t-statistic (un-tabulated) is -10.18. As with Model A, it is also tested whether α and β_1 jointly equal zero and one, respectively. The hypothesis is again rejected as F-statistic is 53.11, and the p-value is less than 0.05.

Finally, the results for Model C show that both IV and HV contain valuable information for predicting RV. The goodness of fit is greater in Model C compared to Models A and B. When the two variables are placed in the same equation, IV somewhat subsumes the information content of HV. As shown in Table 4, IV clearly has more predictive power than HV. The results are similar to the findings of Goyal and Saretto (2009) and Do et al. (2016) who report β_1 and β_2 estimates of around 0.70 and 0.29, and 0.60 and 0.37, respectively. Neither of the coefficients equal one when tested with the Wald test. The joint restriction of whether α, β_1 and β_2 equal zero, one and zero, respectively, is again tested. The F-statistic for the joint restriction is 73.91 and the null is rejected as the p-value is less than 0.05. However, one must be cautious when interpreting the F-statistic for Model C: the test cannot be performed if standard errors are adjusted for cross-sectional correlation. Thus, the standard errors are not adjusted for Model C when the Wald test is performed.

Table 6. Information content of volatility.

Model	Intercept	IV	HV	Adj R^2	F-statistic
A	-0.3630 (-5.65***)	0.8016 (17.89***)		0.30	14.11 (p<0.01)
B	-0.7032 (-9.68***)		0.5851 (14.36***)	0.16	53.11 (p<0.01)
C	-0.2884 (-4.55***)	0.6800 (11.88***)	0.1748 (4.25***)	0.64	73.91 (p<0.01)

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

As the findings show that neither of the coefficients completely subsume each other, it is justified to continue examining the profitability of trading the volatility spread. Both IV and HV contain information about RV which is a requirement for the spread trading strategy to work.

5.2. Straddle portfolio returns

Table 7 presents the average straddle returns when the observations are sorted into tertile portfolios. Portfolio 1 that comprises overpriced options generates a statistically significant average monthly return of -7.18%. Consequently, when taking a short position on Portfolio 1, the sign turns into positive. The result is in line with the hypothesis, and remarkably similar to that of Do et al. (2016) who report an average monthly return of -6.19% for Portfolio 1 of tertile portfolios. However, Portfolio 2, whose average spread is only 0.51%, generates even more negative return. The result is statistically significant and quite not what expected. Portfolio 3 that comprises underpriced options generates also negative return although according to the hypothesis it should generate positive return. However, the result is not statistically significant as neither is the result of the long-short portfolio.

Table 7. Tertile straddle portfolios.

Portfolio	1	2	3	3-1
Panel A: Portfolio returns				
Mean	-0.0718	-0.0803	-0.0368	0.0350
	(-2.44**)	(-2.69***)	(-1.16)	(0.8585)
StDev	0.7194	0.7290	0.8056	0.9982
Median	-0.2062	-0.2107	-0.2303	0.0289
Min	-1.0000	-1.0000	-1.0000	-3.6937
Max	2.9837	2.4815	4.7414	4.4938
Panel B: Stock characteristics				
Past 1-mth return	-0.0006	0.0089	0.0139	
Past 12-mth return	0.0078	0.0075	0.0074	
Market cap (€m)	53,109	59,101	56,112	
BTM	0.5774	0.5835	0.6565	
Panel C: Volatility characteristics				
HV-IV	-0.0331	0.0051	0.0411	
IV	0.2575	0.2279	0.2165	
HV (past 12-mth)	0.2244	0.2330	0.2577	
HV (past 1-mth)	0.2472	0.2324	0.2396	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

Table 8 presents the average straddle returns when the observations are placed in quintile portfolios. Portfolio 1 that comprises the most overpriced options generates a statistically significant average monthly return of -9.26%. The result is expected as the quintile portfolios comprise more extreme levels of spreads. However, similarly to the pattern displayed in Table 7, Portfolio 3 generates statistically significant average return that is even more negative. The average spread for the options in Portfolio 3 is 0.52%: thus, if the hypothesis was true, the average return generated by Portfolio 3 should be slightly positive. The average spread for Portfolio 5, that comprises underpriced options, is 5.14%. Thus, the average return generated by Portfolio 5 should be positive. As shown in Table 8, the average return nonetheless is negative. However, the result is not statistically significant as neither is the result of the hedge portfolio.

Table 8. Quintile straddle portfolios.

Portfolio	1	2	3	4	5	5-1
Panel A: Straddle returns						
Mean	-0.0926	-0.0424	-0.0949	-0.0419	-0.0469	-0.0045
	(-2.45**)	(-1.09)	(-2.36**)	(-0.99)	(-1.20)	(-0.09)
StDev	0.7243	0.7447	0.7216	0.8127	0.7523	0.9331
Median	-0.2278	-0.1641	-0.2768	-0.2005	-0.2148	0.0300
Min	-0.9936	-1.0000	-0.9922	-1.0000	-1.0000	-2.5894
Max	2.9837	2.7179	2.4815	4.7414	3.2988	3.0817
Panel B: Stock characteristics						
Past 1-mth return	-0.0018	0.0030	0.0101	0.0094	0.0167	
Past 12-mth return	0.0081	0.0081	0.0065	0.0070	0.0080	
Market cap (€m)	51,294	56,188	60,063	57,913	55,571	
BTM	0.5930	0.5424	0.5924	0.6201	0.6795	
Panel C: Volatility characteristics						
HV-IV	-0.0440	-0.0118	0.0052	0.0213	0.0514	
IV	0.2694	0.2368	0.2258	0.2217	0.2151	
HV (past 12-mth)	0.2254	0.2250	0.2310	0.2430	0.2665	
HV (past 1-mth)	0.2512	0.2383	0.2306	0.2420	0.2354	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

Table 9 presents the average straddle returns when the observations are placed in two portfolios depending on the sign of the spread. Portfolio N that comprises straddles on options with negative spreads generates statistically significant average monthly return of -4.96%. This is again in line with the hypothesis: by shorting the overpriced options the attainable average monthly returns are 4.96%. Surprisingly, Portfolio P generates even more negative average return (-7.29%) that is also statistically significant. That is completely against the hypothesis. As a conclusion, the strategy seems to work when it comes to options with negative volatility spreads. By shorting straddles of overpriced options remarkably high average monthly returns are attainable. However, a positive spread does not seem to signal underpricing.

Table 9. Sign difference portfolios.

Portfolio	N	P	P-N
Panel A: Straddle returns			
Mean	-0.0496	-0.0729	-0.0580
	(-1.86*)	(-3.06***)	(-1.50)
StDev	0.7352	0.7646	1.0713
Median	-0.1896	-0.2459	-0.0276
Min	-1.0000	-1.0000	-3.8437
Max	2.9837	4.7414	5.1260
Panel B: Stock characteristics			
Past 1-mth return	-0.0083	0.0191	
Past 12-mth return	0.0086	0.0068	
Market cap (€m)	55,068	56,876	
BTM	0.5846	0.6215	
Panel C: Volatility characteristics			
HV-IV	-0.0433	0.0397	
IV	0.2644	0.2114	
HV (past 12-mth)	0.2211	0.2512	
HV (past 1-mth)	0.2545	0.2288	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

A closer scrutiny of the volatility spread distribution among months is carried out to investigate the reasons for the unexpected results for the portfolios of positive spread. As shown in Figure 9, the volatility spreads do not distribute evenly among months. From December 2014 to June 2016, and from July 2017 to December 2018 the distribution is rather even. However, from July 2016 to June 2017 the volatility spread distribution is strongly clustered on the positive side. In September 2016, for example, none of the observations were negative. The non-even distribution of the spreads inevitably affects the returns generated by the straddle portfolios sorted on the spread. Simply put, sorting the options in each month based on the spread gives biased results if in some months there are nothing but spreads of the other sign.

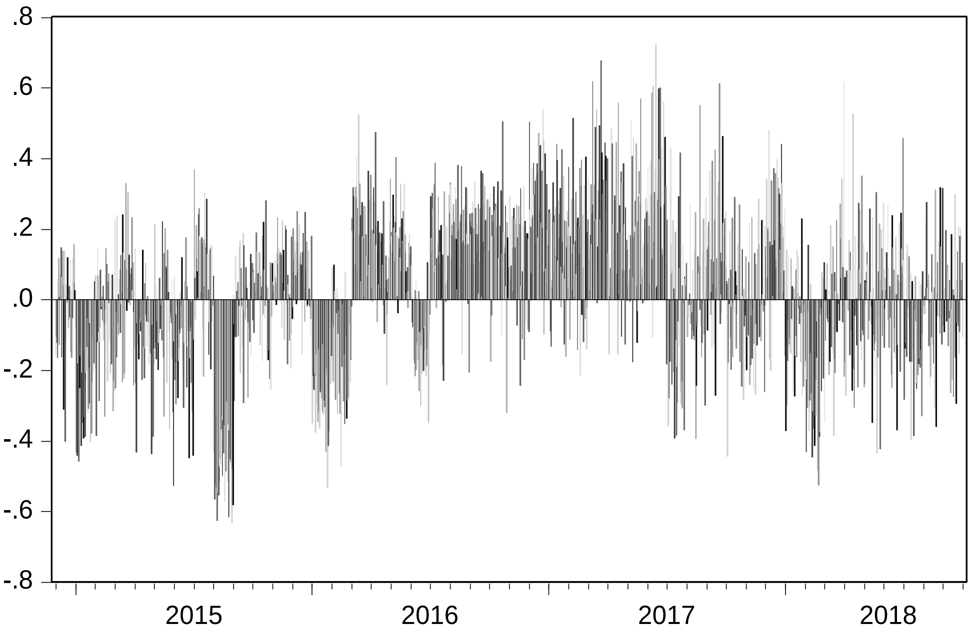

Figure 9. Volatility spread distribution among months.

To confirm the assumption that the volatility spread distribution affects the straddle portfolio returns, the tertile, quintile and sign difference portfolios are formed again so that the period from July 2016 to June 2017 is excluded from the sample. Although the number of observations drops when the sample period is shorter, the results may be more reliable when the volatility spread distribution among months is somewhat even. The tertile straddle portfolio returns are reported in Table 10. The assumedly overpriced options in Portfolio 1 again generate statistically significant negative average return. By taking a short position on the overpriced straddles, a positive average monthly return of 7.08% is attainable. Other straddle portfolios generate returns that are not statistically significant. Overall, the results are now better in line with the hypothesis.

Table 10. Tertile straddle portfolios when the time period of unevenly distributed volatility spreads is excluded from the sample.

Portfolio	1	2	3	3-1
		Panel A: Portfolio returns		
Mean	-0.0708	-0.0385	-0.0097	0.0611
	(-2.11**)	(-1.08)	(-0.25)	(1.29)
StDev	0.7046	0.7474	0.8193	0.9988
Median	-0.2021	-0.1707	-0.2140	0.0463
Min	-1.0000	-1.0000	-1.0000	-3.0070
Max	2.9837	2.4815	3.6842	3.9469
		Panel B: Stock characteristics		
Past 1-mth return	-0.0039	0.0038	0.0067	
Past 12-mth return	0.0084	0.0075	0.0082	
Market cap (€m)	53,434	59,382	55,711	
BTM	0.5975	0.5772	0.6192	
		Panel C: Volatility characteristics		
HV-IV	-0.0460	-0.0087	0.0250	
IV	0.2646	0.2343	0.2188	
HV (past 12-mth)	0.2186	0.2256	0.2438	
HV (past 1-mth)	0.2531	0.2393	0.2486	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

Table 11 shows the quintile straddle portfolio returns when the period from July 2016 to June 2017 is excluded from the sample. Portfolio 1 generates statistically significant negative average return. By taking a short position on the overpriced straddles, a positive average monthly return of 10.34% is attainable. The other portfolios do not generate statistically significant average returns. However, the direction is right and more in line with the hypothesis: except for portfolio 2, when moving from portfolio 1 to portfolio 5, the returns grow from strongly negative to almost zero. The results are better in line with the hypothesis when the period of unevenly distributed spreads is excluded from the sample, even though still no positive returns are generated by the portfolios of options with positive spreads.

Table 11. Quintile straddle portfolios when the time period of unevenly distributed volatility spreads is excluded from the sample.

Portfolio	1	2	3	4	5	5-1
			Panel A: Straddle returns			
Mean	-0.1034	-0.0059	-0.0511	-0.0379	-0.0015	0.1019
	(-2.42**)	(-0.13)	(-1.07)	(-0.78)	(-0.03)	(1.79*)
StDev	0.7042	0.7522	0.7392	0.8049	0.7862	0.9379
Median	-0.2278	-0.1262	-0.2151	-0.2074	-0.2077	0.0913
Min	-0.9936	-1.0000	-0.9878	-1.0000	-1.0000	-3.3045
Max	2.9837	2.4345	2.4815	3.6842	3.2988	4.1864
			Panel B: Stock characteristics			
Past 1-mth return	-0.0061	0.0004	0.0047	0.0036	0.008663	
Past 12-mth return	0.0089	0.0082	0.0067	0.0074	0.008766	
Market cap (€m)	51,907	57,274	57,372	59,381	55093.63	
BTM	0.6059	0.5592	0.6043	0.5783	0.642943	
			Panel C: Volatility characteristics			
HV-IV	-0.0567	-0.0253	-0.0084	0.0064	0.0347	
IV	0.2751	0.2457	0.2322	0.2250	0.2174	
HV (past 12-mth)	0.2184	0.2203	0.2238	0.2314	0.2521	
HV (past 1-mth)	0.2567	0.2430	0.2383	0.2514	0.2445	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

Table 12 shows the straddle portfolio returns when the options are sorted based on the sign of the spread and the period from July 2016 to June 2017 is excluded from the sample. As in tertile and quintile portfolios, when the period of positively clustered spreads is excluded, the average returns generated by the sign difference portfolios are more in line with the hypothesis. Again, Portfolio N generates average monthly return of -6.10% while Portfolio P does not generate statistically significant return.

Table 12. Sign difference straddle portfolios when the time period of unevenly distributed volatility spreads is excluded from the sample.

Portfolio	N	P	P-N
Panel A: Straddle returns			
Mean	-0.0610	-0.0149	0.0615
	(-2.26**)	(-0.46)	(1.40)
StDev	0.7223	0.7984	1.0843
Median	-0.1935	-0.2095	0.0235
Min	-1.0000	-1.0000	-3.4607
Max	2.9837	3.6842	3.7554
Panel B: Stock characteristics			
Past 1-mth return	-0.0089	0.0151	
Past 12-mth return	0.0088	0.0072	
Market cap (€m)	55,548	56,907	
BTM	0.5854	0.6127	
Panel C: Volatility characteristics			
HV-IV	-0.0443	0.0302	
IV	0.2637	0.2108	
HV (past 12-mth)	0.2193	0.2410	
HV (past 1-mth)	0.2558	0.2367	

T-statistics are shown in brackets. Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

As a conclusion, the negative volatility spread seems to signal overpricing of options that is subsequently corrected. By shorting straddles on overpriced options, both statistically and economically significant average monthly returns are attainable. Depending on the way the options are sorted, the average monthly returns vary from 4.96% to 9.26%. However, the positive volatility spread does not seem to signal underpricing. The returns the top portfolios generate are not statistically significant.

It is important to notice that the strategy may give biased results if a time period where the volatility spreads are unevenly distributed among months is included in the sample. Due to the rather short sample period in this study, the impact of unevenly distributed spreads is more pronounced. If the overall sample period was longer covering several years or even a decade along with a wider range of companies, the problem would most likely be mitigated. When the period of unevenly distributed spreads is excluded from the sample, the results are more in line with the hypothesis.

The question why the negative volatility spread seems to signal overpricing, but not the other way around, arises. Intuitively, well-established quality stocks are rarely underpriced. Expensive, even overpriced, quality stocks seem like a more familiar concept. The same logic may apply when it comes to options on well-established quality stocks. Although it conflicts with the original hypothesis that IV's divergence from HV indicates mispricing in both directions, it could be the case that there are no underpriced options on blue-chip stocks, but overpriced options on them do exist.

5.3. The Sharpe ratio

Many formulas have been developed to measure portfolio performance. One of the most commonly used formulas for measuring risk-adjusted performance is developed by William F. Sharpe (1966). The Sharpe ratio is a risk-adjusted performance measure that compares the portfolio excess return to the standard deviation of portfolio returns as follows:

(28) $SR_p = \frac{R_p - R_f}{\sigma_p}$.

In the equation,

R_p= portfolio return

R_f= risk-free return

σ_p= standard deviation of the portfolio return.

Although the returns from shorting overpriced straddles are high, Tables 7–12 show that the standard deviation of the straddle returns is also high, ranging from 0.70 to 1.08. It is important to scale the returns by the risk to examine whether the high returns are driven merely by high risks. The Sharpe ratios of the straddle portfolios are calculated in Table 13. Before discussing the results, a few remarks are made below.

The risk premium rises in direct proportion to time while the standard deviation rises in direct proportion to square root of unit of time. Thus, the Sharpe ratio will be higher when annualized from higher frequency returns. When annualizing the Sharpe ratio from monthly rates, the numerator is multiplied by 12 and the denominator by $\sqrt{12}$. (Bodie et al. 2014: 134.) The Sharpe ratios displayed in Table 13 are annualized to improve comparability.

The risk-free rate used in equation 28 is the one-month Euribor rate. The average rate is negative during the sample period. The risk-free rate is deducted from the portfolio return to obtain the excess return; in case the rate is negative, it is added to the portfolio return.

As concluded earlier, shorting overpriced straddle portfolios is the only way to exploit the option mispricing signaled by the volatility spread in this study. Hence the Sharpe ratios are calculated only for negative sign portfolios and portfolio 1s from Tables 7–12. In Table 13, the asterisks following three portfolios denote the portfolios from Tables 10–12 in which a time period of unevenly distributed volatility spreads is excluded from the sample. The returns for the N portfolios and portfolio 1s are negative in Tables 7–12 as they are reported from the perspective of long position. However, when shorting the portfolios of negative returns, the sign of the returns turns into positive. Thus, the statistics displayed in Table 13 are presented from the perspective of short position.

Table 13. Annualized Sharpe ratios.

Portfolio	1/3	1/5	N	1/3*	1/5*	N*
Excess return	0.0746	0.0954	0.0496	0.0733	0.1059	0.0632
StDev of returns	0.7194	0.7243	0.7352	0.7046	0.7042	0.7352
Sharpe ratio$_A$	0.36	0.46	0.22	0.36	0.52	0.30

The asterisks following three portfolios denote the portfolios from Tables 10–12 when a time period of unevenly distributed volatility spreads is excluded from the sample.

Table 13 shows that the highest Sharpe ratios are for portfolio 1s of quintile portfolios. The highest ratio, 0.52, is for Portfolio 1 of quintile portfolios in which a time period of unevenly distributed volatility spreads is excluded from the sample. The lowest Sharpe ratios are for N portfolios. The high Sharpe ratios are driven by the high returns as the volatility is somewhat the same in every portfolio.

To determine whether these Sharpe ratios are good, it is sensible to compare them to those of other investment strategies. Instead of trading the options, a trader can invest directly in the EURO STOXX 50 Index fund. The annualized Sharpe ratio of the index for the period of past 5 years is 0.3 (STOXX Limited 2019). Thus, shorting Portfolio 1s of tertile and quintile portfolios generates better risk-adjusted returns than investing in the EURO STOXX 50 Index fund.

Faias and Santa-Clara (2017) propose an option portfolio optimizing strategy that delivers an annualized Sharpe ratio of 0.82. They examine a sample period from 1996 to 2003. They find that the S&P 500 total index has an annualized Sharpe ratio of 0.29 in this period. Goyal and Saretto (2009) sort options into decile portfolios during the sample period from 1996 to 2006 and find a monthly Sharpe ratio of 0.90 for the 10-1 straddle strategy. The ratios are nevertheless not fully comparable due to different sample periods.

It can be concluded that the Sharpe ratios obtained from shorting overpriced options are competitive to that obtained from investing in the market index fund. However, the Sharpe ratio may not be the best measure of risk-return trade-off in an option framework. The main problem with the Sharpe ratio is that it does not take into account all the moments of the return distribution (Goyal and Saretto 2009). Faias and Santa-Clara (2017) point out the same and refer to Bernardo and Ledoit (2000) and Ingersoll, Spiegel, Goetzmann, and Welch (2007) for problems with the Sharpe ratio. Broadie, Chernov and Johannes (2009) nevertheless show that although the Sharpe ratio is not the best measure to evaluate performance in an option framework, other alternative measures such as Leland's alpha or the manipulation-proof performance metric face the same problems. Thus, when comparing two option trading strategies, the Sharpe ratio may be a decent measure.

5.4. Explanation for the spread and the straddle returns

As discussed earlier, there are two main proposals to what might cause IV to diverge from HV. Goyal and Saretto (2009) conclude that their results are consistent with the model of Barberis and Huang (2001) according to which recent poor (strong) stock returns may lead the traders on to think the stocks are riskier (safer) than they actually are. Do et al. (2016) propose an alternative explanation drawing on the overreaction theory of Stein (1989) and Poteshman (2001). According to it, traders overemphasize the recent volatility in their volatility estimations.

As premises in investigating the reason for IV's divergence from HV, the straddle portfolios along with the stock and volatility characteristics are studied again. The results in Panel Bs in Tables 7–9 are in line with the theory of Barberis and Huang (2001). Traders may project their considerations of the stock riskiness based on the stock's recent performance to the IV, thus making it diverge from the long-run HV. Every time the average spread is negative, the past one-month average stock return is lower than the past 12-month average monthly return. Correspondingly, when the average spread is positive, the past one-month average stock return is higher than the past 12-month average monthly return. When studying Tables 10–12 where the time period of unevenly distributed spreads is excluded, the results are not as pronounced. However, the same pattern applies to the portfolios of negative spreads.

The volatility characteristics in Panel Cs in Tables 7–9 show that also the overreaction theory proposed by Stein (1989) and Poteshman (2001) may hold true. Traders may overemphasize the recent volatility level in their current volatility estimations, which causes IV to diverge from HV. Every time the average spread is negative, the past one-month average HV is higher than the past 12-month average HV. Correspondingly, when the average spread is positive, the past one-month average HV is lower than the past 12-month average HV. Again, when studying Tables 10–12 in which a time period is excluded, the pattern holds true every time only for the portfolios with negative average spreads.

To further investigate how the difference between stock returns over the past month (R1) and the past 12 months (R12), and the difference between the long-run HV (HV) and the past one-month HV (HV1) affect the volatility spread, a panel regression of the spread on explanatory variables is run. Table 14 shows that both R1-R12 and HV-HV1 are strongly and statistically significantly related to the spread. As a conclusion, traders may overemphasize both recent stock returns and recent volatility when they estimate the current volatility. Hence, H_2 is accepted.

Table 14. Variables explaining the volatility spread.

Variable	Coefficient	t-Statistic
Intercept	-0.2496	-3.95***
R1-R12	0.3879	4.64***
HV-HV1	0.3147	4.74***
ln(size)	0.0272	4.53***
ln(BTM)	0.0236	2.75***
Adjusted R^2	0.55	

Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

Following Do et al. (2016), the extent to which the potential explanatory variables explain straddle returns is examined. Table 15 reports the results of the panel regressions of straddle returns on explanatory variables using four different models. Time fixed effect is included in the model and standard errors are corrected for heteroskedasticity and cross-sectional correlation (White 1980).

In Model 1, the straddle returns are regressed on the spread and control variables: size and book-to-market ratio. The spread is not statistically significantly related to the returns. In Model 2, the straddle returns are regressed on the difference between the stock returns over the recent month and the past 12 months along with the control variables. No statistically significant relationship is found. In Model 3, the straddle returns are regressed on the difference between long-run historical volatility and prior one-month volatility along with the control variables. Again, no statistically significant relationship is found. Finally, in Model 4, all the potential explanatory variables are included in the same equation. However, none of the variables of interest are significantly related to the straddle returns. The control variable size, as measured by the log of market capitalization, is the only variable that is weakly related to the straddle returns.

Table 15. Variables explaining the straddle returns.

Variable	1	2	3	4
Intercept	-0.8021	-0.7763	-0.7991	-0.7629
	(-1.93*)	(-1.84*)	(-1.92*)	(-1.83*)
HV-IV	-0.0085			0.0554
	(-0.08)			(0.46)
R1-R12		-0.5761		-0.5657
		(-1.38)		(0.18)
HV-HV1			-0.2838	-0.2835
			(-1.50)	(-1.42)
ln(size)	0.0682	0.0660	0.0683	0.0649
	(1.76*)	(1.68*)	(1.76*)	(1.66*)
ln(BTM)	-0.0062	-0.0028	0.0002	0.0020
	(-0.21)	(-0.10)	(0.01)	(0.07)
Adj R^2	0.16	0.16	0.16	0.16

Statistical significance is indicated with asterisks: *10%, **5% and ***1% level of confidence.

As a conclusion, it is unclear whether the straddle returns are attributed to trading the volatility spread. According to Table 15, the spread is not related to the straddle returns even if other variables are controlled for. However, as shown in Figure 9, the volatility spread is not evenly distributed among months. In some months, there are no spreads of the other sign observed at all. The consequence is that the strategy cannot be consistently executed since the sorting of the options cannot be done appropriately. When the problematic months are excluded from the data, the results are more in line with the hypothesis. The data that is used for regressing the straddle returns on the explanatory variables in Table 15 comprises the data for the whole sample period, including the months in which the volatility spreads are distributed unevenly among months. Thus, the results may be different if only the periods with evenly distributed volatility spreads are examined.

5.5. The authenticity of the returns

The straddle portfolio returns presented earlier do not take transaction costs into account. Transaction costs in option trading are in the form of bid-ask spreads. Due to lack of data, the straddles in this study are entered at the settlement quotes of each portfolio formation date. The results might be different if the long straddles were entered at the prevailing ask quotes while the short straddles were entered at the prevailing bid quotes. As discussed earlier, wide bid-ask spreads are non-trivial in option trading. If a trader does not manage to achieve effective spreads that are narrower than the quoted spreads, much of the profits may be eroded.

In this study, only shorting straddle portfolios is found profitable. The results are calculated using the settlement quotes of the options. A trader may nevertheless wish to execute the trade anytime during the trading day: in that case, the settlement quote of the trading day as the option price does not necessarily apply. The quotes may vary throughout the day. The findings of De Fontnouvelle et al. (2003) and Mayhew (2002) show that typically the ratio of effective to quoted spread is less than 0.5. The results of Battalio et al. (2004) nevertheless show that for a small sample of large stocks the ratio of effective spread to quoted spread fluctuates between 0.8 and 1. Thus, in the worst case, the trader must enter the straddle at the quoted bid and accept decreased profits. On the other hand, as transaction costs are lower for more liquid options, and the ratio of effective spread to quoted spread is only rarely 1, the implication is that volatility spread trading profits may be eligible for the sample of liquid options on the largest blue-chip stocks in Europe.

The implied volatilities in this study are estimated from the settlement prices of the options. The baseline analysis draws the mispricing signal from the volatility spread estimated on the portfolio-formation date. The portfolio-formation date is the first trading day immediately following the expiration Friday of the month. The straddles are initiated on the second trading day. Even if the volatility spread signals mispricing on portfolio formation date, it may be eliminated by the time the straddles are entered. However, the trader can delay the trade until the quote is sufficiently close to the price used to estimate the IV. Do et al. (2016) examine the strategy and find that the approach highly profitable.

The possible loss on short option positions is unlimited, therefore investors are required to deposit funds or securities as collateral for covering the possible losses. The impact of these initial margins on profits cannot be ignored especially now that in this study trading volatility spread is found profitable only for straddle portfolios with overpriced options. Murray (2013) suggests scaling the returns to short option positions by the initial margins. If initial margins are ignored, the returns to short option positions are exaggerated.

The transaction costs of trading the underlying asset must be considered as well when calculating the profits on volatility spread trading strategy. Regarding the settlement, the option contract specifications at Eurex require physical delivery of underlying stocks two exchange days after exercise. The cost is incurred at expiration of the option.

All the above-mentioned aspects must be considered when assessing the profitability of the volatility spread trading strategy. The seemingly high profits may be diminished when the returns are scaled by the initial margin and the transaction costs incurred from the settlement of the underlying asset are considered and moreover if the trader does not achieve effective spreads that are narrower than the quoted spreads. The extent to which these affect the profits of the shorted straddles are left for future research.

6. CONCLUSIONS

As volatility in the option pricing equation is the only variable that cannot be directly observed, it is potentially the source of option mispricing. Goyal and Saretto (2009) find that when the implied volatility (IV) diverges from the historical volatility (HV), the option becomes mispriced. They call the difference between HV and IV the volatility spread. When IV is low (high) compared to HV, the spread is positive (negative), and the option is underpriced (overpriced). The authors derive their logic from the mean-reverting nature of volatility. Goyal and Saretto (2009) test their hypothesis of mispricing in the U.S. equity option markets during 1996–2006. The authors find that when taking a long position on straddle portfolios of underpriced options and simultaneously shorting the straddle portfolios with overpriced options, the returns are both economically and statistically significant: 22.7% per month at the highest. The reasons for the mispricing may be that traders overweight the recent extreme behavior of the underlying asset, and underestimate the mean reversion of volatility.

Do et al. (2016) question the authenticity of the returns found by Goyal and Saretto (2009). They examine the Australian option market during 2000–2012 using tick data. Tick data provides more accurate information on the bid-ask spreads that impact the profitability of the volatility spread trading strategies. Do et al. find that the returns are largely reduced when transaction costs are taken into account. They also state that returns to short option positions should be scaled by the initial margin to provide a more realistic view on the profits. However, reasonable monthly returns are still attainable if a trader times the trades wisely.

This thesis closely follows the methods of Goyal and Saretto (2009) and Do et al. (2016) using European option data from December 2014 to October 2018. It is found that the transaction costs are lower for liquid options, thus the strategy is more profitable when trading liquid options. The underlying stocks in this study are required to be a member of the EURO STOXX 50 Index to ensure liquidity. The data comprises altogether 46 months and 39 unique companies, making the final sample consist of 1 794 matched pairs of call and put options.

Each month the options are sorted into tertile, quintile and sign difference portfolios based on the spread. The lowest one-third (one-fifth) of observations is placed in Portfolio 1, whereas the highest one-third (one-fifth) is placed in Portfolio 3 (5). In sign difference portfolios the options with negative (positive) volatility spread are placed in Portfolio N (P). Within each portfolio, option straddles of the call-put pairs are established. Straddles are used because the interest is in option returns based on the volatility characteristics only. According to the hypotheses, the portfolios of lowest (highest) spread observations generate negative (positive) returns.

The results of this study show that the negative volatility spread signals overpricing of the option. By shorting straddles on overpriced options, both statistically and economically significant average monthly returns are attainable. Depending on the way the options are sorted, the average monthly returns vary from 4.96% to 9.26%. The annualized Sharpe ratios for the returns vary from 0.22 to 0.52. The returns – and the Sharpe ratios – are higher for Portfolio 1s of tertile and quintile portfolios than for Portfolio N. This is expected as they comprise of options with more extreme levels of spreads. The Sharpe ratio for the EURO STOXX 50 Index for the period of past 5 years is 0.3. The results show that shorting Portfolio 1s of tertile and quintile portfolios generates better risk-adjusted returns than investing in the EURO STOXX 50 Index fund.

The strategy works better when those months are included in the sample in which the spreads are distributed evenly among the months; the strategy gives biased results if in some months there are only either negative or positive spreads. However, the positive volatility spread does not seem to signal underpricing even if the period of unevenly distributed spreads is excluded. The returns generated by the portfolios of positive spreads are statistically not significant.

The question why the negative volatility spread seems to signal overpricing, but not the other way around, arises. Intuitively, well-established quality stocks are rarely underpriced. Expensive, even overpriced, quality stocks seem like a more familiar concept. The same logic may apply when it comes to options on well-established quality stocks. Although it conflicts with the original hypothesis that IV's divergence from HV indicates mispricing in both directions, it could be the case that there are no underpriced options on blue-chip stocks, but overpriced options on them do exist. However, closer examinations to find the answer to this question are left for future research.

To investigate the reason for IV's divergence from HV, the straddle portfolios along with the stock and volatility characteristics are studied. As premises in the investigations, the recent and the long-run stock returns are compared as well as the recent and the long-run levels of volatility. To advance the investigations, a panel regression of the spread on the difference between the stock returns over the past month (R1) and the past 12 months (R12) and the difference between the long-run HV and the past one-month HV (HV1) along with control variables is run. The results show that both R1-R12 and HV-HV1 are strongly and statistically significantly related to the spread. As a conclusion, traders may overemphasize both recent stock returns and recent volatility when they estimate the current volatility, making it diverge from its historical levels.

The extent to which the potential explanatory variables HV-IV, R1-R12 and HV-HV1 explain the straddle returns is examined. Panel regressions using four different models are run. The results show that none of the explanatory variables are statistically significantly related to the spread. Thus, it is unclear whether the straddle returns are attributed to trading the volatility spread. However, the volatility spreads are not evenly distributed among months. The consequence is that the strategy cannot be consistently executed since the sorting of the options cannot be done appropriately. When the problematic months are excluded from the data, the results are more in line with the hypothesis. The data that is used for regressing the straddle returns on the explanatory variables comprises the data for the whole sample period, including the months in which the volatility spreads are distributed unevenly. Thus, the results may be different if only the periods with evenly distributed volatility spreads are examined.

The transaction costs on profits are discussed. The seemingly high profits may be diminished when the returns are scaled by the initial margin and the transaction costs incurred from the settlement of the underlying asset are considered. The assumption is that the trader achieves effective spreads that are narrower than the quoted spreads. If not managed to do accordingly, the transaction costs arising from the bid-ask spreads may erode the profits. The exact extent to which these affect the profits of trading liquid options are left for future research.

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