Trading on deviations from put-call parity and mean-reversion

Evidence based on the American market

Copenhagen Business School

Master Thesis

Jesper Kjær Bahlke
MSc. Finance and Accounting

Natalia Kornela Setlak
MSc. Applied Economics and Finance

Supervisor: Professor Christian Wagner

Hand-in date: 15.05.2017
Number of characters: 219,074
Number of normal pages: 96,3
Total number of pages: 82

Acknowledgements

We would like to acknowledge the efforts and contribution of others, without whom completion of this thesis would not have been possible. First of all, we would like to thank our supervisor, Professor Christian Wagner, for priceless advice and patient guidance throughout the writing process. Additionally, we would like to express our gratitude to all the teaching staff at Copenhagen Business School we were lucky to meet along our studies, for sharing their knowledge, improving our skills and preparing us for our future careers.

Computation for the work described in this master thesis was supported as a DeIC pilot project with some of the computations done on the Abacus 2.0 supercomputer at the DeIC National HPC Centre, SDU. Specifically, we would also like to thank PhD Jens Svalgaard Kohrt for his assistance and guidance regarding technical aspects of using Abacus 2.0.

Finally, we are happy to have caring friends and family, whose encouragement and support have increased our motivation further throughout the process.

Abstract

This thesis builds on information regarding utilizing predictive signals embedded in put-call parity deviations and past stock price paths. Using daily option and stock price data from January 2011 until December 2015 and following Cremers & Weinbaum (2010) and Hong (2013), we set up trading strategies based on the open interest-weighted option-implied volatility spread and price to moving average ratio and subsequently measure portfolio performance using the 3-fama French (1993) factors and the Carhart (1997) momentum factor. It is demonstrated that stocks with relatively expensive calls relative to puts outperform equities characterized by relatively expensive puts relative to calls. A portfolio longing high volatility spread stocks and shorting low volatility spread stocks yielded on average an 4-factor abnormal risk adjusted return of 19 bps (t-stat 2.45) and 73 bps (t-stat 2.79) one and four weeks after the investment. Further, evidence indicates that recent loser stocks outperform recent winner stocks confirming the return reversal phenomenon. A portfolio longing past losers and shorting past winners yields on average an 4-factor abnormal risk adjusted return of 17 bps (t-stat 1.46) and 46 bps (t-stat 1.05) one and four weeks after the investment. A strategy utilizing both predictive measures in conjunction successfully yielded on average an 4-factor abnormal risk adjusted return of 64 bps (t-stat 2.47) and 151 bps (t-stat 2.83) one and four weeks after the investment. Moreover, as the long arm of the hedge portfolio was largely responsible for the alpha returns, doubts that short-sale restrictions are driving profits are evaporated.

Fama-Macbeth two-step regression procedure fails to reconfirm the economic utility, which the initial analysis suggested, as none of the factor risk premiums were statistically significant. Adjusting for non-synchronicity bias between option and stock markets significantly distorts the strategies profitability. Single sorted hedge portfolios experienced an overall loss of statistical significance as well as reduced profitability, while the double-sorted hedge portfolio only experienced reduced profitability, but still enjoys 5% significance. Overnight returns from Friday to Monday were thus found to be positive, contrary to findings presented by Harris (1986). Finally, results indicate that predictability is improved at times when option liquidity is high, but provided mixed conclusions for stock liquidity level, hence only partially supporting the model presented by Easley, O'Hara, & Srinivas (1998).

Our main contribution to the literature lies in improving the theoretical understanding of asset pricing and examining practical applications of it in the given investment strategies. Results can be generalized to the US equity market, but not necessarily other developed and emerging markets, as the US market is characterized by high liquidity and market capitalization of companies.

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I. Introduction

Efforts to predict stock returns have a long-standing tradition within finance, especially on the American market, yet there is still no clear consensus to what extent returns are predictable. The idea of fully efficient financial markets have for long been the cornerstone of modern finance. Upon introduction of the Capital Asset Pricing Model, brought in the early 1960s by Lintner (1965)a, (1965)b, Mossin (1966), Sharpe (1964) and Treynor (1962), the idea that investors only should be compensated by the undertaken systematic risk was presented. Systematic risk drives stock returns, which follow a random walk, implying a fixed relationship between risk and return as well as the inability to generate statistically significant abnormal returns ("alpha").

Due to a number of market imperfections and behavioural factors, asset mispricing in financial markets frequently occur, facilitating the possibility for investors to use temporary price deviations for generating abnormal returns. The put-call parity, introduced by Hans Stoll (1969), is one of the simplest no-arbitrage relations. It does not require assumptions regarding return probability distribution of the underlying asset or continuous trading. However, it is well known, and observed in the data, that the parity is often violated on several accounts. Examination of these put-call parity violations often concludes that practical circumstances hinder tradable arbitrage profits, this is mostly due to e.g. occurring dividend payments, early exercise possibility of American options, restrictions or ban on short-selling, different levels of lending and borrowing rates and transaction costs as pointed out by Brenner & Galai (1986) Kamara & Miller (1995) Klemkosky & Resnick (1979), (1980) and Nisbet (1992).

The purpose of this thesis is to examine the informational content embedded in option prices and to explain and assess three investment strategies, their economic motivations and their historical ability to generate abnormal returns as well as discuss the robustness of the profitability across different settings. We aim to improve the understanding of why and in which situations option prices contain information about future equity prices together with why and when equity prices, trending in channels, reverse temporarily to their means i.e. "mean revert". This will hopefully facilitate a deeper understanding of equity and option pricing, as well as make pricing predictability more robust. This paper will focus on three basic investment strategies – the first strategy is to trade on deviations from the put-call parity, the second strategy trades on very short-term mean reversals, finally, the two strategies will be used in conjunction to explore if predictive signals embedded in both measures complement each other in stock selection.

1.1 Problem Statement

Given the interest in predictability, this thesis aims to find empirical evidence into the predictability on the American stock market from 2011 up until and including 2015 by using motivated theoretical relations between the pricing of options and change in short-term price trends. Concretely, it seeks to answer the question:

Is it possible to persistently earn abnormal return by trading on the underlying stocks based on deviations from put-call parity and short-term price reversals?

To facilitate this discussion and to provide a wider perspective to elucidate the topic, the paper introduces following sub-questions:

- *What does the option-implied volatility spread imply? What can be the underlying motivation of such finding in the data?*
- *What drives price trends and why do they reverse?*
- *Which of the three underlying sorting methods and which of the strategies have proven best? What can explain that outperformance?*
- *What additional factors can explain the anomaly and why?*

By providing an in-depth and comprehensive analysis we hope to succeed in our endeavour of answering these questions in a profound, compelling and reflective manner, ultimately improving on the understanding of this research area.

1.2. Academic relevance of the topic and motivation for choosing it

The topic of this thesis can be considered relevant in multiple ways. In academia, the findings of this paper can serve as an inspiration for further research to adjust the financial models to incorporate key findings from this thesis. An example could be to include option implied volatility spreads in asset pricing models in order to motivate pricing conclusions based on this factor as it has been proven to be a significant predictor of future stock price movements.

From a practical perspective, conclusions presented in the thesis can be used for active investing in financial markets, which should yield abnormal return after controlling for the 3-factor Fama French model (1993) and Carhart momentum factor (1997). Main inspiration for the empirical part of the thesis comes from findings presented by Cremers & Weinbaum (2010) and L. J. Hong (2013). However, as both authors include sample periods encompassing full business cycles, our findings largely improve the understanding of asset pricing in the sole period of expansion post the financial crisis.

1.3. Delimitation

As mentioned, the thesis will be limited to only evaluate predictability using the proposed measures on the American stock market, which in this context comprises 1466 companies whom are all constituents of either the Standards & Poor's large, middle or small cap indices. The choice of market is motivated by a desire to continuously compare our results to the literature, which is predominantly built upon the American market. We do not see direct transferability of the analysis to the global market, due to different characteristics of national financial markets, especially emerging economies. Predictability will only be evaluated on a 1 and 4-week horizon. Only American options are considered when calculating the volatility spreads. Furthermore, although the thesis seeks to answer to what extent abnormal profits could have been made in the sample data, it is not within the scope of this thesis to formally test the efficient market hypothesis. Likewise, transaction costs are ignored and returns are all considered to be pre-tax returns. Extensive econometric tests to validate assumptions and results have been excluded. Due to natural time constraints in producing this thesis, the asset-pricing model utilized features the 3-factor Fama French model (1993) and the Carhart (1997) momentum factor, however, the literature often also considers a stock systematic co-skewness factor. The study looks into two single-sorting parameters, (1) is the open interest-weighted option-implied volatility spread and (2) is the price to moving average ratio and as well as a double sorting based on both parameters. We do not examine various measures of volatility and price trend or the changes in levels of different sorting measures, which can be pursued further in future research to find the best predictor out of a range of parameters.

1.4. Main conclusions and findings

A number of reasons have been put forward as explanations to the existence of put-call parity deviations. Reasons include non-synchronicity bias (Manaster & Rendleman, 1982), hedging activities ongoing in option markets (Anthony, 1988), infrequent trading of options (Chan, Chung, & Johnson, 1993), pointing mostly to market inefficiencies being the underlying issue. Most recent research has, however, shown that option prices contain information about future stock price movements, as informed traders will try to benefit from the embedded leverage and lower regulation provided by trading in the option markets. Due to informed trading first occurring on the option market, option prices can be pressured by the market supply and demand, leading to deviations from the well-known put-call parity relation. Even though the presence of transaction costs might not allow trading directly on the mispricing within the option markets, initial price pressures transfer from the option markets to equity markets within days, eliminating the initial mispricing by adjustments in equity prices.

Following Cremers & Weinbaum (2010), we use the open interest-weighted option-implied volatility spread on American style options to measure price pressures and observe signals of future stock price movements. The strategy implies longing a portfolio with high option volatility spread stocks and shorting a portfolio with low option volatility spread stocks, which is an effective bet on market normalization. By utilizing the strategy, we were able to confirm previous results presented in the literature, observing an average Carhart (1997) 4-factor risk adjusted alpha return of 19 bps (t-stat of 2.45) and 73 bps (t-stat of 2.79) within a 1 and 4-weeks holding period respectively.

The second strategy is based on temporary mean reversals, where a short-term insufficient level of liquidity in the market, initial overreaction to news or the negative serial first autocorrelation of asset prices have been named as the underlying causes for the phenomenon. Following this argument and L. J. Hong (2013), we utilize a contrarian investment strategy i.e. longing a portfolio of last week's most underperforming stocks and shorting a portfolio of last week's most outperforming stocks, thus being an effective bet on a temporary price trend reversal. The analysis did not yield significant results as it shows that an investor can earn an average Carhart (1997) 4-factor risk adjusted alpha return of 17 bps (t-stat of 1.46) and 46 bps (t-stat of 1.05) within a 1 and 4-weeks holding period respectively.

Subsequent to the portfolios formed on the individual sorting factors, we perform a final analysis with double sorting on both factors. Our analysis shows that the double sorting significantly dominates the single sorting strategy.

A zero net investment hedge portfolio comprising a portfolio longing past week loser stocks with high implied volatility spread and a portfolio shorting past week winner stocks with low implied volatility spread generates an average Carhart (1997) 4-factor risk adjusted alpha return of 64 bps (t-stat of 2.47) and 151 bps (t-stat of 2.83) within a 1 and 4-weeks holding period respectively. The double-sorted portfolio has not only dominated the single sorting strategies, but also abnormal portfolio returns formed by Cremers and Weinbaum across the 4-week investment horizon. That might indicate that sorting based on multiple factors leads to an improvement in the investment strategies and stock selection, resulting in a higher yield.

The sample data consists of 1466 stocks from S&P 500 Large Cap, S&P Midcap 400 and S&P Small Cap 600, representing a large share of the overall stocks on the American market and a wide range of liquidity levels and industry palette. Thus, we find our sample to be sufficiently diversified for representing the whole US market. Our contribution to the literature lies in an improvement of predicting equity prices based on a number of sorting measures and due to their simplicity it enables investors to use them directly in the market. However, further research is needed to uncover whether the strategies also work in less liquid financial markets than the American one.

In order to make our analysis more comprehensive, various robustness tests have been conducted. Fama Macbeth regressions are used to analyse whether allocation strategy based on volatility spread and price to moving average ratio are actually associated with a factor premium. Although the analysis indicates positive returns in the strategy, the sorting mechanism is not found statistically significant, indicating it cannot be ruled out that the sorting entails no economic value.

To mitigate the risk that predictability originates from non-synchronicity and intraday effects, we tried executing the strategy at Monday opening prices instead of Friday closing prices. Across all time periods and types of sorting mechanism these portfolios entailed lower return than the original strategy, indicating that stocks accrue positive returns from Friday close to Monday open, contrary to findings presented by Harris (1986). Only the abnormal returns of the hedge portfolio in the double-sorted strategy retained its statistical significance, pointing to improvement in stock selection based on twofold trading signal.

To investigate how returns are associated and impacted by both option and stock liquidity we constructed option-implied volatility spreads based only on 1/3 highest option pair average bid-ask spread (indicating low liquidity) and 1/3 lowest option pair average bid-ask spread (indicating high liquidity). Performance suggested by the high liquidity portfolios entailed an average Carhart (1997) 4-factor risk adjusted alpha return of 23 bps (t-stat of 4.02) and 21 bps (t-stat of 0.94) within a 1 and 4-weeks holding period respectively. This indicates that the predictive signal derived from highly liquid options entails higher economic utility than less liquid options, in line with findings presented by Cremers & Weinbaum (2010) and Easley, O'Hara, & Srinivas (1998). We proxied stock liquidity through the Amihud (2002) illiquidity ratio and market equity capitalisation. Pooled cross sectional regressions showed that low stock liquidity did not entail better predictive power neither when using predictive signals obtained from option-implied volatility spread or price to moving average ratio, which contradicts the findings of Cremers & Weinbaum (2010). However, these results are not conclusive as the main finding of the literature is that highest predictability is found using high liquidity option on low liquidity stocks, while this analysis only concludes on the two separately.

1.5. Paper structure

The remaining part of this dissertation is decomposed into three parts: literature and theory (Chapter II & III), methodology (Chapter IV) and application (chapter V and VI).

Chapter II reviews previous research related to volatility spread and price trends.

Chapter III explores basic option theory as well as price trends.

Chapter IV presents data and methodology used in conducting the analysis. Moreover, it provides basic descriptive characteristics of the data.

Chapter V analyses the preformation portfolio characteristics as well as the post formation risk-adjusted performance of the three strategies in time lengths ranging from one to four weeks.

Chapter VI explores the robustness of the motivated conclusions with the Fama Macbeth regressions, non-synchronicity as well as intraday effect and impact of liquidity.

Chapter VII holistically concludes on the analysis and summarises the main findings as well as points to further research.

II. Literature review

2.1. Option markets as a reflection of future stock price movements

The seminal paper of Cremers and Weinbaum (2010) found that it was possible to create sustainable abnormal profits trading on the open interest-weighted option-implied volatility spread. They use both the level and the change in volatility spread as trade signals, and create a portfolio, which on average accrue 50 bps abnormal profits weekly. One explanation for why predicting stock price movements and trend persistence is possible is asymmetric information and presence of informed and non-informed investors. As put forward by Anthony (1988), trading stock options precede trading on the underlying stock by one day. This result is however challenged by Chan et al. (1993) who find the relationship to disappear once they use bid-ask prices instead of transaction prices, thereby proving there does not exist an arbitrage opportunity based on stock-option lag-lead relationship. Some researchers put in question the ability to predict stock prices through the option markets as they thought it could be connected with the non-synchronicity bias of option trades being made after the equity markets are closed, thereby reflecting new information which will soon be incorporated in the equities once the markets open up again. Manaster & Rendleman (1982) gave empirical evidence that even after accounting the non-synchronicity bias, option prices reflect the information that is not incorporated in the stock prices for a period of up to 24 hours. On the other hand, Easley et al. (1998), who find similar result as Anthony, suggested that such a finding should be considered natural as trades in stocks are partially preceded by hedge-related trading activities on the option markets. However, they revealed that option volumes lead future stock price movements and can be used to predict stock prices in cases where informed investors choose to trade on information they possess. This means that option prices deviate from equilibrium value in the direction the information they possess points to.

Therefore, option volume, just like option price, should not just be viewed as a result of trading, but also a piece of information investors can trade on, as it reflects information possessed by informed traders. Blume, Easley, & O'Hara (2014) present evidence that investors who use market statistics like this in their investment strategies indeed yield a higher return than those who do not. Holowczak, Simaan, & Wu (2006) went further to prove that option trading volume is even more important for future stock price discovery in times when option trading activity gives net buy or net sell pressure on the underlying asset. An empirical analysis of a strategy based on option trading volume made by Pan & Poteshman (2006) indicate that the demand (volume) for an option affects its price i.e. stocks with high put-call ratios will become relatively expensive to those with low put-call ratios. Therefore, shares with a low put-call ratio will on average be able to outperform those with high put-call ratios. The authors were also able to prove that their result could be associated with non-public information possessed by informed traders and not the fact that market was inefficient as this time. A put-call ratio, together with the volatility indicator (VIX) and the TRIN (stock market trading indicator based on technical analysis) have also been proved by Simon & Wiggins (2001) to hold a significant predictive power in their analysis on S&P future returns. The findings, that those three sentiment indicators, are useful for developing a contrarian strategy accommodates the fact that over long periods of time, stock values reverse to their means. This means that a poor stock market performance is followed by a change in risk sentiment and a strong stock market performance.

In their work, T. L. Johnson & So (2012) were able to prove that the O/S (the total option volume divided by the total equity market volume) is negatively associated with future stock market movements. That happens due to the fact that as a result of regulatory requirements in place, informed trading on negative information has already been ongoing in the option markets. In line with their argument, equity market predictability based on O/S measure improves when the short-selling constraints are high or the option leverage available is low.

The authors find the O/S to be a better predictor than put-call ratio, as it reflects the sign of trading on non-public information better. However, they also prove that the put-call volume ratio is a valuable predictor of the skewness of the returns in the nearest future, linking it to the momentum strategy profitability presented by Daniel & Moskowitz (2016) and Jacobs et al. (2015).

Aside the O/S ratio, the implied volatility of options, as mentioned briefly earlier, seems to be a crucial factor for the stock return predictability as explained by Cremers & Weinbaum (2010). According to their empirical analysis an investor that longs stocks with relative expensive calls and shorts stocks with relatively expensive puts, yield an abnormal profit of 50 basis points on a weekly basis. Liquidity plays an important role in predictability, where the predictability is improved at times, when option liquidity is high and stock liquidity is low, while it diminishes when the opposite is true. Robust to the size effect, the authors find that the deviations from put-call parity are more likely at times when the underlying asset faces more information risk, such as for example before the earnings announcement. Furthermore, their evidence points to the fact that the deviations stem mainly from option buyers, opening new positions and therefore there is a relationship between the option transaction volume and the stock price movements that contrarian strategies are based on.

Demand for options also affects future volatility of the underlying stocks – thereby, investors who trade on volatility also impacts option prices and can lead to increases in information asymmetry in the days of increased risk e.g. days just before a new earning announcement. Hence, option market makers change prices at such times to protect themselves when the information asymmetry is particularly high as pointed out by Ni, Pan, & Poteshman (2008). Other researchers such as Xing, Zhang, & Zhao (2010) used the volatility skew variable and found that options on corporate stocks with the steepest volatility smirks were most prone to negative earning shocks in the upcoming months, thereby these stocks will underperform stocks with options which have a less steep volatility smirk by around 10.9% on a yearly on a risk-adjusted basis. Those results confirm the view that the information is incorporated in the equity market slower than in the option market and that the informed traders trading on a negative non-public news will choose to do it in out-of-money puts, which will contribute to more steep volatility smirks.

As one of the main motivations for the informativeness of option prices is insider trading, the predictability of future stock returns should be strong at times when crucial pieces of corporate information are published, such as earning announcements. Atilgan (2014) was able to prove that stocks with relatively expensive calls outperforms these with relatively expensive puts during the 2 day time window around earnings announcement, proving the pre-announcement trade in option markets had already been ongoing. Thereby, the increased demand for puts signals negative corporate event, while the increase demand for calls indicates a positive corporate event in the nearest future. Volatility spread can, in this setting, be used to reflect the relative price pressures in the option markets, which is created by investors trading on non-public information ahead of announcement. The results are robust to 3-factor Fama-French, momentum and skewness, but predictability of stock returns is significantly improved for stocks with a high probability of trading on non-public information and low liquidity. The latter is also in line with the prediction of model proposed by Easley et al. (1998) on sequential trading. Compared to Cremers & Weinbaum (2010), whose portfolios earned 50 bps abnormal return on weekly basis based on their double-sorted strategy, Atilgan (2014) was able to form portfolios yielding 94.6 bps weekly, indicating that volatility spreads are a much more pronounced measure for forecasting future stock prices at the times of earning releases.

Digging into the statistical predictive power of implied volatilities on options, Driessen, Lin, & Lu (2012) find that implied volatility spread and skew are significantly better at predicting stock returns, when movements are related to changes of recommendations, revisions of analyst forecasts and releases of earnings. The implied volatility spread is positively associated with stock returns, while the implied volatility skew is negatively associated with the stock returns. Both relations are results of not fully liquid markets. Hence, option prices diverge from their initial values in the direction of the informed trades.

Option markets are believed to reflect information possessed by informed traders predominantly due to the benefits of lower margin requirements and trading restrictions as well as higher leverage available in option markets compared to the usual equity trading venues as indicated by Black (1975). Frazzini & Pedersen (2011) also mentions that as many investors and financial institutions are constrained by either regulations or their own wealth, the use of direct leverage is not too common. However, one can gain substantial advantage of the outright leverage by using embedded leverage instead through investing in financial instruments such as leveraged EFTs or options. Due to the advantage of increased market exposure and low loss risk provided by such instruments, investors are willing to pay a premium, equal to requiring a lower risk-adjusted rate of return. Options can give an investor a level of 300 times embedded leverage benefit, depending on the moneyness and time to maturity, with OTM options and options with short time to maturity having the highest embedded leverage. Empirical research has proven that a premium paid for embedded leverage exists and the results provided by Frazzini & Pedersen (2011) are therefore an explanation why other researchers found options to be relatively expensive relative to their fundamental values.

In line with the fact that OTM options provide the highest embedded leverage benefit, Kang, Kim, & Lee showed that a large share of OTM puts trading volume divided by total option trading volume signals a negative future movement in the price of the underlying asset, while the opposite is true when the share of OTM call options is large. Using OTM put-call ratio the authors were able to prove that investor can earn an excessive return, and that the measure they used are better at forecasting the prices of large stocks compared to small. Neither the predictability of small stock returns, nor the predictability measure of deep OTM options is significant, due to the lack of satisfying amount of liquidity in both instruments. The authors also found support for higher leverage being main driver for OTM option demand and not regulatory restrictions on short-selling. The measure of OTM put-call ratio has also been proved useful in predicting major corporate events such as earning announcements and takeovers. Surprisingly, the market is, by far, faster adjusted to the information contained in OTM puts than OTM calls.

An empirical analysis made by Chakravarty, Gulen, & Mayhew (2004) points out that option markets can on average explain around 17% of the stock price movements and that the discovery is associated with spreads, trading volume in both stock and option markets and stock volatility.

Option markets were found to convey more information at times when stock spreads are wide compared to option spreads and when stock trading volume is low compared to the option trading volume. Limited evidence also points to a better price discovery at times when the underlying stocks volatility is lower than the corresponding options. Matching Black's arguments, Pan & Poteshman (2006) presented evidence of greater stock return predictability on a condition of higher leverage available for a given option contract and with a higher share of informed investors trading on the non-public information. Their result holds for stock options but not for index option, consistent with the view that the non-public information, some traders possess, is firm-specific and not market-wide information affecting the universe of securities. Another explanation for stock options usefulness in predicting future stock movements is the positive cross-autocorrelation between securities, as uncovered by Lo & MacKinlay (1990). The authors were able to demonstrate that less than a half of contrarian profits are connected with an overreaction that makes stock prices deviate from their fundamental values. Rest of the profits can be attributed to cross-autocorrelation between securities. Lo & MacKinlay (1990) also presented a lead-lag relationship where small stock returns, in general, follow previous developments in large stock returns.

Some researchers choose to explain put-call parity deviations by option markets being less regulated than equity markets, thereby investors can use options as a substitute for a short-sale transactions in markets where such transactions in equities is not possible or too costly. Mugwagwa, Ramiah, & Moosa (2015) investigates the impact of short-sale restrictions and find that options can under certain market conditions increase the profit of a contrarian strategy. In line with previous research, the authors found that imposing short-selling restrictions has a significant negative effect on a portfolio formed based on a contrarian strategy. Moreover, they found that price reversals are indeed facilitated by hedging activities, which also cause a change in option sensitivity to the underlying security, where OTM options become more sensitive to price changes in the underlying stocks than ITM options. They also uncovered the contrarian phenomena on the Australian stock exchange, but in line with existing literature, it was driven by investing in value and small cap stocks (i.e. value and size effect). However, the authors find that the illiquid stocks do not contribute to contrarian profits, contrary to the results uncovered by Cremers & Weinbaum (2010). An analysis of the market state impact on contrarian strategy profits is inconclusive, contrary to Chopra, Lakonishok, & Ritter (1992) who found that the contrary profits are significantly higher in bearish markets.

Holistically, the implications option markets can have on financial markets is ambiguous: even though options can incorporate and convey new, sometimes non-public, information and thus improves market efficiency, it also enlarges the amount of different trading strategies investors trading on non-public information can follow. Inside traders makes it costly and ineffective to conduct regular trading activities – according to Biais & Hillion (1994), an introduction of options diminishes this issue by allowing risk sharing and thereby completing the market. The forward-looking information contained in option prices can be used for calculating option-implied betas, which Buss & Vilkov (2012) find to be more accurate than conventionally used betas hence allowing for a better portfolio construction. However, as markets become more co-integrated and advancements in technology allows for use of automated quoting algorithms for option prices, which instantly incorporate stock price movements into the option price quotes, the informativeness of option prices was found to diminish over time by (Holowczak et al., 2006). This finding also implies that arbitrage possibilities slowly disappear across time and markets in this sense are becoming more efficient as put forward by Cremers & Weinbaum (2010).

2.2. Predictability of stock returns through market trends and serial correlation

According to the efficient market hypothesis, financial markets are efficient and financial assets trade at fundamental values at all times, hence making it impossible for an investor to beat the market by using market timing or asset selection. The theory presented by E. Fama (1965) and Samuelson (1965) indicates that the only way to achieve higher returns is to invest in more risky financial assets, as prices follow a random walk. However, the weak form of the efficient market hypothesis (i.e. that historic price and volume data does not affect current prices) has been continuously rejected in empirical studies conducted by among others Dong, Bowers, & Latham (2013), Markiel (2003) and Saeedi, Miraskari, & Ara (2014). Research shows it is possible to time and select investments using historical data to make continuous abnormal profits, thereby beating the market. Using historical data usually two strategies based on price trends are utilised: contrarian or momentum strategies.

Contrarian strategy takes advantage of negative serial asset return correlation as identified by E. Fama (1965). It is based on buying stocks which demonstrated poor past performance while selling the stocks with good past performance, betting assets will experience mean reversal – a strategy put forth by Thaler & De Bondt (1987). It is mainly motivated by human bias of overreaction to the news, driving the prices away from their fundamental values. Using an investment horizon of 3 to 5 years the authors have been able to ascertain that mean reversal over the period analysed led to an excess return earned by utilizing a contrarian strategy on US stock returns.

Early research on the contrarian strategy profits has shown that excessive returns are mostly associated with presence of speculative traders. Stiglitz (1989) and Summers & Summers (1989) recommends introducing tax policies to counteract them, as they believed that a benefit of a reduction in speculative traders on the market would outweigh potential cost of lower liquidity and increased costs of capital due to the new tax. Another potential cause uncovered by Grossman & Miller (1988) and Jegadeesh N. & Titman S. (1995) was that the short-term return reversal are caused by markets inefficiency to offset short-term price swings at times when buying and selling pressure unexpectedly intensifies, due to a temporary lack of sufficient liquidity. Further literature discussed behavioural causes of the initial overreaction to news and lead-lag relationships between big and small cap stocks as possible explanations for contrarian strategy profitability. As examined by Jegadeesh & Titman (1995), the behavioural causes of contrarian strategy can be split into a delayed reaction to common market factors and an overreactions to firm-specific information. That finding, in itself, explains the lead-lag relation between big and small cap stocks. The authors were also able to evidence that it is by large the overreaction to firm-specific information that drives short-term contrarian profits, while only a small part of the excess returns of the strategy can be attributed to a delayed reaction to common factors and the lead-lag relation.

Contrarian strategies profitability is also thought to be market state dependent i.e. investors are able to earn higher excess returns in bearish markets than in bullish markets. This effect, as explained by Chopra et al. (1992), is due to the fact that "winner" portfolios have strong positive relationship with bullish markets relative to bearish markets, compared to the strength of the negative relationship "loser" portfolios have with bearish markets. L. J. Hong (2013) was able to prove that earning abnormal profit on sustainable basis is possible while using price to moving average ratio as the trade indicator and betting on the effective trend reversal by purchasing stocks that underperformed the market and selling these equities that outperformed it recently.

Contrary to betting on short-term mean reversal, the idea of following a trend is called momentum investing. It is a strategy, which takes advantage of prices following the same positive or negative trend, betting the trend will persist during the investment period. Hence, an investor taking a long positions in assets with good past performance and a short position in stocks with bad past performance will be able to earn a positive abnormal return, as presented by Jegadeesh & Titman (1995). The strategy examined yields positive excess returns over an investment period of 3 to 12 months.

Both contrarian and momentum investing have been proven to work in the past simultaneously namely because each of the strategies works on varying investment horizons. It has been indicated by Chui, Titman, & Wei (2010) and Griffin, Ji, & Martin (2003) that momentum investing is more applicable in the short to medium run, while contrarian investing is more applicable in the very short run or very long run. This is confirmed by Khil & Lee (2002) who find positive serial correlation of stocks in a short investment horizons and negative serial correlation of stocks in a long investment horizon, exhibiting mean reversal phenomenon. Over the very short-run of one week, Lehmann (1988) found that the stock returns exhibit negative first-order autocorrelation, supporting a mean reversal hypothesis under a very short investment horizon. His results are robust also after including bid-ask spreads and transaction costs as control variables.

The Fama-French 3-factor model is known to account for many of the previously unexplainable financial market anomalies, including the profitability of contrarian strategies, but it still fails to explain the momentum investing as proven in E. F. Fama & French (1996). When the Fama-French 3-factor model, together with macroeconomic variables is utilized, abnormal excess returns diminishes but does still not fully rule out the momentum effect – these results are more robust during market upswings and when lagged variables are used, as indicated by Sarwar & Muradoglu (2013). Even though this thesis's focus will be on contrarian strategy, momentum strategy - being its clear contradiction - it is also found important to understand the interplay between different factors and how they impact each other.

Researchers have presented a number of explanations for why momentum investing might be a sustainably profitable strategy. An analysis of European stocks points out that momentum effect should be mostly assigned to the initial underreaction to news on company earnings, which points to the fact that it is important to assess and predict analysts' behaviour, while following the momentum investing strategy, as pointed out by Van Dijk & Huibers (2002). A study conducted by Merlo & Konarzewski (2016) suggests, in line with Van Dijk and Huibers, that irrational investor decisions have a decisive impact on the creation of momentum effect. In addition to that, Merlo and Konarzewski point to the fact that presence of active and passive investors in financial markets also contributes to the phenomenon. Active and passive investors will be evaluating new information coming to the market at a different pace and proceeding with the decision on how to act on the news differently. Chen & Zhao (2012) proved that higher probability of informed trading enhances the momentum effect, making results more robust to information uncertainty i.e. firm age, size and analyst coverage.

Furthermore, it is suggested by Leippold & Lohre (2012) that momentum profits have no association with macroeconomic risks and that the trend-based investment strategy works best when it focuses on stocks with high idiosyncratic risk or lower liquidity. This is because these two factors pose limits to exploiting arbitrage opportunities by the rational investors. Moreover, an empirical analysis by Pastor & Stambaugh (2003) suggests that the average return on stocks with high sensitivity to aggregate liquidity is higher than on stocks with opposite characteristics and the strategy based on trading on this factor yields 7.5% annual return, adjusted for value, size and momentum factors as well as the market return. The authors were also able to show the liquidity factor is able to explain around half of the momentum strategy profits in the period they analysed, as investors need to be compensated for the liquidity risk they take on. Contrary to the results already mentioned, McLean (2010) finds that momentum has no relationship with the idiosyncratic risk, but the magnitude of transaction costs deters investors from acting on the arbitrage possibility and eliminating the mispricing. Bandarchuk & Hilscher (2013) finds that the momentum profits research must take a starting point in past returns and volatility as well as the interaction between the two. They mention the result of Vayanos and Wooley, who found that investing in stocks with higher implied volatility, should bring about increased momentum profits, as well as the work of Grundy and Martin verifying that extreme past returns are associated with higher momentum profits.

Most recently, research in this field has uncovered that the momentum profits are negatively skewed, indicating that the excessive return gained while using a momentum strategy simply reflects a skewness premium, as indicated by Daniel & Moskowitz (2016). Their work on "momentum crashes" documents that momentum effects appear mostly in times subsequent to market declines or when market volatility is high. When the market rebounds after a long downturn, "losers" tend to have extreme gains, leading to a momentum crash. The worst momentum crashes that happened since 1927 took place in July-August 1932 and March-May 2009. These events are extreme outliers and thus often excluded from analysis on momentum strategies. Anchoring on these findings, Jacobs et al. (2015) proved that expected skewness is significantly connected to momentum profits i.e. the strategy is more profitable at times when winners have a weak positive skewness and losers have strong positive skewness, and vice versa. Results presented by Jacobs et al. (2015) are primarily driven by limits to short-selling and overly optimistic expectations of future firm cash flows.

A study conducted by H. Hong, Lim, & Stein (1998) suggests momentum strategy is also negatively associated with analyst coverage and size, as for smaller stocks, the news travels rather slowly and it is gradually incorporated into price across time. Momentum profits are reported to reflect strong cyclical variations i.e. winner stocks gain more than losers stocks in times of economic expansion, while winners lose less than losers in the economic downturn, thereby leading to different business cycle momentum premiums that can be explained by different growth options and leverage possibilities given the current economic conditions according to Kim, Roh, Min, & Byun (2014).

III. Theory

This chapter is split into two sections, the first section introduces principles of options and option pricing models, such as Black & Scholes methodology, which is needed to understand motivations behind trading on the option-implied volatility spread. The second section looks at theoretical motivations behind the use of technical trading.

3.1. Put and call options

Derivative securities are crucial in managing financial risks as they allow for exchanging financial risks in between speculators and hedgers. The use of financial derivatives has been steeply growing in popularity in the last decades. Return on derivatives is derived from the underlying asset, which can be e.g. a stock, a bond, a currency, a commodity, a future or an index etc. Standardized options are traded on the official financial exchanges, while less standardized contracts are traded in the Over-The-Counter (OTC) market, where buyers and sellers mutually agree on all the contract terms and adjust it to each other's needs, (Chance & Brooks, 2013, p.1-5).

This thesis focuses exclusively on equity options, which are contracts that give an option buyer the right, but not obligation, to buy (call option) or sell (put option) a given company share for a pre-agreed fixed price called strike price. The writer of the option is obliged to fulfil the transaction if the buyer decides to exercise the option. This decision will depend on the moneyness of the option the investor possesses at a time when it can be exercised:

- Options in-the-money will be exercised as exercising the option at its strike price X gives an investor a competitive advantage relative to current stock price (S) at the market.
- Options at-the-money are options which strike price X is equal to the current market price and thereby an investor would be indifferent between exercising an option and buying a share directly in the market.
- Options out-of-the-money will not be exercised as exercising the option at its strike price X is not attractive relative to the current market price (Chance & Brooks, 2013, p.66, 80).

Table 1. Option moneyness depending on the current stock price

	S > X	S = X	S < X
Call option	In-the-money	At-the-money	Out-of-the-money
Put option	Out-of-the-money	At-the-money	In-the-money

Call buyers and put writers, are trades taken by bullish investors who believe in a price appreciation of the underlying asset. An investor buying a call option limits his/her downside risk to the option premium while a put writer can maximally get a profit of the option premium while his/her loss potential is huge, defined by the amount of how much the stock price will decrease during option lifetime.

Call option writers and put buyers are by nature bearish investors, undertaken by these market participants who believe in a decrease in the price of underlying asset. Put buyers downside is limited to the premium paid at the time of entering the contract while the call writer loss can be infinite, as it will be the amount of the increase in the underlying stock price (Bateson, 2011, p. 35-37).

Apart from financial risk exchange, options give investors a possibility to replicate short-selling by writing a put contract as well as levering up portfolios by trading OTM options, which also partly explains the growth of popularity in these derivative instruments. As options give the holder a valuable right of entering a given transaction at some point in the future as well as managing the financial risk, the option buyers are willing to pay some price at the beginning of the contract, called option premium.

Option premium (price) is determined by its market price and consists of 2 parameters: intrinsic value and time value. Intrinsic value of the option is calculated as the difference between current share price and exercise price ($\max(S - X, 0)$) for call options and a difference between exercise price and current share price ($\max(S - X, 0)$) for put options. As option contracts give no obligation to be exercised, the lower bound of the intrinsic value is 0. The intrinsic value of the call (put) option will move in the same (opposite) direction as the share price - it will increase (decrease) with an increase in the share price and it will decrease (increase) with a decrease in the share price.

Time value of an option contract is the difference between its intrinsic value and current market price. Maximum time value is achieved when the option is at-the-money because at that time the uncertainty around the option profitability is maximized. Time value gradually falls as options enter deep-in-the-money and deep-out-of-the-money states, because at these states, uncertainty is minimized and both the owner and the writer can see whether the option is likely to be exercised. As time value is always positive, the value of options increases with time to maturity. As the expiration date of an option comes closer, its time value diminishes and approaches the intrinsic value of the option, (Bateson, 2011, p.36-37).

Option premium depends on a number of parameters, including:

- time to maturity (T),
- strike price (X) determining its moneyness,
- volatility (σ) of the underlying asset ,
- interest rates (r)
- dividends paid on the underlying asset (D)
- and the price of the underlying asset (S).

In general, deep out-of-the-money options with low time to maturity (T) and low volatility (σ) will be trading at a low value due to a statistically lower chance of actually being exercised and vice versa. Prices of options on volatile assets with a long time to maturity will be relatively high, compared to options where the volatility of the underlying is low or its time to maturity is short (and thereby its time value is low) will be relatively low.

Prices of call (put) options are negatively (positively) related to the option strike price (X) i.e. the price of a call (put) option will increase (decrease) as the strike price decrease because it increases (decreases) the chances of the option being in the money. The longer time to maturity, the higher time value of the option and thereby also higher the possibility of being exercised. Dividends paid on the underlying asset have a negative impact on call option prices and positive impact on put option prices, as the stock price is expected to decrease by amount close to the dividend amount on the ex-dividend date, being effectively a good change for put holders and bad change for call holders. Call (put) prices are positively (negatively) related to the changes in interest rates. This is because by comparing call options to buying shares, it is relatively cheaper to invest in options and while an interest rate hike makes savings more attractive, investors are more willing to pay higher premium for calls to save up and buy a stock in the future. The overview of the all the relationships between call and put option prices and various variables is presented in table 2. (Hull, 2011, p.227-231)

Depending on the option type, options can be exercised either at the time of maturity T (European type), at some given times (Bermudan) or at any time until maturity (American). An American call will never be early exercised, provided that the stock pays no dividends as an early exercise will produce cash flow of $S_0 - X$ which is lower than lower bound of the call equal to $S_0 - \frac{X}{(1+r)^{-T}}$. If there is an expected dividend on the underlying asset, an American call should be exercised as close as possible to the ex-dividend day. An American put can be early exercised at times when the stock price is very low, while the dividends effectively reduce the probability of early exercise of this type of option. Due to the early exercise possibility, American options are always more valuable than European and thereby traded at higher prices (early exercise premium), (Chance & Brooks, 2013, p. 76,86).

Table 2. Relationship between option prices and chosen variables

Increase in	Impact on call option price	Impact on put option price
Time to maturity	*Increase*	*Increase*
Strike price	*Decrease*	*Increase*
Volatility of the underlying asset	*Increase*	*Increase*
Interest rate	*Increase*	*Decrease*
Dividend paid	*Decrease*	*Increase*
Price of the underlying asset	*Increase*	*Decrease*

3.2. Black Scholes Model

Although earlier work on option pricing models exists, the model proposed in the seminal paper by Black and Scholes in 1973 was the first one to make use of only observable parameters. The model makes use of variables mentioned above and relies on the following assumptions:

a) The interest rate is known and invariant throughout the lifetime of the option.
b) Stock prices follow random walk and their distribution is log-normal with a constant variance of stock returns.
c) There are no dividends paid throughout the lifetime of the option.
d) Options are European, meaning that no early exercise is possible.
e) There are no transaction costs in both equity and option markets.
f) Borrowing of any fraction of security is possible at the short-term term interest rate.
g) Short-selling is possible, (Black & Scholes, 1973).

The Black Scholes formula can be formulated as:

$C = S_0 N_{d_1} - Xe^{-rT} N_{d_2}$ for European call options, where the stock does not pay dividends

And $P = Xe^{-rT} N_{-d_2} - S_0 N_{-d_1}$ for European put options, where the stock does not pay dividends,

where:

$$d_1 = \frac{\ln\left(\frac{S_0}{X}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

And where $N(x)$ is the cumulative probability function under the assumption that the variable is standardized and normally distributed, meaning that its mean equals 0 and its standard deviation equals 1. As the formula is made for non-dividend paying assets, the price of European call option is equal to the American one. For pricing American put options, a price-path in binomial tree must be used. In theory, the formula should only be used when interest rate is invariant but in practice a risk-free interest rate prevailing for time T is used as an input, (Hull, 2011, p.298-301).

Even though some assumptions are unrealistic (e.g. fully liquid and efficient markets), the model performs well in empirical tests and it lets investors derive unobserved values of implied volatility, which is the volatility making price estimated by the model equal to the currently observed market price. Implied volatility is usually formed in way of a smile or a smirk, which happens because implied volatility usually is lowest for at-the-money options and highest for out-of-the-money and in-the-money options, making the overall implied volatility to moneyness graph look like a smile, (Bateson, 2011, p.41-45).

The Black Scholes formula also allows calculating the option price sensitivity to a number of parameters, including changes in interest rates and implied volatility in the underlying asset, which are unrealistically assumed to be invariant in the model. Sensitivities are collectively called "greeks", as their names are letters from Greek alphabet and comprise of:

- Delta (Δ) – option price sensitivity to the changes in the underlying price. Delta is the parameter used in so-called delta-hedging, where an investor should sell delta amount of stock for each call option he/she holds in order to maintain market-neutral position. The sensitivity of the option price approaches 0 for an out-of-the-money option and 1 for in-the-money option, where the option prices almost mimics equity price movements. For options at-the-money delta, it hovers around 0.5.

- Gamma (γ) – option price is sensitive to the changes in the underlying asset price. It is a second differential of the option price and it shows how delta will gradually change and the hedge will have to be adjusted together with changes in the underlying asset price. Gamma is maximized when delta's slope is highest and minimized at times when delta's slope is relatively flat. That means that gamma is highest for options at-the-money while it approached 0 for options, which are deep in-the-money or out-of-the-money.
- Vega (V) – option price sensitivity to the changes in the implied volatility. Vega the same for both put and call options with identical characteristics. Vega is maximized for options at-the-money, where uncertainty around the final payoff is highest. Options which are deep out-of-the-money or deep in-the-money are not too prone to changes in the underlying asset volatility levels. Option's vega also increases with time to maturity, consistent with the fact that uncertainty close to the final payoff is increased if time to option's maturity is long.
- Theta (θ) – option price sensitivity to a change in its time value. This parameter is always negative as it shows how much value is lost as time to maturity decreases. Theta is the highest for at-the-money options.
- Rho(ρ) – option price sensitivity to changes in interest rates. The option prices do not respond too much to changes in interest rates as the changes are relatively small, but are in general positive for calls and negative for puts (Bateson, 2011, p. 46-50; Benhamou, 2007, p.90-94).

Table 3. Greek calculation

Greeks	European call	European put
Delta	$N(d_1)$	$N(d_1) - 1$
Gamma	$\frac{N'^{(d_1)}}{S\sigma\sqrt{T}}$	$\frac{N'^{(d_1)}}{S\sigma\sqrt{T}}$
Theta	$\frac{-SN'^{(d_1)}}{2\sqrt{T}} - rXe^{-rT}N(d_2)$	$\frac{-SN'^{(d_1)}}{2\sqrt{T}} - rXe^{-rT}N(d_2)$
Vega	$S\sqrt{T}N(d_1)$	$S\sqrt{T}N(d_1)$

Source: Directly adapted from table 4.2. Benhamou (2007)

3.3. Put-call parity

The put-call parity, derived by Stoll (1969), determines the no-arbitrage relationship that should hold between the put (P) and call (C) option prices on the same underlying asset (S) with the same exercise price (X) and time to maturity (T), given current risk-free rate (r):

$$C + Xe^{-rT} = P + S$$

The no arbitrage-relation should hold for all European options, provided the implied volatility of the call option and put option equates the observable market price in the Black-Scholes model. As American options have the possibility to be exercised prior to the expiration date, the put-call relationship takes form of an inequality rather than a direct no arbitrage-relation.

Table 4. Payoffs

		Payoff from portfolio given stock price at expiration	
Payoff from	**Current value**	$S_t \leq X$	$S_t > X$
	Portfolio 1		
Stock	S_0	S_t	S_t
Put	$P(S_0, T, X)$	$X - S_t$	0
		X	S_T
	Portfolio 2		
Call	$C(S_0, T, X)$	0	$S_t - X$
Bonds	$X(1+r)^{-T}$	X	X
		X	S_T

Source: Directly adapted from table 3.11. Chance & Brooks (2013)

As presented in table 4, expected payoff of both sides of the put-call parity, in any price state of the underlying asset, is equal. According to the law of one price, financial instruments with same payoffs should also have the same price to rule out a possibility of arbitrage, (Chance & Brooks, 2013, p. 13-14,87-90).

Nevertheless, in real life, the put-call parity gets rejected in empirical tests. As proven by Wagner, Ellis, & Dubofsky (1996) around 21% of options do not fulfil the put-call parity condition. To explain violations of the parity condition, authors have used variables such as the interest rate, trading volume, dividends, intraday price trend, intraday volatility and time to maturity of the options. The majority of the variables turned out to be insignificant in the study. Dividends contribute to some of the mispricing, but the main factor causing the deviations is the overpricing of puts relative to calls, especially when options expiration date is close.

Trading directly on put-call parity deviations might be difficult due to a number of reasons, including:

- It might be not possible or technically difficult to sell/buy exactly the amount defined by the arbitrage condition.
- If arbitrage requires short-selling, the legal rules or the uptick rule (i.e. that shorting must be done at a price higher than the current stock price) might impede the arbitrage possibility.
- The arbitrage possibility might just be an illusion created due to nonsynchronous trading in option markets.
- The possibility to earn risk-free profit might disappear after accounting for transaction costs.

Authors also name cyclical mispricing of options, reflected in days where either none or all of the options in the sample have been mispriced. Even though the violation from put-call parity might not in itself represent an arbitrage opportunity, it might contain information about future stock price movements that one can consistently trade on as analysed thoroughly by Cremers & Weinbaum (2010).

3.4. Technical analysis in trading

Technical analysis is an examination of past price and volume data of a given financial asset. Even though technical analysis is not widely used in academia, technical analysis has been widely recognized as a useful tool by practitioners.

Technical analysis is primarily based on the following logic:

a) Market value of any asset is determined by supply and demand forces.
b) Even though there exist minor fluctuations within the trends, stock prices usually move in long-term persisting trends.
c) The force causing trends to reverse are shifts in supply and demand for a given stock, which can be discovered by using charts.
d) The patterns seen in charts are repeatable and give a set of indicators/patterns, which entails a particular trading signal.

The theory is built around the assumption that financial markets consist of three major types of movements:

a) Temporary daily price fluctuations.
b) Temporary secondary market movements.
c) Persisting, long-time primary trends.

The theory relies primarily on the expectation that primary trends are recognizable and long-lasting, despite having daily fluctuations in various directions. Financial assets trade on daily basis in price ranges. The lower bound of the price range is called the support level and upper bound is called the resistance level. A breakout is experienced when the asset price increases above its resistance level or decreases below its support level. Such an event is significant as it indicates that the old trading range has been broken and investors now expect a relatively higher asset price for breaking the resistance level or lower asset price for breaking the support level. (Bauer Jr. & Dahlquist, 1999, p. 1-6)

Market timing indicators are used to improve the reliability of charts analysis and provide signals for discovering future trading opportunities. One of the most popular market timing indicators is the moving average. The moving average shows a past trend based on a defined time span, thereby the time series is "smoothed" out i.e. deprived of some degree of volatility. Moving averages are used across a wide range of different time spans, from as little as couple of days to 200 days. There is no ideal time span to be used – different time spans tell different stories, all depending on the sensitivity of the moving average to the price changes. Shorter time spans are more sensitive to changes in the price of the underlying asset. In general, a buy signal is generated when current asset price is higher than the moving average applied, indicating a beginning of an uptrend. A sell signal is generated when current asset price declines and crosses the moving average applied, marking the start of a downtrend and further decreases in the price. Dual moving average is the most popular combination used, as investors get two trading signals (one long term moving average and one short term moving average), thereby diminishing the probability of a mistake. A buy (sell) signal is generated when the short-term moving average line crosses the long-term moving average line from below (above). Positions are maintained until another crossover of the moving average is observed. In general, technical traders utilize stock market quoted close prices, as this mimics stocks that are actually held over night. In addition to the moving averages, a range of other indicators can be used to confirm trading signals given by moving averages and eliminate false signals. The confirmatory indicators may consist of pattern formations such as triangles, rectangles or pennants, (Edwards, Magee, & Bassetti, 2007, p. 644-652).

Investors also use general market statistic e.g. volume and open interest. Volume indicates the sentiment currently observed in the stock market and can be used as a confirmation of what other technical trading signals are signalling. High volume signals bullish markets, while low volume signals bearish markets. However, volume shows only a part of the picture and it is less informative than open interest. Open interest measures the number of contracts outstanding on a specific asset at an official exchange. Open interest increases when both sides of the trade are new and declines if both sides of trades close out and remains unchanged when one side of the trade is new and the other one is old. Thereby, open interest clearly depicts the money flow in and out of the market. As each trade has a buyer and seller side, the overall number of buyers and sellers in the market is always equal. Hence, rising (falling) open interest signals a bullish (bearish) market with newly opened (closed) long positions. When open interest decreases but asset prices rise, it can indicate a bearish market, even though it might be temporarily a bullish market. This is because despite there is a small increase in the long positions in the market, money is flowing out as open interest falls, indicating future price decreases. Finally, when prices are falling, but open interest rises it signals a bearish market. This is because new money flows into the market, but those trades are likely to be short positions, thereby generating a selling pressure in the market, implying an anticipated future price declines. An overview of the influence of these factors on the market is presented in the table below, (Edwards et al., 2007, p. 658-661).

Table 5. Relationship between open interest and volume

Price Action	Open Interest	Interest in asset	Market
Up	Up	Up	Strong
Up	Down	Down	Weak
Down	Up	Up	Weak
Down	Down	Down	Strong

Source: Directly adapted from (Edwards et al., 2007, p. 660)

IV. Data and methodology

The purpose of the following chapter is to shed light on both the data applied and the methodology employed in order to answer the put-forth problem statement. Regarding the methodology and representation of the volatility-spread analysis, we are at large inspired by the work done by Cremers & Weinbaum (2010), while the empirical work centred around price to moving average ratio is by far following L. J. Hong (2013). The section is arranged as follows: firstly, a thorough examination of the data, where an account of the data origination as well as basic descriptive statistics will be provided. Next, a display of the methods for how the volatility spread and price to moving average ratio have been computed is specified and descriptive statistics on the volatility spread and price to moving average data is presented. Finally, an account of how portfolio performance is measured will be provided.

4.1. Sample selection

Data used in the thesis is obtained through Wharton Research Data Services (WRDS), through which access to OptionMetrics database was gained. Variables retrieved from OptionMetrics comprise of option open interest, expiration dates, highest closing bids, lowest closing asks, strike prices, volume and implied volatility. Only options with American-style execution have been considered. Through WRDS we also gained access to The Center For Research in Security Prices (CRSP) where daily equity open and close price as well as cumulative adjusting factors (adjusting for dividends, splits etc.[1]), market capitalisation and volume data are provided. The sample period includes five years of daily observations, spreading from 1st January 2011 to 31st December 2015, containing 1258 trading days. This enables a profound examination of how a strategy based on the volatility spread trading strategy functions after the financial crisis as we are using a different sample than e.g. Cremers & Weinbaum (2010) or Bali & Hovakimian (2009) did. As the recovery from the financial crisis was long and marked by a pro-longed period of low economic growth and persistent low interest rates, the analysis might uncover interesting conclusions regarding the information in option prices in the new post-crisis economic environment.

The sample of stocks is based on 3 indexes: S&P 500 Large Cap with a single constituent market capitalization of up to 650bn USD, S&P Midcap 400 including companies with a market capitalization of around 1-10bn USD and S&P Small Cap 600 consisting of smaller companies, which meet the

[1] http://www.crsp.com/products/documentation/crsp-calculations

specific inclusion criteria[2]. Companies originate from a wide range of industries including information technology, financials, industrials, consumer discretionary, real estate, materials, health care, utilities, consumer staples, energy and telecommunication services, which makes the sample less prone to sole industry risk.

Table 6. Data statistics

Number of stocks	1466
Number of trading days	1258
Mean Daily Return	0.05%
Daily Return Standard Deviation TS	2.03%
Daily Return Standard Deviation CS	1.72%
Max Daily Return	363.21%
Min Daily Return	-65.25%

Due to data constraints, the sample includes 1466 stocks instead of actual 1500, which are included in the indexes. CRSP was not able to provide full data for the missing 34 companies. The sample, consisting of three S&P stock indexes, constitutes of the large share of the whole US equity market and represents all industries. Therefore, the sample is a genuine representation of the whole market, thus internal validity of the examination is high, and hence conclusions can be generalized to the entire US market. Regarding external validity, further analysis would have to be conducted, as the characteristics of the US financial market are quite particular due to large capitalization, turnover and liquidity as well as strict regulation, especially compared to smaller markets in Europe or emerging economies. Finally, the US has also been more successful to recover after the financial crisis, which might have affected the equity pricing and risk appetite differently.

As seen in table 6, mean daily return lies at 0.05%, signalling an expected general positive drift in equity prices. The cross-sectional standard deviation across the shares lies at 1.72%, slightly lower than the average standard deviation recorded across the individual stock price time series at 2.03%. Overall, daily volatility seems high, which is confirmed by looking at the extreme daily return observations in our sample, where the maximum daily price gain lies above 360%, while the maximum loss was recorded at 65.25%, marking a stock losing almost 2/3 of its value within one trading day.

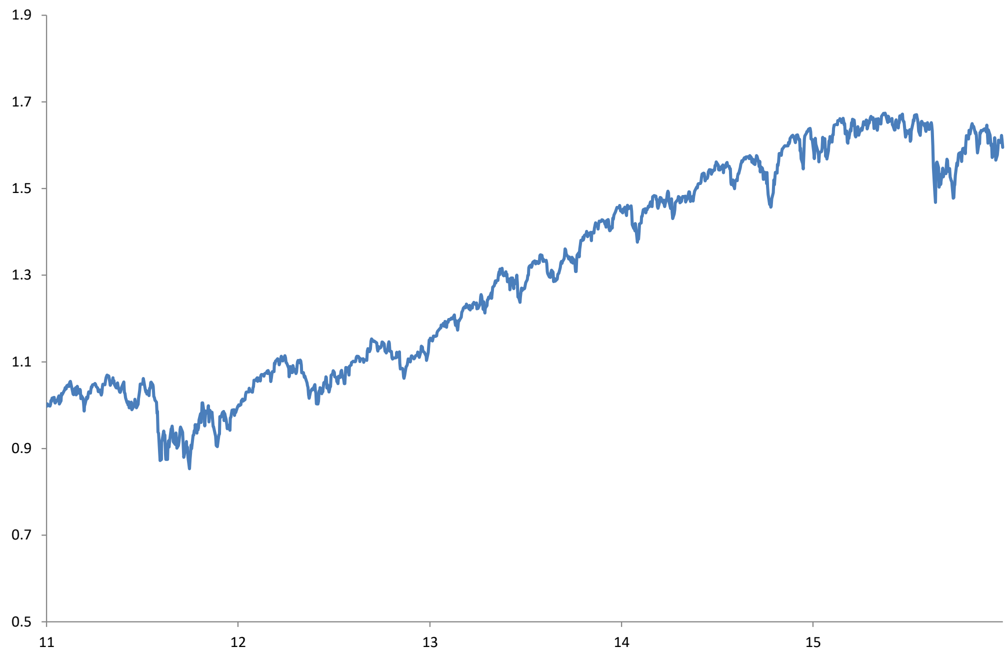
To gain a holistic view of the price data, a customized value-weighted (i.e. market capitalisation weighted) index is constructed from the sample population and annualized measurements of performance are presented in the table below.

[2] http://us.spindices.com

Table 7. Market performance of the stocks

	2011	2012	2013	2014	2015
Annualized returns	-1.73%	13.93%	33.92%	15.33%	-1.95%
Annualized volatility	80.97%	59.39%	126.62%	92.64%	69.04%
Average risk free asset	0.08%	0.14%	0.05%	0.03%	0.05%
Sharpe Ratio	-0.02	0.23	0.27	0.17	-0.03

Graph 1. Daily value-weighted index performance



The average annualized return of the value weighted index ranges from -1.95% in 2015 to 33.92% in 2013. Returns are slightly negative in 2011 and 2015, but positive in all the other years, overall suggesting equity price increases across these 5 years, thereby it has generally been a bullish market. Annualized volatility varies from 59.39% in 2012 to 126.62%. As a result of the FED expansionary monetary policy, the average of 1 month Treasury bill, used as proxy for the risk-free asset, is low reaching a maximum of 0.14% in 2012 and a minimum of 0.03% in 2014. The Sharpe ratio, measuring the risk-adjusted performance of stocks, is slightly negative in 2011 and 2015 and strongly positive between 2012-2014 varying from 0.17 in 2014 to 0.27 in 2013, indicating e.g. that in the best performing year, for every 1% of risk undertaken, on average an investor have been compensated by 27 bps of premium return. It is clear the data reflects a period arising post the financial crisis, as the 2012-2014 returns are significantly higher than returns from 2011, where the economy was still doing poorly.

4.2. Volatility spread as a forward-looking measure of deviations from the put-call parity

As pointed out by Bali & Hovakimian (2009) solely relying on the level of option-implied volatility cannot in itself be considered a good predictor of future stock returns. However, they suggest two uses for implied volatility for which they achieved satisfying predictive results. First, the authors suggest utilizing the spread between the implied volatility and realized volatility. They used the difference between the one month lagged realized volatility (RVol) and implied volatility (IVol) on stocks calculated as the average of put and call implied volatilities as a proxy for volatility risk. In the empirical analysis both on a firm- and portfolio level, they were able to find a significant negative relationship between expected returns and the spread between realized and implied stock volatility. This indicates that when realized volatility on a stock is higher (lower) than the implied option volatility, future stock returns will decrease (increase). Second, Bali & Hovakimian (2009) examined the relationship between expected stock returns and the spread between call and put implied volatilities – using it as a proxy for jump risk. Their results indicated a positive correlation between the two, implying that a trader longing stocks with high call option-implied volatility relative to put and simultaneously shorting stocks with low call option-implied volatility relative to put should be able to earn an abnormal return.

This thesis follows Bali & Hovakimian's (2009) second suggestion by using the volatility spread between call and put options, as it has also been pronounced to be a measure for deviations from put-call parity and used by multiple authors such as Amin, Coval, & Seyhun (2004) and Cremers & Weinbaum (2010). The open interest-weighted implied volatility spread (VS) is computed as:

$$VS_{i,t} = IV_{i,t}^{calls} - IV_{i,t}^{puts} = \sum_{j=1}^{N_{i,t}} w_{j,t}^{i} * (IV_{j,t}^{i,call} - IV_{j,t}^{i,put})$$

Where j is an index used for pairs of put and call options with same maturity and strike price, $w_{j,t}^{i}$ denotes open interest weights and $IV_{j,t}^{i}$ is the option-implied volatility calculated from the Black-Scholes model. There are $N_{i,t}$ valid option pairs on the underlying asset i, measured on day t. Weights are measured as the sum of daily open interest of all options pairs on the underlying asset i.

The put-call parity equation predicts a no-arbitrage relation in the case of European options but in the case of American options, it takes the form of an inequality. Thereby, a non-zero volatility spread indicates presence of buying or selling pressure, leading to deviations from the inequality. If there is high demand for calls, they will look relatively expensive compared to puts, making call implied volatility higher than put implied volatility. Longing stocks with high volatility spread whilst shorting stocks with low volatility spread is a bet on option markets will lead equity market developments. If that happens, stocks with temporarily overpriced calls will appreciate in value and stocks with temporarily overpriced puts will depreciate in value making the option pricing fair. Such a development is also a practical confirmation of informed trading, where informed traders will first act in option markets instead of equity markets as a probable consequence of embedded leverage and lower regulation benefits it provides.

4.2.1. Descriptive statistics on volatility spreads

Stocks with valid volatility spreads are merged with CRSP stock data following Cremers & Weinbaum (2010). The final sample includes 1 540 217 volatility spreads for 1466 different firms from 11 different sectors, making our sample diversified in terms of the industry sector risk.

In order to make our sample consistent with Cremers & Weinbaum (2010) data has been cleaned for option pairs where at least one of the following conditions has been true for either call or put option:

- Open interest data is missing or equal to 0.
- Highest bid or lowest ask price is equal to 0.

Before cleaning we have a total of 152 592 259 single call option price entries and 152 590 367 single put option price entries. After cleaning we have 59 779 070 single call options entries and 61 917 211 single put option entries, resulting in a total 43 932 523 option pairs. Descriptive statistics on the final 1 540 217 volatility spreads has been developed to get an overview of the characteristics of the aggregate volatility spreads. All stocks with at least one valid option pair for calculating volatility spreads on a given day are included in the sample.

Table 8. Volatility spreads – descriptive statistics

Table 8 shows an overview of the descriptive statistics on the volatility spreads measured as the weighted average difference in option-implied volatilities between calls and puts on the same underlying equity on a given day. The full sample time period running from 1st January 2011 to 31st December 2015 is divided into 2 sub-periods ranging from January 2011 – December 2013 and January 2014 – December 2015. Panel A shows a number of basic statistical parameters, including number of observations, the average volatility spreads and its standard deviations measured across the individual time series and across firms. Panel B shows the percentage breakpoints for each quintile while panel C and D measures the persistence of the data in two different ways. In panel C, the average autocorrelation of the volatility spreads across a period from 1 to 5 days is recorded, while panel D presents the average share of stocks that have remained in the same quintile they initially were allocated to across 1, 2 and 4 week time horizons.

		Sample	
	Full sample	**2011-13**	**2014-15**
Panel A. Summary statistics			
Mean	-0.36%	-0.50%	-0.16%
Standard deviation TS	4.21%	3.75%	4.45%
Standard deviation CS	4.67%	4.46%	4.98%
Number of observations	1,540,217	890,408	649,809
Panel B. Quintile averages			
1st quintile	-5.33%	-5.06%	-5.75%
2nd quintile	-1.19%	-1.18%	-1.19%
3rd quintile	-0.11%	-0.20%	0.03%
4th quintile	0.98%	0.75%	1.29%
5th quintile	4.47%	3.96%	5.20%
5th - 1st quintile	9.81%	9.02%	10.95%
Panel C. Persistence - autocorrelations			
Autocorrelation (1)	0.126	0.112	0.100
Autocorrelation (2)	0.147	0.218	0.113
Autocorrelation (3)	0.110	0.182	0.076
Autocorrelation (4)	0.136	0.112	0.114
Autocorrelation (5)	0.044	-0.007	0.023
	1 week	**2 weeks**	**4 weeks**
Panel D. Persistence – portfolio allocations			
1st quintile	34.79%	33.26%	32.98%
2nd quintile	25.05%	24.72%	24.99%
3rd quintile	26.09%	30.55%	30.26%
4th quintile	22.17%	20.18%	21.17%
5th quintile	30.06%	28.42%	27.34%

As presented in table 8, panel A, mean volatility spread is negative across all analysed time periods, indicating that on average there is a stronger selling than buying pressure in the option market. As all quintiles from 1st to 3rd are negative in the full sample, median volatility spread must be negative. The negative skew of the median of volatility spreads confirms findings presented by Ofek, Richardson, & Whitelaw (2004) of put-call parity deviations being more likely in the direction of expensive puts rather than calls. This could arise from short-sale restrictions on stocks, which were mentioned in the Chapter II (Literature review) and Chapter III (Theory), and will be shortly discussed further in chapter V (Portfolio performance). The average standard deviation lies at 4.21% and

4.67%, measured respectively on the time series and cross-sectionally. Average volatility has increased with 0.5-0.7 percentage points between 2011-13 and 2014-15. Number of observations per year is slightly increasing in the second sub-period, lying at the beginning at around 296 000 and rising to around 325 000 observations annually in the end.

In panel B, results are sorted into quintiles, the 1st quintile represents the lowest volatility spreads i.e. stocks with the highest selling pressure and the 5th quintile consists of stocks with highest volatility spread, marking equities experiencing highest buying pressures. The difference between the two extreme quintiles lies at 9.81% with a maximum of 10.95% recorded in 2014-15. Such an increase might indicate that markets have become less efficient across the time periods analysed and might open up for a larger possibility of utilizing the deviations in the second sub-period in our strategy. Both the negative mean and panel B with the largest share of quintiles recording negative volatility spreads are in line with results presented by Cremers & Weinbaum (2010) and Ofek's (2004) argument that the deviations from put-call parity are experienced more regularly due to expensive puts relative to calls. As stated in the theory section and pointed out by Wagner et al. (1996) general mispricing of options is to a smaller degree a result of occurring dividends, but the main factor explaining the existence of the phenomenon is that it might be technically difficult to trade the exact amount as defined by the put-call parity relation or the existence of restrictions on short-selling that are in place.

Finally, persistence in volatility spread is measured twofold. In panel C it is measured as average autocorrelation of first to fifth order, measuring the volatility spread correlation with 1 up to 5-day lags. In panel D it is measured as the share of stocks remaining in the same quintile within 1, 2 and 4 weeks after they have been initially assigned to it. Autocorrelation is low, ranging from 0.044 to 0.147 in the sample measured on the full time period, reaching a maximum of 0.218 on the second day lag auto-correlation in years 2011-13. Auto-correlations seem to be on average higher in the initial sub-period measured in 2011-13 relative to the following 2 years, reflecting a decline in autocorrelation across time. As seen in panel D, a large share of stocks remains within the same quintile as allocated to in the beginning. However, persistence varies across quintiles and time periods, ranging from 20.18% to 34.79%. Note that the highest persistence is found in the two extreme portfolios (1st and 5th), indicating a higher persistence in the most extreme quintiles compared to non-extreme quintiles. Even though persistence is slightly lower for stocks in 2nd, 3rd and 4th quintile, it still remains at a level of approximately 20-25%.

4.3. Price to Moving average ratio as a backward-looking measure of future stock price path

As described in Chapter II (Literature review), stock prices seem to follow same price channels in short- to medium-run, while price corrections i.e. "mean reversals" appear to happen predominantly in the very short-run due to temporarily lacking liquidity or in the long-run when the overreaction of investors has driven prices away from their fundamentals. Technical trading rules are widely used by practitioners and have been reported to work well in the empirical analysis of the financial markets.

As explained in the theory chapter, moving average is one technical trading indicator, giving a binary signal to buy when the current price of the asset crosses the moving average used from below and to sell when the market price crosses the moving average from above. This paper focuses on very short-term price fluctuations, hence examining whether 5-day moving average have a significant power to predict future price movements. Technical trading rules have been reported useful and outperforming general econometric models in 1990s by Brock, Lakonishok, & LeBaron (1992). Moreover, researchers such as Neely, Rapach, Tu, & Zhou (2014) also reported that moving averages to be superior in predicting future stock prices compared to macroeconomic events.

As the price to moving average ratio has been proven to be better predictor than conventional moving average and price return factors, the ratio is used to measure past performance of stocks included in the contrarian strategy. Park (2010) uses different types of moving average ratio lengths where one of them is based on short-term while the other on a long-term time period. However, his investment period equals 6 and 12 months, signalling that a momentum strategy for short- to medium-term investments is appropriate as indicated in chapter II (Literature review). As the investment period in this thesis is very-short, based on weekly rebalancing of the portfolio, similar approach is employed, such as one presented by Chui et al. (2010) Griffin et al. (2003) Khil & Lee (2002). They argue that very-short run contrarian strategies are more applicable than momentum strategies. Moreover, identical holding periods and portfolio rebalancing frequency in both the forward- and backward-looking strategy will allow for mutual comparison between the two. As a result, a time period based on a five-day stock price moving average is chosen. Due to the fact that moving average needs to be standardized for sorting purposes, following L. J. Hong (2013), a ratio of the current stock price divided by the 5-day moving average called overall price to moving average ratio will be used.

The general price to moving average ratio (PMA) formula can be expressed as follows:

$$PMA_{n,t} = \frac{S_t}{\left(\frac{1}{n}\sum_{i=t-n+1}^{t} S_i\right)}$$

where n marks the number of observations included. As we use the 5-day price to moving average ratio, it will be computed according to the formula below:

$$PMA_5 = \frac{S_t}{\frac{(S_t + S_{t-1} + S_{t-2} + S_{t-3} + S_{t-4} + S_{t-5})}{5}}$$

Where S_t denotes the stock price at the market close at day t and the measurement uses a period of 5 previous trading days. If any data is missing, the algorithm uses whatever data is available. Using price to moving average ratio reflects not only the direction of prices, but also on the magnitude of the uptrend or downtrend, therefore the measure should be better than following only a simple moving average as it allows for a sorting scheme to be implemented. Moreover, since PMA ratio hold currents price relative to recent price changes, it is less sensitive to volatility of the underlying stock. When current price of a stock is higher than its 5-day moving average, the PMA ratio will be high indicating a winner stock, while if current stock price is lower than its 5-day moving average, PMA ratio will be low, signalling a loser stock. PMA observations are sorted into quintiles based on the magnitude of the uptrend or downtrend experienced. Group 1 consists of stocks with the 20% lowest PMA ratios while group 5 contains these with the 20% highest. By taking a long position in the 1st group of stocks, which has recorded largest loss, and a short position in the 5th group of stocks, which enjoyed the largest gains, the investment strategy is an effective bet on a short-term trend reversal. The success of a strategy indicates that weak efficient market hypothesis does not hold at all time and a simple reversal strategy like this can earn an abnormal profit on a sustainable basis. As indicated in chapter II (Literature review), this can happen due to initial investor overreaction to news or temporary lack of liquidity, leading to price swings not supported by fundamentals.

4.3.1. Descriptive statistics on price to moving average ratio

Identical to the sample of volatility spreads, the final sample based on price to moving average includes observations for 1466 different firms originating from 11 different sectors. The sample consists of 1 732 267 observations in total within the time period of January 2011 – December 2015.

In order to get a data overview, descriptive statistics of the price moving average ratio is presented in the table below.

Table 9. Portfolios based on price to moving average ratio – descriptive statistics

Table 9 shows the descriptive statistics of the price to moving average ratio. Panel A looks into the basic characteristics such as number of observations, mean and the average standard deviation measured both across firms and across the time series. In panel B, average price to moving average ratio of each portfolio quintile is reported, reflecting on the magnitudes of differences between the portfolios formed. Panel C and D shows the persistence of the measures twofold. Panel C reports average autocorrelation between 1st and 5th order, measured up until 5 days lag indicating how high current stock price correlation is with prices observed in the past few days. Panel D reflects on the average share of stocks, which remained in the same quintile as they had initially been allocated to across the time period of 1, 2 and 4 following weeks.

		Sample	
	Full sample	**2011-13**	**2014-15**
Panel A. Summary statistics			
Mean	100.08%	100.15%	99.99%
Standard deviation TS	2.44%	2.50%	2.26%
Standard deviation CS	2.10%	2.12%	2.08%
Number of observations	1,732,267	1,013,444	718,823
Panel B. Quintile averages			
1st quintile	0.975	0.975	0.974
2nd quintile	0.993	0.993	0.993
3rd quintile	1.001	1.001	1.000
4th quintile	1.008	1.009	1.008
5th quintile	1.027	1.028	1.026
5th – 1st quintile	5.27%	5.32%	5.21%
Panel C. Persistence - autocorrelations			
Autocorrelation (1)	0.763	0.782	0.735
Autocorrelation (2)	0.507	0.551	0.442
Autocorrelation (3)	0.279	0.330	0.201
Autocorrelation (4)	0.114	0.178	0.012
Autocorrelation (5)	0.023	0.100	0.102
	1 week	**2 weeks**	**4 weeks**
Panel D. Persistence – portfolio allocations			
1st quintile	22.74%	22.54%	22.34%
2nd quintile	20.75%	20.63%	20.25%
3rd quintile	22.07%	21.94%	22.06%
4th quintile	20.85%	21.03%	20.69%
5th quintile	22.06%	22.12%	21.84%

As underlined in the table 9, the overall PMA mean signals that equity prices were on average appreciating in value throughout all five years, indicating a continued upturn in financial markets, which was also the case when the US economy started recovery after the financial crisis. In the period of 2014-15, markets were almost neutral on average, as indicated by 99.99% mean of the PMA ratio, while in the initial period of 2011-13, they were strongly bullish with the current stock prices lying around 0.15% higher than their past week's average. Average standard deviation of the stock returns time series across five years is 2.44% while average standard deviation of all stocks included in the sample and measured cross sectionally is 2.10%. Both are quite low, also relative to the results presented in table 8.

Average number of observations per year increases throughout sample period, indicating slightly increasing amount of stocks available in the sample. This happens as some of the 1466 companies experienced spin offs or split offs and the database we used, returns by default all of the stock data for newly established companies. The sample consists of 1,732,267 data points throughout the five years and represents a large share of the American stock market, solidifying the internal validity of the examination.

Panel B reports PMA averages within each quintile across time. As a natural consequence of the quintile sorting, PMA means are increasing monotonically across quintiles 1 to 5, ranging from 0.975 to 1.027 in the full sample. The average difference between the 5th quintile and the 1st quintile is 5.27% over the full sample period, indicating the mean spread between gains of winner stocks and losses of loser stocks. Even though, the quintiles seem to be stable across the subsamples, the spread was slightly higher in the initial period of 2011-13, when it recorded 5.32% compared to 2014-15 where it was equal to 5.21%.

Finally, persistence of price to moving average ratio is measured in the same way as previously with volatility spreads. Panel C indicates a significant and positive autocorrelation ranging from 0.763 to 0.023, and it is monotonically decreasing across all 5 lags and throughout all periods. The results stand in contrast with the efficient market hypothesis, according to which stock prices should not be predictable using historical data and should follow a random walk. In the sample data, there is significant positive correlation on a 2-3 day horizon. As seen in panel D, approximately one fifth of stocks remain in the same quintile as the one they got allocated to within the period varying from 1 week to 1 month. Moreover, in contrast to the volatility spreads, the persistence as well as all the other statistical parameters for price to moving average ratio seems to be quite consistent across time as the results are similar across the two subsamples. The difference in the persistence across groups and across time periods measured in panel D is also smaller compared to the one measured on volatility spreads. However, the most extreme quintiles (1st and 5th) are still those experiencing the highest persistence in allocation across 1, 2 and 4 weeks after the initial allocation.

4.4. Measuring Portfolio Performance

Portfolio quintile returns (R_t) at time t are computed on value-weighted basis from all the stocks d allocated to a given portfolio quintile. Returns are recorded weekly from previous Friday close to current Friday close and can be computed as follows:

$$R_t = \sum_{d=1}^{D} w_{d,t} * \frac{p_{d,t}}{p_{d,t-1}} - 1$$

Where p is the Friday accumulative adjusted closing price, $w_{d,t}$ is the value weight of stock d included in the quintile portfolio on day t. Value weight $w_{d,t}$ is measured as the dollar-denominated market capitalisation of stock d on day t divided by the total sum of market capitalization of the whole portfolio on the day of rebalancing t, also called "value weight":

$$w_{d,t} = \frac{Mkt_{d,t}}{\sum_{d=1}^{D} Mkt_{d,t}}$$

The return of the portfolios will be measured against the 3-factor Fama French model (1993) and the Carhart momentum factor (1997) to ensure the abnormal performance of the portfolio does not come from basic, well-known anomalies. Rebalancing occurs Friday to conform with the return data to the weekly Fama-French return factors, which are also rebalanced every Friday. Cremers & Weinbaum (2010) reports that rebalancing Friday or Wednesday have no material alterations on their conclusions.

The Carhart (1997) 4-factor model will be used, which on top of the old model proposed by E. F. Fama & French (1993) adds an additional momentum factor and is formulated as follows:

$$R - r_f = \alpha + \beta_1 (R_M - r_f) + \beta_2 * SMB + \beta_3 * HML + \beta_4 * MOM + \varepsilon$$

Where excess return on asset i at a given time period t depends on the following 4 factors:

- Excess market return in a given period t
- Outperformance of small stocks relative to big stocks (SMB - based on market value of equity)
- Outperformance of value stocks over growth stocks (HML - based on the equity book-to-market value)
- Momentum factor of daily premiums of winner stocks over loser stocks

Despite recent development of Fama French 5-factor model, the performance analysis is based on the older 3-factor model and Carhart 4-factor model. The 5-factor model is built on the 3-factor model created by the same authors in 1993 with additional factors of firm profitability (outperformance of highly profitable firms over less profitable ones based on the operating profit) and investment (outperformance of firms with more conservative approach to growth in assets measured by investment amounts) motivated by input provided by other researchers. The addition of two new factors has made the actual old value factor redundant in the sample examined by E. F. Fama & French (2015) themselves.

However, Blitz (2015) found the addition of 2 factors a bit premature and not thoroughly thought through. The 5-factor model is more complex, but not necessarily better than the initial 3-factor model developed two decades before. Both new factors are criticised regarding the category "quality". The criticism is based on the choice definitions of the new factors, which are not fully explained. The new model also significantly increases the interpretation complexity, while still ignoring both momentum and low volatility factors. Moreover, the new model contradicts previous findings from the authors themselves. They argued that profitability and investment (asset growth) are not as robust as other anomalies, pointing to little evidence of unprofitable firms recording low returns and large stocks' returns being impacted by the asset growth they have. Finally, due to the novelty of the 5-factor Fama-French approach, there has not been extensive research on the empirical results of the new model. Therefore, this thesis retains the conventional 3-factor model complemented by Carhart momentum factor. The conventional model has been widely researched and reported to outperform the basic CAPM mode in both the US and the emerging markets as pointed out by Sehgal & Balakrishnan (2013).

Inclusion of the momentum effect and thereby a shift towards Carhart 4-factor model is motivated by the fact that Fama French model fails to explain returns driven by momentum according to E. F. Fama & French (1996). Moreover, the results obtained in the analysis presented in chapter V seem to be driven in large part by continuation of price trend, so-called momentum, so it is an interesting point to investigate further. Besides, momentum profits have also a strong interrelation with business cycles, where winning stocks gain higher return and lose lower amounts than losing stocks in times of expansion and recession. According to Kim et al. (2014) that happens due to various leverage possibilities and growth options companies have throughout a business cycle and is reflected by different momentum premiums through times of different economic conditions.

Using Carhart 4-factor model has initially had mostly empirical foundations, where it has been widely used to explain leverage and financial distress puzzles by among others George & Hwang (2010), Choi (2013), T. C. Johnson, Chebonenko, Cunha, D'Almeida, & Spencer (2011) and Gomes & Schmid (2010). Ozdagli (2012) was able to prove that market leverage is able to explain a large share of the value premium represented by factor HML. Following Ozdagli (2012), Rath & Durand (2015) tried to decompose the other factors from the model. Their results point to the fact that momentum factor is interrelated to market leverage and total company liabilities. Findings presented by Cakici, Fabozzi, & Tan (2013) and Nartea, Ward, & Djajadikerta (2009) suggest that momentum factor is significant in both developed and emerging markets.

For robustness check, we employ a standard Fama-Macbeth procedure. The portfolios are influenced by the same macroeconomic events e.g. when one portfolio sustain a large negative return between two time periods, it is likely that other portfolios will experience similar loss. This is expressed as systematic risk, which does not diversify away even when clustering individual stocks into portfolios. Standard OLS regressions, which are used in the 4-factor model, will still be consistent under these circumstances. However, standard errors will not. Therefore, it is important to correct the standard errors for this cross-sectional correlation as pointed out by Cochrane (2005).

Fama-Macbeth regression is a two-step procedure for estimation of risk premia. First, the time series of excess returns for each asset i is regressed on the L factor return series for each stock i on day t as seen in the formula below:

$$R_t^i - R_{f,t} = \alpha^i + \sum_{j=1}^{L} \beta_j^i F_{j,t} + \epsilon_t^i, \qquad i = 1, \dots, N \;\; t = 1, \dots, T$$

In second step of the approach, a cross sectional regression is conducted for each time period t. It is computed by regressing excess return of each asset i in time period t on the L estimated factor coefficients $\hat{\beta}$ on day t:

$$R_t^i - R_{f,t} = \lambda_0^t + \sum_{j=1}^{L} \lambda_j^t \beta_{j,i} + \epsilon_i^t \qquad i = 1, \dots, N \;\; t = 1, \dots, T$$

A time series of coefficients on every cross sectional variable is obtained from the above regression. That enables estimation of λ_0 and λ_j by taking simple average of the coefficients in all cross sectional regressions by dividing it by T as shown below:

$$\hat{\lambda}_0 = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{0,t}$$

$$\hat{\lambda}_j = \frac{1}{T}\sum_{t=1}^{T} \hat{\lambda}_{j,t}$$

The coefficients $\hat{\lambda}_0$ and $\hat{\lambda}_j$ can be interpreted as the intercept and the expected risk premium for every risk factor.

Variance of the estimated coefficients is computed as the sum of deviations from the estimate $\hat{\lambda}_{0,t}$ (or $\hat{\lambda}_{j,t}$) computed at time t and the average coefficient $\hat{\lambda}_0$ (or $\hat{\lambda}_j$) divided by the squared amount of days included in calculation T^2 to obtain the variance of an average. In mathematical terms, that can be formulated as follows:

$$\sigma^2(\hat{\lambda}_0) = \frac{1}{T^2}\sum_{t=1}^{T} (\hat{\lambda}_{0,t} - \hat{\lambda}_0)$$

$$\sigma^2(\hat{\lambda}_j) = \frac{1}{T^2}\sum_{t=1}^{T} (\hat{\lambda}_{j,t} - \hat{\lambda}_j)$$

All in all, the static variation in λ_t over time is used to calculate the variation in the portfolios, explaining the respective risk premia.

V. Portfolio Performance Analysis

After having examined basic data characteristics in chapter IV, chapter V aims to conduct a thorough examination of the proposed three trading strategies (PMA and VS separately, and then combined). First, the two separate trading schemes preformation portfolio characteristics are described and commented. Next, for all three strategies, postformation performance will be reported and analysed.

5.1. Preformation Portfolio Characteristics

5.1.1. Preformation portfolio characteristics based on volatility spreads

Sample stocks have been sorted into quintiles. Each group is formed according to the volatility spread or price to moving average ratio, which a given stock experienced on Friday. Portfolios are always sorted on Fridays – whenever Friday happens to be a non-trading day, the trade will take place the day before. That occurs 8 times within the sample period of 5 years and does not impact the results in any significant way. Returns are measured as non-annualized holding period returns i.e. a 4-week alpha 1% means the portfolio generated 1% alpha return over the duration of 4 weeks. Overlapping observations are used when holding period return exceeds one week. As presented in chapter IV, the returns are strongly auto-correlated, thus strategies should be expected to yield similar results despite the time horizon. In order to correct for the autocorrelation, Newey West standard errors are used. We use standard setup for Newey West standard errors available in MatLab, which automatically selects optimal lag length contingent on plug-in procedure[3]. Further, the sample size is large enough to assume normal distribution. Consequently, value of 1.96 will be used as the cut-off value for statistical significance, corresponding to a 95% confidence level. These significance criteria will be applied throughout the entire thesis. Size of data varies, as only option pairs with valid volatility spread in a given week are included. The five weekly-rebalanced portfolios comprise of approximately 300 different stocks in each, representing a large sample and thus less prone to individual extreme observations within the data (outliers). Portfolio returns presented here are computed in the week prior to portfolio formation.

[3] https://se.mathworks.com/matlabcentral/fileexchange/41275-newey-west-standard-errors

Table 10. Portfolios based on volatility spread – period preceding investment

Table 10 presents the characteristics and performance of the five-quintile portfolios formed from the three S&P indexes based on the volatility spread. Stocks are sorted into portfolios based on the open interest-weighted average of the option-implied volatility spread between calls and puts, a given listed company experienced last Friday. Panel A shows average market capitalization of stocks in a given portfolio and its standard deviation as well as average loadings of the portfolios' returns measured 1-week before portfolio formation regressed against the Fama French factors (1993) and Carhart momentum factor (1997). Panel B shows the performance of the portfolios in the period of 1 and 4-weeks preceding the investment, measured from previous Friday close to current Friday close. Table reports average and excessive portfolio returns and statistical significance of the excessive return indicating whether the alpha value is statistically robust. All returns are value-weighted, holding period return is measured over either 1 or 4 weeks. Returns are expressed as percentages and are not annualized. Due to use of overlapping observations for the time horizon of 4 weeks, Newey West standard errors are uses to correct for the autocorrelation.

	Volatility spread portfolio quintiles				
	Low VS (1)	(2)	(3)	(4)	High VS (5)
Panel A. Characteristics					
Market cap mean	5,671.25	11,304.19	12,027.83	11,815.01	7,751.26
Market cap standard dev.	3,485.02	5,022.59	4,682.07	4,644.03	3,965.89
Beta	1.06	0.98	0.97	0.98	1.08
SMB	0.14	-0.02	-0.12	0.01	0.07
HML	0.13	0.11	0.06	0.07	0.15
MOM	-0.09	-0.05	-0.02	-0.02	-0.06
Panel B. Performance	**1 week before portfolio formation**				
Mean return	0.77%	0.43%	0.22%	0.01%	-0.40%
3-Factor Alpha	0.52%	0.19%	-0.01%	-0.22%	-0.66%
t-stat	11.30	6.48	-0.48	-5.05	-14.63
4-Factor Alpha	0.62%	0.25%	0.01%	-0.20%	-0.59%
t-stat	11.22	6.93	0.38	-3.58	-10.73
	4 weeks before portfolio formation				
Mean return	1.67%	1.24%	0.76%	0.44%	-0.17%
3-Factor Alpha	0.88%	0.51%	-0.03%	-0.46%	-1.05%
t-stat	1.93	1.15	-0.06	-0.96	-1.97
4-Factor Alpha	1.17%	0.73%	0.16%	-0.12%	-0.53%
t-stat	2.02	1.29	0.29	-0.20	-0.79

Results presented in table 10 panel A indicate the lowest mean market capitalization and highest standard deviation (relative to mean) is experienced in the extreme quintiles. On average these quintiles are 40% smaller than their peers located in the middle. This is in line with the expectation that principally small stocks, which are less liquid, have higher transaction costs and information risk, experience large put-call parity deviations. Portfolio preformation returns are measured against the three Fama French factors and the Carhart Momentum factor. The data for the risk factors were obtained from the Dartmouth's website[4]. Market betas vary from 0.97 to 1.08 indicating market risk in line with the overall market. However, systematic market risk is highest in the extreme quintiles, which record betas of 1.06 and 1.08. This is as expected due to higher volatility experienced in the extremes. SMB factors have positive loadings on 1st, 4th and 5th quintile portfolios, again in line with the hypothesis that extreme portfolios comprise of small stocks and in line with the original results

[4] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research

presented by Fama and French. Looking at the third factor, HML, all quintiles seem to have a positive loading, reflecting outperformance of value stocks over growth ones. All loadings on momentum factor are negative, and once again the most extreme factor loadings are seen in the 1st and 5th quintile portfolios. That indicates that alpha returns presented here do not originate from the momentum factor.

Panel B describes performance of the portfolio quintiles one and four weeks preceding the portfolio formation. One week before making the investment, both mean and alphas are monotonically decreasing from 1st to 5th portfolio quintile, varying from 0.77% to -0.40% and 0.52% to -0.66% for 1 or 4-week holding period, respectively. The abnormal return is statistically significant across all quintiles except from the 3rd portfolio quintile on 1-week time horizon. Four of five quintiles recorded positive average returns, indicating an overall appreciation of the stock prices. Similar to Cremers and Weinbaum (2010), this strategy turns out to be contrarian. Consequently, the strategy takes a long position in stocks underperforming the market (5th quintile), which on average underperformed the market by 66 and 59 bps across one week, controlling for Fama French 3-factor model and Carhart 4-factor model, respectively. Likewise, it shorts stocks outperforming the market (1st quintile), which on average outperformed the market by 52 and 62 bps over one week controlling for Fama French 3-factor model and Carhart 4-factor model, respectively. Over the four-week horizon, excessive returns in vast majority of portfolios are not statistically significant, indicating that portfolios performance by large are in line with the overall market. However, the decreasing trend in mean return and alpha from 1st to 5th quintile is preserved. Mean return ranges from 1.67% to -0.17%, while abnormal return varies from 0.88% to -1.05% (3-factor alpha) and 1.17% to -0.53% (4-factor alpha) in the extreme portfolios. Because of the monotonic decrease in mean return from 1st to 5th portfolio, the strategy effectively bets on a mean-reversal the week following portfolio formation. Therefore, it is interesting to explore to what extent alphas are simply derived from momentum risk exposure, which will be assessed in the post formation section.

Relative to Cremers' findings, mean quintile size is larger, which is a result of the overall stock appreciation compared to stock prices measured in 1996-2005, this might also indicate portfolio quintiles will have a relatively higher stock liquidity. Cremers and Weinbaum's (2010) preformation characteristics are on average less positive and more negative compared to this thesis, which might be caused by the time period used by the authors encompasses the burst of the internet bubble, leading to equity price losses while our time period almost exclusively comprises of an economic expansion.

5.1.2. Preformation portfolio characteristics based on price to moving average ratio

After having looked at the overall picture of the price to moving average data in chapter IV, stocks are again sorted into five portfolios based on the price development seen last Friday – whenever that seems to be a non-trading day portfolios will be formed on Thursdays. Whenever data is missing, the 5-day calculation period will comprise of whatever data is available. Weekly quintile portfolios consist of approximately 300 stocks, which should provide a wide range of different industries and other characteristics within the quintiles themselves and make them less sensitive to individual extreme observations (outliers).

Table 11. Portfolios based on price to moving average ratio – period preceding investment

Table 11 presents characteristics and performance of portfolios formed on price to moving average ratio. Stocks are sorted into portfolios every Friday, based on price to moving average ratio recorded throughout that week. Panel A reflects average market capitalization of stocks within each portfolio quintile and standard deviation. Moreover, it presents loadings of the portfolio preformation returns measured 1 week before portfolio formation regressed against Fama French 3-factor model (1993) and Carhart momentum factor (1997). Panel B describes characteristics of the portfolios 1 and 4 weeks before the investment took place, it comprises mean and excessive returns as well as the statistical significance of the excessive returns to ensure the outperformance is statistically robust. All returns are value-weighted, holding period return is measured over either 1 to 4 weeks Returns are expressed as percentages and not annualized. Due to use of overlapping observations for the time horizon of 4 weeks, Newey West standard errors are uses to correct for the autocorrelation.

	PMA portfolio quintiles				
	Low PMA ratio (1)	(2)	(3)	(4)	High PMA ratio (5)
Panel A. Characteristics					
Market cap mean	7,847.86	10,590.86	11,162.07	10,362.62	7,386.00
Market cap standard dev.	3,086.13	2,752.80	2,089.30	2,821.70	2,992.43
Beta	1.05	1.01	0.97	0.99	1.06
SMB	0.58	0.34	0.27	0.29	0.40
HML	0.13	0.12	0.14	0.17	0.16
MOM	-0.03	0.02	0.01	0.00	-0.08
Panel B. Performance	**1 week before portfolio formation**				
Mean return	-3.57%	-1.05%	0.22%	1.49%	4.04%
3-Factor Alpha	-3.80%	-1.28%	0.00%	1.26%	3.80%
t-stat	-59.61	-43.93	-0.15	38.03	57.15
4-Factor Alpha	-3.77%	-1.30%	-0.02%	1.26%	3.90%
t-stat	-47.69	-36.10	-0.57	30.66	47.53
	4 weeks before portfolio formation				
Mean return	-3.26%	-0.43%	0.86%	2.09%	4.70%
3-Factor Alpha	-4.14%	-1.25%	0.02%	1.27%	3.85%
t-stat	-7.41	-2.61	0.05	2.68	8.24
4-Factor Alpha	-4.08%	-1.09%	0.32%	1.54%	4.33%
t-stat	-5.74	-0.01	0.58	2.57	7.36

Looking at the portfolio characteristics in table 11 panel A, it can be noted again that average market capitalization of the extreme quintiles is significantly lower (roughly 30%) than their middle peers and the standard deviation is also relatively higher than rest of the quintiles. As the investment strategy is taking a long position in past "loser" stocks in quintile 1 while shorting old winners in quintile 5, it will be focused on investments in smaller companies and thereby probably also less liquid stocks. Compared to L. J. Hong (2013), stocks included in our quintile portfolios have on average higher market capitalization, also due to choice of time period as his time period encompasses full business cycle around the global financial crisis.

Fama French beta factor loadings show that portfolio returns are in line with average market return, with betas ranging from 0.97 to 1.06. As the amount of stocks in each quintile is large, it should make the portfolio not too different from the overall market composition and less prone to individual stock or industry shocks, thereby in line with expectations. The largest SMB factor loadings are seen at the two extremes, 1st and 5th quintile. These quintiles are, on average, 30% smaller than their middle peers, they have higher volatility thus higher betas, which solidify the conclusion that smaller stocks tend to decrease and increase in value in a more extreme manner than larger stocks. Finally, loadings on the HML factor are not as distinctive distributed across the portfolios as the other factors are. It ranges from the 0.12 to 0.17 with largest loadings on 4th and 5th quintile and lowest loadings on 1st and 2nd quintile. Momentum loading is positive in all quintiles, except from the extreme ones, in general hovering around zero and thereby not accounting for explanation of large part of the return. Furthermore, it is notable that stocks in the 1st and 5th quintiles are, in generally, more explained by common Fama French risk factors (i.e. higher loadings) compared to the same quintiles on the volatility spread data.

Panel B presents statistics of the portfolio performance 1 and 4 weeks preceding portfolio formation. Overall the market has been bullish as most quintiles shows positive returns, the best performing stocks recording higher gains than the losses of worst performing stocks. Mean returns varies between -3.57% to 4.04% and -3.26% to 4.70% within 1 and 4 weeks' time horizon, respectively. As a natural consequence of the sorting mechanism, mean returns are monotonically increasing from 1st to the 5th quintile portfolio. The best performing stocks, located in quintile 5, recorded an excessive return of 3.80% (3-factor alpha) and 3.90% (4-factor alpha) in the time horizon of 1 week as well as 3.85% (3-factor alpha) and 4.33% (4-factor alpha) after 4 weeks. All alphas are strongly statistically significant. Negative excessive return of -3.80% (3-factor alpha) and -3.77% (4-factor alpha) has been observed in the 1st quintile across 1 week as well as -4.14% (3-factor alpha) and -4.08% (4-factor alpha) across 4 weeks investment horizon - once again, these figures are statistically significant. Excessive return of the 3rd quintile portfolios in 1 week holding period and the 3rd as well as 2nd quintile portfolio based on 4 factors in 4 weeks holding period are not statistically significant, indicating that these portfolios performed in line with the market.

5.2. Post-formation performance

5.2.1. Post-formation performance of portfolios based on volatility spreads

The portfolio performance analysis continues with an assessment of performance subsequent to implementing the investment strategy based on volatility spreads. The 5th quintile marks stocks with the highest estimated option volatility spread while the 1st quintile consists of the portfolio of stocks with the lowest estimated option-implied volatility spread. The hedge portfolio longs high option volatility spread stock, while shorting low option volatility spread stocks, thus the hedge portfolio is calculated as if an investor took a long position in the 5th quintile portfolio while shorting the 1st quintile portfolio, making it a zero net investment portfolio.

Table 12. Portfolio formed on volatility spreads – post-investment period

Table 12 denotes characteristics and average performance of the portfolios formed on volatility spreads. Stocks are sorted into portfolios on Friday and their returns are measured from Friday close until next Friday close. Panel A reports the loadings on the Carhart 4-factor model measured one week after the portfolio formation. In panel B, portfolio performance subsequent to portfolio formation is measured. Hedge portfolio returns are reported as returns on a zero investment portfolio, which is longing stocks with the highest volatility spread and shorting stocks with the lowest volatility spreads. All returns are value-weighted, holding period return are measured over either 1 to 4 weeks and controlled for the Fama French 3 factors (1993) as well as these combined with Carhart momentum factor (1997) to make sure well-known anomalies do not cause the presence and significance of the abnormal return discovered. Returns are expressed as percentages and are not annualized. The analysis encompasses mean and excessive returns as well as significance of the excessive returns. Due to use of overlapping observations for the time horizon of 4 weeks, Newey West standard errors are used to correct for the autocorrelation.

	Volatility Spread Quintile Portfolios					Hedge Portfolio
	Low VS				High VS	
Panel A. Characteristics	(1)	(2)	(3)	(4)	(5)	(5)-(1)
Beta	-0.15	-0.15	-0.16	-0.17	-0.15	0.00
SMB	0.19	0.13	0.18	0.14	0.13	-0.06
HML	0.21	0.14	0.09	0.07	0.18	-0.04
MOM	-0.10	-0.05	-0.10	-0.10	0.11	-0.01
Panel B. Performance	**1 week after portfolio formation**					
Mean return	0.08%	0.18%	0.22%	0.25%	0.25%	0.18%
3-Factor Alpha	0.13%	0.22%	0.27%	0.30%	0.30%	0.17%
t-stat	0.90	1.71	2.11	2.22	2.07	2.82
4-Factor Alpha	0.24%	0.28%	0.38%	0.41%	0.43%	0.19%
t-stat	1.35	1.73	2.42	2.49	2.36	2.45
	4 weeks after portfolio formation					
Mean return	0.45%	0.79%	0.60%	0.64%	1.19%	0.74%
3-Factor Alpha	0.64%	0.99%	0.73%	0.77%	1.37%	0.73%
t-stat	1.15	1.98	1.44	1.48	2.45	4.01
4-Factor Alpha	0.79%	1.06%	0.94%	1.16%	1.51%	0.73%
t-stat	1.07	1.59	1.39	1.69	2.06	2.79

Results presented in panel A table 12 show that the strategy has negative exposure to the market, giving investor insurance against negative market developments. Hedge portfolio's beta is equal to 0, indicating that this portfolio is fully market risk neutral. All loadings on SMB and HML are positive indicating outperformance of small and value stocks, which is in line with expectations as stated previously in the preformation section. However, this does not hold in the hedge portfolio, due to higher loading in quintile 1 than in quintile 5. Finally, factor loading on momentum is negative across all quintiles except from the 5th one, pointing to the return reversal phenomenon holding at least across the 1 week time horizon.

Panel B indicates that the vast majority of individual quintile portfolios experiences excessive returns that are not statistically significant. Over a 1 and 4 week horizon, mean returns increase gradually from 1st to 5th quintile, which is in line with theoretical expectation, as the highest volatility spread caused by relatively high call prices translates to the equity markets in the nearest future leading to stock price gains and the lowest volatility spread, being a result of relatively low put prices, also conveys to the equity markets within short time frame. The highest holding period return is recorded across the 4-week investment horizon, indicating the strategy continues to accrue returns over time.

The hedge portfolio is able to earn a statistically significant abnormal return across all time horizons. This is in line with the argument that the option markets lead equity price movements due to a number of benefits they provide e.g. attracting informed investors to trade leading to occurrence of price pressures showing in the deviations from put-call parity. Thereby, the option-implied volatility spread is an important forward-looking indicator of movements in the equity markets. The hedge portfolio is able to earn 19 bps abnormal 4-factor return, on average, rebalancing weekly and 73 bps across a holding period of 4 weeks, indicating that ca. 25% of the 4-week return is generated in the first week, indicating a linear accrual of returns across time. As the returns seem to display no signs of reversal during the 4-week period after the initial investment, profits seem to originate from information rather than explicit short-term price pressures, as these should only be observed shortly after the trade. This could be an effect of option traders effort to remain delta neutral i.e. as they purchase put option (negative delta), the trader will purchase the underlying (positive delta) to remain delta neutral, thereby diminishing the price pressure, as pointed out by Cremers and Weinbaum (2010).

As the strategy is a bet on the negative and positive price pressures from option markets translating to similar movements in the stock market, returns obtained might be largely driven by momentum. Our analysis encompasses additionally Carhart 4-factor alpha. The 4-factor alpha is bigger than 3-factor alpha in all of the single portfolio quintiles across both time horizons, signalling that momentum factor does not contribute positively to the mean returns yielded in that period and confirms a phenomenon of return reversal taking place across the very-short run. Moreover, the significance of abnormal returns is preserved across all the quintiles except from 2nd quintile portfolio on a 4-week investment horizon.

The strategy presented in this chapter yields sustainable abnormal profits – however, it is only an indirect way of trading on deviations from put-call parity. As mentioned in chapter III (theory section), there are a number of reasons why trading directly on it might not be profitable. It includes difficulties of trading exact amounts implied by the arbitrage condition or limitations to short-selling (addressed shortly below). Moreover, an arbitrage opportunity might simply be an illusion due to non-synchronicity of stock and option markets (which will be explored in chapter VI).

Relative to Cremers & Weinbaum (2010) our hedge portfolio 4-factor abnormal return is 2 bps lower across 1-week investment horizon, but 22 bps higher when looking at the 4-week horizon. Outperformance of our long term returns over theirs might be because our sample does not include a number of smaller stocks, included by Cremers & Weinbaum (2010). For smaller stocks, due to elevated liquidity risk, the translation of the option market price pressures to the equity markets might take longer time, and thereby it may, on average, be less effective strategy when holding periods near 1 month. Returns are not driven by short-sale constraints, as it is the long arm of the portfolio, which generates returns in the hedge portfolio (4-factor alpha of 43 bps vs. -24 bps). This is in line with Cremers & Weinbaum (2010), but they find both arms of the portfolio generating the hedge portfolio returns, with the short side only contributing to around 1/3 of total return. However, Cremers & Weinbaum (2010) utilizes a shorter sample of data for which they have rebate rates, a proxy for difficulty of short selling the underlying stock from the lenders market, and show that their results are not directly driven by stocks which are difficult to short. Hence, all evidence points to the fact that alpha returns are not driven by short-sale restrictions.

5.2.2. Post-formation performance of portfolios based on price to moving average ratio

Subsequent to the analysis of portfolio performance preceding the investment, a similar analysis is conducted on the PMA portfolio performance after the investment. First quintile portfolio marks "loser" stocks, which have performed poorly the recent five days, while the fifth quintile represents stocks with the highest returns observed the last 5 days – so called "winners". Following Lehmann (1988), it is believed there exists short-term reversal in the stock price path due to temporary lack of liquidity or simple small correction, the strategy presented here is contrarian. The hedge portfolio is a bet on a reversal of the trends, where an investor buying the 1st quintile portfolio, consisting of past losers, and shorting the 5th quintile portfolio, consisting of past winners, will be able to earn excessive return, provided the current trends do not continue in the investment period.

Table 13. Portfolio formed on price to moving average ratio – post-investment period

Table 13 describes the performance of the portfolios formed on price to moving average ratio. Stocks are sorted into portfolios every Friday based on the price developments experienced throughout the week. Panel A reports basic portfolio return characteristics consisting of loadings on the Carhart 4-factor model measured 1-week after the portfolio formation. Panel B reports the performance of quintile portfolios subsequent to the formation. Hedge portfolio returns are reported as returns on a strategy of forming portfolios going long on stocks with highest losses experienced the prior five trading days and short on stocks with highest gains recorded in the past five trading days. Returns are value-weighted and measured throughout an investment period of 1 and 4 weeks. Returns are not annualized, but they are controlled for Fama French 3 factor model (1993) as well as these combined with Carhart momentum factor (1997) to ensure the well-known anomalies do not account for explanation of our abnormal return discovered. The analysis consists of mean and excessive returns as well as the statistical significance of excessive returns. To measure the statistical robustness of the results Newey West standard errors are used to correct for the autocorrelation due to use of overlapping observations across 4-week time horizon.

	PMA Quintile Portfolios					Hedge Portfolio
Panel A. Characteristics	Low PMA ratio (1)	(2)	(3)	(4)	High PMA ratio (5)	(1)-(5)
Beta	-0.17	-0.17	-0.16	-0.15	-0.13	-0.04
SMB	0.27	0.16	0.12	0.15	0.11	0.16
HML	0.28	0.21	0.06	0.07	0.08	0.20
MOM	-0.10	-0.04	-0.07	-0.07	-0.13	0.02
Panel B. Performance	**1 week after portfolio formation**					
Mean return	0.24%	0.23%	0.23%	0.15%	0.07%	0.17%
3-Factor Alpha	0.30%	0.29%	0.27%	0.20%	0.11%	0.19%
t-stat	1.87	2.08	2.11	1.55	0.78	2.08
4-Factor Alpha	0.42%	0.33%	0.35%	0.28%	0.25%	0.17%
t-stat	2.10	1.94	2.21	1.76	1.48	1.46
	4 weeks after portfolio formation					
Mean return	0.97%	0.83%	0.74%	0.79%	0.48%	0.48%
3-Factor Alpha	1.31%	1.07%	0.95%	1.00%	0.67%	0.64%
t-stat	2.26	2.08	1.85	1.78	1.10	1.83
4-Factor Alpha	1.42%	1.19%	1.23%	1.10%	0.96%	0.46%
t-stat	1.95	1.84	1.92	1.55	1.26	1.05

As seen in panel A table 13, all portfolios have negative loadings on beta, giving an investor insurance against negative developments on the stock market. All loadings on SMB and HML factors are positive indicating that value stocks in the hedge portfolio outperform growth stocks and small stocks outperform large stocks, which is in line with expectations and initial findings presented by Fama and French back in 1993. Momentum loading is negative throughout all single portfolios, signalling that the phenomenon of return reversal and not momentum is present in the data. However, returns generated by the hedge portfolio experiences positive MOM factor loading, due to more negative loading in the 5th quintile portfolio. It shows that, on average, 2 bps (1 week) and 18 bps (4 weeks) abnormal return originates from the momentum risk factor.

Panel B shows the mean portfolio returns vary from 0.07% to 0.24%, while 3-factor excessive return ranges from 11 bps to 30 bps within the first week after the investment has been placed. As expected the portfolio consisting of the best performing stocks (5th quintile) perform worst after the investment has been made while the worst performing stocks (1st quintile) now perform best, signalling a price trend reversal. Of the stand-alone portfolios, only the excessive returns in 2nd and 3rd quintile portfolios (rebalanced weekly) are statistically significant at 5% level.

Looking at the hedge portfolio investment strategy shown in table 13, average mean and 3-factor excessive return lies at 17 bps and 19 bps, respectively, within 1 week after the investment has been made. Excessive returns are statistically significant, proving the strategy's ability to generate abnormal returns. This is in line with the argument that temporary lack of liquidity might contribute to temporary price swings and that stock prices are significantly negatively auto-correlated in the very short-term, making contrarian strategies profitable across very short investment horizons. Relative to the results presented by L. J. Hong (2013), our hedge portfolio underperforms results presented by Hong strongly on both time horizons, earning less than a half of the returns yielded by portfolios created by him. As mentioned in Chapter II (Literature review), Chopra et al. (1992) argues that contrarian strategies works better in bearish markets compared to bullish markets. Hence, our underperformance could be due to choice of time period. Hong (2013) utilizes both pre- and post-financial crisis data i.e. covering a full economic cycle, while this thesis only incorporates the general economic expansion since 2011.

Returns of the single quintile portfolios within the 1st week are positive and continue the same positive trend after 4 weeks. The positive returns signal a trend reversal compared to the preformation negative returns in table 11. The returns of the hedge portfolio show that return accrual is more or less linear, like in the case of volatility spread sorting. The strategy is able to earn on average an abnormal 3-factor return of 64 bps across 4 weeks - roughly 3 times - higher than 19 bps earned over a one-week investment. However, excessive return of the hedge portfolio loses its statistical significance when looking at an investment horizon of 4 weeks. This could suggest that a bigger portion of returns across a slightly longer time horizon of 4 weeks can be explained by market factors and momentum.

Our analysis includes also a 4-factor alpha, which is added to examine whether some portion of returns could be explained by momentum trend in stock prices. The 4-factor alpha is in general higher, indicating that momentum factor loading is negative and confirming the theory about trend reversal across very-short investment time horizons. Statistical significance of 4-factor abnormal return seems to be by far preserved also while controlling for the Carhart 4-factor model. Additionally, in untabulated results, changing the PMA window of 5 days to 2, 10 and 15 days results in 4-factor alpha (on weekly rebalancing) of 25 bps (t-stat of 2.15), 10 bps (t-stat of 0.91) and 8 bps (t-stat of 0.61), respectively. It confirms the very short-term nature of the mean-reversal strategy where abnormal profits remain significant only on time horizons spanning up to a few days.

5.2.3. Portfolio formation and performance based on both sorting measures

Finally, postformation portfolio performance analysis on the double sorted portfolios is conducted. First, the sorting is done independently like in the case of the single-sorted portfolios based on two different indicators giving us 5x5 independently standing portfolios. The second sorting excludes all the stocks which have not been assigned to the same quintile based on both measures. Sorting the volatility spread portfolios in ascending order and price to moving average ratio in descending order results in formation of 25 (5x5) portfolios. Only the five diagonal portfolios performance are reported i.e. (1,5), (2,4), (3,3), (4,2), (5,1) and the hedge portfolio (5,1)-(1,5). The short arm of the hedge portfolio consists of quintile (1,5) i.e. the winner stocks with lowest volatility spreads, while the long arm consists of quintile (5,1) i.e. the loser stocks with highest volatility spreads. As the portfolios have been double-sorted according to both backward- and forward-looking measures, it is expected that the hedge portfolio yields higher returns as a consequence of a more calibrated precision of the stock selection for the overall strategy.

Table 14. Portfolio formed on volatility spreads and price moving average

Table 14 describes the performance of portfolios formed on both open interest-weighted option-implied volatility spread and price to moving average ratio. Stocks are sorted into portfolios on Friday based on the volatility spread and price developments experienced throughout the week. Panel A reports basic characteristics of returns, including loading on Carhart 4-factor model measured 1-week after portfolio formation. Panel B presents performance of portfolios after their formation. Returns are value-weighted and reported across an investment horizon of 1 and 4 weeks. The hedge portfolio is an investment consisting of long position in stocks with highest volatility and lowest price to moving average ratio and a short position in stocks with lowest volatility and highest price to moving average ratio. Holding period returns are not annualized, but controlled for the Fama French 3 factor model (1993) as well as these combined with Carhart momentum factor (1997) to ensure that the well-known anomalies do not explain the abnormal returns found. Analysis encompasses mean and excessive returns as well as the statistical significance of the latter. Newey West standard errors are used to correct for the degree of autocorrelation due to use of overlapping observations.

	Double-Sorted Quintile Portfolios					Hedge Portfolio
	Low VS and high PMA ratio				High VS and low PMA ratio	
Panel A. Characteristics	(1,5)	(2,4)	(3,3)	(4,2)	(5,1)	(5,1)-(1,5)
Beta	-0.14	-0.15	-0.15	-0.17	-0.19	-0.05
SMB	0.16	0.10	0.10	0.16	0.25	0.09
HML	0.14	0.17	0.17	0.05	0.37	0.22
MOM	-0.18	-0.04	-0.04	-0.05	-0.16	0.02
Panel B. Performance	**1 week after portfolio formation**					
Mean return	-0.06%	0.08%	0.23%	0.30%	0.31%	0.37%
3-Factor Alpha	-0.02%	0.12%	0.28%	0.34%	0.37%	0.39%
t-stat	-0.10	0.90	2.13	2.36	2.14	3.23
4-Factor Alpha	-0.08%	0.16%	0.33%	0.41%	0.56%	0.64%
t-stat	-0.04	0.95	2.04	2.31	2.55	2.47
	4 weeks after portfolio formation					
Mean return	0.31%	0.71%	0.95%	0.78%	1.73%	1.42%
3-Factor Alpha	0.61%	0.89%	1.09%	0.98%	2.02%	1.41%
t-stat	0.89	1.53	2.20	1.55	2.93	3.47
4-Factor Alpha	0.71%	0.72%	1.46%	1.26%	2.23%	1.51%
t-stat	0.82	0.99	2.37	1.59	2.56	2.83

Panel A shows the loadings on 4-factor Carhart model the portfolios recorded one week subsequent to portfolio formation. Results presented here, in general, align with the results of the single-sorted portfolio quintiles. Market beta is once again negative across all of the portfolios, pointing to the fact that portfolios offer an insurance against market developments. All factors on SML and HML are positive, indicating that as expected small and value stocks performed better than large and growth stocks in the quintile portfolios. Momentum factor loading is negative, confirming the expectation of return reversal and not momentum phenomenon being observed across very short-time periods.

Panel B shows that mean returns in single portfolio quintiles vary from -6 bps to 173 bps while the 3-factor abnormal returns range from -2 bps (t-statistic of -0.10) to 202 bps (t-statistic of 2.93). Half of the abnormal returns in the single portfolio quintiles are not statistically significant at 5% level. Hedge portfolio value-weighted mean return ranges from 37 bps to 142 bps. Mean returns are, in general, higher across all time periods relative to the single-sorted hedge portfolios, indicating an improvement in stock selection due to the employed strategy. The hedge portfolio generates 64 bps (t-statistic of 2.37) value-weighted 4-factor alpha after 1 week and 151 bps (t-statistic of 2.83) after 4 weeks. This indicates that the portfolio returns in the strategy of double-sorting accrue strongly in the first week, but also roughly in a linear manner. Using a simple equal weighted portfolio allocation strategy returns similar results as the value weighted scheme currently employed. The excessive return using double-sorting are outperforming single-sorting on PMA and VS across all time horizons. It is also noted that the return structure of the combined strategy seems not to be additive compared to the individual strategies. The combined strategy yields a 4-factor alpha of 64 bps, which is significantly higher than the sum of the weekly individual alphas of 36 bps (19 bps + 17 bps). Same holds on a 4-week basis, where the combined strategy yields 151 bps, compared to the sum of the individual ones of 119 bps (73 bps + 46 bps). Relative to Cremers and Weinbaum's double sorting, this strategy outperforms the excessive returns in 1-week horizon and 4-week horizon. One explanation for this difference could be that in contrast to Cremers & Weinbaum (2010) the data period used in the thesis does not encompass a full business cycle, but only economic recovery. Their sample period goes from 1996-2005, starting with a period of economic boom, passing through a slowdown and recession due to the dot.com crisis and finally finishing at the following economic recovery.

Furthermore, due to the negative correlation between volatility spreads and price to moving average ratio, the hedge portfolio comprise, on average, only of 89 stocks traded on the long side and 93 on the short side, which is a decline of around three quarters compared to the single-sorted portfolios. Thereby, results are less likely to be simply an outcome achieved due to the use of a large sample size, inflating the overall statistical significance observed in the data. It also makes the practical relevance of the strategy higher, since in reality investors are only able to trade a limited number of stocks and excessive returns found through large sample sizes might not be able to be exploited by arbitrageurs through smaller sample sizes as pointed out by Lesmond & Wang (2006).

The impact of momentum factor can also be deducted from the differences between 3 and 4 factor alphas. The abnormal return measured against 4-factors is generally higher than the one measured against 3-factors, indicating the loading on momentum factor is negative and gives support to the phenomenon of return reversal in very short-term.

Alike the volatility-spread individual trading scheme, performance doesn't originate from short-sale restrictions. The dominating fraction of returns is by far generated by the long arm of the portfolio (37 bps vs. 2 bps in 3-factor alpha or 56 bps vs. 8 bps in 4-factor alpha), in weekly rebalancing. Both abnormal and mean returns of the hedge portfolio seem to be growing across time horizons, indicating trend continuation on which the investment strategies are based on.

5.4 Portfolio Performance Conclusion

The purpose of this chapter was to establish to what extent abnormal profits could have been achieved in the period 2011 until and including 2015 using predictive signals embedded in listed companies open interest-weighted option-implied volatility spread and their price to moving average ratio. In the preformation analysis, it was determined that 1st and 5th quintiles of both the volatility spread and price to moving average ratio comprised of smaller stocks. All these companies underperformed the market in the week preceding the investment. It was demonstrated that using the volatility spread measure, an average 4-factor abnormal return of 19 bps (t-stat of 2.45) and 73 bps (t-stat of 2.79) over a holding period of one and four weeks were achieved respectively. Because returns were mostly generated in the long arm of the portfolios, doubts that portfolio returns originated from sort-sale restrictions were mitigated. Using the price to moving average measure, the hedge portfolio were able to earn on average a Carhart 4-factor risk-adjusted value-weighted abnormal return of 17 bps (t-stat of 1.46) and 46 bps (t-stat of 1.05) across 1 and 4 weeks respectively. Using the predictive measures in conjunction turned out to significantly increase the 4-factor alphas on both a 1 and 4-weeks' time horizon. Strategy based on double sorting yielded on average Carhart 4-factor risk-adjusted value-weighted abnormal return of 64 bps (t-stat of 2.47) and 151 bps (t-stat of 2.83) over 1 and 4 weeks respectively.

VI. Robustness to other factors

The abnormal returns of the contrarian strategy proposed in chapter V is able to generate stand in contrast with the efficient market hypothesis and stock prices following a random walk. In order to make the conclusions more vigorous and compelling, this section conducts a profound threefold robustness analysis. First, this chapter features Fama Macbeth Regressions - a method used for determining parameters for asset pricing models. This method will equip us with associated risk premiums to the sorting mechanism and thus compliment the time-series approach laid out in chapter V. Second, the original strategy will be reviewed by excluding the first overnight return, so the portfolio holding period return will encompass Monday open until Friday close to counter intraday effects as well as non-synchronicity between option and stock markets. Finally, this section will explore to what extent option and stock liquidity affects predictive signals and weekly stocks excess returns.

6.1. Fama Macbeth Regressions

Fama Macbeth regression was developed by E. F. Fama & Macbeth (1973), who proved that the market portfolio is efficient and there is a positive trade-off between return and risk. The method has subsequently grown in popularity, being used in a number of scientific papers for purpose of testing the robustness of estimated risk premiums, e.g. by Du & Hu (2012), Pereira & Zhang (2010) and Doukas, Kim, & Pantzalis (2010). This paper will employ the methodology to further understand if the volatility spread and price to moving average ratio allocations are truly associated with additional return i.e. positive risk premium.

Weekly individual stock excess returns are regressed on quintile dummy variables and control variables, which consists of the 3-factor Fama French model as well as the Carhart momentum factor. Next, factor betas are regressed on the weekly excess return in the cross section and factor risk premiums comprising the average of these cross section loadings following what was laid out in Chapter 4 (Methodology). It is not possible to draw direct comparisons between results presented here and the analysis of quintile portfolio performance in chapter V as returns measured in cross-sectional regressions are equal-weighted in contrast to the value-weighted presented in chapter V.

Table 15. Fama-Macbeth Regression – on groups

Table 15 describes the results of Fama-Macbeth regressions where weekly stock excess returns are regressed against volatility spread, price to moving average, dummy variables and controls. Stocks are sorted into quintiles every Friday. Returns are measured on a weekly, non-annualized basis and controlled for Fama-French 3 factors and Carhart momentum factor to ensure that the well-known anomalies do not explain the effects found. Regressions show the results of pooled panel regressions of stock returns on the created quintile dummy variables. Just like before, Q1 denotes low volatility spread or low price to moving average ratio, while Q5 stands for the opposite. Returns are converted to percentages and measured without ignoring the first overnight return allowing direct comparison to chapter 5. T-statistics for each coefficient is provided in the brackets.

Independent variables	Volatility Spread	Price to moving average ratio
Intercept	0.21%	0.20%
	(1.63)	(1.65)
Dummy Q1	-0.16%	0.14%
	(-0.76)	(0.83)
Dummy Q2	0.10%	-0.13%
	(0.62)	(-0.70)
Dummy Q4	0.19%	0.08%
	(1.82)	(0.70)
Dummy Q5	0.06%	-0.16%
	(0.48)	(-0.96)
R square	5.17%	5.30%

Table 15 shows the dummy coefficients created for the groups based on volatility spread are statistically insignificant, implying no difference between the dummy allocations, hence no statistical importance of the sorting. The abnormal 4-factor return obtained by the hedge portfolio formed on volatility spread can be measured as the difference between 5th and 1st quintile i.e. 22 bps, yet the alpha is not significant. The alpha of 22 bps is larger than the 19 bps obtained in table 12, but returns in table 12 are also value-weighted.

Alike volatility spread dummy variables, PMA dummy variables are also statistically insignificant. Returns of the hedge portfolio can be inferred by the difference between 1st and 5th quintile, which implies an abnormal 4-factor return of 29 bps on weekly basis. However, the difference is not statistically significant. Nevertheless, a return of 29 bps is a large improvement compared to positive abnormal return of 17 basis points measured previously on value-weighted basis in table 13. The discrepancy is driven by different ways of weighted the returns as these are equal weighted i.e. smaller stocks experiencing larger deviations would have equal weight as the larger stocks.

Subsequently, to investigate how the numerical values of volatility spread and price to moving average impacts weekly stock excess returns as well as to what extent the forward-looking measure is complimented by the backward-looking measure in predicting returns, additional cross sectional regressions are used.

Table 16. Fama-Macbeth Regression – on sorting measures

Table 15 describes the results of Fama-Macbeth regressions, where stocks are not sorted into groups. Weekly excess returns are regressed against individual volatility spreads and price to moving average ratio as well as its interaction. Returns are measured on a weekly, equal-weighted basis and controlled for Fama-French 3 factors (1993) and Carhart momentum factor (1997) to ensure that the well-known anomalies do not explain the effects found. Returns are non-annualized, converted to percentages and measured without ignoring the first overnight return allowing direct comparison to chapter 5. T-statistics for each coefficient is provided in brackets.

Independent variables	Volatility Spread	Price to moving average ratio	Both measures	Both measures and its interaction
Intercept	0.18%	0.19%	0.18%	0.20%
	(1.98)	(1.99)	(1.97)	(1.64)
Volatility Spread	0.22%		0.21%	0.09%
	(1.23)		(1.13)	(1.05)
Price to moving average ratio		-0.07%	-0.07%	0.02%
		(-0.53)	(-0.60)	(0.20)
Volatility Spread * Price to moving average ratio				0.09%
				(1.06)
R square	4.56%	4.88%	4.92%	4.98%

Results presented in table 16 confirm previous findings shown in table 15. All coefficients, except the intercepts, are statistically insignificant, thus they have no predictive power. Column 1 and 2 presents coefficients of individual measures of volatility spread and price to moving ratio which lie at 22 and -7 bps, respectively. Column 3 reports regressions with both volatility spread and price to moving average ratio included, coefficients are by large preserved (compared to column 1 and 2) and equal to 21 and -7 bps, respectively. Finally, column 4 illustrates the regression including both individual measures and the interaction between volatility spread and price to moving average. Once again, all coefficients are not statistically significant. Although the coefficient on the interaction term between volatility spread and price to moving average ratio is positive and equal to 9 bps, as it lacks significance, it cannot be concluded that the two measures complement each other in predicting weekly excess returns.

Compared to previous literature, a longer time horizon is usually used in estimation of the Fama Macbeth regressions. Cremers and Weinbaum utilize a 10-year horizon, while we use a 5-year horizon. It might be the case that significance is derived from higher number of observations as their number of 1-week returns amounts to approximately 520 where ours is 260 across the time horizon.

6.2. Non-synchronicity bias and intraday effects

Because option markets close at 4:02 EST and stock markets close at 4:00 EST, a non-synchronicity bias may arise causing researchers to find deviations from the put-call parity, where none exist. The phenomenon has been documented by Battalio & Schultz (2006). In order to investigate the impact this bias may have on returns, the adjustment proposed by Cremers & Weinbaum (2010) is followed. This entails that implied volatilities are calculated at 4:02 EST, but returns begin accruing on the market opening the following day, meaning that the returns will accumulate in the period Monday open - Friday close.

This intraday effect was documented already in 1980s by among others: French (1980), Harris (1986) and Smirlock & Starks (1986). According to evidence based on transaction data, large firms were recording negative close-to-open returns between Friday close and Monday open prices, while for small companies, negative returns were accumulating throughout the whole Monday trading day, both pointing to market inefficiencies. Harris (1986) also uncovered that the first 45 minutes upon market opening is decisive for the differences in weekday returns with the prices rising the first 45 minutes all days except from Mondays. Negative Monday opening returns have been confirmed by French (1980) and Smirlock & Starks (1986). One of the explanations put forward for the existence of this phenomenon is investor inattention to news happening on Fridays, delaying incorporation of the news into stock prices, which has been proven to be the case for both merger and earnings announcements, according to Dellavigna & Pollet (2009) and Louis & Sun (2010).

Furthermore, Kudryavtsev (2013) (2014) has been able to prove that opening prices tend to rise if stocks had a relatively high opening return and relatively low open-to-close return the day before. The anomaly of the opening and closing prices has been proven to be effective in portfolio formation based on both S&P 500 and Dow Jones Industrial Index, yielding abnormal returns on a strategy where investors long stocks with high expected opening returns and short stocks with low expected opening returns.

Mispricing of stocks at market open is also connected with a size and illiquidity premia that investors demand within the last half an hour of market trading, as liquidity level on the market deteriorates towards market closure. Another explanation of the extraordinary trade pressure at market open, is that investors trade on the news announced outside of trading hours, as indicated by Bogousslavsky (2016). The intraday liquidity jumps are related to both macroeconomic as well as firm specific news, as proven by Ghys, Boudt, & Mikael (2010).

Returns of the strategies presented in chapter V are measured from previous Friday close to current Friday close. Such an investment strategy relies on the academic assumption that when observing a given trade signal, the trader is able to execute the trade instantly, which may not represent a realistic picture of the strategy's profitability. In the real world, executing a trading strategy, in an economical way, is not possible when financial markets are closed, and it is essential to backtest an investment strategy using realistic assumptions where there exists a time lag – as the trade signals based on Friday close data are used, it will first be allowed to execute the trade on the Monday following the measurement.

6.2.1. Post-formation portfolio performance

6.2.1.1. Post-formation portfolio performance based on volatility spread

The analysis investigates the impact of non-synchronicity bias and intraday effect on returns generated in the three strategies. Similar to chapter V, the analysis starts with investigating returns based on volatility spread, 5^{th} quintile portfolio consists of stocks with high option-implied volatility spread while 1^{st} quintile portfolio includes stocks with low option-implied volatility spread.

Table 17. Portfolio formed on Volatility Spreads – post-investment period

Table 17 presents the performance of the portfolios in the period subsequent to portfolio formation. Stocks are sorted into quintiles based on the volatility spread experienced last Friday, but accrual of returns begins only on Monday market opening price and runs until Friday market close. Returns are value-weighted, measured across time horizons varying from 1 to 4 weeks and are not annualized. The hedge portfolio consists of a long position in stocks allocated to the 5^{th} quintile and a short position in stocks allocated to the 1^{st} quintile. All reported excessive returns are measured controlling for the Fama French 3 factors (1993) and Carhart momentum factor (1997). Both mean and excessive returns as well as the statistical significance of the abnormal returns are computed. To correct for degree of auto-correlation due to use of overlapping observations, Newey West standard errors are used.

	Volatility Spread Quintile Portfolios					Hedge Portfolio
	Low VS (1)	(2)	(3)	(4)	High VS (5)	(5)-(1)
Portfolio performance	**1 week after portfolio formation**					
Mean return	0.06%	0.10%	0.13%	0.12%	0.11%	0.05%
3-Factor Alpha	0.09%	0.12%	0.16%	0.15%	0.14%	0.05%
t-stat	0.81	1.27	1.69	1.45	1.28	1.44
4-Factor Alpha	0.13%	0.14%	0.20%	0.20%	0.20%	0.07%
t-stat	0.97	1.16	1.68	1.55	1.41	1.39
	4 weeks after portfolio formation					
Mean return	0.73%	0.94%	0.83%	0.84%	1.35%	0.61%
3-Factor Alpha	0.61%	1.07%	0.91%	0.94%	1.46%	0.84%
t-stat	1.55	2.30	1.90	1.92	2.70	3.20
4-Factor Alpha	0.66%	0.80%	0.69%	0.80%	1.10%	0.44%
t-stat	0.98	1.29	1.10	1.25	1.56	1.75

Mean returns of the hedge portfolio vary from 0.05% (1-week) to 0.61% (4-weeks). All hedge portfolios mean returns are lower than returns measured in table 12. Returns of the single portfolio across 1-week time horizon are also lower relative to returns of the same portfolios measured between previous Friday close to current Friday close. This indicates that returns recorded between Friday market close to Monday market open are on average positive, contrary to Harris' (1986) findings. The 3-factor excessive return of the hedge portfolio ranges from 0.05% (1-week) to 0.84% (4-weeks), which is 12 bps lower and 11 bps higher, respectively, compared to the returns in table

12. Decline in excessive returns across both time horizons is recognized in the 4-factor alphas, which are 12 bps and 29 bps on 1-week and 4-week rebalancing, respectively. Furthermore, all hedge portfolios based solely on the volatility spread in chapter V are statistically significant at the 5% level, but it turns out that buying stocks on Monday morning compared to Friday close leads to a loss of statistical significance of all the hedge portfolios formed on volatility spread except from 3-factor alpha on the 4-week rebalancing.

Thereby, the adjustment in stock prices throughout the weekend effectively decreases the profit investment yields, indicating a reduction in market inefficiencies making it even more difficult to sustainably earn an abnormal profit. This reduction in market efficiency is consistent with presence of arbitrageurs exploiting the deviations from put-call parity as soon as they occur. The fact that the Friday-Monday overnight return is positive means there is no reversal of the returns, indicating that the effect is driven mostly by insider information and not the price pressures occurring due to ongoing hedging activities in the option markets.

The role of intraday effects in the investment strategy based on volatility spreads is significant. The adjustment does seem to have a negative impact on the hedge portfolios' alphas. Additionally, vast majority of returns is no longer significant on a 5% level, which was not the case in table 12.

6.2.1.2. Post-formation portfolio performance based on price to moving average ratio

Turning to the impact on the PMA strategy: like chapter V, 1st quintile consists of worst performing stocks while 5th quintile constitutes best performing stocks.

Table 18. Portfolio formed on price moving average – post-investment period

Table 18 presents the performance of the portfolios subsequent to the portfolio formation. Stocks are sorted into portfolios on Friday, but returns start first accumulating from Monday opening, ignoring the first overnight return. Returns are value-weighted, non-annualized and controlled for Fama French 3 factors (1993) as well as Carhart momentum factor (1997) and measured across time horizons from 1 to 4 weeks. Performance of hedge portfolio, which is long in low price to moving average ratio and short in high price to moving average ratio, is also shown. Mean and excessive returns as well as the statistical significance of the latter are presented for all quintile portfolios and the hedge portfolio across all time horizons. Newey West standard errors are used to control for the degree of auto-correlation due to use of overlapping observations.

	PMA Quintile Portfolios					Hedge Portfolio
	Low PMA ratio (1)	(2)	(3)	(4)	High PMA ratio (5)	(1)-(5)
Portfolio performance	**1 week after portfolio formation**					
Mean return	0.11%	0.11%	0.15%	0.10%	0.05%	0.06%
3-Factor Alpha	0.13%	0.14%	0.18%	0.14%	0.08%	0.05%
t-stat	1.11	1.39	1.88	1.43	0.76	0.85
4-Factor Alpha	0.20%	0.15%	0.20%	0.15%	0.14%	0.06%
t-stat	1.35	1.18	1.64	1.28	1.04	0.83
	4 weeks after portfolio formation					
Mean return	1.14%	0.95%	1.00%	1.04%	0.78%	0.36%
3-Factor Alpha	1.32%	1.06%	1.09%	1.16%	0.89%	0.43%
t-stat	2.62	2.32	2.38	2.24	1.63	1.58
4-Factor Alpha	1.07%	0.84%	0.92%	0.92%	0.85%	0.22%
t-stat	1.62	1.40	1.52	1.36	1.17	0.58

In table 18, mean and excessive 3-factor alpha portfolio return ranges from 0.05% to 0.15% and 0.08% to 0.18% within the first week, respectively. This is lower compared to previous measurement on prices measured from previous Friday close to current Friday close. Nevertheless, the development confirms the theory of price reversal. It also indicates that overnight returns from Friday to Monday are on average positive. Both mean returns and 3-factor alpha's rise gradually across time horizon in all 5 quintiles – however, 5th quintile 3-factor excessive portfolio return at 4 week horizon is not statistically significant at the 5% level. Hedge portfolio returns are, in general, lower compared to those in table 13. On a weekly basis, the 4-factor value-weighted alpha return is 11 bps lower and on a 4-weekly basis 24 bps lower than the original strategy. None of the abnormal returns in the hedge portfolio is statistically significant, reconfirming result obtained in table 13.

6.2.1.3. Post-formation portfolio performance based on double-sorting

Finally, the impact of changing the investment day is investigated using the double-sorting scheme with preliminary sorting into quintiles based on volatility spreads and price to moving average ratio. The investment strategy based on two trading signals should improve the stock selection progress and lead to higher returns recorded from Monday open price to Friday close price than seen in the previous two individual strategies.

Table 19. Portfolio formed on volatility spreads and price moving average – post-investment period

Table 19 describes the returns of the double-sorted portfolios. Stocks are sorted into portfolios based on volatility spreads and price to moving average ratio every Friday and returns are measured from Monday open to Friday close. Hedge portfolio is constructed as longing stocks experiencing both high option-implied volatility spread and low price to moving average ratio. Returns are value-weighted, non-annualized and measured controlling for Fama French 3 factor model (1993) and Carhart momentum factor (1997) ensuring that the well-known anomalies do not explain the abnormal return discovered. Mean and excessive returns and the significance of the latter are reported. To correct for the auto-correlation created by use of overlapping observations, Newey West standard errors are used.

	Double-Sorted Quintile Portfolios					Hedge Portfolio
	Low VS and high PMA ratio (1,5)	(2,4)	(3,3)	(4,2)	High VS and low PMA ratio (5,1)	(5,1)-(1,5)
Portfolio performance	**1 week after portfolio formation**					
Mean return	-0.01%	0.09%	0.14%	0.12%	0.16%	0.16%
3-Factor Alpha	0.02%	0.12%	0.17%	0.14%	0.19%	0.16%
t-stat	0.17	1.23	1.73	1.44	1.46	2.25
4-Factor Alpha	0.08%	0.11%	0.18%	0.18%	0.26%	0.19%
t-stat	0.51	0.88	1.45	1.42	1.65	2.02
	4 weeks after portfolio formation					
Mean return	0.64%	0.94%	1.13%	0.95%	1.84%	1.20%
3-Factor Alpha	1.20%	1.11%	1.24%	1.08%	1.90%	0.71%
t-stat	1.29	2.14	2.88	1.86	3.07	3.22
4-Factor Alpha	0.61%	0.63%	1.09%	0.86%	1.62%	1.01%
t-stat	0.77	0.93	1.89	1.11	2.03	2.17

Mean return of hedge portfolios ranges from 0.16% (1-week) to 1.20% (4-week) and are relatively lower to the ones measured from previous Friday close to current Friday close, indicating that the hedge portfolios have on average recorded positive returns between Friday market close to Monday market open. It supports the existence of intraday effect, but indicates results in contrast with findings presented by Harris (1986).

The 3-factor value-weighted excessive returns of the hedge portfolio ranges from 0.16% (1-week) to 0.71% (4-week) and remain positive, but 23 bps and 70 bps lower, respectively, compared to returns measured from Friday to Friday. The 4-factor excessive hedge portfolio returns ranges from 0.19% (1-week) to 1.01% (4-week), which is likewise lower by 45 bps and 50 bps, respectively, compared to chapter V. Nonetheless, the hedge portfolio retains its significance both rebalancing weekly and every fourth week, motivating that the two separate strategies seem to gain synergies from being utilized in conjunction.

6.2.2. Conclusion on intraday effect

The intraday effect is found to be present in the data with strong deviations between Friday market close prices and Monday market open prices distorting the practical profitability of the investment strategies. In general, the two individual hedge portfolios experienced a loss of their statistical significance. Nonetheless, the combined strategy experienced a loss of alpha ranging from 23 to 70 bps, but retains statistical significance at the 5% level. All in all, the combined investment strategy seems to be robust to intraday effect and to adjustment for the non-synchronicity bias while the individual strategies are not. Overall, the results point to synergies obtained in the stock selections when incorporating both forward-looking and backward-looking information in the two measures.

In contrast with previous research, overnight returns from Friday to Monday are in general found to be positive, which indicates the put-call parity deviations and price trends are continuously being exploited by arbitrageurs present in the markets, making the strategy less profitable and the market more efficient overnight.

6.3. Liquidity

The model presented by Easley et al. (1998) indicates that return predictability arising from the use of volatility spreads improves when option liquidity is high. Moreover, the authors found that insider trading becomes more widespread in cases when option liquidity is high and stock liquidity is low.

As mentioned in the literature review, other arguments put forward for explaining the presence of the profitability of contrarian strategies is the inefficiency of the market to offset short-term price swings when liquidity is temporarily lacking due to an unexpectedly intensified buying or selling pressure. In the very short-term the contrarian strategy is applicable to such temporary price swings and will thereby enjoy mean reversion within days or weeks. It is possible to earn abnormal profit by betting on the mean-reversal, according to Grossman & Miller (1988) and Jegadeesh N. & Titman S. (1995). The liquidity factor has been able to explain ca. 50% of momentum strategy profits in the return sample analysed by Pastor & Stambaugh (2003), as investors demand compensation for consuming liquidity risk. Finally, Conrad & Kaul (1998) have proven that bid-ask spreads for illiquid stocks are the main driver for abnormal profits in contrarian strategies.

Liquidity was found to explain stock returns across different markets, including Australia, France, Hong Kong, Ireland, Japan, Norway, the US, Japan, Canada, Denmark, Finland, France, Germany, Ireland, New Zealand and Sweden (Amihud (2002) Li, Sun, & Wang (2014), Liang & Wei (2012), Marshall & Young (2003), Pastor & Stambaugh (2003)), signalling the significance of that factor in predicting stock prices. It is thus unambiguous that liquidity plays an important role in strategies based on price-trends. Following Acharya & Pedersen (2005), who proved liquidity risk and not only liquidity level is priced in American stock returns, the analysis provided by Li et al.

(2014) yields identical results on the Japanese market through use of liquidity-adjusted CAPM model. The liquidity factor has been proven robust also after controlling for the Fama French 3-factor model and the Carhart 4-factor model, leaving a significantly positive abnormal return, Ze-To (2016).

In the widely cited research piece, Amihud (2002) came up with the following liquidity proxy for stock illiquidity to be calculated as:

$$ILLIQ_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{|R_{iyd}|}{VOLD_{iyd}},$$

Where D_{iy} is number of days for which data on stock i in year y is available, R_{iyd} is the absolute return on stock i on day d in a year y while $VOLD_{ivyd}$ is the daily (US Dollar) volume traded of stock i on day d in year y. Amihud (2002) was able to prove that by using liquidity proxy seen above, stocks with higher illiquidity yield higher returns, as investors needs to be compensated for their liquidity risk, thereby explaining the phenomenon of liquidity premium. Following Amihud's result, Bali & Hovakimian (2009) conducted an analysis on stocks using option volatility spread as predictor of future returns, and presented empirical evidence that even though there is statistically significant relationship between stock illiquidity and future stock returns, positive excess return is still present in the data. Similar conclusions are reached by Cremers & Weinbaum (2010) who indicated that the predictability of stock price path improves at times when the option liquidity is high and stock liquidity is low.

In this section, the role of liquidity will be explored twofold. First, the hypothesis that predictive signals from options with higher liquidity improves alpha returns is to be tested using option bid-ask spread as a proxy for liquidity. Secondly, the impact of stock liquidity on returns predictability will be analysed by use of both the Amihud's (2002) illiquidity ratio and market equity capitalisation of the firm as a proxy for the level of liquidity in the firm.

Option liquidity is proxied by the average bid-ask spread on option pairs as suggested by Cremers & Weinbaum (2010). To understand option liquidity, every Friday, all options pairs have been split into low (1/3 highest bid-ask spreads), middle (1/3 middle bid-ask spreads) or high (1/3 lowest bid-ask spreads) liquidity groups. Afterwards, hedge portfolios are constructed on the basis of low and high option liquidity groups using the same methodology as employed in chapter V.

Table 20. Liquidity effects in the option markets

Table 20 presents performance of quintile portfolios formed on volatility spreads. Contingent on Fridays average option pair bid-ask, volatility spreads have been sorted into low (1/3 highest bid-ask spreads), middle (1/3 middle bid-ask spreads) and high liquidity groups (1/3 lowest bid-ask spread). Low (high) liquidity groups have been formed exclusively on the basis of the volatility spreads in the low (high) liquidity group. Portfolios are formed on Fridays and returns are measured including the first overnight return. Returns are non-annualized, but converted to percentages and controlled for Fama French 3 factors (1993) and Carhart momentum factor (1997) to ensure well-known anomalies do not explain the abnormal return found. Newey West standard errors are used to correct for autocorrelation in the data and returns are measured across 1 and 4-week horizon, thereby including overlapping observations. The hedge portfolio is constructed by longing high volatility stocks (quintile 5) and shorting low volatility spread stocks (quintile 1). Analysis encompasses mean and excessive returns as well as the statistical significance of the latter.

	Volatility Spread Quintile Portfolios					Hedge Portfolio
	Low VS (1)	(2)	(3)	(4)	High VS (5)	(5)-(1)
Portfolio performance	**1 week after portfolio formation**					
Low liquidity group						
Mean return	0.14%	0.01%	0.44%	0.17%	0.21%	0.07%
4-factor Alpha	0.31%	0.06%	0.42%	0.23%	0.36%	0.06%
t-stat	1.76	0.42	3.43	1.57	2.16	0.93
High liquidity group						
Mean return	0.11%	0.11%	0.93%	0.36%	0.25%	0.14%
4-factor Alpha	0.25%	0.15%	0.13%	0.30%	0.47%	0.23%
t-stat	1.48	1.21	3.33	2.42	2.60	4.02
Portfolio performance	**4 weeks after portfolio formation**					
Low liquidity group						
Mean return	0.70%	0.31%	1.07%	0.44%	0.91%	0.21%
4-factor Alpha	1.05%	0.15%	0.92%	1.12%	1.18%	0.13%
t-stat	1.40	0.24	2.04	1.81	1.70	0.59
High liquidity group						
Mean return	0.64%	0.82%	2.58%	1.22%	0.77%	0.13%
4-factor Alpha	0.97%	0.67%	0.08%	0.91%	1.18%	0.21%
t-stat	1.46	1.08	0.37	2.38	1.58	0.94

Abnormal returns earned by the high option liquidity group on a 1-week horizon is 23 bps (t-stat 4.02) compared to 6 bps (t-stat 0.93) by the low option liquidity group. The intergroup difference of 17 bps is statistically significant (t-stat 3.09), indicating the predictive power of higher liquid option pairs dominates that of the lower liquid options on a horizon of 1-week. Across 4-week investment horizon, single quintile portfolios earn, in general, higher mean and excessive returns than across 1-week time period. Hedge portfolio yields 4-factor value-weighted excessive return of 13 bps (t-stat 0.59) and 21 bps (t-stat 0.94) across low and high liquidity group respectively. Both the abnormal returns of hedge portfolio and the intergroup difference between them of 8 bps are not statistically significant.

The outperformance of high liquidity option group over the low liquidity option group across both time horizons conforms to our theoretical expectations, as well as Cremers and Weinbaum's and Easley's findings. The 1-week hedge portfolio strategy earns 23 bps, which is 4 bps more than the original strategy based upon all volatility spreads (column 6, table 12). This is not the case for the 4-

weeks holding period strategy, which is 52 bps lower than the original volatility spread strategy (column 6, table 12). It is noteworthy that the additive nature of how abnormal returns accrued over time in the original strategy seemingly disappears when utilizing more liquid options for stock selection. It seems that the abnormal return from the underlying stock of liquid options adjusts to information pressure embedded in options prices quicker compared to using the full spectrum of options to estimate the volatility spread.

Subsequent to the analysis of option liquidity effects, we explore the impact of stock liquidity on weekly excess stock returns. The analysis encompasses two liquidity proxy measures, comprising of Amihud illiquidity ratio and firm size based on market equity capitalization of the firm. Two dummies are created called low stock liquidity, which is equal to 1 if the stock is located in bottom 20% based on Amihud illiquidity ratio or firm market capitalization, and high stock liquidity, equal to 1 if the stock lands in the top 20% based on same measures. Both Amihud illiquidity ratio and market capitalization is measured as the average of 5 trading days throughout the week every Friday.

Table 21. Liquidity effects in the stock markets

Table 21 shows the result of pooled cross sectional regressions of weekly stock returns on both the volatility spread and price to moving average measure as well as the two liquidity groups. Low (high) stock liquidity group is equal to 1 if the stock is located in the bottom (top) 20% of stocks sorted based on either Amihud illiquidity ratio or on firm market capitalization. Returns are non-annualized and converted to percentages and measured including the first overnight return and controlled for Fama French 3-factors (1993) and Carhart momentum factor (1997) to ensure the well-known anomalies do not explain results obtained. T-statistics is reported in brackets.

	Volatility Spread		**Price to moving average ratio**	
Independent variables	**Amihud Illiquidity Ratio**	**Market Capitalization**	**Amihud Illuqidity Ratio**	**Market capitalization**
Intercept	0.08%	0.08%	-0.17%	-0.14%
	(1.01)	(1.05)	(-0.38)	(-0.31)
Volatility Spread	0.20%	0.19%		
	(1.03)	(1.02)		
Price to Moving Average Ratio			0.25%	0.23%
			(0.86)	(0.79)
High Stock Liquidity	0.04%	0.57%	0.44%	-0.12%
	(0.06)	(0.66)	(0.25)	(-0.07)
Low Stock Liquidity	-0.24%	-0.19%	-1.96%	0.16%
	(-0.38)	(-0.18)	(-0.68)	(0.46)
R-square	10.20%	10.23%	7.33%	7.33%

None of the estimated coefficients in table 21 are statistically significant. However, looking at the results based on volatility spread, the high stock liquidity group has by large outperformed low stock liquidity group, as it recorded positive returns of 4 and 57 bps compared to returns of -24 bps and -19 bps obtained in low stock liquidity group. This could indicate low predictability for the volatility spread measure for stocks with low liquidity. These results are not in line with the previous in the literature and contrasts the finding presented by Easley et al. (1998) who proved that illiquid stocks should yield higher returns, also consistent with existence of liquidity risk premium. However, the results are not fully conclusive, as our results do not account for the interrelation between stock and option liquidity. The conclusion made in Easley et al. (1998) was that predictability of excess returns improves when investing in equities that have relatively liquid options compared to their shares traded on the stock market, which was also confirmed by Cremers & Weinbaum (2010).

Results based on price to moving average ratio indicate that high stock liquidity group yields, once again, higher returns and better predictability than low stock liquidity group based on Amihud illiquidity ratio. Return on the dummy variable high stock liquidity (Amihud) yields 44 bps, which is higher compared to low stock liquidity, experiencing a -196 bps loss. However, that finding does not hold for results based on firm market capitalization, where the opposite is true. Returns on the dummy variable "High Stock Liquidity" (market capitalization) yields a 12 bps loss contrary to "Low Stock Liquidity" (market capitalization), experiencing a 16 bps gain. Such discrepancy is hard to explain and further research would be needed to uncover reasons behind it.

6.4. Robustness conclusion

The robustness analysis, which entailed Fama Macbeth regressions, intraday and non-synchronicity analysis as well as liquidity effects delivered, in general, disputing and ambiguous results. Overall, Fama Macbeth regressions were not able to confirm and solidify the significance of the abnormal returns derived from the time-series analysis of the original trading strategy in chapter V. This is despite the fact that the magnitude of the suggested alpha returns conformed to those found in chapter V. Moreover, it also didn't find any significant economic profitability in using volatility spread and price to moving average ratio in conjunction. Adjusting for non-synchronicity and intraday effects, levels of excessive returns were, in general, reduced and the significance of the individual strategies evaporated. Utilization of the volatility spread and price to moving average ratio as sorting measures in conjunction proved useful as they achieved strong significant results, overall confirming that the core of this strategy still has economic fruition. Finally, the liquidity analysis confirmed the hypothesis that predictive signals derived from more liquid options are stronger than those arising from less liquid options. Predictive results using either stock's implied open-interest volatility spread or price to moving average ratio on more liquid stocks versus less liquid stocks were inconclusive and statistically insignificant, but in general indicating higher returns arising from the use of stocks with higher liquidity, contrasting previous results presented in the literature.

VII. Conclusion

The overall purpose of this thesis was to explore equity return predictability and to ascertain whether it is possible to earn abnormal profit by exploiting put-call parity deviations whilst betting on the reversal of short-term price trends. This incorporates both a forward-looking measure (volatility spread) and a backward-looking measure (price to moving average ratio) into stock picking. Using the option-implied volatility spread between call and puts, it has been demonstrated that this measurement encompasses forward-looking information about equity price movements. Inspection of option-implied volatility spreads indicates that stocks with relatively expensive calls perform significantly better than stocks with relatively expensive puts. A trading strategy longing high volatility spread stocks and shorting low volatility spread stocks earned on average an Carhart 4-factor risk-adjusted value-weighted abnormal return of 19 bps (t-stat of 2.45) and 73 bps (t-stat of 2.79) with 1 and 4 weeks rebalancing, respectively, from 2011 up to and including 2015.

Previous research points to a price trend reversal over a very short period of time – stocks which have underperformed in the past have dominated the old winning stocks as a result of short term mean reversal. This effect is driven by rising price pressure and temporary lack of liquidity in the market. To examine the phenomenon, price to moving average ratio was used to calculate the magnitude of out- and underperformance of stocks and allocate them to quintile portfolios. Scrutinizing these price trends, it has been verified that a trend reversal in price data were mildly present within a hedge portfolio longing past loser stocks and shorting past winner stocks. It was able to earn on average a Carhart 4-factor risk-adjusted value-weighted abnormal return of 17 bps (t-stat of 1.46) and 46 bps (t-stat of 1.05) across 1 and 4 weeks respectively. These returns are not statistically significant and thereby it cannot be statistically proven that they yield any positive abnormal return.

A double-sorted portfolio was constructed to incorporate information of future returns from both the forward- and backward-looking measures in conjunction. This measure enhanced the selection strategy of stocks and improved its alpha. The hedge portfolio was able to earn an average Carhart 4-factor risk-adjusted value-weighted abnormal return of 64 bps (t-stat of 2.47) and 151 bps (t-stat of 2.83) over 1 and 4 weeks respectively. General fear that returns could have been driven by short-sale restrictions was reduced, as it was predominantly the long arm of the portfolios generating the alpha returns.

To further enlighten and validate the preliminary conclusions, a robustness analysis of the initial results were conducted. Fama Macbeth regressions suggested positive risk premiums for the sorting mechanism and respectively implied a return of 22 and 29 bps for the volatility spread and price to moving average strategy. However, all dummy variables turned out statistically insignificant, indicating only a weak interrelation between the returns and the sorting strategies.

On top of Fama Macbeth regressions, impact of intraday effects and non-synchronicity bias were examined. The intraday effect was present in the data as overnight returns measured from Friday to Monday were on average positive, signalling that arbitrageurs act in the market, which decreases the market inefficiencies and limited the mispricing of financial assets. In general, adjusting for these effects i.e. altering holding period from Friday close to Friday close to Monday open to Friday close, decreased the hedge portfolio alpha returns. Single sorting trading strategies lost 12 bps and 11 bps 4-factor alpha on a weekly basis and 29 bps and 24 bps 4-factor alpha on a 4-week basis for volatility spread and price to moving average ratio, respectively. All individually sorted hedge portfolios failed to achieve significant results. When the measures were used in conjunction, the strategy lost 45 bps and 50 bps 4-factor alpha on a weekly and four-week basis, respectively. Nevertheless, the strategy retained its 5% statistical significance.

Liquidity analysis concluded that volatility spreads formed on the 1/3 most liquid option pairs significantly dominated the 1/3 least liquid options by 17 bps 4-factor alpha. The portfolio also dominated the original strategy on a 1-week rebalancing frequency by 4 bps. This indicates that the informative content embedded in liquid options is higher compared to illiquid options. However, it seemed that exclusively utilizing the most liquid options deterred the accrual of returns over longer horizons as returns accrued between the first and the fourth week were on average -2 bps. This indicates that price pressures are quickly normalized and priced into the underlying stock.

As average market capitalization of the 1st and 5th quintiles portfolios was significantly lower (using both sorts) than the middle peers and as lack of liquidity is known to drive the occurrence of temporary price swings, stock liquidity was also investigated. Using both average market capitalisation and the Amihud illiquidity ratio to proxy the level of stock liquidity, we examined interplay between the predictive measures and stock liquidity. Looking solely at high and low stock liquidity groups, the high stock liquidity group seems to outperform the low stock liquidity group based on volatility spread sorting. Based on the price to moving average ratio sorting, the results are inconclusive, as the two measures used – average Amihud illiquidity ratio and average market capitalization point to different conclusions. Overall, this could indicate that relatively lower predictability for stocks with low liquidity. However, as all coefficients were insignificant, it is ambiguous how stock liquidity interacts with the predictive power of the measures.

Our contribution to the existing literature lies in improving the understanding of asset pricing and presenting strategies exploiting the mispricing in practice. The sample time period encompasses only the period of economic expansion, which might imply that results would be different if the investment strategy is used in another economic setting. Furthermore, results might not apply to other developed economies and emerging markets as the US equity market is quite unique, characterized by extremely high liquidity and average firm capitalization compared to other countries. Future research could emphasise understanding of how the interplay between using both a forward- and backward-looking measure complements return accrual surrounding news events such as earnings announcement or analyst recommendation change.

Bibliography

Acharya, V. V., & Pedersen, L. H. (2005). Asset pricing with liquidity risk. *Journal of Financial Economics*, *77*(2), 77. 10.1016/j.jfineco.2004.06.007

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-serieseffects. *Journal of Financial Markets 3156*, *5*(2), 5.

Amin, K., Coval, J. D., & Seyhun, H. N. (2004). Index Option Prices and Stock Market Momentum *. *Journal of Business*, *77*(4), 77.

Anthony, J. H. (1988). The Interrelation of Stock and Options Market Trading Volume Data. *Journal of Finance*, *43*(4), 43.

Atilgan, Y. (2014). Volatility spreads and earnings announcement returns. *Journal of Banking & Finance*, *38*, 38. 10.1016/j.jbankfin.2013.10.007

Bali, T. G., & Hovakimian, A. (2009). Volatility Spreads and Expected Stock Returns. *Management Science*, *55*(11), 55. 10.1287/mnsc.1090.1063

Bandarchuk, P., & Hilscher, J. (2013). Sources of momentum profits: Evidence on the irrelevance of characteristics. *Review of Finance*, *17*(2), 17. 10.1093/rof/rfr036

Bateson, R. D. (2011). *Financial derivative investments: An introduction to structured products*.

Battalio, R., & Schultz, P. (2006). Options and the bubble. *Journal of Finance*, *61*(5), 61. 10.1111/j.1540-6261.2006.01051.x

Bauer Jr., R. J., & Dahlquist, J. R. (1999). *Technical market indicators analysis & performance*.

Benhamou, E. (2007). *Global derivatives: Products, theory and practices*.

Biais, B., & Hillion, P. (1994). Insider and Liquidity Trading in Stock and Options Markets. *The Review of Financial Studies*, *7*(4), 7. 10.1093/rfs/7.4.743

Black, F. (1975). Fact and Fantasy in the Use of Options. *Financial Analysts Journal*, *31*(4), 31. 10.2469/faj.v31.n4.36

Black, F., & Scholes, M. (1973). Black and Scholes, The pricing of options and corporate libilities. *The Journal of Political Economy*. 10.1086/260062

Blitz, D. (2015). Fama-French 5-factor model: why more is not always better. *Robeco Institutional Asset Management*. 10.1016/S0377-2217(03)00351-5

Blume, L., Easley, D., & O'Hara, M. (2014). Market Statistics and Technical Analysis: The Role of Volume. *The Journal of Finance*, *49*(1), 49.

Bogousslavsky, V. (2016). The Cross-Section of Intraday and Overnight Returns, (2011).

Brenner, M., & Galai, D. (1986). Implied Interest Rates. *The Journal of Business*, *59*(3), 59. 10.1086/296349

Brock, W., Lakonishok, J., & LeBaron, B. (1992). Simple technical trading rules and the stochastic properties of stock returns. *Journal of Finance*, *47*(5), 47.

Buss, A., & Vilkov, G. (2012). Measuring equity risk with option-implied correlations. *Review of Financial Studies*, *25*(10), 25. 10.1093/rfs/hhs087

Cakici, N., Fabozzi, F. J., & Tan, S. (2013). Size, value, and momentum in emerging market stock returns. *Emerging Markets Review*, *16*, 16. 10.1016/j.ememar.2013.03.001

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of Finance*, *52*(1), 52. 10.2307/2329556

Chakravarty, S., Gulen, H., & Mayhew, S. (2004). Informed trading in stock and option markets. *Journal of Finance*, *59*(3), 59. 10.1111/j.1540-6261.2004.00661.x

Chan, K., Chung, Y. P., & Johnson, H. (1993). Why Option Prices Lag Stock Prices: A Trading???based Explanation. *The Journal of Finance*, *48*(5), 48. 10.1111/j.1540-6261.1993.tb05136.x

Chance, D. M., & Brooks, R. (2013). *An introduction to Derivatives and Risk Management*.

Chen, Y., & Zhao, H. (2012). Informed trading, information uncertainty, and price momentum. *Journal of Banking & Finance*, *36*(7), 36. 10.1016/j.jbankfin.2012.03.016

Choi, J. (2013). What drives the value premium?: The role of asset risk and leverage. *Review of*

Financial Studies, *26*(11), 26. 10.1093/rfs/hht040

Chopra, N., Lakonishok, J., & Ritter, J. R. (1992). Measuring abnormal performance: Do stocks overreact? *Journal of Financial Economics*, *31*(2), 31. 10.1016/0304-405X(92)90005-I

Chui, A. C. W., Titman, S., & Wei, K. C. J. (2010). Individualism and momentum around the world. *Journal of Finance*, *65*(1), 65. 10.1111/j.1540-6261.2009.01532.x

Cochrane, J. H. (2005). Asset Pricing. 10.1111/j.1540-5915.1998.tb01351.x

Conrad, J., & Kaul, G. (1998). An Anatomy of Trading Strategies: Evidence from China. *The Review of Finanancial Studies*, *11*(3), 11. 10.2753/REE1540-496X460205

Cremers, M., & Weinbaum, D. (2010). Deviations from Put-Call Parity and Stock Return Predictability. *Journal of Financial and Quantitative Analysis*, *45*(2), 45. 10.1017/S002210901000013X

Daniel, K., & Moskowitz, T. J. (2016). Momentum crashes. *Journal of Financial Economics*, *122*(2), 122. 10.1016/j.jfineco.2015.12.002

Dellavigna, S., & Pollet, J. M. (2009). Investor inattention and friday earnings announcements. *Journal of Finance*, *64*(2), 64. 10.1111/j.1540-6261.2009.01447.x

Dong, H., Bowers, H. M., & Latham, W. R. (2013). Evidence on the Efficient Market Hypothesis from 44 Global Financial Market Indexes. *Economics Research International*, *2013*, 2013. 10.1155/2013/238253

Doukas, J. A., Kim, C. (Francis), & Pantzalis, C. (2010). Arbitrage Risk and Stock Mispricing. *Journal of Financial and Quantitative Analysis*, *45*(4), 45. 10.1017/S0022109010000293

Driessen, J., Lin, T.-C., & Lu, X. (2012). Why do option prices predict stock returns ? *Working Paper*.

Du, D., & Hu, O. (2012). Foreign exchange volatility and stock returns. *Journal of International Financial Markets, Institutions and Money*, *22*(5), 22. 10.1016/j.intfin.2012.07.001

Easley, D., O'Hara, M., & Srinivas, P. S. (1998). Option volume and stock prices: Evidence on where informed traders trade. *Journal of Finance*, *53*(2), 53. 10.1111/0022-1082.194060

Edwards, R. D., Magee, J., & Bassetti, W. H. C. (2007). *Technical analysis of stock trends*.

Fama, E. (1965). The Behaviour of Stock-Market Prices. *Journal of Business*, *38*(1), 38.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*(1), 33. 10.1016/0304-405X(93)90023-5

Fama, E. F., & French, K. R. (1996). Multifactor Explanations of Asset Pricing Anomalies. *The Journal of Finance*, *LI*(1), LI. 10.2307/2329302

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, *116*(1), 116. 10.1016/j.jfineco.2014.10.010

Fama, E. F., & Macbeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests.

Frazzini, A., & Pedersen, L. H. (2011). Embedded Leverage. *NBER Working Paper*, *No. w18558*, No. w18558. 10.3386/w18558

French, K. R. (1980). Stock returns and the weekend effect. *Journal of Financial Economics*, *8*(1), 8. 10.1016/0304-405X(80)90021-5

George, T. J., & Hwang, C.-Y. (2010). A resolution of the distress risk and leverage puzzles in the cross section of stock returns. *Journal of Financial Economics*, *96*(1), 96. 10.1016/j.jfineco.2009.11.003

Ghys, H., Boudt, K., & Mikael, P. (2010). Intraday liquidity dynamics of the DJIA stocks around price jumps.

Gomes, J. F., & Schmid, L. (2010). Levered Returns. *The Journal of Finance*, *65*(2), 65. Retrieved from http://www.jstor.org/stable/2978933

Griffin, J. M., Ji, X., & Martin, J. S. (2003). Momentum Investing and Business Cycle Risk: Evidence from Pole to Pole. *Journal of Finance*, *58*(6), 58. 10.1046/j.1540-6261.2003.00614.x

Grossman, S. J., & Miller, M. H. (1988). Liquidity and Market Structure. *Journal of Finance*, *43*(3), 43. Retrieved from http://links.jstor.org/sici?sici=0022-1082%28198807%2943%3A3%3C634%3ALAMSD%3E2.0.CO%3B2-N

Harris, L. (1986). A transaction data study of weekly and intradaily patterns in stock returns. *Journal of Financial Economics*, *16*(1), 16. 10.1016/0304-405X(86)90044-9

Holowczak, R., Simaan, Y. E., & Wu, L. (2006). Price discovery in the U.S. stock and stock options markets: A portfolio approach. *Review of Derivatives Research*, *9*(1), 9. 10.1007/s11147-006-9004-0

Hong, H., Lim, T., & Stein, J. C. (1998). Bad news travels slowly: size, analyst coverage and the profitability of momentum strategies. *Working Paper 6553*.

Hong, L. J. (2013). Deviations from Put-Call Parity and Contrarian Profits. 10.1213/00000539-200201000-00027

Hull, J. (2011). *Fundamentals of futures and options markets*.

Jacobs, H., Regele, T., & Weber, M. (2015). Expected Skewness and Momentum, (May). 10.1016/S1043-2760(97)84344-5

Jegadeesh, N., & Titman, S. (1995). Overreaction, Delayed Reaction, and Contrarian Profits. *The Review of Financial Studies*, *8*, 8. 10.1017/CBO9781107415324.004

Jegadeesh N., & Titman S. (1995). Short-Horizon Return Reversals and the Bid-Ask Spread. *Journal of Financial Intermediation*, *4*(2), 4. 10.1006/jfin.1995.1006

Johnson, T. C., Chebonenko, T., Cunha, I., D'Almeida, F., & Spencer, X. (2011). Endogenous leverage and expected stock returns. *Finance Research Letters*, *8*(3), 8. 10.1016/j.frl.2010.12.003

Johnson, T. L., & So, E. C. (2012). The option to stock volume ratio and future returns. *Journal of Financial Economics*, *106*(2), 106. 10.1016/j.jfineco.2012.05.008

Kamara, A., & Miller, T. W. (1995). Daily and Intradaily Tests of European Put-Call Parity. *The Journal of Financial and Quantitative Analysis*, *30*(4), 30. 10.2307/2331275

Kang, C.-M., Kim, D., & Lee, G. (n.d.). Market Segmentation of Stock and Options.

Khil, J., & Lee, B.-S. (2002). A Time-Series Model of Stock Returns with a Positive Short-Term Correlation and a Negative Long-Term Correlation. *Review of Quantitative Finance and Accounting*, *18*(4), 18. Retrieved from http://resolver.scholarsportal.info/resolve/0924865x/v18i0004/381_atmosrcaanlc

Kim, D., Roh, T.-Y., Min, B.-K., & Byun, S.-J. (2014). Time-varying expected momentum profits.

Journal of Banking & Finance, *49*, 49. 10.1016/j.jbankfin.2014.09.004

Klemkosky, R. C., & Resnick, B. G. (1979). Put-Call Parity And Market Efficiency. *Journal of Finance*, *34*(5), 34. 10.2307/2327240

Klemkosky, R. C., & Resnick, B. G. (1980). An ex ante analysis of put-call parity. *Journal of Financial Economics*, *8*(4), 8. 10.1016/0304-405X(80)90008-2

Kudryavtsev, A. (2013). Interday drifts in opening stock returns, *XX*(11), XX.

Kudryavtsev, A. (2014). When Opening Stock Returns Tend to be Higher? *International Economic Journal*, *28*(May), 28. 10.1080/10168737.2014.905620

Lehmann, B. N. (1988). Fads, Martingales and Market Efficiency. *NBER Working Paper*, (Number 2533).

Leippold, M., & Lohre, H. (2012). International price and earnings momentum. *The European Journal of Finance*, *18*(6), 18. 10.1080/1351847X.2011.628683

Lesmond, D., & Wang, W. (2006). The Long and the Short of Accrual Based Trading Strategies. *Working Paper Tulane University*. 10.1257/jep.15.4.157

Li, B., Sun, Q., & Wang, C. (2014). Liquidity, liquidity risk and stock returns: Evidence from Japan. *European Financial Management*, *20*(1), 20. 10.1111/j.1468-036X.2011.00629.x

Liang, S. X., & Wei, J. K. C. (2012). Liquidity risk and stock returns around the world. *Journal of Banking & Finance*, *36*(12), 36. 10.1016/j.jbankfin.2012.07.021

Lintner, J. (1965a). Security Prices, Risk and Maximal Gains from Diversification. *Journal of Finance*. 10.1016/j.cie.2009.02.012

Lintner, J. (1965b). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics*.

Lo, A. W., & MacKinlay, C. A. (1990). *When are contrarian profits due to stock market overreaction? Review of Financial studies* (Vol. 3). 10.1093/rfs/3.2.175

Louis, H., & Sun, A. X. (2010). Investor Inattention and the Market Reaction to Merger

Announcements. *Management Science*, *56*(10), 56. 10.1287/mnsc.1100.1212

Manaster, S., & Rendleman, R. (1982). Option Prices As Predictors of Equilibrium Stock-Prices. *Journal of Finance*, *37*(4), 37. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1540-6261.1982.tb03597.x/pdf

Markiel, B. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, *17*(1), 17.

Marshall, B. R., & Young, M. (2003). Liquidity and stock returns in pure order-driven markets: evidence from the Australian stock market. *International Review of Financial Analysis*, *12*(2), 12. 10.1016/S1057-5219(03)00006-1

McLean, R. D. (2010). Idiosyncratic Risk, Long-Term Reversal, and Momentum. *Journal of Financial and Quantitative Analysis*, *45*(4), 45. 10.1017/S0022109010000311

Merlo, P., & Konarzewski, P. (2016). The momentum effect exemplifies the influence of investors' irrational behaviour on changing prices of shares and stocks: an analysis of the momentum effect on the Warsaw Stock Exchange. *"e-Finanse" Financial Internet Quarterly*, *12*(1), 12. 10.14636/1734-039X

Mossin, J. (1966). Equilibrium in a Capital Asset Market. *Econometrica*. 10.1057/palgrave.jors.2602596

Mugwagwa, T., Ramiah, V., & Moosa, I. (2015). The profitability of option-based contrarian strategies: An empirical analysis. *International Review of Finance*, *15*(1), 15. 10.1111/irfi.12042

Nartea, G. V., Ward, B. D., & Djajadikerta, H. G. (2009). Size, BM, and momentum effects and the robustness of the Fama-French three-factor model: Evidence from New Zealand. *International Journal of Managerial Finance*, *5*(2), 5. 10.1108/17439130910947895

Neely, C. J., Rapach, D. E., Tu, J., & Zhou, G. (2014). Forecasting the Equity Risk Premium: The Role of Technical Indicators. *Management Science*, *60*(7), 60. doi:10.1287/mnsc.2013.1838

Ni, S. X., Pan, J. U. N., & Poteshman, A. M. (2008). Volatility Information Trading in the Option Market. *Finance*, *LXIII*(3), LXIII. 10.1088/1741-2560/4/2/R03

Nisbet, M. (1992). Put-call parity theory and an empirical test of the efficiency of the London Traded Options Market. *Journal of Banking & Finance*, *16*(2), 16. 10.1016/0378-4266(92)90021-Q

Ofek, E., Richardson, M., & Whitelaw, R. F. (2004). Limited arbitrage and short sales restrictions: evidence from the options markets. *Journal of Financial Economics*, *74*(2), 74. 10.1016/j.jfineco.2003.05.008

Ozdagli, A. K. (2012). Financial leverage, corporate investment, and stock returns. *Review of Financial Studies*, *25*(4), 25. 10.1093/rfs/hhr145

Pan, J., & Poteshman, A. M. (2006). The information in option volume for future stock prices. *Review of Financial Studies*, *19*(3), 19. 10.1093/rfs/hhj024

Park, S.-C. (2010). The Moving Average Ratio and Momentum. *The Financial Review*, *45*(2), 45. 10.1111/j.1540-6288.2010.00254.x

Pastor, L., & Stambaugh, R. (2003). Liquidity risk and expected stock returns. *The Journal of Political Economy*, *111*(3), 111. 10.1086/374184

Pereira, J. P., & Zhang, H. H. (2010). Stock Returns and the Volatility of Liquidity. *Journal of Financial and Quantitative Analysis*, *45*(4), 45. 10.1017/S0022109010000323

Rath, S., & Durand, R. B. (2015). *Decomposing the size, value and momentum premia of the Fama–French–Carhart four-factor model*. *Economics Letters* (Vol. 132). https://doi.org/10.1016/j.econlet.2015.05.003

Saeedi, A., Miraskari, S. R., & Ara, M. S. (2014). The Investigation of the Efficient Market Hypothesis: Evidence from an Emerging Market. *Taylor's Business Review*, *4*(2), 4. 10.7603/s40

Samuelson, P. A. (1965). Proof That Properly Anticipated Prices Fluctuate Randomly , Industrial Management Review, 6:2 (1965:Spring) p.41. *Management*, *2*, 2.

Sarwar, S. M., & Muradoglu, G. (2013). Macroeconomic risks, idiosyncratic risks and momentum profits. *Borsa Istanbul Review*, *13*(4), 13. 10.1016/j.bir.2013.10.001

Sehgal, S., & Balakrishnan, A. (2013). Robustness of Fama-French Three Factor Model: Further Evidence for Indian Stock Market. *Vision (09722629)*, *17*(2), 17. 10.1177/0972262912483526

Sharpe, W. F. (1964). Capital Asset Prices: A Theory of Market Equilibrium Under Conditions of Risk. *Journal of Finance*.

Simon, D. P., & Wiggins, R. A. (2001). S&P futures returns and contrary sentiment indicators. *Journal of Futures Markets*, *21*(5), 21. 10.1002/fut.4

Smirlock, M., & Starks, L. (1986). Day-of-the-week and intraday effects in stock returns. *Journal of Financial Economics*, *17*(1), 17. 10.1016/0304-405X(86)90011-5

Stiglitz, J. E. (1989). Using tax policy to curb speculative short-term trading. *Journal of Financial Services Research*, *3*(2–3), 3. 10.1007/BF00122795

Stoll, H. R. (1969). the Relationship Between Put and Call Option Prices. *The Journal of Finance*, *24*(5), 24. 10.1111/j.1540-6261.1969.tb01694.x

Summers, L. H., & Summers, V. P. (1989). When Financial Marktets Work Too Well: A Cautious Case For a Securities Transacrions Tax. *Journal of Financial Services Research*, *3*, 3.

Thaler, R. ., & De Bondt, W. (1987). Further Evidence on Investor Overreaction.pdf. *The Journal of Finance*.

Treynor, J. L. (1962). Toward a Theory of Market Value of Risky Assets. 10.1037/0033-2909.114.1.174

Van Dijk, R., & Huibers, F. (2002). European Price Momentum and Analyst Behavior. *Financial Analysts Journal*, *58*(2), 58. 10.2469/faj.v58.n2.2526

Wagner, D., Ellis, D. M., & Dubofsky, D. A. (1996). Factors Behind Put-Call Parity Violations of S&P 100 Index Options. *The Financial Review*, *31*(3), 31.

Xing, Y., Zhang, X., & Zhao, R. (2010). What Does the Individual Option Volatility Smirk Tell Us about Future Equity Returns? *Journal Of Financial & Quantitative Analysis*, *45*(3), 45. 10.2469/dig.v41.n1.2

Ze-To, S. Y. M. (2016). Asset liquidity and stock returns. *Advances in Accounting*, *35*, 35. 10.1016/j.adiac.2016.08.002