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# VOLATILITY INDEX AS A TIMING TOOL IN S&P 500 WITH STYLE ROTATION

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## ABREVIATIONS

| | |
|---|---|
| BSM | Black-Scholes option pricing model |
| CAPM | Capital Asset Pricing Model |
| CBOE | Chicago Board Options Exchange |
| GSVI | Google search volume indices |
| SPY | SPDR S&P 500 ETF |
| S&P 100 | Standard and Poor's 100 index |
| S&P 500 | Standard and Poor's 500 index |
| VDAX | Volatility Index of Deutsche Börse |
| VIX | Volatility Index |
| VXN | Nasdaq Volatility Index |

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## ABSTRACT

The strong negative correlation between contemporaneous changes of VIX and stock returns is well-documented by multiple studies such as Fleming, Ostdiek and Whaley (1995), Giot (2005) and Rubbaniy, Asmerom, Abbas and Naqvi (2014). Due to the highly negative relationship between VIX and stock returns, timing possibilities with VIX in the equity markets are an increasingly examined topic in economic science. Giot and Banerjee, Doran and Peterson (2007) find that future stock returns are always positive (negative) for very high (low) levels of VIX regardless of the holding period length. This thesis contributes to these previous studies by investigating VIX as a potential timing tool when investing in equity markets and whether style rotation has an additional effect on the returns of a VIX timing strategy.

This thesis examines data from 29th January 1993 to 31st December 2018 and investigates how positions selected in S&P 500, Fama-French 5 factors (Fama and French 2015) and momentum factor perform on different levels of VIX with different holding periods. The key method in this thesis is a 500-day rolling ranking method inspired by Giot (2005) to create relative ranks for different levels of VIX. The factor return results are used to construct long-short portfolios for each factor to examine if VIX timing strategies with style rotation produce excess returns compared to conventional factor portfolios.

The results show that the highest VIX levels are excellent indicators for positive future returns in S&P 500. However, the findings of this study do not support the results of Giot (2005) and Banerjee, Doran and Peterson (2007) that low levels of VIX always lead to negative stock returns. In addition, this thesis reveals that the Fama-French 5 and momentum factors exhibit different future returns depending on the level of VIX and that the size and operating profitability factors can be used by investors in profitable style rotation strategies combined with VIX timing.

**KEYWORDS**: VIX, market timing, Fama-French 5 factors, negative correlation

# 1. INTRODUCTION

Implied volatility is an increasingly relevant research topic in modern finance due to its growing importance for predicting and modelling asset volatility. It is one of the most basic volatility concepts used in the academic literature in economics and can be regarded as the market uncertainty of the future price of an underlying security, such as an option or a stock. The implied volatilities of various Standard and Poor’s 500 index (S&P 500) options are used to construct the widely used Volatility Index (VIX) published by the Chicago Board Options Exchange (CBOE), which shows the expectations for future market volatility. VIX is widely considered to be the best method for measuring expected market volatility and is freely available to all investors at the CBOE website.

What makes VIX even more intriguing is its negative correlation with equity market returns which is documented by many studies such as Fleming, Ostdiek and Whaley (1995), Giot (2005), Hibbert, Daigler and Dupoyet (2008), Whaley (2009), Sarwar (2012) and Antonakakis, Chatziantoniou and Filis (2013). However, unlike stock returns to compensate for investors’ capital risk, volatility is not expected to grow over time due to its mean-reverting nature and Banerjee, Doran and Peterson (2007) find that VIX usually reverts to its mean after around 44.1 trading days. Due to the mean-reverting nature of VIX and its negative relationship with stock index returns, it can be argued that VIX has the potential of being a valid indicator of future stock returns and hence different market profit possibilities regarding VIX movements have been researched. Especially evidence of a connection between high volatility and high expected stock returns and therefore viable market timing possibilities by using VIX have beeen found by researchers such as Giot (2005), Banerjee, Doran and Peterson (2007), Rubbaniy, Asmerom, Abbas and Naqvi (2014) and Smales (2017).

The possibility of constructing profitable timing strategies with VIX combined with style rotation has not been studied as extensively as the basic relationship between future stock returns and VIX. However, the main findings of Copeland and Copeland (1999), Boscaljon, Filbeck and Zhao (2011) and Durand, Lim and Zumwalt (2011) suggest that especially the value effect is positively correlated with VIX movements and could therefore lead to good results in a VIX timing strategy. The strong correlation between

VIX changes and the value factor implies that during rising market uncertainty investors want to move their capital to safer investments from riskier investment vehicles and this can provide timing possibilities to investors interpreting VIX. In addition, Durand, Lim and Zumwalt (2011) find that the size and momentum premiums are as well positively correlated with VIX though the correlations are considerably weaker than with the value-growth premium.

## 1.1. Purpose of the thesis

The purpose of this study is to investigate VIX as a potential timing tool when investing in equity markets and whether style rotation has an additional effect on the returns of a VIX timing strategy. The thesis examines how positions taken in S&P 500, Fama-French 5 factors (Fama and French 2015) and momentum factor perform on different levels of VIX with different holding periods. The key method in this thesis is a 500-day rolling ranking method inspired by Giot (2005) to create relative ranks for different levels of VIX. The results of the Fama-French 5 and momentum factors' returns on different levels of VIX are used to construct long-short portfolios for each factor so that a long position is taken in a factor portfolio on particular relative levels of VIX and a short position in the factor portfolio on certain other relative VIX levels. It needs to be highlighted, that the factor portfolios are not traditional long-short portfolios since only one position (long, short or no position) is taken at a time during the sample period whereas in a conventional long-short strategy a long and a short position is taken simultaneously. The long-short portfolio approach is used to examine how well in practice the VIX timing strategy combined with style rotation performs in the equity market and whether this kind of strategy generates acceptable trading costs from an investing perspective.

## 1.2. Hypotheses

Giot (2005) and Banerjee, Doran and Peterson (2007) find that future stock returns can be expected to be positive (negative) for very high (low) levels of VIX at least on a short-term basis due to the mean-reverting nature of VIX and its strong relation with stock returns. These studies also agree that highest returns are generated for the longer short-term holding periods and that average to moderately high levels of VIX result in unfavourable future returns. The findings of Rubbaniy, Asmerom, Abbas and Naqvi

(2014) are in line with the results of Giot (2005) and Banerjee, Doran and Peterson (2007) but differ for the holding periods of 1- and 5-day returns as the future returns for those holding periods provide no significant results in their research. Smales (2017) as well finds that the relation between market uncertainty and imminent stock returns is negative and that VIX provides superior explanatory power regarding future market returns. Furthermore, his results imply that changes in VIX, instead of its levels, seem to be better indicators in explaining market returns. Mainly based on these studies and the great amount of economic literature that documents a highly negative correlation between volatility and stock returns, the following first hypothesis for this thesis is formed:

Hypothesis 1: Highest relative levels of VIX always lead to positive future stock returns in S&P 500 regardless of the holding period.

The studies by Copeland and Copeland (1999) and Boscaljon, Filbeck and Zhao (2011) find evidence that especially the value effect is positively correlated with VIX movements. A notable difference between the studies is that Copeland and Copeland discover significant results with a holding period of two or more days while Boscaljon, Filbeck and Zhao find positive returns only for holding periods of 30 or more days. However, Boscaljon, Filbeck and Zhao argue that this difference can be explained by the heightened market awareness of the anomaly or shifts in correlations between S&P 500, value and growth portfolios followed by the study of Copeland and Copeland. The study by Durand, Lim and Zumwalt (2011) supports the findings of Copeland and Copeland (1999) and Boscaljon, Filbeck and Zhao (2011) regarding the value effect while additionally finding evidence of the size and momentum premiums being positively correlated with VIX. The results of Smales (2017), on the other hand, suggest that VIX affects returns across value and firm-size and that especially small-cap stocks and firms more susceptible to value are most exposed to market sentiment and in a negative relation with VIX changes. In addition, Peltomäki and Äijö (2015) find evidence of the contemporaneous correlations between VIX and the value and momentum factors being highly time-varying as their results show that the value effect becomes negatively correlated with VIX during financial crises and that the momentum premium becomes negatively correlated with VIX during expansionary states. This could suggest that it would in fact be more profitable to invest in growth (value) stocks rather than value (growth) stocks when VIX is at its highest (lowest) levels which is the opposite of a value strategy. Based on these studies the second hypothesis for this study is formed:

Hypothesis 2: The future returns of the size, value, profitability, investment pattern and momentum factors are affected by VIX levels.

## 1.3. Structure of the thesis

This study is comprised of a literature review, a theoretical part and the actual research part. In chapter 2, previous literature about the subject is presented and reviewed. In this part, several studies concerning the relation between volatility and stock market returns are reviewed both from a contemporaneous and a future perspective. In addition, style rotation and stock market timing with VIX is discussed in this chapter. The third chapter covers the theory of financial market risk and what basic volatility is. Implied volatility and its different features are also given a closer look in the chapter. The fourth chapter concentrates on the function and formation of VIX. VIX futures and options are also introduced in chapter 4. The fifth chapter addresses the theory of the Fama-French 5 factors and the momentum factor and possible explanations for the factor effects.

The research part of this study starts from chapter 6 where the research data is introduced. Then, the methodology for the study is presented in chapter 7. The eighth chapter covers the results and discussion of the research and finally, in chapter 9, the conclusions drawn from the study are presented.

# 2. LITERATURE REVIEW

## 2.1. Negative asymmetric correlation between VIX and stock market returns

Stock prices fall (rise) if expected market volatility increases (decreases) due to investors demanding higher (lower) rate of return on stocks. Thus, there is a negative correlation between stock index returns and VIX levels. This causality between S&P 500 and VIX can be easily detected below from **figure 1** and is most noticeable especially during extreme market conditions. VIX was at its highest peak during years 2008 and 2009 which is explained by the credit and financial crises of that time. Another interesting and easily noticeable feature of figure 1 is the mean-reversion pattern of VIX. This means that when VIX level is high it tends to revert to its long run mean by going down, and when VIX is low it has a habit of being pulled back up. Thus, volatility is not expected to increase over time although stock values are anticipated to grow over the years to compensate for investors' capital risk. (Whaley 2009.) By researching this phenomenon Banerjee, Doran and Peterson (2007) find that VIX usually reverts to its mean after around 44.1 trading days. Due to the mean-reverting nature of VIX and its negative relationship to stock index returns, it can be argued that VIX is a valid indicator of stock returns.

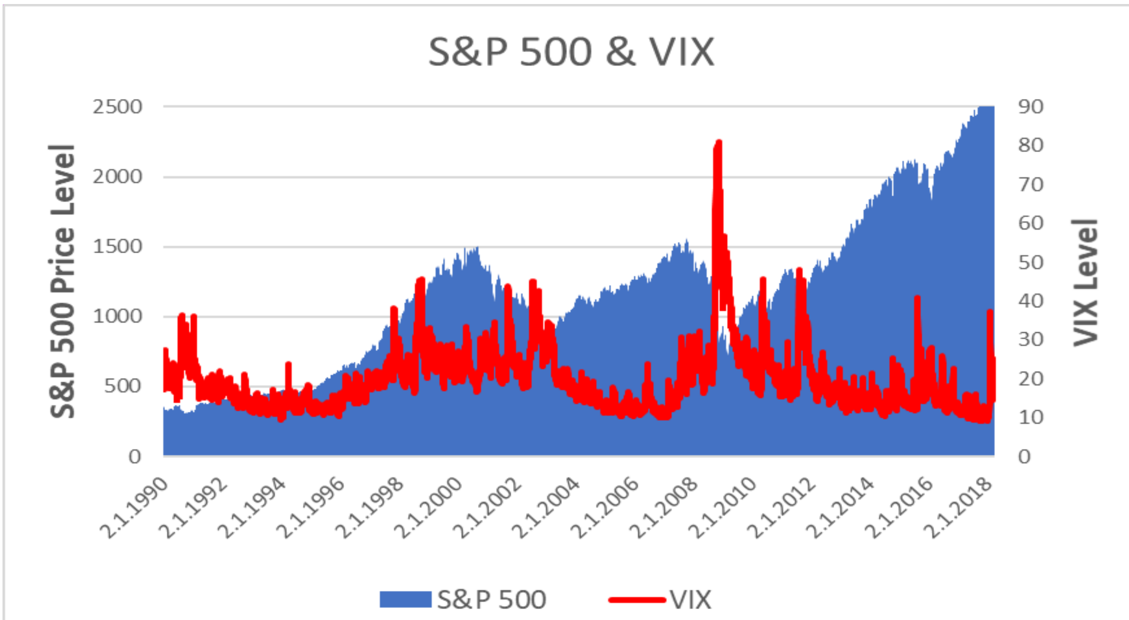


**Figure 1**: Historical daily closing values of VIX and S&P 500 index throughout January 2nd of 1990 until January 2nd of 2018 (Data Source: Yahoo Finance 2019).

The negative relation between volatility and stock returns is also asymmetric and therefore much more complex than it would seem at first glance. In practice, the asymmetric feature of the correlation means that negative return shocks tend to result in greater future volatility than equally sized positive return shocks. Therefore, the magnitude of the variation in future uncertainty is highly dependent on the return shock's nature. Like the negative correlation between VIX and stock returns, the asymmetry is as well most evident during stock market crashes especially when a large drop in stock prices causes a significant rise in market volatility. (Wu 2001: 837.) Since market volatility is more prone to increase than decrease when stock return shocks occur, it can be stated that VIX is more of a measure of market fear than investors' positive sentiment. Quite befittingly, it is also often referred to as the *fear gauge*. (Whaley 2009: 101.)

Giot (2005) shows evidence of asymmetry in a simple extended regression analysis that allows for an asymmetrical correlation between simultaneous changes in one-day returns of S&P 100 and one-day relative changes in VIX between January 1986 and August 2002:

$$\text{(1)} \qquad \mathrm{VIX1d_t} = \beta_0 \mathrm{D_t^-} + \beta_1 \mathrm{D_t^+} + \beta_2(\mathrm{y1d_t D_t^-}) + \beta_3(\mathrm{y1d_t D_t^+}) + \epsilon_t$$

Where

$\mathrm{VIX1d_t}$= one-day relative changes of VIX and price of stock index

$\mathrm{y1d_t}$= one-day returns on the stock index

$\mathrm{D_t^+}$= dummy variable that is equal to 1 (0) when $\mathrm{y1d_t}$ is negative (positive)

$\mathrm{D_t^-}$= dummy variable that is equal to 1 (0) when $\mathrm{y1d_t}$ is positive (negative)

$\epsilon_t$= error term

The ending results show that $\beta_2 \neq \beta_3$ ($\hat{\beta}_2 = -4.72$ and $\hat{\beta}_3 = -2.87$) significantly, and therefore negative returns lead to comparably greater shifts in implied volatility (increase) than positive returns (decrease).

Fu, Sandri and Shackleton (2016), on the other hand, find evidence of asymmetry between VIX and stock returns by decomposing VIX into volatility calculated from out-of-the-money call options and out-of-the-money put options. Their results reveal that the negative asymmetric relationship is stronger when using out-of-the-money put options. Information captured by out-of-the-money put options represents upward movement in volatility and downward movement in stock returns whereas out-of-the-money call options reflect the opposite effects. Thus, put options are more useful than call options in predicting future stock returns and contain especially negative news about the stock market.

Various explanations for the asymmetric negative relationship between volatility and stock returns have been proposed and one of the most used explanations is the leverage effect which is discussed in studies such as Black (1976), Christie (1982), Schwert (1989) and Carr and Wu (2006). However, Schwert (1989) and Black (1976) among others conclude that leverage alone is not enough to give reason for the detected negative correlation and the asymmetry. The idea behind the leverage effect being the explanatory factor is that the risk of a firm's stock increases when the equity level of the firm decreases while keeping the debt level fixed. This theory can then be also applied in a market level. Evidence for another popular explanation for the negative asymmetric relationship, which is called volatility feedback or time-varying risk premium theory, is found in numerous studies such as Pindyck (1984), Poterba and Summers (1986), French, Schwert and Stambaugh (1987), Haugen, Talmor and Torous (1991), Campbell and Hentschel (1992), Bekaert and Wu (2001) and Mayfield (2004). Volatility feedback refers to a phenomenon where a surge in volatility increases the anticipated future volatility and therefore the required compensation on stocks if volatility is persistent and priced. Furthermore, another suggested explanation by Whaley (2009) is that asymmetry is caused when there is an increased demand to buy index put options. Whaley argues that long index put options have started to dominate S&P 500 option markets in portfolio hedging as insurances when downside movement in stock markets is expected. Thus, further increase in volatility takes place due to increased demand for the options which are the underlying assets of VIX.

The leverage and volatility feedback effects may together explain mostly the negative correlation and for example Bae, Kim and Nelson (2007) and Bekaert and Wu (2000) show in their empirical findings that both financial leverage and volatility feedback can be causing the negative relationship although they both find that volatility feedback seems to be the more explanatory factor. Wu reasons these findings through an example event of supposed foreign market turmoil which has caused traders to be reluctant to buy and willing to sell as they await a volatile market. This leads to the volatility feedback effect as stock prices must decline to harmonize the buying and selling volume and therefore an immediate price drop follows the anticipated increase in volatility. Thus, the leverage ratio rises and as a result volatility increases and stock prices drop even more which is in keeping with the leverage effect.

Hibbert, Daigler and Dupoyet (2008) suggest that neither the volatility feedback nor the leverage hypothesis is the main root of the return-implied volatility correlation. Instead, they argue that representativeness, affect and extrapolation biases, which are theories based on behavioral finance, are the key factors causing the phenomenon. Talpsepp and Rieger (2010) highlight that especially factors regarding non-professional investor behavioral sentiment such as short selling, economic development, analyst coverage, and stock market participation are causing the effect. Avramov, Chordia, and Goyal (2006), on the other hand, suggest that herding and contrarian trades are behind the negative asymmetric return-volatility phenomenon. They argue that, regardless of trading activity and volatility measures, contrarian trades cause a drop in volatility as stock prices rise while herding trades raise the market’s uncertainty when stock prices decline. By investigating the sources of asymmetric volatility and volatility clustering Yamamoto (2010) links the asymmetric return-volatility anomaly to borrowing constrained herding agents since binding borrowing constraints add more selling pressure to the market as agents will wait to sell their shares. Due to herding the actions of agents are correlated which results in them being most likely to sell at once. This eventually leads to the overall phenomenon where negative return shocks tend to result in greater future volatility than an equally sized positive return shocks

## 2.2. VIX as a predictor of future stock index returns

Many studies find that VIX can function as a predictor of expected stock index returns and therefore also offer timing possibilities for investing in stock indices. Especially high levels of VIX are noticed to have a connection with high expected returns by multiple studies such as Giot (2005), Banerjee, Doran and Peterson (2007) and Rubbaniy, Asmerom, Abbas and Naqvi (2014). This is a very logical theory due to the mean-reverting nature of VIX: as VIX is at its highest levels it can be expected to come down in recent future while stock index returns increase simultaneously. In practice, however, it is hard to know when the VIX level is at its peak.

Giot (2005) investigates whether the highest VIX levels can work as buying signals for investors and therefore indicate oversold stock markets. Giot confirms this assumption by dividing the historical level of VIX into 21 equally distributed rolling percentiles and investigating the S&P 100 stock returns for the future 1-, 5-, 20- and 60-day holding periods for each of these percentiles. The results indicate that future returns are always positive (negative) for very high (low) levels of VIX regardless of the holding period length even though the highest returns are generated for the 60 days holding period. Therefore, at least on a short-term basis, very high levels of VIX indicate an upcoming increase in stock indices. Giot also finds that average to moderately high levels of VIX result in unfavourable returns and therefore traders should then wait for further increases in VIX until it reaches extremely high levels.

Banerjee, Doran and Peterson (2007) find similar results as Giot (2005) with VIX and S&P 500 stock returns in their study and notice that the relationship is stronger for the 60-day returns than the 30-day returns. Unlike Giot, they also make a distinction between low-beta and high beta portfolios and find interesting evidence of higher beta portfolios having a stronger negative relationship with VIX. Thus, it should be more profitable to invest in high beta stocks as VIX reaches its peak to fully take advantage of the mean reversion pattern of VIX.

Rubbaniy, Asmerom, Abbas and Naqvi (2014) research the forecasting power of implied volatility indices VIX, VXN (Nasdaq Volatility Index) and VDAX (Volatility Index of Deutsche Börse) regarding future stock returns for 1-, 5-, 20- and 60-day returns. Their findings for 20- and 60-day returns are consistent with the previously mentioned studies of Giot (2005) and Banerjee, Doran and Peterson (2007) but differ for the holding periods of 1- and 5-day returns as they find no significant link between short term returns and implied volatility indices for those holding periods. Although Rubbaniy, Asmerom, Abbas and Naqvi (2014) state that implied volatility indices can be useful timing tools for the market, they emphasize that the information content of volatility indices alone is inadequate for predicting future market performance. They argue that volatility indices need to be combined with other forms of technical analysis especially for identifying the crucial points of market extremes or reversals.

Even though most studies look at extremely high VIX levels as best stock index buying signals, there are some researchers who find that also other VIX timing strategies perform well. Lubnau and Todorova (2015) use rolling trading simulations to evaluate the performance of VIX and four other implied volatility indices as predictors of future stock returns. They execute their simulations by using the future returns of the corresponding underlying stock indices from January 2000 to October 2013 and find that significantly positive average returns follow days of very low implied volatility with the holding periods of 20, 40 and 60 trading days. These findings contradict the negative relationship between VIX and stock returns since profits are made when VIX level increases rather than decreases and suggest that markets tend to grow during calm periods and fall after volatility has been high. However, the study doesn’t directly conflict with the previously mentioned studies of Giot (2005), Banerjee, Doran and Peterson (2007) and Rubbaniy, Asmerom, Abbas and Naqvi (2014) since it does not conclusively confirm or deny whether high levels of implied volatility are good buying signals. In addition, the results show a clear difference between the US and non-US markets as the findings for US indices are largely heterogeneous and evidently less significant than for the other markets.

An interestingly different approach to examining the predictive power of VIX is done by Bekaert and Hoerova (2014) as they break down the squared VIX into the equity variance premium and the conditional variance of stock returns. The division is made to assess the individual effects of both components of VIX. Conditional variance refers to stock market uncertainty while the variance premium can be understood as the expected premium that is attained when stock market variance is sold in a swap contract. Bekaert and Hoerova find evidence that the variance premium is evidently a more accurate indicator of stock returns whereas conditional variance only significantly predicts negative economic activity. However, conditional variance seems to indicate better financial instability than the variance premium. These findings suggest that VIX can be decomposed to get more specific information about the markets.

### 2.2.1. Style rotation and stock market timing with VIX

Copeland and Copeland (1999) and Boscaljon, Filbeck and Zhao (2011) research the efficiency of VIX in timing shifts for value and growth stock allocation. They both use a method of percentage changes in VIX as indicators to switch from a growth portfolio to a value portfolio and vice versa. The results by Copeland and Copeland imply that growth stocks are outperformed by value stocks after an increase in VIX and vice versa whereas Boscaljon, Filbeck and Zhao find that positive returns can only be made by switching from growth style portfolios to value portfolios when VIX increases. The other major difference between the studies is that Copeland and Copeland discover significant results with a holding period of two or more days while Boscaljon, Filbeck and Zhao find positive returns only for holding periods of 30 or more days. Boscaljon, Filbeck and Zhao argue that these differences between the studies are most likely a result of the market awareness of the anomaly that followed the study of Copeland and Copeland or simply changes that have gradually happened over the years in the correlations between S&P 500, growth and value portfolios.

Durand, Lim and Zumwalt (2011) examine the market anomalies of value, size and momentum and their relation to expected returns of US equities from 1993 to 2007 by using the Fama-French three-factor model (1993) added with a momentum factor. They find evidence that especially the value factor is affected by VIX fluctuations so that growth stocks underperform (overperform) value stocks following a decrease (increase) in VIX which is in line with the previously mentioned studies of Copeland and Copeland (1999) and Boscaljon, Filbeck and Zhao (2011). In addition, the results show that the size and momentum premiums are as well positively correlated with VIX though the correlations are considerably weaker than with the value-growth premium.

Peltomäki and Äijö (2015) use a non-forecasting approach to examine the contemporaneous relation between returns and cross-sectional anomalies but also investigate the time-varying aspect of those correlations. This is done by regressing the daily returns on VIX and alternative state variables. They use a sample period from 1990 to 2013 and discover interestingly that the relationships are highly time-varying and depend on economic and market conditions. They find evidence that the correlation between VIX changes and value strategy returns are generally positively correlated but show that during the financial crisis from 2007 to 2009 the correlation was significantly negative. The results show that momentum has also a positive relation with VIX movements but during expansionary states the correlation becomes negative implying that a momentum strategy becomes unprofitable when VIX increases during market expansions. These intriguing findings suggest that moving to value or momentum strategies is not always profitable when VIX increases: during financial crises value stock returns become negatively correlated with VIX and during market expansion periods poor momentum returns can be expected.

Smales (2017) takes advantage of bi-directional tests of causality to examine the impact of VIX on stock returns and finds VIX to be a superior indicator of market sentiment that has the capability to provide valid forecasts for future market returns and improvement in model fit. He finds evidence of the relation between VIX and stock returns being negative for future returns and positive for contemporaneous returns and that VIX changes are better signals for explaining market returns than VIX levels. In addition, the results indicate that VIX affects returns across firm-size, value and industry and especially small-cap stocks and firms more exposed to value are most sensitive to market sentiment and in a negative relation with VIX changes. Interestingly, these results contradict the findings by Copeland and Copeland (1999), Durand, Lim and Zumwalt (2011) and Boscaljon, Filbeck and Zhao (2011) who discover a positive relationship between VIX and the value and size premiums. Furthermore, Smales provides evidence of the relations between VIX and cross-sectional anomalies being highly dependent on market conditions and finds that market responses to VIX are even stronger during recession and especially for stocks that are most susceptible to speculative demand.

## 3. FINANCIAL MARKET RISK AND VOLATILITY

Volatility is often misunderstood to be the same as risk even though it more accurately represents uncertainty and fluctuation. In economics, volatility can also be interpreted as the vulnerability of financial markets. Volatility as such is not a particularly useful measure and it needs to be incorporated in a probability distribution of returns to get results that are practical and can be evaluated. It is a crucial variable especially for pricing derivative securities of underlying assets, such as options. (Poon and Granger 2003.) For example, in the case of a stock index, volatility indicates the magnitude of the fluctuation of the index.

As definition, volatility is usually calculated as the sample standard deviation of the historical returns of a financial instrument and it is often presented in an annual form. It is also notable that daily standard deviation can be converted to annual standard deviation and vice versa. Using this approach to calculate volatility results in a lognormal distribution which is almost correct, but not exact. A precise estimate can be attained by transforming the returns to logarithms of one plus the returns and then calculating the standard deviation in the same way. The difference in the accuracy of these approaches becomes greater when the measurement interval lengthens. (Kritzman 1991: 22–23.)

Multiple studies show that stock market volatility changes constantly over time and thus there is a wide range of research regarding this phenomenon and the causes for it. Market volatility fluctuations have significant effects on business cycle variables such as capital investments and even consumption and therefore volatility studies are advantageous equally from an individual’s and society’s perspective. Market volatility changes are discovered to be in a positive relation to recessions and depressions and in a negative relation to trading activity. Financial leverage is also found to influence stock volatility: for instance, when companies issue new debt securities in bigger scale to new equity than before or stock prices decline with respect to bond prices, stock volatility rises. (Schwert 1989.) In addition, even news about volatility, especially when volatility is already high, affect stock market volatility and returns (Campbell and Hentschel 1992).

## 3.1. Implied volatility

Implied volatility is the market's assessment of what the volatility of an underlying asset should be in the future and is most commonly used in the pricing of options. It is therefore a forward-looking volatility estimate as opposed to regular historical volatility. Implied volatility can be calculated by using an option-pricing model, such as the Black-Scholes model (1973) or Cox-Ross-Rubinstein binomial model (1979). In practice, implied volatility is derived from the current option prices when we know all other required variables of the model which are relatively easily observed. (Mayhew 1995: 8.)

The definition of implied volatility can be seen dependent on the option pricing model where it is used. If deterministic variation of the volatility of the underlying asset volatility is allowed, implied volatility can be specified as the market's estimate of the average volatility during the remaining life of the option. On the other hand, if the Black-Scholes model is used and its strict conditions are met, implied volatility is defined as the constant volatility parameter estimated by the market. (Mayhew 1995: 8.)

The implied volatility of an option is widely accepted as an accurate assessment of the market's expectation of the future volatility of an asset, but there are also many studies that show that implied volatility has a weak or even no correlation with realized volatility. From these kind of findings Canina and Figlewski (1993) favour the interpretation that option pricing models lack factors that influence option supply and demand, such as investor behavioural aspects and liquidity considerations. They, however, admit that implied volatility is a useful measure that can be combined with other market information to get the true conditional expectation of future volatility.

### 3.1.1. Black-Scholes option pricing model

Fischer Black and Myron Scholes created a mathematical model used for pricing European options known as the Black-Scholes option pricing model (BSM) (1973). In the same year, Robert Merton (1973) contributed to the model by making an adjusted and more usable version of the model that is valid under weaker assumptions than the original model. The Black-Scholes option pricing model is still widely regarded as one of the best ways of pricing options and it can be easily applied by traders and investors when all the required inputs are known.

The assumptions of the Black-Scholes-Merton model are made on the underlying asset and the actual market. According to the model, the following ideal conditions are expected:

- The risk-free interest rate is constant and same for all maturities
- The underlying asset does not pay a dividend
- Asset prices follow a geometric Brownian motion (random walk) and therefore have the same probability of going up or down. The error term and volatility of the underlying asset price are constant.
- Security trading is continuous
- The markets are frictionless and there are no transaction costs or fees. All securities are perfectly divisible.
- The markets are perfectly liquid and there are no penalties to short selling.
- There are no riskless arbitrage opportunities. (Hull 2015: 331.)

It is not possible to solve implied volatility straightforwardly through the Black-Scholes model, but an it can be calculated by using an iterative search method. Implied volatility can be obtained by trying different values for volatility in the model when the value of a European option and all other inputs are known. The range for volatility can be halved through each iteration and proceeding this way leads eventually to getting the exact implied volatility. In practice, however, more efficient methods are used more often to calculate implied volatility. (Hull 2015: 341.) Below are the standard Black-Scholes-Merton formulas for pricing European call and put options.

$$c = S_0\mathbb{N}(d_1) - Ke^{-rT}\mathbb{N}(d_2) \tag{2}$$

$$p = Ke^{-rT}\mathbb{N}(-d_2) - S_0\mathbb{N}(-d_1) \tag{3}$$

Where

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

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

$S_0$ = current stock price

K = option striking price

T = time to maturity

r = risk-free interest rate

ℕ = cumulative standard normal distribution

σ = volatility of underlying asset

### 3.1.2. Volatility term structure

Volatility term structure refers to the correlation between implied volatility and maturity of an option and it is used by traders when pricing options. When short-dated volatilities are historically low (high), volatility tends to increase (decrease) as maturity increases (decreases). This is caused by the expectation of an increase in volatility due to historically low volatility levels and vice versa. (Hull 2015: 438.) Volatility term structure can be described as the market's view of what future volatility will be with different maturities and it can be presented in an upward or downward sloped linear function depending on the market expectations.

The volatility term structure phenomenon is an abnormity of the BSM since volatility does not stay constant through different maturities. The cause for volatility term structure is not undisputedly clear: some economists rationalize it for example through overreaction and mispricing of securities in predictable ways whereas some simply believe in supply and demand being the explanatory factors for it. Furthermore, evidence of the volatility term structure's slope factor being a significant sign of future short-dated implied volatility has been found. (Mixon 2007.)

### 3.1.3. Volatility smile

The volatility smile is a graphic plot of the implied volatility of an option as a function of its strike price. It contradicts the BSM which expects implied volatility to be the same for all options that have the same maturity and strike price. The reason why volatility smiles occur depends on the type of the option. Valid explanations for equity option volatility smiles are volatility fluctuations due to company's equity value changes and traders being concerned about stock market crashes and thus pricing options accordingly (crashophobia). It is therefore not surprising that volatility smiles for equities were first discovered after the stock market crash in 1987. It is also notable that European call and put options have the same volatility smile where volatility decreases as the strike price increases. (Hull 2015: 431–437.) When implied volatility is derived from an option pricing model that doesn't consider change in volatility or crashophobia, such as the BSM, it becomes curved in relation to different strike prices. The implied volatility forms a graph that is shaped as a downward skewed smile.

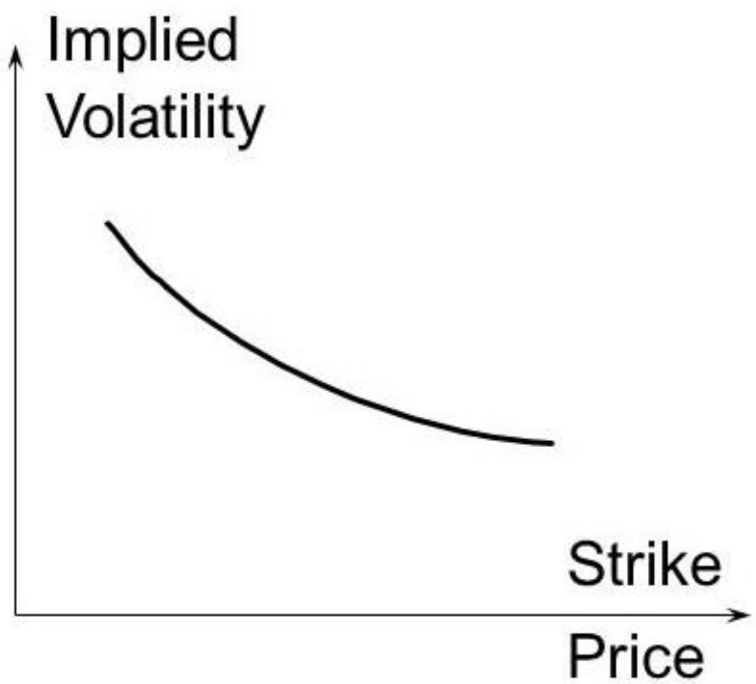


**Figure 2**: Volatility smile for equities (Hull 2015: 436).

An implied or risk-neutral probability distribution for an asset price at a future time at maturity can be derived from the volatility smile. The implied distribution has a heavier left tail compared to its right tail than the regular lognormal distribution and therefore it can be stated that the lognormal distribution underestimates the likelihood of severe negative shifts and overstates the positive movements in asset prices. Therefore, the volatility of a stock can be expected to be a declining function of the stock price. It is also notable that mediocre fluctuations have a lower probability in an implied distribution. (Hull 2015: 433–437.) Jackwerth and Rubinstein (1996) study these probability distributions due to increased popularity of derivatives and many overt failures to control the risk that they contain. Through stock market crashes and large drops in stock indexes they show that lognormal distributions don't capture the true probability of extreme events and this is due to the smile effect of stock options.

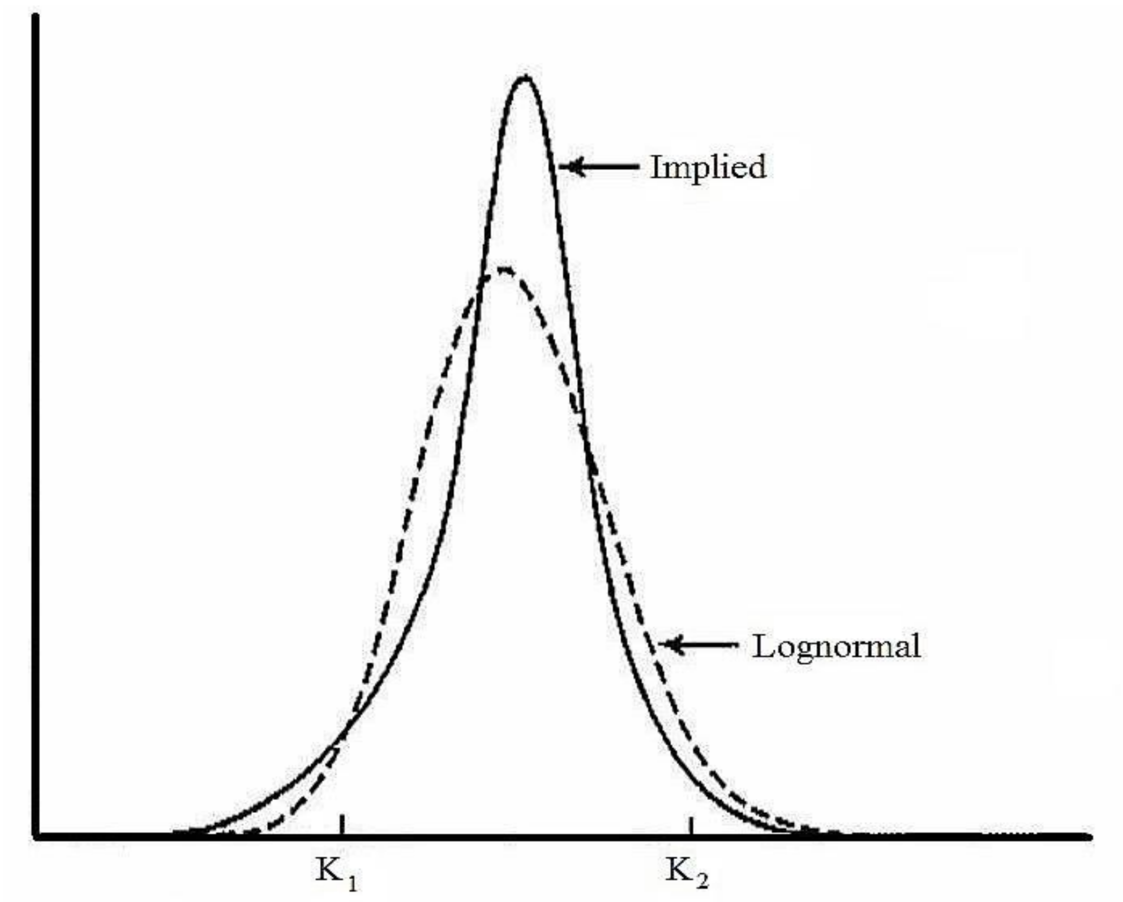


**Figure 3**: Implied distribution and lognormal distribution for equity options (Hull 2015: 437).

Volatility smiles and volatility term structures can be combined to make tables which show the explicit volatilities for pricing options with any maturity and strike price. (Hull 2015: 438–439). Volatility surfaces have also been adjusted in other ways to for example take into account arbitrage possibilities (Fengler 2009).

## 4. VOLATILITY INDEX

Volatility index (VIX) is a measure that reflects the stock market's volatility expectations calculated and published by the Chicago Board Options Exchange (CBOE). It makes an estimation of expected volatility over the next 30 days by averaging the weighted prices of S&P 500 calls and puts over various strike prices. VIX is a popular indicator of stock market uncertainty and is therefore often referred to as the *fear gauge*. It was initially presented in 1993 as a gauge of the market's expectation of 30-day volatility implied by at-the-money Standard and Poor's 100 Index (S&P 100) option prices. In 2003 CBOE constructed in cooperation with Goldman Sachs the current and improved VIX based on the S&P 500 index which is the most important index for U.S. equities. VIX was further enhanced in 2014 when CBOE chose to add also weekly S&P 500 options in the formation of the index. (CBOE 2019.)

Blair, Poon and Taylor (2001) compare the predictive power of VIX to ARCH models regarding volatility forecasting throughout a sample period from 1987 to 1999 in S&P 100. They find that in-sample analyses of low- and high-frequency data using ARCH models are clearly less effective in forecasting volatility than VIX. The results remain the same regardless of the length of the forecast or the definition of realized volatility. Blair, Poon and Taylor also notice in their study that the already superior performance of VIX compared to ARCH models increases even further when the forecast horizon grows and combinations of VIX and other forecasts are merely more informative than VIX when using 1- or 5- day forecasting. Furthermore, the predictive power of VIX has been compared to other indices that reflect pessimistic market sentiments and for example Habibah, Rajput and Sadhwani (2017) find that VIX is a superior predictor of stock market returns compared to the popular Google search volume indices (GSVI).

It is important to highlight that VIX is a forward-looking index since it is constructed from the implied volatilities of S&P 500 options and therefore doesn't measure volatility that has been realized. From this perspective, VIX can be compared to a bond's yield to maturity which connects a bond's price to the current value of the payments it promises. Thus, the yield of a bond is implied by the bond's price and depicts the bond's expected future return until it reaches maturity. VIX functions in the same way as it is implied by the present S&P 500 option prices and shows expected future stock market volatility for the next 30 calendar days. (Whaley 2009: 98.) The historical daily closing level of VIX has usually been between 10 to 20 points, but there have also been larger spikes even up to 80 points especially during financial crises which can be seen below in **figure 4**.

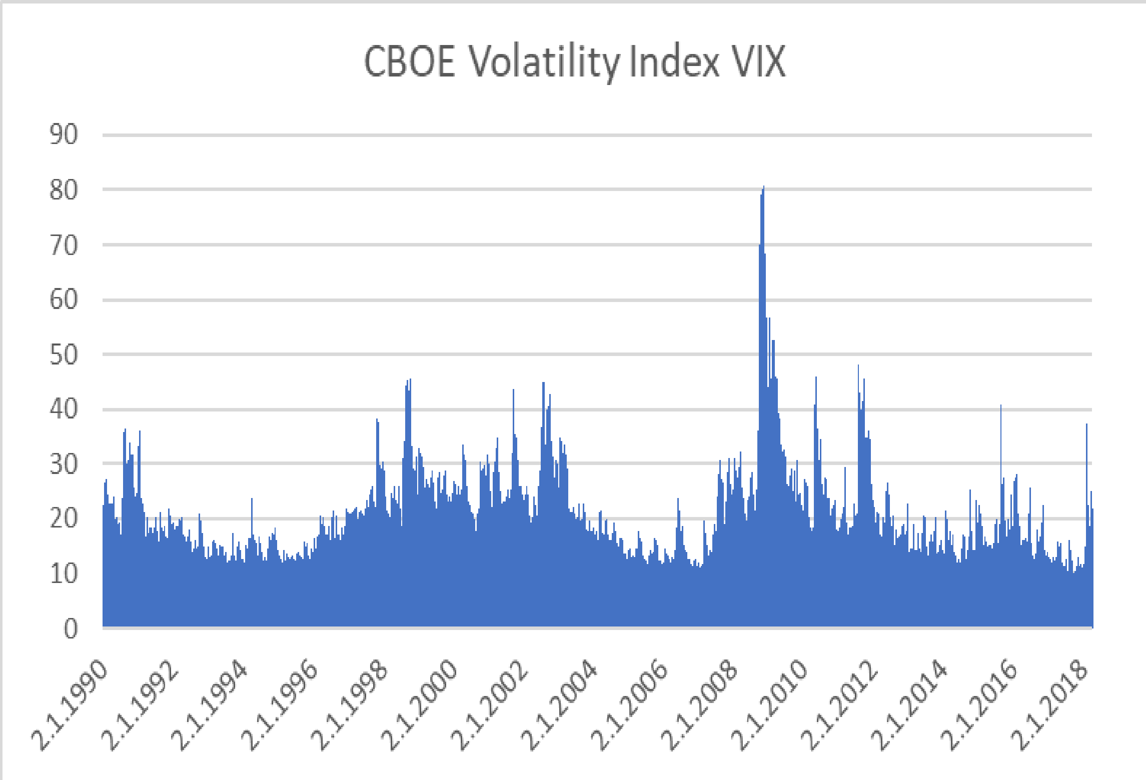


**Figure 4**: Historical daily closing values of VIX throughout January 2nd of 1990 until January 2nd of 2018 (Data Source: Yahoo Finance 2019).

Regarding the use of VIX it is worth noting that while it provides an estimate of the average level of individual stock volatilities, it is mostly utilized by market participants for assessing portfolio or market risk which cannot be mitigated through portfolio diversification (Fleming, Ostdiek and Whaley 1995). It is also shown in multiple studies that VIX can offer various timing possibilities for different portfolio strategies. Copeland and Copeland (1999), for instance, find that when volatility increases (decreases) large-cap and value portfolios outperform (underperform) small-cap and growth portfolios. Another interesting and timely aspect of VIX has been the introduction of VIX futures and options that have become popular and attractive tradable products for investors.

Especially VIX options have been very successful since CBOE launched them in 2016. (CBOE 2019.)

## 4.1. VIX calculation

VIX was originally calculated from the prices of only eight at-the-money S&P 100 index call and put options since they were the most traded options at the time. As S&P 500 index options became gradually more favoured than S&P 100 index options, CBOE decided in 2003 to start using instead S&P 500 index option prices in the calculation of VIX. Another reason adding to the shift was that S&P 500 index options are European styled options which means that they are exercisable only at expiration and therefore simpler to value by using option pricing formulas. When CBOE started using S&P 500 index option prices for calculating VIX, they also decided to add out-of-the-money options in the index computation since they hold essential information concerning portfolio insurance demands and, thus, market volatility. Furthermore, incorporating supplementary option series simply helped to make the VIX less responsive to any single option price, and thus less vulnerable to manipulation. (Whaley 2009: 99.)

The generalized formula used in the VIX calculation is:

$$\sigma^2 = \frac{2}{T}\Sigma_i \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T}\left[\frac{F}{K_0} - 1\right]^2 \qquad (4)$$

Where

$\sigma = VIX/100 \Rightarrow VIX = \sigma \times 100$

T = time to expiration

F = Forward index level derived from index option prices

$K_0$ = First strike below the forward index level, F

$K_i$ = Strike price of $i_{th}$ out-of-the-money option; a call if $K_i > K_0$ and a put if $K_i < K_0$ and both put and call if $K_i = K_0$

$\Delta K_i$ = Interval between strike prices – half the difference between the strike on either side of $K_i$:

$\Delta K_i = (K_{i+1} - K_{i-1})/2$

(Note: $\Delta K$ for the lowest strike is simply the difference between the lowest strike and the next higher strike. Likewise, $\Delta K$ for the highest strike is the difference between the highest strike and the next lower strike.)

R = Risk-free interest rate to expiration

$Q(K_i)$ = The midpoint of the bid-ask spread for each option with strike Ki. (CBOE 2019.)

The formula for VIX differs considerably from the BSM formula. VIX is derived from a weighted sum of option prices, whereas a Black-Scholes implied volatility is acquired from a single option price. VIX also takes into account the volatility smile or volatility skew that emerged after the stock market crash in 1987. Thus, VIX is a more consistent and reliable measure that doesn’t compel volatility to be constant and therefore a better option for measuring expected volatility. The VIX calculation uses S&P 500 at-the-money and out-the-money call and put options with 23 to 37 days to maturity and includes Weekly S&P 500 options and S&P 500 options with the standard expiration day which is the third Friday of the month. Weekly S&P 500 options expire each Friday excluding the third Friday of each month. The calculation therefore uses a rolling method where the S&P 500 options roll forward into new contract maturities every week. (CBOE 2019.)

## 4.2. VIX futures and options

VIX futures and options provide investors a way to trade directly volatility and make a profit from volatility increases or decreases. The most obvious difference between the two derivatives is that a VIX futures contract represents $1000 times the index whereas the corresponding multiplier for VIX options is $100. CBOE launched the first exchange-traded VIX futures contract in 2004 which was followed by the introduction of VIX options two years later in 2006. VIX futures and options have been popular products among traders and just after ten years since their launch the joint trading volume of VIX options and futures had grown to over 800,000 contracts daily. VIX futures and options can also be used for example for diversification benefits in investment portfolios due to the well documented negative correlation between volatility and stock market returns. (CBOE 2019.) Open interest and volume of VIX derivatives have increased considerably especially due to the significant volatility changes throughout the recent financial crisis that started in 2008 and the elevated need for hedging against volatility changes (Zhang, Shu and Brenner 2010: 810).

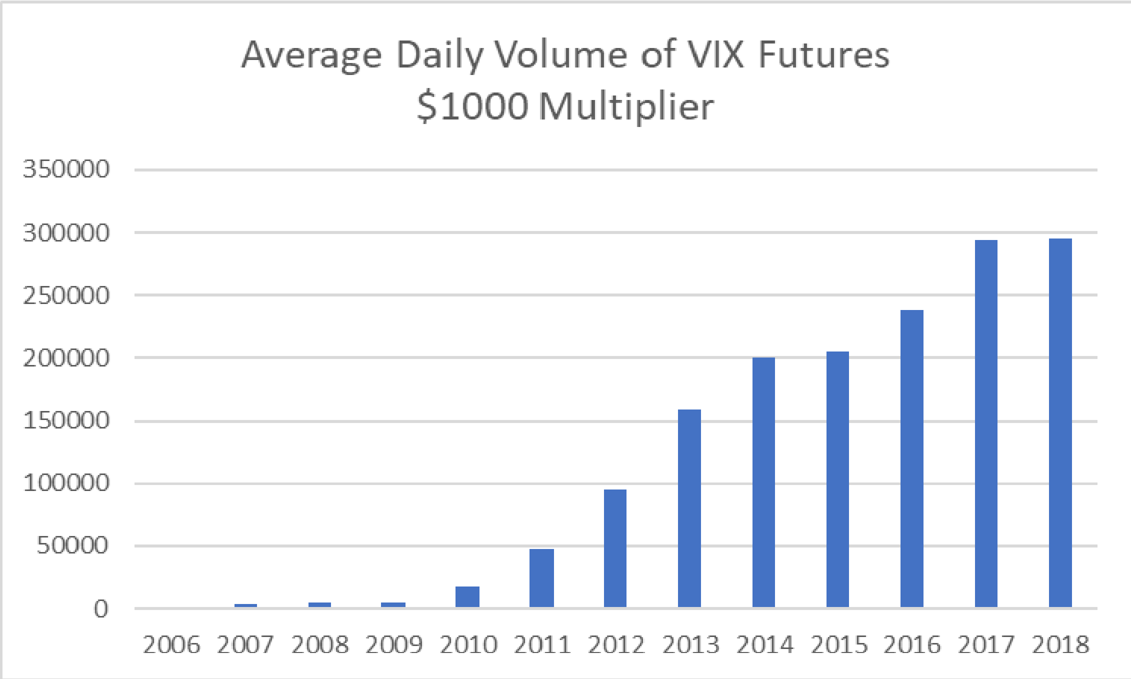


**Figure 5**: Average daily volumes of VIX futures per year (Data source: CBOE 2019).

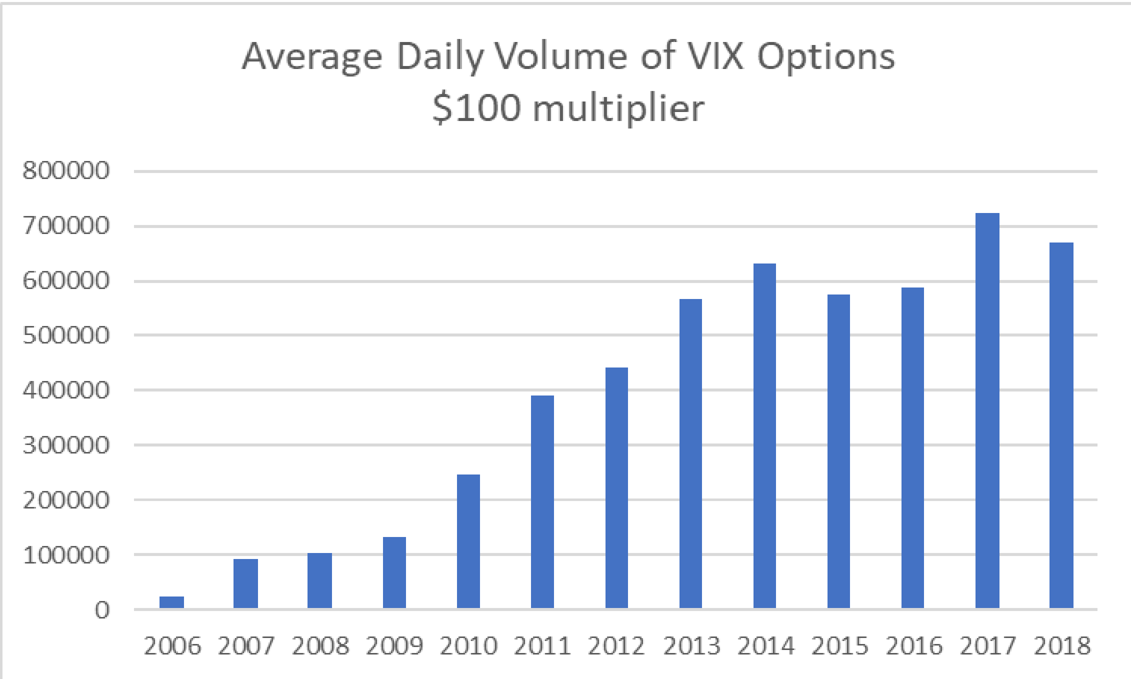


**Figure 6**: Average daily volumes of VIX options per year (Data source: CBOE 2019).

It is possible to invest in VIX by taking a position in VIX futures or VIX options. VIX fluctuations depend on actual changes in implied volatility whereas the prices of VIX futures and options depend on the current predictions of what the expected 30-day volatility is going to be on the expiration date. Therefore, hypothetically, VIX options and futures should converge to the spot rate of VIX at expiration. In practice, however, this is very exceptional as there can be major differences between spot VIX and VIX futures and options before and at expiration. (Szado 2009: 72–73.)

VIX cannot be sold or bought and therefore there is no tradable asset underlying the VIX futures. Hence, there is not a usual cost-of-carry relation and arbitrage mechanism between VIX futures and VIX like with regular market futures. The mean-reverting nature of volatility makes the connection between spot VIX  and VIX futures even more complicated since it partially leads to VIX being considerably more volatile than VIX futures. The mean-reverting nature of volatility must also be reflected in the pricing of VIX options. VIX options have many other unique features and for instance tend to exhibit extremely high volatilities which is in accordance to the phenomenon of high volatility of volatility. This means that the volatility of VIX tends to be much higher compared to equity indices or even separate equities' volatilities. (Szado 2009.)

VIX futures and options can be used for diversification and hedging benefits although the subject is very controversial. Dash and Moran (2007) find evidence that investing in VIX reduces the risk of the portfolio, but it also means giving up on some returns. Their results show that including even a modest amount of exposure to volatility can be used to control downside risk and boost an equity portfolio's risk-return characteristics. Alexander and Korovillas (2013), on the other hand, find that VIX derivatives portfolios perform better than portfolios that consist purely of equities during severe market conditions.

## 5. FAMA-FRENCH 5 FACTORS AND MOMENTUM FACTOR

In 1992 Fama and French (1993) introduced their three-factor model to explain the cross-sectional variance of returns that consists of three common risk factors for stocks: market risk, firm size and book-to-market. The model broadens on the capital asset pricing model (CAPM) by incorporating value and size risk factors with the already existing market risk factor in CAPM and is based on their previous findings that the CAPM is horizontal when book-to-market ratios and market values in returns are controlled for (Fama and French 1992). Incorporating the market risk variables into the model is not straightforward and thus Fama and French use mimicking portfolios that convert firm fundamentals into more flexible and frequent series to create the factors. Their model shows that indeed firm size and book-to-market factors are sensitivity proxies to common risk factors in stock returns and tend to generate better returns than expected by the CAPM. Thus, the Fama-French three-factor model has become a major benchmark for investigating new factors and striving to create a more complete CAPM. Later, in 2014, Fama and French (2015) expanded their three-factor model by including profitability and investment pattern risk factors into the original model and thus created the widely popular Fama-French 5-factor model. In their study, Fama and French show that the five-factor model performs even better than the three-factor model in explaining the cross-section of U.S. stock returns and according to the model small, profitable and high book-to-market companies with no major growth prospects attain the highest expected returns. Below is the formula for the Fama-French 5-factor model (Fama and French 2015):

$$R_{it} - R_{Ft} = \alpha_i + b_i(R_{Mt} - R_{Ft}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{it} \quad (5)$$

Where

$R_{it}$ = return on a security or portfolio i for period t

$R_{Ft}$ = risk-free return

$R_{Mt}$ = value-weighted market portfolio return

$SMB_t$ = difference between the return on diversified portfolios of small and big stocks portfolio minus the return on a diversified portfolio of big stocks

$HML_t$ = difference between the returns on diversified portfolios of high and low book-to-market stocks

$RMW_t$ = difference between the returns on diversified portfolios of stocks with robust and weak profitability

$CMA_t$ = difference between the returns on diversified portfolios of the stocks of low and high investment firms

$e_{it}$ = zero-mean residual. (Fama and French 2015.)

5.1. Size effect

The first to make a detailed paper regarding the connection between market values and the cross section of returns was Banz (1981). He investigates the empirical connection between NYSE common stocks' returns and market values and discovers that, on average, small firms have significantly higher risk-adjusted returns compared to large firms. In addition, Banz detects that the prime anomaly response is found within the smallest firms and there is only a slight discrepancy between the returns generated by large and average sized firms. Thus, he demonstrates that the size effect is not linear regarding market value. Banz fails to provide a definite explanation for the size effect but proposes that it might be caused by mergers as large corporations have the advantage of being able to pay a premium for small firms' stocks due to their ability to discount identical cash flows at a considerably lower discount rate.

Two years after the publication of their three-factor model, Fama and French (1995) connected the size and book-to-market factors to profitability as they tried to provide an economic foundation for the factor effects. In their study they focus on whether the behavior of stock prices reflects the behavior of earnings with respect to size and book-to-market-equity and discover that smaller and high book-to market firms that have high earnings maintain high earnings around earnings announcements and vice versa. Thus, they find evidence of the size effect being a result of the riskiness of low earnings persistence.

Chan and Chen (1991), on the other hand, propose that the size effect is linked to firms that carry more risk and are therefore more sensitive to economic downturns. They notice in their study that a small firm portfolio consists largely of firms with high financial leverage and low production efficiency and thus argue that there ought to be a risk premium for investing in small firms. After the early discovery of the size premium the effect has been considered to have died by some studies as the markets have presumably exploited the effect away (Ang 2014). This has also led to the recent economic literature regarding the size effect not being as comprehensive as the early studies of the anomaly.

### 5.2. Value effect

In 1934 Graham and Dodd laid the groundwork for value investing with their book “Security Analysis” as they proposed that investors should emphasize buying comparably undervalued and selling overvalued stocks. Later, the research by Graham and Dodd inspired groundbreaking studies such as Stattman (1980), Rosenberg, Reid and Lanstein (1985) and Fama and French (1993) that showed that book-to-market ratios have the capability to explain cross-sectional variations in stocks and confirmed that indeed high book-to-market (value) stocks seem to outperform low book-to-market (growth) stocks.

Many of the explanations proposed for the value effect are the same as the risk-based explanations for the size effect anomaly and for example earnings persistence (Fama and French, 1995) and relative distress premia (Chan and Chen 1991) have been found to be linked to the phenomenon. Likewise, Petkova and Zhang (2005) find evidence of value (growth) stock betas being positively (negatively) correlated with expected market risk premiums indicating that growth stocks are less responsive to wide market fluctuations than value stocks. Thus, value stocks follow more closely economy-wide trends than growth stocks and are more affected by both economic downturns and upturns.

Lakonishok, Shleifer and Vishny (1994), however, argue that a behavioral explanation is behind the value effect instead of value stocks being fundamentally riskier. They propose that the higher returns of value strategies are caused by the suboptimal behavior of typical investors which is then capitalized on by more superior and optimal investors. Furthermore, they find evidence that value betas are higher than growth betas during good economic states, but lower during poor times of the economy. Bhushan (1989), Daniel and Titman (1997) and Jegadeesh, Kim, Krische and Lee (2004) show evidence of the value effect being caused by investors’ preferences for certain stock characteristics. They suggest that the value effect anomaly is due to high book-to-market companies being unattractive to investors while low book-to-market companies are found to be more glamorous and exciting by investors.

### 5.3. Profitability and investment effects

Fama and French (2015) added the robust-minus-weak (RMW) profitability factor and the conservative-minus-aggressive (CMA) investment factor to their three-factor model to create the five-factor model. Their inspiration for incorporating the two new components to the model came from papers such as Novy-Marx (2013) and Aharoni, Grundy and Zeng (2013) that criticized the three-factor model for leaving much of the variation in stock prices unexplained and showed that expected stock returns are positively correlated to profitability and negatively correlated to investment.

Although Haugen and Baker (1996) already discovered the profitability effect empirically in 1996, researchers started to pay more attention to it as late as around the publication of the Fama-French 5-factor model (2015). Thus, the economic literature regarding the effect is not as comprehensive as for example for the size and value effects. Sun, Wei and Xie (2014) provide a behavioural explanation for the profitability effect as they find evidence of the effect being more powerful in countries that have lower frictions for investing, such as the U.S. and weaker in countries with high limits to arbitrage such as China. Lam, Wang and Wei (2016) discover similar results as they show that adding a mis-valuation factor based on investor sentiment to macroeconomic risk factors helps substantially in explaining the anomaly. In addition, they find that unexpected cash-flows have a significant effect on the profitability anomaly as their results imply that high profitability firms that are considered low in value by the market generate substantially greater abnormal returns around earnings announcements and have more forecast reexaminations and modifications as well as errors in analyst earnings forecasts.

The negative investment-return effect has been studied more extensively than the profitability effect and both risk-based and behavioural explanations have been proposed for it in economic literature. Berk, Green and Naik (1999) link the investment effect to the decline of systematic risk due to high availability of low risk projects. They argue that firms tend to invest more when the amount of low risk projects increases. Thus, as systematic risk and returns are positively correlated, higher investment activity should result in both a decrease in systematic risk and returns allowing lower returns especially for aggressive growers. The paper by Carlson, Fisher and Giammarino (2004) supports the findings by Berk, Green & Naik (1999) as they use a similar approach but add to their study steady adjustment expenses, reversible real options, operating leverage and limited growth opportunities. They find that the systematic risks of assets change throughout time with historical investment decisions and that a firm's beta decreases through investing. Cooper and Priestley (2011) as well confirm in their paper that systematic risk declines during large investment periods. Furthermore, they propose that the negative investment premium might be the result of conservative investors being often large firms that are more sensitive to economic cyclicality while aggressive investors tend to be more flexible growth firms that can effortlessly reduce their activity when the economy is trending down. Titman, Wei and Xie (2004), on the other hand, propose a behavioural explanation for the investment effect and argue that the constant underreaction of investors to the implications of increased investment expenditures by so-called empire building managers are causing the phenomenon.

## 5.4. Momentum effect

The fundamental concept behind a momentum strategy is to take advantage of stocks that are experiencing a positive or negative trend and is often summarized as a strategy of buying "winners" and selling "losers". In practice, the strategy is executed by constructing winner and loser portfolios during the past J months and keeping them for K months. Thus, the strategy uses historical stock prices to find the momentum trends and is classified as an anomaly in economic science as according to the weak forms of efficiency historical prices should not include any information regarding the forthcoming development of stock prices. The anomaly has been widely researched and documented to generate excess returns in numerous markets. (Bodie, Kane and Marcus 2011: 386.)

The benchmark study for momentum research is the study by Jegadeesh and Titman (1993) where they document the momentum effect in the U.S. stock market between 1965 and 1989. They discover substantial positive returns for the holding periods from 3 to 12 months. In addition, Jegadeesh and Titman argue that the anomaly is not caused by postponed market responses to common factors or systematic risk. The research by Rouwenhorst (1998) supports the findings by Jegadeesh and Titman (1993) as they examine international momentum effects and find that the positively trending stocks outperform the negatively trending stocks roughly by one percent per month. Multiple studies, however, have linked the performance of momentum strategies to riskiness. Moskowitz and Grinblatt (1999) show that momentum strategies become much less rewarding when industry momentum is controlled for suggesting that the momentum effect is tilted only towards a few industries. Chordia and Shivakumar (2002) link the momentum effect to market risk as they discover a connection between the predictability of a series of lagged macroeconomic variables associated with the business cycle and momentum profits. When they control for these variables all significant momentum payoffs are eliminated. In addition, they show evidence of the momentum effect being time-varying and only present in expansionary periods of the economy. Avramov, Chordia, Jostova and Philipov (2007), on the other hand, argue that the momentum premium is due to firm credit ratings as they show evidence that only firms with low credit ratings exhibit positive momentum returns. Thus, their findings imply that extreme winner and loser portfolios mostly consist of low-grade stocks in terms of credit rating.

In addition to risk-based views, multiple behavioural explanations for the momentum effect have been proposed although the majority of them agrees with the studies by DeBondt and Thaler (1985, 1987) that the anomaly is due to the tendency of most market participants to overreact to sudden and climactic stock news. DeBondt and Thaler (1985, 1987) justify their position by showing that prior losers distinctly outperform previous winners and have produced approximately 25% more than the winners thirty-six months after the construction of the portfolios. DeLong, Shleifer, Summers and Waldman (1990) argue that the overreaction phenomenon is due to noise traders who cause rational speculators to strengthen the trend with more purchases. This can then lead to noise traders becoming even more eager to push prices further away from their fundamental values. Daniel, Hirshleifer and Subrahmanyam (1998) rationalize the overreaction effect by showing that stock prices underreact to public information and overreact to private news signals. This tendency of the markets to over- or underreact to various types of news then causes the momentum pattern.

# 6. DATA

All data for this thesis is collected from the world wide web and can be accessed by anyone freely. The VIX and S&P 500 data is compiled from the website www.finance.yahoo.com. Due to S&P 500 not being directly tradable, the data for exchange-traded fund SPY (SPDR S&P 500 ETF) is utilized to reflect the movements of S&P 500. Furthermore, all data is modified to consider dividends and splits and all the returns applied in this thesis are transformed into logarithmic returns. The daily data used for SPY, Fama-French 5 factors and momentum factor is collected from a period starting from 29th January 1993 and ending on 31st December 2018. For VIX the used data starts 500 trading days prior to 29th of January to determine the ranks for VIX for the beginning of the equity data. The final trading day for VIX is also 31st December 2018.

The definitions and data for the Fama-French 5 factors and the momentum factor can be found from Kenneth French's website (Kenneth French Data Library 2019):

Mkt-Rf is the excess return on the market. The market return in this data is a value weighted return of a large number of firms listed on NYSE, AMEX or NASDAQ minus the one-month treasury bill rate.

SMB is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios formed as follows:

(6)
$$\text{SMB}_{(\text{B/M})} = {}^{1}/_{3}\,(\text{Small Value} + \text{Small Neutral} + \text{Small Growth}) - {}^{1}/_{3}\,(\text{Big Value} + \text{Big Neutral} + \text{Big Growth})$$

$$\text{SMB}_{(\text{OP})} = {}^{1}/_{3}\,(\text{Small Robust} + \text{Small Neutral} + \text{Small Weak}) - {}^{1}/_{3}\,(\text{Big Robust} + \text{Big Neutral} + \text{Big Weak})$$

$$\text{SMB}_{(\text{INV})} = {}^{1}/_{3}\,(\text{Small Conservative} + \text{Small Neutral} + \text{Small Aggressive}) - {}^{1}/_{3}\,(\text{Big Conservative} + \text{Big Neutral} + \text{Big Aggressive})$$

$$\text{SMB} = {}^{1}/_{3}\,(\text{SMB}_{(\text{B/M})} + \text{SMB}_{(\text{OP})} + \text{SMB}_{(\text{INV})}),$$

where B/M indicates value or growth stock, OP stands for operating profit and INV means investment pattern of conservative or aggressive stock.

HML is the average return on the two value portfolios minus the average return on the two growth portfolios.

(7) $$\text{HML} = {}^{1}/_{2}\,(\text{Small Value} + \text{Big Value}) - {}^{1}/_{2}\,(\text{Small Growth} + \text{Big Growth})$$

RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios.

(8) $$\text{RMW} = {}^{1}/_{2}\,(\text{Small Robust} + \text{Big Robust}) - {}^{1}/_{2}\,(\text{Small Weak} + \text{Big Weak})$$

CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios.

(9) $$\text{CMA} = {}^{1}/_{2}\,(\text{Small Conservative} + \text{Big Conservative}) - {}^{1}/_{2}\,(\text{Small Aggressive} + \text{Big Aggressive}).$$

A complete and more detailed description of the Fama-French 5 factor returns can be found in the paper of Fama and French (2015).

MOM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios. The median of NYSE market equity is the daily size breakpoint for the factor and the daily prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles.

(10) $$\text{MOM} = {}^{1}/_{2}\,(\text{Small High} + \text{Big High}) - {}^{1}/_{2}\,(\text{Small Low} + \text{Big Low})$$

# 7. METHODOLOGY

The methodology of this thesis is based on the research made by Giot (2005) and examines whether high (low) VIX levels are useful buying (selling) indicators for SPY, Fama-French five factors and momentum factor. The holding periods used in this study are 1, 5, 20 and 60 days which are the same as in the study by Giot (2005). These holding periods are optimal and valid for this study as Banerjee Doran and Peterson (2007) discover the mean reversion of VIX to be approximately 44.1 trading days.

Firstly, a plain analysis between VIX and SPY, Fama-French 5 factors and momentum factor correlations is carried out in this study by using daily logarithmic returns. After that, in the main study, the usability of relative VIX levels as timing indicators is under examination by dividing VIX levels into 20 percentiles with a 500-day rolling method. Relative values of VIX are used because it is not possible to define absolute boundaries for high and low levels of VIX. In addition, long-short portfolios for each factor are formed based on the ranking method results so that for example extremely low (high) levels of VIX are signals to take a short (long) position in a certain factor portfolio. This is done to determine how well the factors perform when they are used in an equity investing strategy that relies on VIX as a timing tool.

## 7.1. VIX ranking system

Since the ranking system used in this study utilizes a 500-day rolling approach, the estimation interval for VIX is 500 days, $T_0$ so that $T_0+1$ is then given a rank between 1 and 20. The given rank is determined by the rolling approach so that, for example, rank 1 signifies that the observation belongs at least to the lowest 5% levels of VIX over the previous 500 days and rank 20 implies that the measurement is higher than at least 95% of VIX observations in the sample during the previous 500 days. This method is almost identical to the one used by Giot (2005) since Giot uses a two-year rolling method and the same ranking system in his study. A major benefit of the rolling method is that the outer limits for the percentiles do not fluctuate rapidly even though VIX might occasionally exhibit drastic daily changes.

**Table 1** is a demonstration of the ranking for VIX if the whole sample history would have been used instead of the rolling method. The rank can be seen in the first column and the second column represents the equivalent percentile for every rank. The third column demonstrates what the actual upper boundaries would be in in terms of VIX values for the ranks if the sample history would have been used. The table shows that VIX receives the highest rank when its values are between 80.86 and 33.96 and the lowest rank when its values are equal to or below 11.15. It is also notable that the differences between VIX percentile boundaries become continuously smaller from higher ranks to lower ranks.

**Table 1:** Historical percentile ranks and upper boundaries for VIX from 29th January 1993 to 31st December 2018.

| RANK | Percentile | Upper boundary |
|---|---|---|
| R20 | 95-100 | 80.86 |
| R19 | 90-95 | 33.96 |
| R18 | 85-90 | 28.81 |
| R17 | 80-85 | 26.00 |
| R16 | 75-80 | 24.33 |
| R15 | 70-75 | 22.88 |
| R14 | 65-70 | 21.65 |
| R13 | 60-65 | 20.59 |
| R12 | 55-60 | 19.52 |
| R11 | 50-55 | 18.49 |
| R10 | 45-50 | 17.39 |
| R9 | 40-45 | 16.43 |
| R8 | 35-40 | 15.59 |
| R7 | 30-35 | 14.75 |
| R6 | 25-30 | 14.03 |
| R5 | 20-25 | 13.37 |
| R4 | 15-20 | 12.84 |
| R3 | 10-15 | 12.30 |
| R2 | 5-10 | 11.76 |
| R1 | 0-5 | 11.15 |

**Table 2** shows the minimum, maximum, mean and median values for VIX for the sample period. The highest value, 80.86, occurred in the middle of the financial crisis on 20th November 2008 and the lowest value, 9.14, on 3rd November 2017.

**Table 2:** Historical VIX statistics from 29th January 1993 to 31st December 2018.

| | VIX | Date |
|---|---|---|
| Min | 9.14 | 3.11.2017 |
| Max | 80.86 | 20.11.2008 |
| Mean | 19.33 | |
| Median | 17.39 | |

7.2. Return calculation method for different ranks

The return calculation approach that is utilized to estimate the average returns for SPY and factor portfolios is the same that is used by Giot (2005). The SPY and factor portfolio returns are regressed on 20 ranks and each rank is represented by a dummy variable. The ranks receive either the value of 0 or 1 which is determined by the rank that VIX has on a particular day so that only one rank is given the value of 1 and all other ranks the value 0. Below are the regression models applied in this study.

$$(11) \qquad r1d = \beta_1 D1_t + \beta_2 D2_t + \ldots + \beta_{21} D20_t + \varepsilon t$$

$$(12) \qquad r5d = \beta_1 D1_t + \beta_2 D2_t + \ldots + \beta_{21} D20_t + \varepsilon t$$

$$(13) \qquad r20d = \beta_1 D1_t + \beta_2 D2_t + \ldots + \beta_{21} D20_t + \varepsilon t$$

$$(14) \qquad r60d = \beta_1 D1_t + \beta_2 D2_t + \ldots + \beta_{21} D20_t + \varepsilon t$$

Where r1d, r5d, r20d and r60d are the 1-, 5-, 20- and 60-day returns for SPY and factor portfolios and D1, D2, D3…, D19 and D20 depict the dummy variables for different ranks. Each return coefficient may be understood as the anticipated return at the given time horizon when VIX is ranked into category $R_t$ at time t and thus it is crucial to highlight that all regression returns are separate and individual.

## 8. RESULTS AND DISCUSSION

The results segment of this study starts with two correlation analysis tables where the correlation between VIX and SPY and factor portfolios is examined. **Table 3** below displays the overall correlation between VIX and SPY and factor portfolios from 29th January 1993 to 31st December 2018. The excess return on the market has the highest negative correlation with VIX (-0.726) and the second strongest negative correlation is between SPY and VIX (-0.718). These results are not surprising since they support the results of studies such as Fleming, Ostdiek and Whaley (1995), Giot (2005), Hibbert, Daigler and Dupoyet (2008) and Whaley (2009) that have documented VIX to be highly negatively correlated with equity market returns. The results also show that HML, RMW, CMA and MOM factor portfolios have been mostly positively correlated and SMB marginally negatively correlated with VIX.

**Table 3:** Correlations between VIX and different benchmarks from 29th January 1993 to 31st December 2018.

| Benchmark | Correlation with VIX |
|---|---|
| SPY | -0.718 |
| Mkt-Rf | -0.726 |
| SMB | -0.031 |
| HML | 0.049 |
| RMW | 0.244 |
| CMA | 0.209 |
| MOM | 0.029 |

More detailed correlation results compared to the previous table can be seen in **table 4** as it shows what the correlations between VIX and SPY and factor portfolios have been yearly from 29th January 1993 to 31st December 2018. Although most of the correlations have remained more or less the same over the years, there has been a clear change in the correlations of HML and SMB factors with VIX in the recent history. For the last ten years VIX has been eight out of ten years negatively correlated with SMB and seven out of ten years negatively correlated with HML. These results would suggest that investors prefer to hold large company stocks rather than small company stocks when VIX increases. In addition, investors seem more willing to hold growth stocks rather than value stocks when VIX increases. The negative correlation between VIX and HML has been less significant than the negative correlation between VIX and SMB in the recent years and it is also notable that for the last five years HML has been more positively than negatively correlated with VIX. In addition, the statistics for SMB and HML suggest that their correlations with VIX tend to be positive during low market uncertainty and vice versa since during and around the financial crisis period both factors became negatively correlated with VIX.

**Table 4:** Yearly correlations between VIX and different benchmarks from 29th January 1993 to 31st December 2018.

| Year | SPY | Mkt-Rf | SMB | HML | RMW | CMA | MOM |
|---|---|---|---|---|---|---|---|
| 1993 | -0.50 | -0.54 | 0.08 | 0.14 | -0.07 | 0.21 | -0.25 |
| 1994 | -0.69 | -0.74 | 0.20 | 0.25 | 0.12 | 0.32 | -0.28 |
| 1995 | -0.45 | -0.49 | 0.00 | 0.26 | 0.19 | 0.21 | -0.19 |
| 1996 | -0.69 | -0.70 | 0.24 | 0.48 | 0.10 | 0.37 | -0.33 |
| 1997 | -0.69 | -0.72 | 0.42 | 0.48 | -0.16 | 0.38 | -0.49 |
| 1998 | -0.81 | -0.82 | 0.33 | 0.58 | 0.18 | 0.53 | -0.14 |
| 1999 | -0.76 | -0.79 | 0.56 | 0.54 | 0.14 | 0.50 | -0.39 |
| 2000 | -0.72 | -0.77 | 0.12 | 0.54 | 0.42 | 0.52 | -0.32 |
| 2001 | -0.81 | -0.82 | 0.22 | 0.51 | 0.48 | 0.56 | 0.55 |
| 2002 | -0.80 | -0.82 | 0.38 | 0.28 | 0.35 | 0.16 | 0.52 |
| 2003 | -0.63 | -0.65 | 0.04 | 0.10 | 0.40 | -0.24 | 0.11 |
| 2004 | -0.80 | -0.77 | -0.42 | 0.08 | 0.44 | -0.39 | -0.40 |
| 2005 | -0.84 | -0.82 | -0.37 | 0.15 | -0.02 | 0.15 | -0.31 |
| 2006 | -0.85 | -0.82 | -0.48 | 0.22 | 0.09 | 0.16 | -0.47 |
| 2007 | -0.88 | -0.85 | -0.20 | -0.03 | -0.15 | 0.16 | -0.18 |
| 2008 | -0.85 | -0.84 | 0.10 | -0.31 | 0.21 | 0.30 | 0.53 |
| 2009 | -0.76 | -0.75 | -0.27 | -0.57 | 0.43 | 0.15 | 0.50 |
| 2010 | -0.85 | -0.84 | -0.39 | -0.60 | 0.49 | -0.50 | -0.63 |
| 2011 | -0.87 | -0.86 | -0.52 | -0.27 | 0.67 | -0.13 | -0.02 |
| 2012 | -0.76 | -0.76 | -0.27 | -0.13 | 0.33 | 0.19 | 0.35 |
| 2013 | -0.83 | -0.83 | -0.21 | -0.26 | 0.49 | -0.06 | -0.40 |
| 2014 | -0.85 | -0.85 | -0.16 | 0.19 | 0.31 | 0.28 | -0.33 |
| 2015 | -0.88 | -0.88 | 0.10 | 0.08 | 0.12 | 0.28 | 0.02 |
| 2016 | -0.81 | -0.81 | -0.29 | -0.06 | 0.30 | 0.11 | 0.28 |
| 2017 | -0.74 | -0.74 | -0.29 | -0.01 | 0.18 | 0.15 | -0.37 |
| 2018 | -0.81 | -0.81 | 0.06 | 0.24 | 0.23 | 0.29 | -0.35 |

The results of table 4 mostly support the flight-to-quality, or flight-to-safety, phenomenon documented by studies such as Abel (1988), Barsky (1989) and Durand, Junker and Szimayer (2010) where investors modify their portfolios towards less volatile and more quality assets during difficult economic times. According to the statistics, investors prefer larger and more conservative stocks with higher operating profitability when risk increases. The HML statistics support the findings of Peltomäki and Äijö (2015) that HML becomes negatively correlated with VIX during financial crises: the major negative observations occur during and few years after the financial crisis, that started in 2007 and ended in 2009. Thus, it seems that the correlation between VIX and HML is normally positive but becomes negative under times of severe market turmoil such as financial crises. Novy-Marx (2014) shows in his research that value investing does not necessarily mean the same as investing in quality and it can often be the exact opposite as quality tends to attain best results as conventional value experiences a significant decline. While conventional value strategies concentrate on acquiring securities at discount prices, strategies based on quality focus on investing in exceptionally productive assets. In other words, attention to quality, which according to Novy-Marx is measured foremost by gross profitability, helps traditional value investors make the crucial distinction between undervalued bargain stocks and so-called value traps that are cheap for good reasons. Therefore, the HML factor correlation results support the flight-to-quality effect as well.

The RMW, CMA and MOM factors have been quite randomly correlated with VIX throughout the whole sample period although RMW and CMA have mostly been positively and MOM negatively correlated with VIX. RMW has only been four times negatively correlated with VIX and even then, the highest negative correlation has been only -0.16 in 1997 while the highest positive correlation has been 0.67 in 2011. CMA has only been five times negatively correlated with VIX but the highest negative correlation (-0.50) in 2010 has been much more significant compared to the RMW factor. The highest positive correlation between CMA and VIX has been 0.56 in 2001. The overall interpretation of the RMW and CMA results is that investors tend to prefer conservative stocks with higher operating profitability when market uncertainty and risk increases which supports the flight-to-quality theory. The MOM factor has been mostly negatively correlated with VIX although it has been eight times positively correlated with VIX during the sample period. Most notably, from 2001 to 2002 and from 2008 to 2009, MOM had a positive correlation of 0.50 or above with VIX. The highest negative correlation between MOM and VIX was -0.49 in 1997  The yearly MOM correlation results suggest that a momentum strategy generates better returns when volatility is low although the MOM factor results are not as coherent as the results for SPY and the  Fama-French 5 factors.

Another notable finding from the results in table 4 is that the negative correlation between VIX and S&P 500 returns has become significantly stronger in recent years especially compared to what it was in the early 1990s. For example, the average correlation between VIX and SPY was approximately -0.60 for the five first years of the sample period from 1993 to 1997 whereas for the last five years of the sample period from 2014 to 2018 the average correlation was approximately -0.82. Guo and Wohar (2006) provide evidence that market volatility changes over time by discovering in their study that there have been significant historical shifts in the average level of implied volatility. These shifts can be divided into three distinct regimes or two structural breaks for VIX: pre-1992, 1992–1997 and post-1997. In addition, Guo and Wohar find that the mean volatility was lowest during the period of 1992 to 1997. Since Giot (2005) mostly only examines the period of 1990s in his study whereas the data used in this thesis expands till the end of 2018, the results of this thesis might differ significantly from the findings of Giot.

## 8.1. VIX & SPY

**Table 5** presents the outcomes of buying SPY with different VIX ranks and holding it for different periods. The first column represents the VIX rolling ranks whereas the second column shows the amount of VIX values received from the 500-day rolling ranking method for every specific rank. Most notably, the highest and lowest ranks have the most observations as the number of observations for rank 1 is 841 and 665 for rank 20. The middle ranks, on the other hand, have all slightly above 200 observations. The average returns for different holding periods are represented by 1d, 5d, 20d and 60d. To consider autocorrelation and heteroscedasticity, all standard errors are Newey-West standard errors. Both the average returns and standard errors are presented in percentages. Lastly, the t-statistics display the notability of the results for the average returns and whether they are statistically significantly dissimilar from zero.

**Table 5:** SPY returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | 5d | std.error | t-stat | 20d | std.error | t-stat | 60d | std.error | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | -0.021 | 0.021 | -1.012 | -0.064 | 0.078 | -0.812 | 0.106 | 0.226 | 0.470 | 0.905 | 0.462 | 1.957 * |
| R02 | 469 | 0.039 | 0.029 | 1.359 | 0.020 | 0.100 | 0.200 | 0.462 | 0.218 | 2.120 ** | 1.574 | 0.414 | 3.797 *** |
| R03 | 353 | -0.021 | 0.033 | -0.640 | -0.017 | 0.100 | -0.172 | 0.288 | 0.251 | 1.148 | 1.197 | 0.513 | 2.332 ** |
| R04 | 345 | 0.010 | 0.042 | 0.243 | 0.185 | 0.120 | 1.545 | 0.503 | 0.304 | 1.654 * | 1.604 | 0.599 | 2.677 *** |
| R05 | 285 | -0.012 | 0.049 | -0.232 | 0.056 | 0.135 | 0.419 | 0.176 | 0.305 | 0.575 | 2.159 | 0.484 | 4.456 *** |
| R06 | 259 | 0.028 | 0.054 | 0.511 | 0.270 | 0.140 | 1.929 * | 0.926 | 0.272 | 3.408 *** | 1.770 | 0.487 | 3.631 *** |
| R07 | 233 | 0.138 | 0.054 | 2.572 ** | 0.422 | 0.135 | 3.128 *** | 0.912 | 0.348 | 2.617 *** | 2.340 | 0.487 | 4.807 *** |
| R08 | 223 | 0.090 | 0.064 | 1.403 | 0.447 | 0.150 | 2.984 *** | 0.760 | 0.370 | 2.056 ** | 2.741 | 0.553 | 4.959 *** |
| R09 | 218 | 0.049 | 0.061 | 0.797 | 0.222 | 0.158 | 1.405 | 1.097 | 0.343 | 3.201 *** | 2.661 | 0.583 | 4.561 *** |
| R10 | 224 | 0.160 | 0.067 | 2.378 ** | 0.571 | 0.174 | 3.278 *** | 1.261 | 0.387 | 3.262 *** | 3.025 | 0.612 | 4.947 *** |
| R11 | 214 | -0.020 | 0.060 | -0.325 | 0.129 | 0.198 | 0.652 | 0.988 | 0.440 | 2.249 ** | 2.274 | 0.904 | 2.517 ** |
| R12 | 216 | 0.060 | 0.070 | 0.862 | -0.009 | 0.176 | -0.051 | 0.509 | 0.422 | 1.207 | 0.521 | 1.147 | 0.454 |
| R13 | 243 | -0.037 | 0.064 | -0.573 | 0.290 | 0.166 | 1.751 * | 1.054 | 0.393 | 2.681 *** | 2.076 | 0.959 | 2.166 ** |
| R14 | 259 | 0.065 | 0.076 | 0.851 | 0.105 | 0.185 | 0.567 | 0.813 | 0.364 | 2.236 ** | 0.664 | 1.074 | 0.618 |
| R15 | 237 | 0.073 | 0.075 | 0.971 | 0.153 | 0.224 | 0.680 | 1.372 | 0.422 | 3.253 *** | 2.260 | 0.799 | 2.829 *** |
| R16 | 266 | 0.062 | 0.063 | 0.984 | 0.188 | 0.189 | 0.995 | 1.337 | 0.497 | 2.689 *** | 2.858 | 0.792 | 3.610 *** |
| R17 | 268 | -0.068 | 0.079 | -0.856 | 0.049 | 0.261 | 0.187 | 0.499 | 0.616 | 0.811 | 2.957 | 0.980 | 3.016 *** |
| R18 | 329 | -0.059 | 0.088 | -0.669 | -0.096 | 0.250 | -0.385 | -0.371 | 0.689 | -0.539 | 2.457 | 0.959 | 2.562 ** |
| R19 | 381 | -0.016 | 0.076 | -0.207 | -0.114 | 0.198 | -0.576 | 0.360 | 0.426 | 0.844 | 2.598 | 0.850 | 3.056 *** |
| R20 | 665 | 0.175 | 0.066 | 2.671 *** | 0.722 | 0.270 | 2.670 *** | 1.689 | 0.624 | 2.705 *** | 4.091 | 0.916 | 4.467 *** |

*** means significance at 1% level, ** at 5% level and * at 10% level.

The results of table 5 show that only the highest VIX rank leads to positive returns at 1% significance level regardless of the holding period. In addition, the returns for the highest VIX rank clearly grow as the holding period is expanded. These results support the findings of Giot (2005) that very high VIX levels consistently result in positive returns. However, the findings do not show any significant results of low levels of VIX always leading into negative returns and therefore differ from the results of Giot for this part. In fact, all statistically significant return results are positive including the 20- and 60-day returns for lower VIX ranks. Another notable difference with results of Giot is that moderate VIX ranks lead to statistically significant positive returns. Especially ranks 7 and 10 lead to positive returns with every holding period at 5% significance level. These results, however, are mostly explained by the financial crisis since between the end of 2007 and beginning of 2009 all VIX ranks are over 10 and all returns are highly negative. This also partly explains the positive returns of the lowest VIX levels. **Table 6** below presents the corresponding average SPY returns with different holding periods over the period of 29th January 1993 to 31st December 2018. The average returns are displayed in percentages.

**Table 6:** Average returns for SPY with different holding periods.

| Holding period | Average Return |
|---|---|
| 1d | 0.034 |
| 5d | 0.168 |
| 20d | 0.690 |
| 60d | 2.110 |

By merging the results of table 5 and table 6 we can examine more closely in **table 7** the observation results which show what percentage of the observations are above the average return for each rank with different holding periods. Although table 7 provides more detailed information about the observations, it needs to be noted that the table only shows the amount of observations that are above the average returns and not the actual positive or negative differences in returns for different ranks with different holding periods. However, table 7 does support the findings from table 5 that the highest VIX levels result in positive returns with every holding period. The longer the holding period is the higher the percentage of observations above average returns is: for the highest VIX rank the percentage for the 1-day holding period is 57% whereas for the 5- and 20-day holding periods it is 63% and for the 60-day holding period as much as 70% of the observations are above the average return. Again, the moderate levels of VIX have distinctly more positive observations, but as stated before, this is mostly due to the anomaly in the data caused by the financial crisis of 2007 to 2009.

**Table 7:** Percentage of observations above the average corresponding SPY returns.

| Rank | # | 1d | 5d | 20d | 60d |
|---|---|---|---|---|---|
| R01 | 841 | 49 % | 47 % | 48 % | 51 % |
| R02 | 469 | 56 % | 50 % | 52 % | 53 % |
| R03 | 353 | 50 % | 50 % | 52 % | 50 % |
| R04 | 345 | 50 % | 55 % | 61 % | 56 % |
| R05 | 285 | 51 % | 55 % | 51 % | 58 % |
| R06 | 259 | 48 % | 53 % | 63 % | 54 % |
| R07 | 233 | 56 % | 62 % | 64 % | 58 % |
| R08 | 223 | 54 % | 61 % | 59 % | 65 % |
| R09 | 218 | 51 % | 56 % | 59 % | 64 % |
| R10 | 224 | 56 % | 67 % | 63 % | 65 % |
| R11 | 214 | 49 % | 56 % | 57 % | 64 % |
| R12 | 216 | 55 % | 50 % | 56 % | 52 % |
| R13 | 243 | 46 % | 58 % | 58 % | 59 % |
| R14 | 259 | 49 % | 56 % | 62 % | 55 % |
| R15 | 237 | 55 % | 55 % | 65 % | 57 % |
| R16 | 266 | 55 % | 56 % | 67 % | 58 % |
| R17 | 268 | 49 % | 52 % | 56 % | 58 % |
| R18 | 329 | 50 % | 49 % | 48 % | 52 % |
| R19 | 381 | 49 % | 46 % | 47 % | 53 % |
| R20 | 665 | 57 % | 63 % | 63 % | 70 % |

## 8.2. VIX & Fama-French 5 and momentum factor results

In this chapter, the same methodology is utilized for Fama-French 5 factors as previously for SPY on different ranks with different holding periods. Firstly, summary statistics for the Fama-French 5 factors and the change in VIX between 29th January 1993 and 31st December 2018 are presented. Then, the returns of each factor with different VIX ranks and holding periods are shown and analyzed. Again, for more accurate results, the returns are transformed into logarithmic returns and autocorrelation and heteroscedasticity is considered by using Newey-West standard errors.

The summary statistics are displayed in percentages in the below **table 8**. Not surprisingly, all the summary statistics are highest for Mkt-Rf while SMB has the lowest risk premium of 0.005% on daily basis. For other factors, the premium is 0.010% for HML, 0.015% for RMW, 0.012% for CMA and 0.024% for MOM. Another notable finding from the summary statistics is that the standard deviation of the daily change of VIX is more than 6 times the standard deviation of Mkt-Rf and more than 10 times the standard deviation of the other Fama-French 5 factors. This reflects strongly the high daily volatility of VIX compared to different market returns.

**Table 8:** Fama-French 5 and momentum factor summary statistics.

| | Mkt-Rf | SMB | HML | RMW | CMA | MOM | ΔVIX |
|---|---|---|---|---|---|---|---|
| Mean | 0.032 | 0.005 | 0.010 | 0.016 | 0.011 | 0.024 | 0.233 |
| Median | 0.060 | 0.020 | 0.000 | 0.010 | 0.000 | 0.060 | -0.323 |
| Maximum | 11.350 | 4.490 | 4.830 | 4.400 | 2.530 | 7.010 | 115.598 |
| Minimum | -8.950 | -4.320 | -4.220 | -2.920 | -5.930 | -8.210 | -29.573 |
| Std.dev. | 1.134 | 0.580 | 0.616 | 0.470 | 0.425 | 0.886 | 6.839 |

In **table 9** are the results for Mkt-Rf with different VIX ranks and holding periods. The results are expected to resemble the SPY results that were presented previously in table 5. The findings are more inconsistent for Mkt-Rf, but still quite like the SPY return results. Especially the results for the 60-day holding period provide mostly statistically significant results that are in line with the SPY results as lower VIX ranks tend to lead into lower returns than the highest VIX ranks: the highest VIX rank results in a return of 2.898% at 1% significance level whereas the lowest rank has a return of 0.857% at 10% significance level. The 5- and 20-day return results, on the other hand, are mainly statistically insignificant for the highest and lowest VIX ranks. Unlike the 60-day returns, the 1-day returns for the highest VIX rank are negative (-0.454%) and for the lowest VIX rank positive (0,239%) at 1% significance level.

**Table 9:** Mkt-Rf returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | | 5d | std.error | t-stat | | 20d | std.error | t-stat | | 60d | std.error | t-stat | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | 0.239 | 0.017 | 13.876 | *** | 0.179 | 0.077 | 2.323 | ** | 0.295 | 0.228 | 1.291 | | 0.857 | 0.498 | 1.722 | * |
| R02 | 469 | 0.161 | 0.031 | 5.178 | *** | 0.188 | 0.096 | 1.965 | ** | 0.613 | 0.229 | 2.678 | *** | 1.516 | 0.444 | 3.415 | *** |
| R03 | 353 | 0.124 | 0.040 | 3.083 | *** | 0.056 | 0.099 | 0.571 | | 0.281 | 0.267 | 1.049 | | 1.064 | 0.559 | 1.904 | ** |
| R04 | 345 | 0.071 | 0.045 | 1.574 | | 0.177 | 0.116 | 1.525 | | 0.395 | 0.325 | 1.214 | | 1.348 | 0.693 | 1.945 | ** |
| R05 | 285 | 0.180 | 0.042 | 4.278 | *** | 0.261 | 0.134 | 1.951 | * | 0.320 | 0.316 | 1.015 | | 2.122 | 0.544 | 3.902 | *** |
| R06 | 259 | 0.123 | 0.052 | 2.345 | ** | 0.309 | 0.141 | 2.198 | ** | 0.954 | 0.290 | 3.292 | *** | 1.656 | 0.530 | 3.123 | *** |
| R07 | 233 | 0.060 | 0.058 | 1.030 | | 0.394 | 0.137 | 2.863 | *** | 0.886 | 0.378 | 2.346 | ** | 2.074 | 0.532 | 3.897 | *** |
| R08 | 223 | 0.040 | 0.058 | 0.690 | | 0.393 | 0.153 | 2.572 | ** | 0.566 | 0.411 | 1.376 | | 2.179 | 0.600 | 3.630 | *** |
| R09 | 218 | 0.110 | 0.058 | 1.878 | * | 0.336 | 0.150 | 2.237 | ** | 1.188 | 0.358 | 3.317 | *** | 2.212 | 0.642 | 3.446 | *** |
| R10 | 224 | -0.065 | 0.063 | -1.019 | | 0.443 | 0.162 | 2.735 | *** | 0.931 | 0.425 | 2.194 | ** | 2.465 | 0.665 | 3.709 | *** |
| R11 | 214 | 0.092 | 0.070 | 1.312 | | 0.165 | 0.177 | 0.930 | | 0.810 | 0.445 | 1.822 | * | 1.691 | 0.930 | 1.819 | ** |
| R12 | 216 | 0.029 | 0.071 | 0.410 | | -0.045 | 0.164 | -0.276 | | 0.350 | 0.409 | 0.856 | | -0.328 | 1.200 | -0.273 | |
| R13 | 243 | 0.057 | 0.068 | 0.832 | | 0.272 | 0.150 | 1.815 | * | 0.822 | 0.379 | 2.166 | ** | 1.478 | 0.974 | 1.517 | |
| R14 | 259 | -0.091 | 0.070 | -1.294 | | -0.179 | 0.170 | -1.052 | | 0.524 | 0.371 | 1.412 | | -0.235 | 1.052 | -0.223 | |
| R15 | 237 | -0.039 | 0.069 | -0.569 | | 0.184 | 0.194 | 0.948 | | 0.991 | 0.462 | 2.146 | ** | 1.429 | 0.826 | 1.730 | * |
| R16 | 266 | 0.130 | 0.092 | 1.422 | | 0.178 | 0.211 | 0.842 | | 1.145 | 0.500 | 2.290 | ** | 2.151 | 0.879 | 2.449 | ** |
| R17 | 268 | -0.057 | 0.073 | -0.773 | | -0.125 | 0.236 | -0.530 | | 0.279 | 0.597 | 0.467 | | 1.994 | 1.035 | 1.927 | * |
| R18 | 329 | 0.061 | 0.072 | 0.848 | | -0.080 | 0.228 | -0.350 | | -0.649 | 0.675 | -0.961 | | 1.786 | 0.952 | 1.877 | * |
| R19 | 381 | -0.100 | 0.079 | -1.265 | | -0.312 | 0.198 | -1.579 | | -0.075 | 0.444 | -0.170 | | 1.632 | 0.849 | 1.923 | * |
| R20 | 665 | -0.454 | 0.063 | -7.185 | *** | 0.051 | 0.265 | 0.192 | | 0.778 | 0.652 | 1.193 | | 2.898 | 0.920 | 3.150 | *** |

*** means significance at 1% level, ** at 5% level and * at 10% level.

**Table 10:** SMB returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | 5d | std.error | t-stat | 20d | std.error | t-stat | 60d | std.error | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | 0.074 | 0.014 | 5.412 *** | 0.115 | 0.061 | 1.886 * | 0.140 | 0.181 | 0.775 | 0.230 | 0.253 | 0.911 |
| R02 | 469 | 0.034 | 0.023 | 1.491 | 0.126 | 0.072 | 1.743 * | 0.499 | 0.188 | 2.657 *** | 1.093 | 0.313 | 3.486 *** |
| R03 | 353 | 0.043 | 0.027 | 1.598 | 0.028 | 0.080 | 0.348 | 0.283 | 0.189 | 1.498 | 0.947 | 0.317 | 2.988 *** |
| R04 | 345 | -0.014 | 0.028 | -0.494 | 0.148 | 0.086 | 1.725 * | 0.368 | 0.246 | 1.493 | 1.091 | 0.538 | 2.027 ** |
| R05 | 285 | 0.017 | 0.033 | 0.503 | 0.134 | 0.096 | 1.386 | 0.504 | 0.277 | 1.821 * | 1.290 | 0.561 | 2.300 ** |
| R06 | 259 | 0.007 | 0.038 | 0.196 | 0.053 | 0.128 | 0.412 | 0.569 | 0.328 | 1.737 * | 1.151 | 0.506 | 2.276 ** |
| R07 | 233 | 0.016 | 0.032 | 0.497 | 0.179 | 0.089 | 2.018 ** | 0.517 | 0.188 | 2.744 *** | 0.758 | 0.434 | 1.745 * |
| R08 | 223 | 0.051 | 0.039 | 1.302 | 0.200 | 0.113 | 1.775 * | 0.333 | 0.271 | 1.231 | 0.411 | 0.484 | 0.850 |
| R09 | 218 | 0.037 | 0.039 | 0.957 | 0.225 | 0.119 | 1.889 * | 0.973 | 0.334 | 2.916 *** | 0.385 | 0.529 | 0.728 |
| R10 | 224 | -0.052 | 0.037 | -1.409 | 0.101 | 0.093 | 1.087 | 0.267 | 0.282 | 0.947 | 0.036 | 0.509 | 0.071 |
| R11 | 214 | 0.097 | 0.041 | 2.363 ** | 0.185 | 0.120 | 1.544 | 0.372 | 0.298 | 1.251 | 0.155 | 0.528 | 0.294 |
| R12 | 216 | -0.004 | 0.042 | -0.097 | 0.029 | 0.135 | 0.211 | 0.136 | 0.319 | 0.428 | -0.569 | 0.617 | -0.922 |
| R13 | 243 | -0.004 | 0.039 | -0.092 | 0.143 | 0.109 | 1.314 | 0.336 | 0.233 | 1.444 | 0.514 | 0.517 | 0.994 |
| R14 | 259 | -0.044 | 0.038 | -1.146 | -0.034 | 0.102 | -0.334 | 0.165 | 0.230 | 0.716 | -0.089 | 0.536 | -0.167 |
| R15 | 237 | -0.010 | 0.038 | -0.263 | 0.060 | 0.104 | 0.572 | -0.205 | 0.214 | -0.961 | 0.075 | 0.485 | 0.155 |
| R16 | 266 | -0.043 | 0.039 | -1.119 | -0.126 | 0.118 | -1.068 | -0.055 | 0.317 | -0.173 | -0.037 | 0.525 | -0.070 |
| R17 | 268 | -0.029 | 0.038 | -0.758 | -0.119 | 0.118 | -1.013 | -0.586 | 0.282 | -2.080 ** | -0.837 | 0.580 | -1.442 |
| R18 | 329 | -0.022 | 0.032 | -0.683 | -0.065 | 0.100 | -0.652 | -0.561 | 0.253 | -2.213 ** | 0.072 | 0.477 | 0.151 |
| R19 | 381 | -0.058 | 0.033 | -1.758 * | -0.114 | 0.113 | -1.015 | -0.391 | 0.243 | -1.610 | -0.644 | 0.465 | -1.384 |
| R20 | 665 | -0.063 | 0.029 | -2.175 ** | -0.412 | 0.114 | -3.599 *** | -0.814 | 0.324 | -2.513 ** | -0.522 | 0.532 | -0.980 |

*** means significance at 1% level, ** at 5% level and * at 10% level.

**Table 10** presents the results for SMB with different VIX ranks and holding periods which are much more interesting from a style rotation perspective considering VIX timing possibilities. The results indicate whether investors should prefer small cap or large cap stocks with different VIX levels. According to the flight-to-quality phenomenon (Abel 1988; Barsky 1989; Durand, Junker and Szimayer 2010) introduced earlier, investors tend to choose large rather than small stocks when risk increases. Thus, SMB returns should be negative for higher VIX ranks. The results support the flight-to-quality effect as statistically significant negative returns occur only for the highest VIX rank at least at a 5% significance level with all holding periods except for the 60-day holding period. In addition, the findings suggest that small cap stocks tend to perform well during low volatility periods since all statistically significant returns for one or both two lowest VIX ranks exhibit only positive returns with all holding periods at least at a 10% significance level. The positive returns for lower VIX ranks can be seen most notably with the 60-day returns as VIX ranks between 2 to 6 exhibit positive returns that are statistically significant at least at a 5% significance level for the longest holding period.

In **table 11** are the results for HML with different VIX ranks and holding periods. According to Copeland and Copeland (1999), Boscaljon, Filbeck and Zhao (2011) and Durand, Lim and Zumwalt (2011) value stocks outperform growth stocks when VIX increases. Table 11 results, however, suggest that when VIX is at its highest level, future HML returns become negative. These findings support the flight-to-quality phenomenon since HML means often the exact opposite of quality (Novy-Marx 2014). The statistics show statistically significant negative return results for HML with the highest VIX rank for the 60-day and 20-day holding periods at a 1% significance level. Furthermore, rank 18 shows significant negative returns for the 1-day and 5-day holding periods at a 10% significance level. These results, however, do not directly contradict with the previously mentioned studies as the correlation between VIX changes and value strategy returns are generally positive, but becomes negative during periods of very high market uncertainty. In addition, the results show statistically significant positive returns for HML with the two lowest VIX ranks for the 5-, 20- and 60-day holding periods at least at a 5% significance level. An explanation for the results could be that investors prefer value stocks as market uncertainty increases, but when VIX reaches its highest level, growth stocks could be oversold and therefore provide better future returns and vice versa.

**Table 11:** HML returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | | 5d | std.error | t-stat | | 20d | std.error | t-stat | | 60d | std.error | t-stat | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | 0.025 | 0.015 | 1.621 | | 0.150 | 0.067 | 2.259 | ** | 0.631 | 0.194 | 3.258 | *** | 1.329 | 0.429 | 3.099 | *** |
| R02 | 469 | 0.006 | 0.023 | 0.243 | | 0.197 | 0.072 | 2.750 | *** | 0.551 | 0.175 | 3.161 | *** | 1.308 | 0.354 | 3.698 | *** |
| R03 | 353 | 0.007 | 0.023 | 0.297 | | 0.104 | 0.072 | 1.443 | | 0.556 | 0.171 | 3.253 | *** | 1.162 | 0.339 | 3.429 | *** |
| R04 | 345 | -0.022 | 0.023 | -0.962 | | 0.026 | 0.085 | 0.308 | | 0.276 | 0.181 | 1.520 | | 0.767 | 0.412 | 1.860 | * |
| R05 | 285 | 0.001 | 0.030 | 0.031 | | -0.042 | 0.088 | -0.474 | | 0.209 | 0.242 | 0.864 | | 0.754 | 0.567 | 1.329 | |
| R06 | 259 | -0.029 | 0.035 | -0.828 | | 0.019 | 0.096 | 0.192 | | -0.069 | 0.291 | -0.238 | | 0.085 | 0.517 | 0.165 | |
| R07 | 233 | -0.011 | 0.036 | -0.304 | | 0.020 | 0.113 | 0.175 | | 0.360 | 0.365 | 0.988 | | 0.091 | 0.547 | 0.167 | |
| R08 | 223 | 0.067 | 0.036 | 1.868 | * | 0.092 | 0.111 | 0.832 | | 0.680 | 0.334 | 2.033 | ** | 0.761 | 0.579 | 1.314 | |
| R09 | 218 | 0.019 | 0.043 | 0.448 | | 0.207 | 0.131 | 1.576 | | 0.591 | 0.306 | 1.935 | * | 0.749 | 0.519 | 1.442 | |
| R10 | 224 | 0.022 | 0.036 | 0.614 | | 0.099 | 0.099 | 0.995 | | 0.092 | 0.258 | 0.355 | | -0.037 | 0.494 | -0.074 | |
| R11 | 214 | -0.014 | 0.043 | -0.327 | | 0.199 | 0.133 | 1.500 | | 0.426 | 0.325 | 1.311 | | 0.601 | 0.632 | 0.951 | |
| R12 | 216 | -0.028 | 0.041 | -0.670 | | 0.034 | 0.125 | 0.274 | | 0.266 | 0.347 | 0.765 | | 0.307 | 0.526 | 0.584 | |
| R13 | 243 | -0.036 | 0.033 | -1.075 | | -0.010 | 0.088 | -0.118 | | 0.215 | 0.285 | 0.754 | | 1.137 | 0.593 | 1.917 | * |
| R14 | 259 | 0.047 | 0.054 | 0.856 | | 0.103 | 0.129 | 0.800 | | -0.179 | 0.295 | -0.606 | | 0.145 | 0.548 | 0.265 | |
| R15 | 237 | 0.068 | 0.044 | 1.539 | | 0.015 | 0.114 | 0.127 | | -0.068 | 0.229 | -0.297 | | 0.222 | 0.535 | 0.415 | |
| R16 | 266 | 0.057 | 0.055 | 1.041 | | 0.203 | 0.136 | 1.493 | | 0.163 | 0.332 | 0.493 | | 0.257 | 0.459 | 0.560 | |
| R17 | 268 | 0.021 | 0.048 | 0.430 | | 0.005 | 0.141 | 0.033 | | -0.056 | 0.288 | -0.193 | | 0.644 | 0.610 | 1.055 | |
| R18 | 329 | -0.085 | 0.049 | -1.751 | * | -0.271 | 0.155 | -1.754 | * | -0.793 | 0.607 | -1.307 | | 0.492 | 0.812 | 0.606 | |
| R19 | 381 | 0.023 | 0.033 | 0.697 | | -0.068 | 0.098 | -0.696 | | -0.064 | 0.238 | -0.268 | | -0.064 | 0.683 | -0.093 | |
| R20 | 665 | 0.011 | 0.030 | 0.368 | | -0.165 | 0.114 | -1.445 | | -0.647 | 0.301 | -2.152 | ** | -1.801 | 0.603 | -2.988 | *** |

*** means significance at 1% level, ** at 5% level and * at 10% level.

**Table 12:** RMW returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | 5d | std.error | t-stat | 20d | std.error | t-stat | 60d | std.error | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | -0.039 | 0.013 | -2.983 *** | -0.007 | 0.064 | -0.106 | 0.159 | 0.183 | 0.868 | 0.993 | 0.391 | 2.541 ** |
| R02 | 469 | -0.018 | 0.020 | -0.928 | 0.025 | 0.065 | 0.389 | 0.163 | 0.166 | 0.979 | 0.691 | 0.374 | 1.847 * |
| R03 | 353 | 0.010 | 0.023 | 0.437 | 0.051 | 0.067 | 0.770 | 0.434 | 0.178 | 2.431 ** | 0.621 | 0.407 | 1.528 |
| R04 | 345 | 0.011 | 0.025 | 0.445 | 0.096 | 0.070 | 1.358 | 0.290 | 0.216 | 1.340 | 0.344 | 0.480 | 0.717 |
| R05 | 285 | -0.073 | 0.029 | -2.520 ** | -0.007 | 0.092 | -0.079 | 0.238 | 0.264 | 0.903 | 0.552 | 0.660 | 0.835 |
| R06 | 259 | -0.038 | 0.035 | -1.085 | -0.006 | 0.117 | -0.051 | 0.070 | 0.314 | 0.223 | 0.647 | 0.561 | 1.152 |
| R07 | 233 | 0.018 | 0.029 | 0.614 | 0.002 | 0.091 | 0.018 | 0.302 | 0.260 | 1.161 | 0.654 | 0.530 | 1.234 |
| R08 | 223 | 0.026 | 0.037 | 0.702 | 0.024 | 0.118 | 0.202 | 0.531 | 0.309 | 1.720 * | 1.383 | 0.516 | 2.680 *** |
| R09 | 218 | -0.043 | 0.036 | -1.206 | -0.057 | 0.121 | -0.467 | -0.330 | 0.338 | -0.978 | 1.021 | 0.512 | 1.994 ** |
| R10 | 224 | 0.041 | 0.039 | 1.061 | -0.025 | 0.090 | -0.271 | 0.221 | 0.276 | 0.803 | 1.201 | 0.478 | 2.512 ** |
| R11 | 214 | -0.022 | 0.034 | -0.645 | 0.018 | 0.110 | 0.158 | 0.334 | 0.270 | 1.236 | 1.185 | 0.489 | 2.421 ** |
| R12 | 216 | 0.019 | 0.027 | 0.683 | 0.183 | 0.114 | 1.607 | 0.403 | 0.309 | 1.302 | 1.466 | 0.526 | 2.786 *** |
| R13 | 243 | 0.010 | 0.032 | 0.323 | 0.006 | 0.095 | 0.061 | 0.182 | 0.240 | 0.760 | 0.919 | 0.478 | 1.921 * |
| R14 | 259 | 0.036 | 0.038 | 0.958 | 0.173 | 0.105 | 1.645 | 0.448 | 0.177 | 2.533 ** | 1.320 | 0.466 | 2.830 *** |
| R15 | 237 | 0.052 | 0.030 | 1.735 * | 0.100 | 0.078 | 1.277 | 0.165 | 0.194 | 0.851 | 0.560 | 0.411 | 1.363 |
| R16 | 266 | 0.002 | 0.039 | 0.044 | 0.144 | 0.100 | 1.447 | 0.194 | 0.241 | 0.807 | 0.338 | 0.414 | 0.816 |
| R17 | 268 | 0.083 | 0.031 | 2.681 *** | 0.133 | 0.102 | 1.298 | 0.342 | 0.190 | 1.804 * | 0.700 | 0.488 | 1.434 |
| R18 | 329 | 0.029 | 0.030 | 0.957 | 0.044 | 0.084 | 0.522 | 0.231 | 0.205 | 1.127 | 0.658 | 0.384 | 1.712 * |
| R19 | 381 | 0.055 | 0.022 | 2.498 ** | 0.211 | 0.060 | 3.523 *** | 0.553 | 0.192 | 2.880 *** | 1.425 | 0.340 | 4.187 *** |
| R20 | 665 | 0.110 | 0.023 | 4.898 *** | 0.237 | 0.087 | 2.733 *** | 0.659 | 0.242 | 2.730 *** | 1.230 | 0.397 | 3.095 *** |

*** means significance at 1% level, ** at 5% level and * at 10% level.

The RMW results are shown in **table 12**. The results indicate that the future returns of higher operating profitability firms tend to be higher when VIX is at its highest levels. This supports the flight-to-quality theory as higher operating profitability firms are often healthier and less risky than firms with lower operating profitability. Furthermore, economic financial ratios that measure profitability, such as operating profitability, have been among the most popularly applied variables for assessing corporate bankruptcy (Altman et al. 1977; Alfaro et al. 2008; Beaver et al. 2012). The statistics show statistically significant positive return results for RMW with the two highest VIX ranks for all holding periods at least at a 5% significance level. While the lowest VIX ranks also show generally positive returns for RMW, they are distinctly lower when compared to the highest VIX ranks. The only exceptions are the lowest and the fifth lowest VIX ranks with the 1-day holding period since they exhibit statistically significant negative returns at least at a 5% significance level.

The final Fama-French 5 factor, CMA, results can be seen in **table 13**. The results for the highest and lowest VIX ranks with the 1-, 5- and 20-day holding periods are mostly statistically insignificant and do not show any clear pattern for the returns with different VIX levels. However, the results with the 60-day holding period show clearly that the correlation of future CMA returns with VIX is mostly positive until the highest VIX levels are reached. Thus, the future returns of aggressive high-beta stocks tend to exceed conservative low-beta stocks only when VIX reaches its peak levels. The statistics show statistically significant negative return results for CMA with the highest VIX rank at a 5% significance level and positive returns for the six lowest VIX ranks at least at a 5% significance level for the 60-day holding period. In addition, VIX ranks from eight to fifteen are statistically significantly positive at least at a 5% significance level for the 60-day holding period. The CMA results support the findings of Banerjee, Doran and Peterson that (2007) higher beta portfolios have a stronger negative correlation with VIX. Thus, when VIX is at its extreme levels and starts to revert to its mean, high-beta stocks tend increase in value quicker than low-beta stocks. Investors should therefore prefer low-beta stocks during low and average levels of VIX and lean towards high-beta stocks when VIX is at its highest levels.

**Table 13:** CMA returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | | 5d | std.error | t-stat | | 20d | std.error | t-stat | | 60d | std.error | t-stat | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | 0.012 | 0.011 | 1.106 | | 0.062 | 0.048 | 1.302 | | 0.256 | 0.154 | 1.663 | * | 0.778 | 0.381 | 2.042 | ** |
| R02 | 469 | -0.007 | 0.016 | -0.411 | | 0.077 | 0.053 | 1.441 | | 0.184 | 0.144 | 1.280 | | 0.798 | 0.292 | 2.732 | *** |
| R03 | 353 | -0.006 | 0.018 | -0.332 | | 0.143 | 0.057 | 2.532 | ** | 0.490 | 0.153 | 3.205 | *** | 1.025 | 0.308 | 3.328 | *** |
| R04 | 345 | -0.004 | 0.020 | -0.208 | | 0.113 | 0.057 | 1.966 | ** | 0.502 | 0.137 | 3.669 | *** | 1.144 | 0.312 | 3.662 | *** |
| R05 | 285 | 0.001 | 0.022 | 0.060 | | 0.033 | 0.074 | 0.444 | | 0.403 | 0.166 | 2.430 | ** | 1.014 | 0.335 | 3.027 | *** |
| R06 | 259 | -0.017 | 0.021 | -0.776 | | 0.033 | 0.067 | 0.491 | | 0.256 | 0.156 | 1.643 | | 0.654 | 0.300 | 2.177 | ** |
| R07 | 233 | 0.000 | 0.030 | -0.007 | | 0.057 | 0.086 | 0.669 | | 0.489 | 0.273 | 1.796 | * | 0.424 | 0.320 | 1.326 | |
| R08 | 223 | 0.043 | 0.026 | 1.693 | * | 0.160 | 0.077 | 2.080 | ** | 0.732 | 0.210 | 3.487 | *** | 1.092 | 0.347 | 3.147 | *** |
| R09 | 218 | -0.005 | 0.026 | -0.187 | | 0.114 | 0.070 | 1.632 | | 0.484 | 0.170 | 2.855 | *** | 1.025 | 0.304 | 3.373 | *** |
| R10 | 224 | 0.023 | 0.031 | 0.736 | | 0.069 | 0.074 | 0.929 | | 0.149 | 0.174 | 0.858 | | 0.704 | 0.307 | 2.294 | ** |
| R11 | 214 | -0.023 | 0.028 | -0.844 | | 0.155 | 0.084 | 1.850 | * | 0.396 | 0.182 | 2.174 | ** | 1.049 | 0.349 | 3.005 | *** |
| R12 | 216 | -0.014 | 0.035 | -0.395 | | 0.150 | 0.080 | 1.871 | * | 0.459 | 0.204 | 2.254 | ** | 1.106 | 0.319 | 3.470 | *** |
| R13 | 243 | 0.024 | 0.025 | 0.970 | | 0.041 | 0.073 | 0.553 | | 0.322 | 0.178 | 1.807 | * | 1.245 | 0.324 | 3.846 | *** |
| R14 | 259 | 0.030 | 0.034 | 0.891 | | 0.119 | 0.095 | 1.262 | | 0.020 | 0.171 | 0.117 | | 0.988 | 0.320 | 3.086 | *** |
| R15 | 237 | 0.003 | 0.035 | 0.094 | | -0.049 | 0.078 | -0.630 | | 0.006 | 0.161 | 0.036 | | 0.736 | 0.320 | 2.303 | ** |
| R16 | 266 | 0.011 | 0.032 | 0.354 | | 0.064 | 0.085 | 0.751 | | 0.075 | 0.206 | 0.362 | | 0.290 | 0.321 | 0.902 | |
| R17 | 268 | -0.008 | 0.033 | -0.246 | | -0.021 | 0.082 | -0.257 | | -0.096 | 0.178 | -0.538 | | 0.042 | 0.437 | 0.095 | |
| R18 | 329 | -0.006 | 0.026 | -0.228 | | -0.036 | 0.078 | -0.460 | | -0.095 | 0.203 | -0.465 | | -0.161 | 0.414 | -0.390 | |
| R19 | 381 | 0.026 | 0.025 | 1.038 | | 0.051 | 0.068 | 0.745 | | 0.055 | 0.182 | 0.304 | | 0.077 | 0.359 | 0.215 | |
| R20 | 665 | 0.057 | 0.022 | 2.669 | *** | -0.095 | 0.086 | -1.110 | | -0.309 | 0.230 | -1.341 | | -0.735 | 0.339 | -2.170 | ** |

*** means significance at 1% level, ** at 5% level and * at 10% level.

**Table 14:** MOM returns with different VIX ranks on different holding periods.

| Rank | # | 1d | std.error | t-stat | 5d | std.error | t-stat | 20d | std.error | t-stat | 60d | std.error | t-stat |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R01 | 841 | 0.061 | 0.017 | 3.663 *** | 0.044 | 0.077 | 0.564 | 0.542 | 0.213 | 2.544 ** | 2.156 | 0.362 | 5.954 *** |
| R02 | 469 | 0.031 | 0.029 | 1.067 | 0.276 | 0.088 | 3.129 *** | 0.849 | 0.220 | 3.867 *** | 2.402 | 0.393 | 6.105 *** |
| R03 | 353 | 0.028 | 0.032 | 0.882 | 0.335 | 0.095 | 3.505 *** | 0.930 | 0.254 | 3.664 *** | 2.549 | 0.476 | 5.358 *** |
| R04 | 345 | 0.043 | 0.034 | 1.250 | 0.240 | 0.116 | 2.065 ** | 0.673 | 0.300 | 2.242 ** | 2.272 | 0.508 | 4.470 *** |
| R05 | 285 | 0.096 | 0.040 | 2.372 ** | 0.340 | 0.130 | 2.618 *** | 1.229 | 0.335 | 3.669 *** | 3.071 | 0.653 | 4.702 *** |
| R06 | 259 | 0.059 | 0.043 | 1.354 | 0.172 | 0.145 | 1.188 | 0.946 | 0.389 | 2.434 ** | 3.057 | 0.615 | 4.968 *** |
| R07 | 233 | 0.079 | 0.048 | 1.669 * | 0.377 | 0.149 | 2.521 ** | 1.906 | 0.424 | 4.497 *** | 3.447 | 0.586 | 5.885 *** |
| R08 | 223 | -0.047 | 0.048 | -0.982 | 0.075 | 0.167 | 0.449 | 0.762 | 0.509 | 1.497 | 2.319 | 0.713 | 3.253 *** |
| R09 | 218 | -0.036 | 0.063 | -0.569 | -0.168 | 0.197 | -0.850 | 0.216 | 0.544 | 0.397 | 2.090 | 0.777 | 2.688 *** |
| R10 | 224 | 0.023 | 0.056 | 0.411 | 0.161 | 0.147 | 1.095 | 0.620 | 0.435 | 1.424 | 2.127 | 0.681 | 3.124 *** |
| R11 | 214 | 0.027 | 0.061 | 0.450 | -0.137 | 0.210 | -0.653 | 0.224 | 0.439 | 0.510 | 1.864 | 0.776 | 2.403 ** |
| R12 | 216 | -0.052 | 0.073 | -0.712 | 0.178 | 0.194 | 0.922 | 0.701 | 0.524 | 1.338 | 1.900 | 0.919 | 2.067 ** |
| R13 | 243 | 0.002 | 0.053 | 0.031 | 0.004 | 0.164 | 0.025 | 0.558 | 0.423 | 1.320 | 0.724 | 0.974 | 0.743 |
| R14 | 259 | -0.059 | 0.087 | -0.685 | -0.009 | 0.188 | -0.050 | 0.400 | 0.383 | 1.044 | 2.272 | 0.861 | 2.640 *** |
| R15 | 237 | -0.086 | 0.092 | -0.935 | -0.362 | 0.382 | -0.950 | -0.737 | 1.089 | -0.677 | -0.200 | 1.121 | -0.179 |
| R16 | 266 | -0.155 | 0.099 | -1.574 | -0.206 | 0.301 | -0.683 | -0.823 | 1.018 | -0.809 | -1.788 | 1.676 | -1.066 |
| R17 | 268 | 0.054 | 0.075 | 0.720 | 0.232 | 0.251 | 0.923 | 0.110 | 0.655 | 0.168 | -1.187 | 1.439 | -0.825 |
| R18 | 329 | 0.017 | 0.064 | 0.270 | 0.103 | 0.254 | 0.407 | -0.208 | 0.686 | -0.303 | -4.732 | 2.129 | -2.223 ** |
| R19 | 381 | 0.016 | 0.060 | 0.263 | 0.086 | 0.167 | 0.517 | -0.389 | 0.492 | -0.791 | -0.352 | 0.725 | -0.486 |
| R20 | 665 | 0.076 | 0.042 | 1.823 * | 0.076 | 0.190 | 0.399 | -0.099 | 0.536 | -0.186 | -0.242 | 0.765 | -0.316 |

*** means significance at 1% level, ** at 5% level and * at 10% level.

Finally, the MOM factor results are presented in **table 14**. The first distinct finding from the table is that there are many highly statistically significant positive MOM return results for the lowest VIX rankings with all holding periods but only one highly statistically significant finding with the highest VIX rankings which is within the 60-day holding period returns. When the holding period is extended, the more statistically significant the results become: for the 20-day holding period the first seven and for the 60-day holding period the first twelve VIX ranks show statistically significant positive MOM returns at least at a 5% significance level. The t-statistic is very high for the lowest VIX level returns with the 60-day holding period and it is even over six for the second VIX rank. Furthermore, VIX ranks from 2 to 5 and rank 7 show statistically significant positive MOM returns at least at a 5% significance level with the 5-day holding period. Concerning the highest VIX ranks, all six highest VIX ranks for the 60-day holding period show negative results but only the eighteenth VIX rank shows a statistically significant negative return result (-4.732) at a 5% significance level. Overall, the MOM results support the findings of Durand, Lim and Zumwalt (2011) as they discover a generally positive correlation with VIX and the momentum premium. Furthermore, the results support the study by Chordia and Shivakumar (2002) that the momentum effect is solely present in expansionary periods of the economy. Thus, the results suggest that the momentum strategy produces positive future returns when VIX is at its lowest or average levels. However, when VIX reaches its highest levels, negative momentum returns should be anticipated.

The Fama-French 5 and momentum factor return results show clear potential in a VIX timing strategy in S&P 500 with style rotation as all factors show statistically significant future return results with different levels of VIX. Furthermore, especially the highest and lowest VIX levels seem to be driving the future returns with most of the factors. The overall blunt interpretation of the results is that when VIX reaches its highest levels, investors should favour high-beta large cap growth stocks with high operating profitability and do the opposite of a momentum strategy. When VIX is at its lowest levels, on the other hand, low-beta small cap value stocks incorporated with a momentum strategy should exhibit best future returns. To test whether the results remain the same especially for the higher VIX ranks when the financial crisis is accounted for, the same regressions for the Fama-French 5 and momentum factors and SPY are examined in this study by omitting the period between the beginning of December 2007 and the end of March 2009 from the data. The results remain highly similar excluding small variation in the returns of the higher ranks. However, the negative HML return results for the higher VIX ranks become much weaker as all 20-day return results for the higher ranks are statistically insignificant and the 60-day return for the highest rank drops by over one percent to -0.744% and is only statistically significant at a 10% significance level. This suggests that investing in growth stocks when VIX is at its highest levels is not as attractive when the financial crisis period is omitted from the data. For the SMB factor, however, the results for the higher ranks become slightly stronger as one of the higher ranks, rank 17, for the 60-day returns becomes statistically significant and negative at a 5% significance level (-1.267). This further supports the results for the 20-day returns that negative SMB returns can be expected after high VIX levels.

### 8.2.1. Style rotation results

Next, the return results for the Fama-French 4 factors and the momentum factor are used to examine how well in practice the VIX timing strategy combined with style rotation performs. In this empirical analysis, long-short portfolios are formed for SMB, HML, RMW, CMA and MOM. It needs to be emphasized, that the factor portfolios are not traditional long-short portfolios since only one position (long, short or no position) is taken at a time during the sample period. The trading strategy of each factor portfolio is evaluated individually based on the previously presented factor results so that certain levels of VIX are interpreted as signals for buying or shorting the factors. To avoid coinciding holding periods, only 1-day holding period returns are used in the style rotation strategy.

For the SMB portfolio, VIX ranks 1 to 5 are signals for choosing a long position in SMB and VIX ranks 16 to 20 are signals for selecting a short position in SMB. The same strategy is used for the HML, CMA and MOM portfolios. For the RMW portfolio, on the other hand, VIX ranks 16 to 20 are signals for taking a long position in RMW and VIX ranks 1 to 5 are signals for taking a short position in RMW. Below are the formulas for each factor where “l” indicates long position and “s” short position.

(15) $$\text{SMB}_P = \text{lSMB}_{LOW} + \text{sSMB}_{HIGH}$$

(16) $$\text{HML}_P = \text{lHML}_{LOW} + \text{sHML}_{HIGH}$$

(17) $$\text{RMW}_P = \text{lRMW}_{HIGH} + \text{sRMW}_{LOW}$$

(18) $$\text{CMA}_P = \text{lCMA}_{LOW} + \text{sCMA}_{HIGH}$$

(19) $$\text{MOM}_P = \text{lMOM}_{LOW} + \text{sMOM}_{HIGH}$$

The style rotation trading strategy results are presented in **table 15**. The first column shows the breakdown of all the factor portfolios so that for each factor the first two portfolios are the sub-portfolios and the third and bolded portfolio represents the overall results of the trading strategy. The average daily returns for all factor portfolios and their sub-portfolios are presented in the second column. Even if the average return of one of the sub-portfolios is negative, it might eventually be positive for the overall long-short portfolio depending on whether that component is sold short or bought long. The third column depicts the total amount of observations and the fourth column the total returns for the sub-portfolios and the long-short portfolios which are presented in percentages. For all the factors, the trading strategy covers 4202 days of 6528 days so that between VIX ranks 6 to 15 no position is selected in the factor portfolios. In other words, a long or short position is chosen throughout the sample period approximately on 64% of the trading days. It needs to be highlighted that this type of investment approach does not certainly create high trading costs since VIX usually remains several consecutive days between its extreme ranks and therefore an investor would not have to buy or sell his or her position every day. Finally, in the sixth column, the excess return of the long-short trading strategy is shown. This is the most essential column of the table since it shows whether the long-short trading strategies have out- or underperformed the conventional returns of the Fama-French 4 and momentum factors. The conventional factor returns are the sums of the 1-day returns for the whole sample period.

**Table 15**: Style rotation results.

| | Average daily return | # | Sum, portfolios (%) | Conventional portfolio (%) | Excess return |
|---|---|---|---|---|---|
| $SMB_{LOW}$ | 0.041 | 2293 | 93.16 | | |
| $SMB_{HIGH}$ | -0.047 | 1909 | 89.86 | | |
| **$SMB_{P}$** | **0.044** | **4202** | **183.02** | **21.80** | **161.22** |
| | | | | | |
| $HML_{LOW}$ | 0.008 | 2293 | 18.24 | | |
| $HML_{HIGH}$ | 0.005 | 1909 | -8.74 | | |
| **$HML_{P}$** | **0.002** | **4202** | **9.50** | **51.55** | **-42.05** |
| | | | | | |
| $RMW_{LOW}$ | -0.024 | 2293 | 54.18 | | |
| $RMW_{HIGH}$ | 0.066 | 1909 | 126.62 | | |
| **$RMW_{P}$** | **0.043** | **4202** | **180.80** | **95.67** | **85.13** |
| | | | | | |
| $CMA_{LOW}$ | 0.002 | 2293 | 3.96 | | |
| $CMA_{HIGH}$ | 0.025 | 1909 | -46.94 | | |
| **$CMA_{P}$** | **-0.010** | **4202** | **-42.97** | **66.81** | **-109.78** |
| | | | | | |
| $MOM_{LOW}$ | 0.051 | 2293 | 117.89 | | |
| $MOM_{HIGH}$ | 0.018 | 1909 | -35.17 | | |
| **$MOM_{P}$** | **0.020** | **4202** | **82.72** | **133.00** | **-50.29** |

The results of table 15 show that two out of five strategies outperform their corresponding conventional portfolios. The $\mathrm{SMB_P}$ portfolio results are the most interesting since the long-short portfolio outperforms the conventional SMB portfolio by 161.22%. The sub-portfolios of the strategy perform almost equally well and generate together a return of 183.02% which is over nine times higher than the return of the conventional SMB portfolio (21.80%). Based on these results, investing in large cap stocks when VIX is at its highest levels and vice versa is highly more profitable than investing in a conventional SMB portfolio. The second portfolio that outperforms its corresponding conventional portfolio is the $\mathrm{RMW_P}$ portfolio which generates an excess return of 85.13%. Approximately two thirds of the long-short portfolio's returns are generated by the $\mathrm{RMW_{HIGH}}$ sub-portfolio indicating that the trading strategy is most profitable when VIX is at its highest levels. According to these results, investing in firms with higher operating profitability when VIX is at its highest levels and vice versa generates almost twice better returns than investing in a conventional RMW portfolio.

The results for the $\mathrm{HML_P}$, $\mathrm{CMA_P}$ and $\mathrm{MOM_P}$ portfolios, on the other hand, suggest that a VIX timing strategy does not work with the HML, CMA or MOM factors. The $\mathrm{CMA_P}$ portfolio has the worst performance as its excess return is -109.78%. Especially the $\mathrm{CMA_{HIGH}}$ sub-portfolio has a poor performance as it generates a return of -46.94% indicating that taking advantage of the highest levels of VIX by shorting the CMA factor is very unprofitable. In addition, the $\mathrm{CMA_{LOW}}$ generates only a profit of 3.96% meaning that low VIX levels are not either good investment opportunities with the CMA factor. The $\mathrm{HML_P}$ and $\mathrm{MOM_P}$ portfolios, on the other hand, generate quite good profits with the lowest VIX ranks but also fail to perform well when VIX is at its highest levels. As mentioned earlier in this study, these are quite expected results since the HML and MOM factors have been shown to exhibit generally positive returns with almost all VIX levels and negative returns only when VIX is at its most extreme high levels. Both he $\mathrm{HML_{HIGH}}$ and the $\mathrm{MOM_{HIGH}}$ sub-portfolio exhibit negative returns: -8.74% for the $\mathrm{HML_{HIGH}}$ and -35.17% for the $\mathrm{MOM_{HIGH}}$ sub-portfolio. The overall return of the $\mathrm{HML_P}$ portfolio underperforms the conventional HML portfolio by 42.05% while the $\mathrm{MOM_P}$ portfolio underperforms its corresponding conventional MOM portfolio by 50.29%.

Altogether, the $SMB_P$ and $RMW_P$ portfolio results are rather innovative and show that there is indeed potential in a style rotation strategy with different levels of VIX. When VIX is at its highest levels, investors should prefer investing in firms with higher operating profitability and large cap stocks and vice versa to generate significant excess future returns for their portfolios. The results from table 10 and table 12 also support the style rotation results. In addition, the findings from table 15 confirm that a style rotation strategy with different VIX levels does not work for the $HML_P$, $CMA_P$ and $MOM_P$ portfolios although the initial factor return results with different VIX ranks on different holding periods were promising especially for the HML and CMA factors.

## 9. CONCLUSIONS

This study examines the timing possibilities with VIX in the S&P 500 stock index by using style rotation with the Fama-French 5 factors and momentum factor. Firstly, the performance of positions chosen in S&P 500, Fama-French 5-factors and momentum factor with different levels of VIX and holding periods is investigated. The key method in this thesis for creating relative ranks for different levels of VIX is a 500-day rolling ranking method inspired by Giot (2005). Secondly, based on the Fama-French 4 and momentum return results, long-short portfolios are created for each factor to examine how well in practice the VIX timing strategy combined with style rotation performs.

The results of this thesis side with multiple studies such as Giot (2005), Banerjee, Doran and Peterson (2007) and Whaley (2009) that the correlation between VIX and S&P 500 is strongly negative. In addition, the historical correlations presented in this study show that the interrelationship between VIX and S&P 500 is continuously becoming even more negative as time goes by and has even been close to -0.9 in the recent years. The results are also in line with studies such as Giot (2005) and Banerjee, Doran and Peterson (2007) that the highest respective VIX levels consistently result in positive future stock returns in S&P 500 no matter what the holding period is which also confirms the first hypothesis of this paper. However, the results do not advocate the results by Giot (2005) that negative future returns consistently follow after VIX reaches its lowest levels.

The most major finding of this paper is that the size and operating profitability premiums are strongly affected by the VIX levels and can be used in profitable style rotation strategies with VIX timing. Especially the long-short SMB portfolio shows very high excess returns when compared to a conventional SMB portfolio. In addition, the sub-portfolios of the SMB long-short portfolio perform almost equally well indicating that a style rotation strategy with SMB is well-balanced: large cap stocks generate as good returns with high levels of VIX as small cap stocks with low levels of VIX. The long-short RMW portfolio also clearly outperforms its corresponding conventional portfolio, although not as well as the long-short SMB portfolio. However, the long-short RMW portfolio is not as balanced as the long-short SMB portfolio as two thirds of its returns are generated when VIX is at its highest levels. Thus, higher operating profitability stocks generate much better returns with high levels of VIX than low operating profitability stocks with low levels of VIX.

The results for the other factors show that also the value, investment pattern and momentum factors exhibit different future returns with different levels of VIX which confirms the second hypothesis of this thesis. However, the style rotation trading strategy results show that they cannot be used effectively in a VIX timing strategy like the size and operating profitability premiums. The results for the value factor support the findings of Peltomäki and Äijö (2015) by showing that the correlation between VIX changes and HML returns is generally positive and becomes negative only during periods of very high market uncertainty: the 20-day and 60-day future returns for the value factor show statistically significant negative returns at least at a 5% significance level only for the highest level of VIX. Thus, taking advantage of the highest levels of VIX in an HML-driven style rotation trading strategy would not be possible in practice due to high trading costs. The momentum factor exhibits very similar results compared to the HML factor results as the MOM returns with different holding periods and VIX ranks are generally positive with almost all VIX levels and negative only when VIX is at its most extreme high levels. The long-short momentum portfolio returns for the lower levels of VIX are quite good but ultimately overshadowed by the negative returns for the higher levels of VIX just like with the long-short HML portfolio. The initial CMA return results with different holding periods and VIX ranks are promising as they show that aggressive stocks tend to outperform conservative stocks when VIX is at its highest levels and vice versa. However, the style rotation trading strategy results reveal that utilizing the extreme levels of VIX with the CMA factor does not work well in practice as the CMA long-short portfolio greatly underperforms the conventional CMA portfolio.

Overall, this thesis shows that the relative levels of VIX combined with style rotation can be used by investors in an equity timing strategy to gain considerable excess returns in the S&P 500 index. The results indicate that the highest levels of VIX always lead to positive future returns in S&P 500 and should therefore be considered especially in portfolio management by more passive investors. This study contributes to the previous literature by examining the effects of VIX levels on the future returns of the Fama-French 5 factors and momentum factor and discovers that the SMB and RMW factors can in fact be utilized for style rotation in a VIX timing strategy in the S&P 500 index. Thus, more active investors can use the highest and lowest levels of VIX to choose whether to buy small cap or large cap stocks or high or low operating profitability stocks to get superior excess returns compared to the conventional SMB and RMW factor portfolio returns. All findings considered, relative VIX levels and can be used in profitable style rotation timing strategies in S&P 500.

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