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DOES VIX OFFER TIMING POSSIBILITIES IN EQUITIES' SECTOR AND STYLE ROTATION?

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Table of contents

LIST OF FIGURES **page**

LIST OF TABLES

page

UNIVERSITY OF VAASA		
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ABSTRACT

VIX is often referred as an investor's fear gauge. This thesis concentrates on whether the relative VIX levels can be used as a market timing signal for equities. Giot (2005) finds that high (low) relative levels of VIX always lead into positive (negative) returns for S&P 100, no matter what the holding period is. In this thesis equities are divided into 10 industries and Fama and French (2015) five factor portfolios are also used in order to find whether volatility drives the returns of these portfolios. Fama-French portfolios are Market portfolio, SMB (small cap stocks minus large cap stocks), HML (value stocks minus growth stocks), RMW (high operating profitability stocks minus low operating profitability stocks) and CMA (conservative stocks minus aggressive stocks).

This thesis covers data from 29th January 1993 until the end of 2015. In order to define VIX levels, a 500-day rolling method is used to rank each day's close value for VIX. Ranks are always based on the previous 500-day history of VIX values. High negative correlation between VIX and equities are also under consideration. This thesis shows that the closer the observations are on the present day, the higher the negative correlation tend to be.

Results reveal that highest levels of VIX are great at signaling positive future returns. These returns are above average and significant in most of the cases. On the other hand, industries that are less negatively correlated with VIX tend to have better returns on lower volatility levels. Volatility also seems to be driving Fama-French factor returns. Especially results from SMB and HML portfolios are distinctive, but CMA portfolio seem to be affected by volatility too. Small cap stocks perform better on lower volatility levels while large cap stocks perform better on higher volatility levels. Growth stocks outperform (underperform) value stocks on higher (lower) volatility levels. Conservative stocks outperform (underperform) aggressive stocks on lower (higher) volatility levels.

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

1. INTRODUCTION

In this new environment of negative interest rates investors seek alternative options to invest their money in. They are also trying to find new ways to reduce risk without significantly affecting in the return of a portfolio. It is said that there is a positive correlation between risk and return and thus it is hard to get higher profits by lowering the risk at the same time (Markowitz 1952). However, improvements in risk-return profile are possible and CBOE Volatility Index VIX has a potential to enhance the risk-return ratio due to the high negative correlation between VIX and S&P 500. The negative correlation is documented by Fleming, Ostdiek and Whaley (1995) and Giot (2005) who are using S&P 100 returns. Also Whaley (2009) and many others, who use S&P 500 returns, find high negative correlation. The problem is that spot VIX is not investable and other VIX-related products are not as attractive as spot VIX. Rolling VIX futures is expensive during low volatility environment (Alexander and Korovilas 2011). Moran (2007) point that VIX futures are not as volatile as VIX, meaning that when stock market plummets, futures go up, but not as sharply as VIX. In this thesis it is examined how Fama & French (2015) 5 factors perform on different levels of VIX and how would a long-short portfolio using each factor individually work. It is also examined whether there are possibilities to benefit using VIX as a sector rotation tool.

According to Markowitz (1952), it is possible to construct a risk free portfolio, when instruments have a perfect negative correlation. Perfectly negatively correlated products are rare, if non-existent, but VIX could be useful as a diversification tool due to the long history of high negative correlations between VIX and major stock indices, for example S&P 500 (CBOE 2016). Negatively correlated products have a tendency to fluctuate to different directions. The problem is that spot VIX is non-investable and VIX related products are not effective in a long portfolio, especially during periods of low volatility. Several researches indicate the potential of VIX during market turmoil (for example Moran 2007, Szado 2009), but say that VIX-related products tend to erode the benefits of diversification during low volatile periods. However, it has not been examined whether there are possible timing strategies, where VIX levels are signals to buy equities from a certain industry. Or alternatively, if there are possibilities to construct strategies based on firm size, value, profitability and investment patterns (Fama & French 2015). Giot (2005) finds that 60-day holding period has the highest forecasting power for VIX for future returns. Furthermore, Banerjee, Doran & Peterson (2007) estimate that the mean reversion for VIX is approximately 44.1 trading days. Banerjee et al. (2007) results from mean reversion support the results of Giot (2005). Durand, Lim and Zumwalt (2011) argue that the market risk premium factor and HML factor are sensitive to changes in the VIX. Furthermore, changes in VIX drive the value premium, HML, and momentum premium, WML, in ways that are consistent with the theory of flying to quality, when the expected risk rises. They also find that the risk premium of Mkt-Rf portfolio is negatively associated with the unexpected changes in volatility. However, they find that there is at best a marginal effect on the size premium, SMB.

Peltomäki and Äijö (2015) examine the relation between volatility risk and cross-sectional anomalies momentum, size and value. Their study focus on the period of financial crisis between 2007 and 2009. They find that these relations are dependent on the market and economic conditions. The returns to the value strategy are negatively associated with the increase in market volatility during the financial crisis. They also suggest that momentum strategy might be a more defensive strategy during extreme market conditions.

1.1. Purpose of the study

This study examines whether there are profitable ways of using the volatility-based index, VIX, as an investment tool. In this thesis VIX is used with S&P 500 stock index and with 10 different industry indices to examine average returns on different levels of VIX. Giot (2005) finds that very high levels of VIX always lead to positive returns and very low levels of VIX always into negative returns. He suggests that very high levels of VIX could be interesting buying opportunities. These results are re-examined using a longer time period. Fama and French (2015) represented their five factor model and its components are also used to capture the nature of returns in different levels of risk (VIX). Copeland and Copeland (1999) find that value stocks and growth stocks perform differently on different VIX movements. Value stocks outperform (underperform) growth stocks when VIX goes up (down). The same pattern can be seen between large cap and small cap stocks. These findings can give an idea on how different industries perform. They also give an idea for Fama-French factor results. In this thesis it is examined how Fama-French portfolios perform on different levels of VIX.

VIX is often referred as the fear indicator of the market (Whaley 2009). When VIX is in its higher levels, S&P 500 tends to be in its lower levels. VIX can be used in several ways in an investment portfolio, but in this thesis VIX is used as a market timing signal. The key in this thesis is the 500-day rolling ranking method for VIX. Furthermore, it is difficult to determine absolute values when VIX is “high” or “low”. Szado (2009) finds that volatility is conditional and time varying and thus it is challenging to set certain rules when to use VIX in the purpose of hedging equity positions. However, he also says that the conditional nature of the correlation of VIX may provide an effective diversification tool during major down moves in the stock market.

The relative ranking method used in this paper gives a certain rank for VIX every day. The higher the rank the higher the VIX is relative to its 500-day history. Firstly, it is examined how positions taken in S&P 500, Fama-French 5 factors and 10 different industries yield after each rank on different holding periods. Giot (2005) finds that the highest ranks lead always into positive returns and the lowest ranks lead always into negative returns. Motivated by findings of Giot (2005), this thesis expands the study to cover industries and Fama-French five factors. Also a longer time period is under examination. This thesis tries to find market timing benefits with VIX ranking method. Also a strategy where a long position is taken in five factor portfolios on certain VIX levels and a short position on certain other levels is examined. Furthermore, a strategy, where equity allocations between different industries are switched depending on the ranking method, is researched. Conover, Jensen, Johnson and Mercer (2008) state that sector rotation using monetary conditions may provide abnormal returns. Thus it is interesting to examine whether volatility conditions are good signals for sector and style rotation.

1.2. Hypotheses

Copeland & Copeland (1999) find that using one-day percentage change of VIX from its 75-day moving average as a signal to rotate between strategies of style (value stocks versus growth stocks) and size (large cap stocks versus small cap stocks) generates positive excess returns in both directions. They find that when volatility increases, large cap and value portfolios tend to perform better. On the other hand when volatility decreases, small cap and growth portfolios are generating better returns. Giot (2005) finds that very high levels of VIX always lead into positive future returns and very low levels of VIX lead into negative future returns in different holding periods. Banerjee et al. (2007) examine the predictive power of VIX in book-to-market, size and beta portfolios. Furthermore, they control for factors MKT, SMB, HML based on Fama and French

(1993) and UMD based on Carhart (1997). MKT stands for excess market return, SMB is a size premium, HML is a value premium and UMD stands for a momentum factor. Banerjee et al. (2007) find that VIX levels and innovations significantly effect on the returns of most portfolios. Stronger relationship is experienced for high beta portfolios. Based mainly on these three studies the hypotheses in this thesis are as follows:

The first hypothesis is that firm characteristics including size, value, profitability and investment pattern have different returns depending on the level of volatility.

The second hypothesis is that highest relative levels of VIX lead into positive returns in all industries regardless of the holding period.

The third hypothesis is that industries with lower correlation with VIX tend to perform better during periods of lower volatility and hence be more optimal than an investment to S&P 500.

1.3. Structure of the thesis

The structure of this thesis is following. Second chapter covers previous literature about the subject. Several studies about VIX as a diversification tool and a market timer are reviewed. Also sector rotation is under discussion. Third chapter concentrates on volatility and VIX. VIX options and futures are represented, as well as the calculation of VIX. The idea is to introduce VIX and VIX-related products as accurately as possible.

Fourth chapter represents sector and style rotation. Sector rotation will be covered more detailed than in the second chapter. Fifth chapter introduces the data used in this thesis. Sixth chapter covers methodology. In the seventh chapter there are results and discussion and the eight chapter is concluding remark.

2. LITERATURE REVIEW

According to the modern portfolio theory (Markowitz 1952), it is possible to build an "efficient frontier" of optimal portfolios to maximize the expected return for a given level of risk. When choosing negatively correlated products into a portfolio, it is possible to significantly reduce risk without affecting considerably on the returns of a portfolio. However, since risk and return tend to move same direction, it is difficult to get higher returns with a less risky portfolio. The high negative correlation between VIX and S&P 100 or S&P 500 (Fleming et al. 1995, Giot 2005 and Whaley 2009) possibly provides opportunities for portfolio diversification or market timing. Fleming et al. (1995) also observe that changes in VIX are larger for negative changes in the market than for positive changes. This means that VIX tend to spike sharply when the market plummets, but when market spikes, VIX goes down, but not as sharply.

2.1. VIX and S&P 500

There is a well documented negative correlation between VIX and different stock indices. Fleming et al. (1995), Giot (2005), Whaley (2009) and many others find high negative correlation between VIX and S&P 100/S&P 500. S&P 500 is considered the best single gauge of large cap U.S. equities. The index includes 500 leading companies and represents about 80% of available market capitalization (S&P 500 Index 2016). As stated in the previous chapter, there is well documented negative correlation between the VIX and S&P 500. But the more interesting thing is that when S&P 500 index drops, VIX has a tendency to rise much stronger. For example, on October 27, 1997, the S&P 500 index fell by 6.9% and the VIX index rose by 34.3%. The average quote change of VIX on those 26 days, when S&P 500 fell more than 3% during 1990-2006, was +16.8%. The average drop for S&P 500 was 3.8%. (Moran 2007)

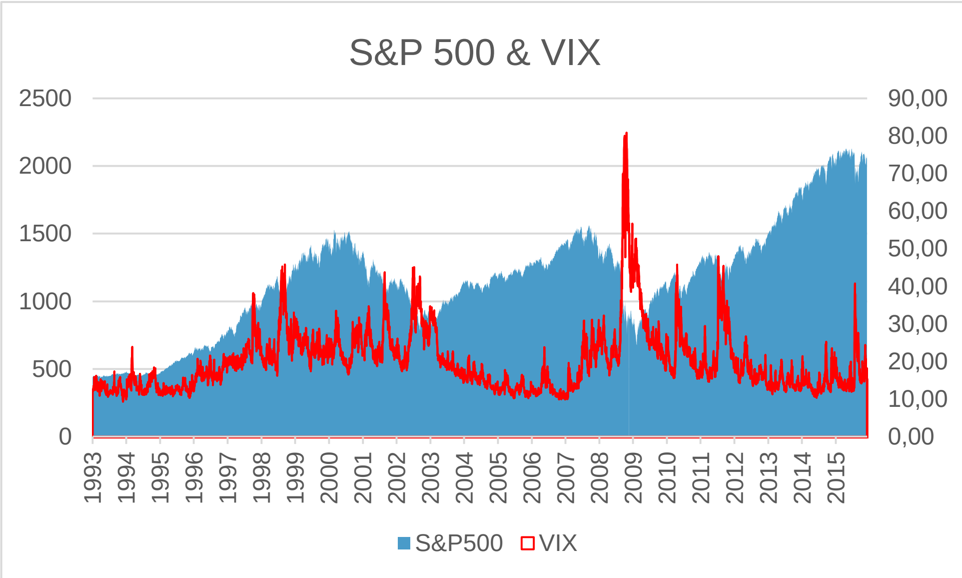

Figure 1: Behavior of VIX and S&P 500. (Finance Yahoo 2016)

In figure 1 there are values for VIX on the right vertical axis and values for S&P 500 on the left vertical axis. Horizontal axis is the timeline. It is quite easy to notice the negative correlation between VIX and S&P 500. When VIX spikes, S&P 500 tends to plummet and vice versa. During the credit crisis in 2008 there are the clearest spikes in both S&P 500 (downwards) and VIX (upwards). However, it seems that in the early 1990s the negative correlation was not as strong as nowadays. This observation is proved right later. Around 1999 VIX started to become more negatively correlated with S&P 500, as we can observe from the graph. It is also shown in the methodology part of this thesis that VIX and S&P 500 indeed become more negatively correlated in the 21st century.

Giot (2005) examines whether extremely high levels of VIX are good buying signals for the S&P 100 index. The time period is from August 1994 to January 2003 and Giot uses 1-, 5-, 20-, and 60-day horizon in his research. He finds that extremely high levels of VIX lead always to positive future returns, and extremely low levels of VIX to negative future returns, no matter what the holding period is. Notable is that there is no clear pattern for middle levels of VIX.

2.2. VIX as a diversification tool

An interesting aspect concerning diversification is the high negative correlation between VIX and S&P 500. Sharp rises in VIX during the drops of stock markets can lead to questions whether VIX can help to smooth out portfolio returns or even improve risk-adjusted returns. There are several studies that include VIX into portfolio as diversification. However, it must be noted that many of these studies use hypothetical approach, since spot VIX is not investable.

From January 31 1990, through March 30 2007, the S&P 500 has annualized returns of 11.8% while the annualized return of VIX is -2.9%. Even though the return of VIX is negative, an addition of spot VIX to a portfolio reduces volatility of the portfolio significantly. Besides, the returns are only slightly lower. For example, if there are two portfolios to be compared: the other has 100% in stocks and the other 95% in stocks and 5% in VIX spot index. The portfolio with a small allocation to VIX has a volatility that is 92 basis points lower and furthermore its annualized returns are 6 basis points lower. Consequently, it leads into a slightly higher Sharpe ratio. However, hypothetical allocations of more than 30% to VIX lead to lower Sharpe ratios of the portfolio. (Moran 2007)

Daigler and Rossi (2006) compare S&P 500-volatility portfolio to S&P 500 only portfolio from 1992 through 2002. Their deduction was that adding volatility into a portfolio improved the risk-return ratio by reducing risk significantly without a substantial effect on returns. Moreover, they tested how using previous year’s optimal weight in VIX affects to next year’s portfolio. The result was almost identical to a minimum risk portfolio. During their 11-year time period daily correlations between S&P 500 and VIX are from -45.4% to -82.4%.

Not only adding volatility to long equity portfolios but also to hedge fund portfolios could be reasonable according to Moran and Dash (2005). They find that VIX and hedge fund returns have relatively high negative correlation and therefore adding VIX to a hedge fund portfolio can be a good diversification and risk management tool. In the research of Lawrence McMillan (2007) it states that VIX is good for hedging, because it provides dynamic protection. Sloyer and Tolkin (2008) argue that VIX futures are better for hedging than VIX options, because they can be more passively managed than options, which need frequent delta hedging to maintain directional neutrality. VIX futures can be rolled over relatively cheap when previous contract expires and they do not have a directional exposure and thus they are fit for a passively managed portfolio. McMillan (2007) says that a relatively small allocation to VIX, around 10%, is enough to hedge an equity portfolio. Due to a small amount of VIX, the costs of hedging are at a low level. But one thing that has to be taken into consideration is, as Moran (2007) states in his paper, that VIX futures tend to be less volatile as the spot VIX index, particularly when the futures are not close to their expiration. This means, when VIX spikes, the futures go up as well, but not as sharply.

Szado (2009) finds that volatility is conditional and time varying and thus it is challenging to set certain rules when to use VIX in the purpose of hedging equity positions. But he also says that the conditional nature of the correlation of VIX may provide an effective diversification tool during major down moves in the stock market. Szado examines the effectiveness of adding VIX futures in three portfolios. One of the portfolios was 100% stocks, the other 60% stocks and 40% bonds and the third 60.5% equities, 30.5% bonds and 9% alternative assets, for example hedge funds and managed futures. In his research he has two different time periods, from March 2006 to December 2008 and from August 2008 to December 2008. From March 2006 to December 2008 a 2.5% allocation to VIX futures in all three portfolios improved returns and decreased standard deviations of the returns. The Sharpe ratios did not improve significantly during this time period, but there is still some improvement observable.

In figure 2 is represented an efficient frontier of portfolio with stocks, bonds and alternatives from March 2006 to December 2008 with different allocations to VIX. Notable is that an allocation up to 10% to VIX futures improves returns while reducing risk.

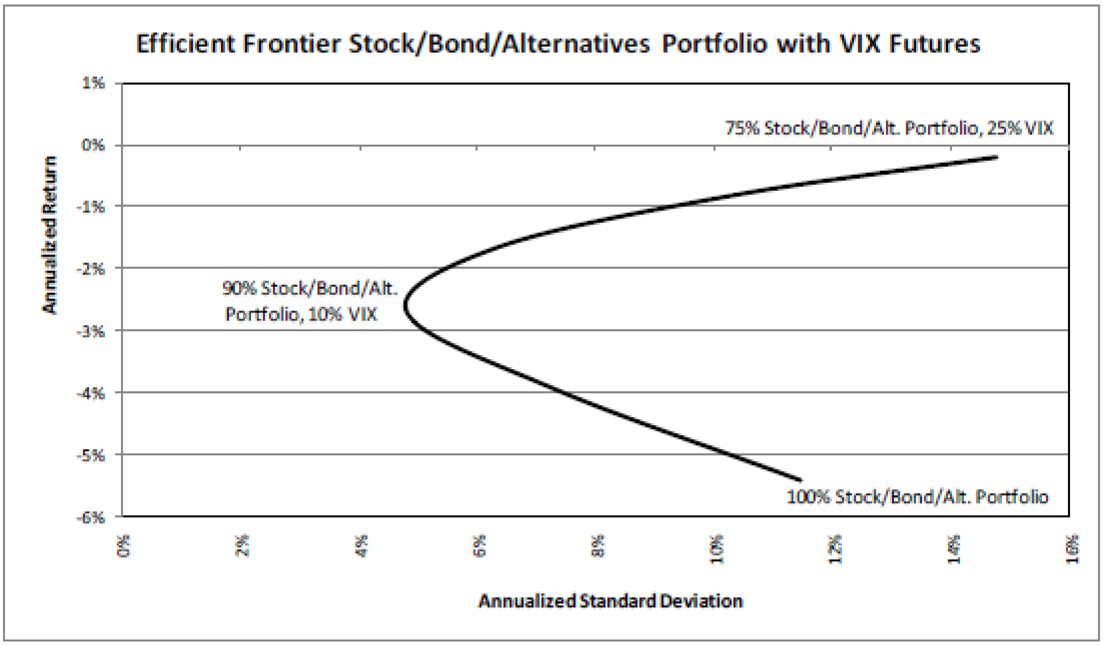

Figure 2: Addition of VIX futures to Stock/Bond/Alternatives portfolio from March 2006 to December 2008. (Szado 2009)

During the short and volatile period from August 2008 to December 2008 the results are even clearer. The stock/bond/alternative-portfolio has a negative return of -20% during that period, while the same portfolio with a 2.5% allocation to VIX futures has a negative return of -16%. With a 10% allocation to VIX futures the return is only -4%. Standard deviations are also lower (25%, 23% and 16%). There is also a clear improvement in Sharpe ratios in all three portfolios. The higher the allocation to VIX is, the higher the Sharpe ratio. (Szado 2009)

In the same paper, Szado (2009) also examines the performance of VIX call options during the same time periods. Using the same portfolios as in the case of VIX futures, but including a 1% or a 3% allocation of at-the-money (ATM) VIX 1-month calls or 25% out-of-the-money (OTM) VIX 1-month calls, provides quite similar results as the VIX futures. During the time period from March 2006 to December 2008, ATM VIX calls reduce losses, but results concerning the standard deviations are mixed. Including 1% ATM calls reduce standard deviations, but a 3% allocation to VIX calls increase the standard deviation of two out of three portfolios. As in the case with VIX futures, the results are clearer during the short time period from August 2008 to December 2008. The enhancement in returns is impressive. The stock/bond/alternative-portfolio does not perform very well, generating a 20% loss, but with a 3% allocation of VIX calls the same portfolio provide a positive return of 21%, while the standard deviation decrease from 25% to 21%. In the case of 25% OTM calls, with the same allocation of 1% or 3%, the results are more extreme. Due to the deep OTM call options, returns are much greater in market drops, but standard deviations also rise. From March 2006 to December 2008, an addition of 25% OTM VIX calls improve returns of the stock/bond/alternative-portfolio as follows: 1% allocation of OTM calls improve returns from -6% to +1% and a bigger allocation, 3%, lead to a return of +6%. During the shorter period, adding a 1% allocation of 25% OTM VIX calls to stock/bond/alternative-portfolio enhance returns from -20% to +18%. With an allocation of 3% the return is +97%.

The usefulness of VIX as a diversifier is not only praised but also questioned. Alexander and Korovilas (2011) argue in their paper that advantages of VIX as a diversifier are clear during stock market crisis, but high transaction costs and negative carry and roll yield on volatility futures during normal market sentiment periods would have a negative impact on returns, unless investors are able to time their trades very carefully.

2.3. Market timing with VIX

Using VIX as a market timing indicator is one possible way to benefit from VIX. Basically, when VIX is at its highest levels stock indices are at their lowest levels and vice versa. The difficulty is that investors can never know when VIX reaches its peak. According to Chadwick (2006), a popular trading wisdom says that a low stock volatility is a bearish signal while high volatility levels are signs for a bullish market. High levels of VIX usually mean that there is fear in the market and buying stocks for long hold might be reasonable. Chadwick tests the correlation of the relative level of VIX to subsequent moves in the S&P 500. Relative level is defined as the ratio of the VIX to its own N-day moving average, minus one. For example, if VIX is 15 and its N-day moving average is 10, its relative level would be 15/10 -1 = 50%. Chadwick’s results suggest that VIX has been a strong indicator of the direction of a market since its foundation. He finds that VIX is best to predict medium-term moves. During 1990-2006 the highest degree of linear predictive power arose using a 186 trading day (9 calendar months) moving average for the relative VIX, predicting 114 trading days (5 calendar months) out on the S&P 500.

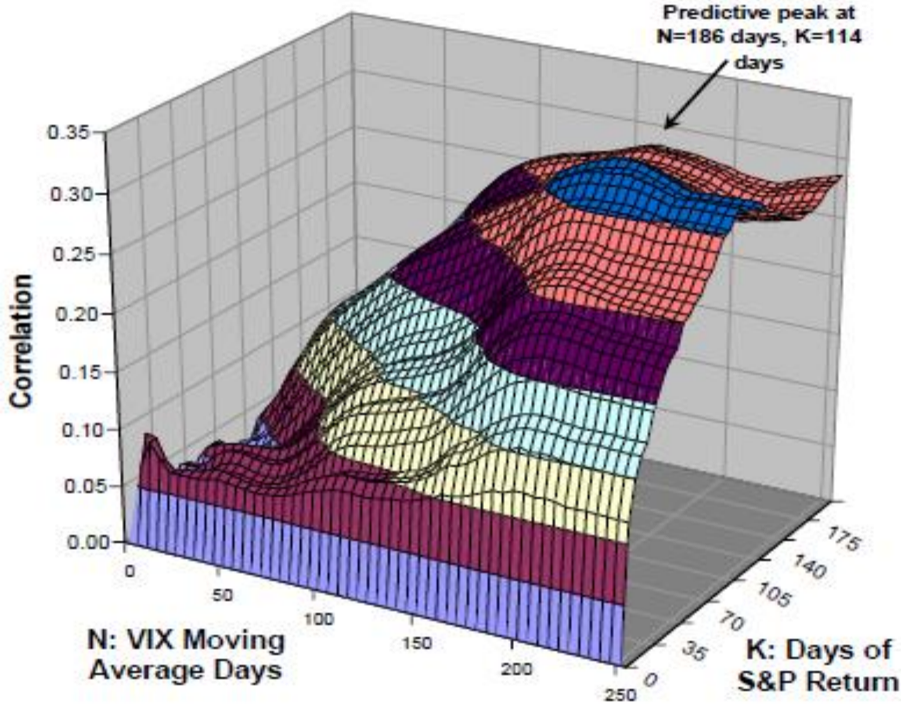

Figure 3: Correlation of “relative VIX” vs. subsequent S&P 500 return. (Chadwick 2006)

The results are nearly as strong with any K and N within a month or two of these two values, N=186 and K=114. As we can see from the figure 3 above, short predictive periods are less effective, but they offer some guidance.

Qadan and Cohen (2011) examine seven different levels of VIX (15, 18, 20, 22, 25, 30 and 35) from January 2004 to June 2009. Their method is to buy S&P 500 when VIX goes below mentioned levels and sell, when VIX goes above the same level. For example, if VIX drops below 20, they buy S&P 500 and when VIX climbs back above 20, then it is time to sell. Buying S&P 500 in January 2004 and selling it in June 2009 would have yielded -14.64%. Figure 4 shows that their strategy with any given level of VIX would have outperformed traditional buy and hold-strategy.

The result of a trading simulation using different VIX scores for the period January 2004-June 2009

VIX	15	18	20	22	25	30	35
Number of Transactions	72	30	30	40	42	15	9
Accumulated return of the strategy (%)	4.55	31.37	12.57	-2.37	-14.43	-7.08	-6.15

Notes (1). The number of transactions includes all transactions (buy and sell) for the examined period according to trading rules based on a specific VIX score. (2) The accumulated return on investment in the S&P 500, according to VIX-based trading rules.

Figure 4: Performance of portfolio using VIX as a timing tool during January 2004-June 2009. (Qadan & Cohen 2011)

As we can see, during this certain time period from January 2004 to June 2009, the most profitable strategy is to buy S&P 500 when VIX goes below 18 and sell it while it climbs back above 18. Qadan and Cohen point out that their strategy does not take transaction costs into account while calculating the returns, but if they would take them into account every other strategy would have outperformed S&P 500 except for VIX level 25. Interesting is that this strategy of Qadan & Cohen's is selling S&P 500 after VIX has climbed. This study is not in line with negative correlation and many other studies due to the fact that Qadan & Cohen are making profit when VIX goes up and S&P 500 is supposed to go down.

Copeland and Copeland (1999) find that value stocks outperform (underperform) portfolios of growth stocks following an increase (decrease) in the VIX index. This is based on the fact that investors prefer value (growth) stocks with increased (decreased) market uncertainty. Boscaljon, Filbeck and Zhao (2011) examine the effectiveness of VIX in timing shifts for style asset allocation. They examine the impact of percentage changes in the VIX index as a market signal. They use a percentage change in VIX as an indicator to switch from value portfolio to growth portfolio and vice versa. Their findings suggest that changes in VIX offer timing benefits for 30 days or longer holding periods. Findings were strongest in large cap companies. In Copeland and Copeland's study the results were significant already when holding period exceeded two days.

Peltomäki and Äijö (2015) examine the relation between returns to cross-sectional anomalies momentum, size and value and volatility risk. They find that the relationships are highly time-varying depending on market and economic conditions. They continue that returns to the value strategy are sensitive and negatively related to increases in market uncertainty during the financial crisis from 2007 to 2009. On the other hand, the returns to the momentum strategy are significantly and positively associated with volatility risk during crisis periods and recessions. However, during non-recessionary periods the relationship is negative, implying that increases in volatility are followed by low momentum returns. This is opposite to value strategy.

3. VOLATILITY AND VIX

The volatility, σ, of a stock is a measure of our uncertainty about the returns provided by the stock. Typically, stocks have a volatility between 15% and 60%. The CBOE publishes indices of implied volatility. The most popular index, the S&P 500 -based VIX, is an index of the implied volatility of 30-day options on the S&P 500 calculated from a wide range of calls and puts. (Hull 2012: 319.)

Implied volatility is a forecast of future volatility and thus differs essentially from realized volatility, which is based on historical prices. Traub, Ferreira, McArdle and Antognelli (2000) find that the realized volatility of the S&P 500 during 1985-1999 is 14.7% while implied volatility at the same time period is 19.8%. In other words, volatility describes the risk in the market and VIX is a volatility-based index. (Mayhew 1995)

3.1. Implied volatility

Conventionally, implied volatility has been calculated using either Black-Scholes (1973) option pricing model or the Cox-Ross-Rubinstein (1979) binomial model. There are also some other option pricing formulas that may be used to calculate implied volatility. It is possible to calculate implied volatility from various underlying assets. Not only from standard stock options or stock index options, but also from the prices of exotic options. The calculation of implied volatility has to be done numerically, because option pricing formulas cannot often be inverted analytically. (Mayhew 1995)

Easy, but not necessary a very fast way to calculate implied volatility is to use an iterative search procedure. If all the other parameters are known, by giving randomly chosen values for volatility σ, it is possible to get the right value after several iterations.

The purpose of the use of implied volatilities is to monitor the market’s opinion about the volatility of a certain stock. While historical volatilities are looking the volatilities already realized, implied volatilities are forward looking. Implied volatility is more often quoted by the traders than the price of an option, because the implied volatility tends to be less variable than the option price. (Hull 2012: 319.)

One of the biggest issues in volatility forecasting has been whether to use implied volatility, historical data or some combination of these two. If option markets are efficient, implied volatility should be an efficient forecast of future volatility. Researchers have not been united with the issue. In early literature, for example Latane and Rendleman (1976), the focus is on static cross-sectional tests. Results are united that implied volatility is a better future forecast than historical data. But in following papers researchers have used other testing methods and the results have been mixed. More recent tests have concentrated on the information content of implied volatility in dynamic settings. There is not only one right answer, but if a conclusion must be drawn from various researches, it is that implied volatility tends to be more useful than historical volatility when predicting the volatility in the future. (Mayhew 1995 & Christensen 1998)

3.2. VIX

“The powerful and flexible trading and risk management tool from the Chicago Board Options Exchange.” VIX is the volatility index of the Chicago Board Options Exchange, CBOE, which was introduced in 1993. It was originally designed to measure the market’s expectation of 30-day volatility implied by at-the-money S&P 100 Index option prices. VIX is often referred as the fear gauge of the market. In 2003, CBOE in cooperation with Goldman Sachs improved the VIX to reflect a new way to measure the expected volatility. The new VIX is based on the S&P 500 Index, SPX, the most important index for U.S. equities, and estimates expected volatility by averaging the weighted prices of SPX puts and calls over a wide range of strike prices. (CBOE 2016)

Figure 5 represents data from 1993 until the end of 2015. On the left vertical axis there are daily closing values for VIX. Horizontal axis is the timeline. The graph shows the nature of VIX quite clearly. Most of the time in the history VIX has fluctuated around 10 to 20 points, but there are also frequent spikes all the way up to 80 points. After these spikes VIX is returning back to more normal levels in a relatively short period of time.

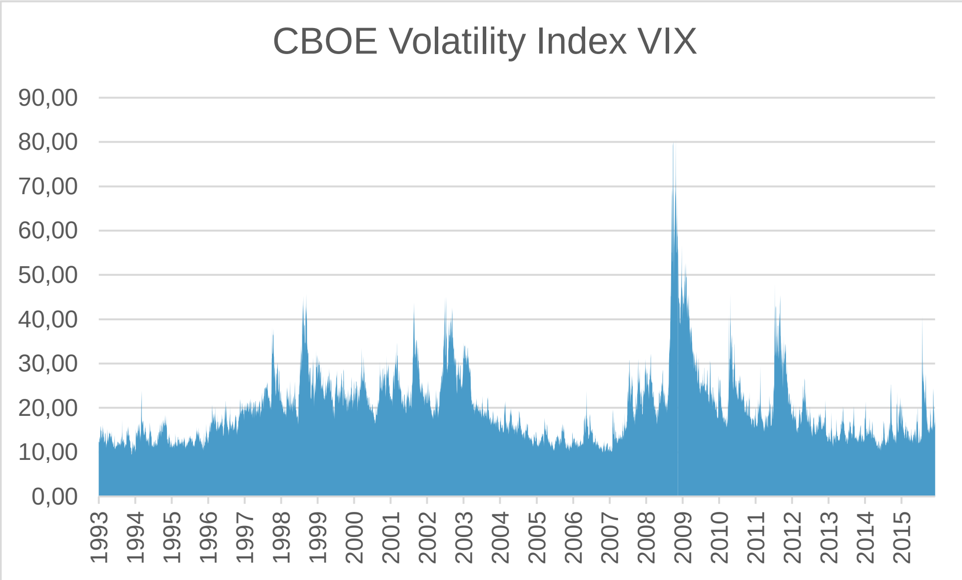

Figure 5: Historical levels of VIX. (Finance Yahoo 2016)

VIX is an index just like S&P 500 for example, but the difference is that VIX measures volatility, not price. It is important to highlight that VIX is forward-looking and measures the expected volatility. It is not measuring volatility that has been recently realized. As Whaley (2009) says in his paper, conceptually, VIX could be considered the same way as a bond's yield to maturity. Yield to maturity is the discount rate that connects a bond's price to the current value of its promised payments. As such, a bond's yield is implied by its current price and represents the expected future return of the bond until the maturity date. Similarly, VIX is implied by the current prices of S&P 500 index options and represents expected future volatility of the market over the next 30 days on annualized basis (Whaley 2009). Thus if VIX is 20 points, it is expected that S&P 500 will fluctuate 5.77% during the next 30-day period. (Fodor 2013)

$$\text{(1)} \qquad \textit{Monthly expected volatility} = VIX / \sqrt{12}$$

In 2004, CBOE introduced the first exchange traded futures contract. Two years later, in 2006, CBOE launched VIX options. These instruments have become very popular. In less than five years, trading activity in VIX options and futures together has grown to more than 100,000 contracts per day. (CBOE 2016)

There is a well-documented negative correlation of volatility to stock market returns. Thus, including volatility in an investment portfolio for diversification could be reasonable (CBOE 2016). Over the 17-year period from 1990 to 2006, the spot VIX price changes were negatively correlated with the S&P 500. The negative correlation is significant in terms of daily returns (-0.66) and monthly returns (-0.61) (Moran 2007). Reason why there is a significant negative correlation between VIX and S&P 500 is typically explained by the panic of investors when the market drops. Specifically, this phenomenon is observable, when market shows signs of weakness. Investors hurry to buy index puts, which creates an imbalance between supply and demand. The reason why VIX has a tendency to drop when market is rising, could be explained by the aggressiveness of option sellers when bullish market sentiment becomes more common. When the market remains constant, there is a better balance between demand for, and supply of options and thus implied volatility remains stable. (Bittman 2007)

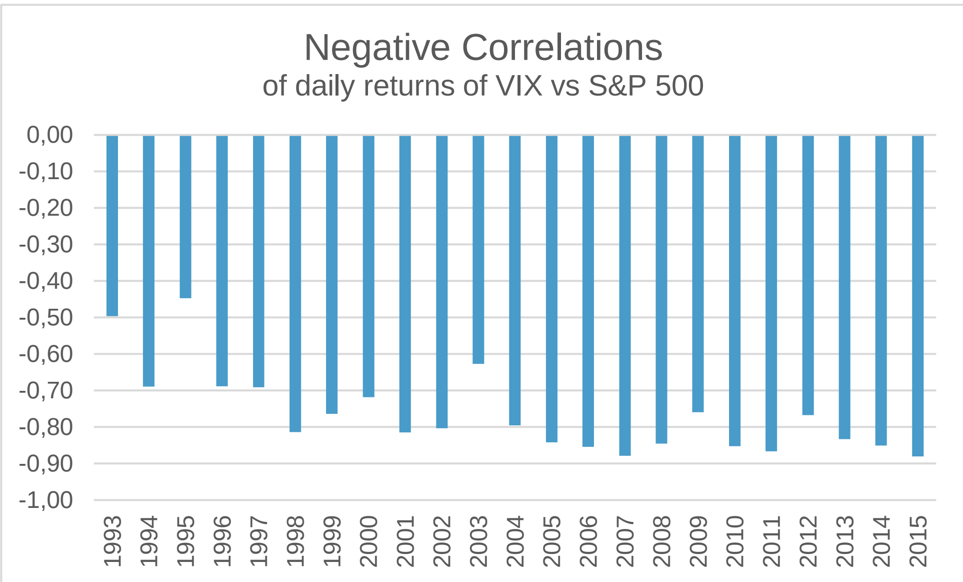

Figure 6: Historical correlations between VIX & S&P 500. (Finance Yahoo 2016)

Figure 6 shows correlations of daily returns on each year since 1993 until 2015. As we can see from the graph, only twice the absolute value of negative correlations has been below 0.60 and only six times below 0.70. Of these six times, five are before year 1998 and the sixth in 2003. Recent history shows highly negative correlations. In 2007 and 2015 the negative correlation is -0.88, which is the highest absolute value in this dataset.

3.3. VIX calculation

In its early stages, VIX was calculated from the prices of S&P 100 index option prices. S&P 100 index options were the most traded options at the time. Originally, VIX was based on the prices of only eight at-the-money index call and put options. But when time passed, the situation turned upside down and the trading activity with S&P 500 index options became significantly more popular than the ones of S&P 100 index. Another considerable reason for calculating VIX nowadays from the option prices of S&P 500 index is that those options are European style, which means that they are exercisable only at maturity, making it easier to value them by using a certain option pricing formula. In 2003, when CBOE decided to use S&P 500 index option prices instead of S&P 100 index option prices to calculate the VIX, they included out-of-the money options in the index computation since especially out-of-the money put option prices contain important information regarding the demands for portfolio insurance and, hence, market volatility. (Whaley 2009)

The generalized formula used in the VIX calculation is:

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

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 $K_i = K_0$

ΔK_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: ΔK for the lowest strike is simply the difference between the lowest strike and the next higher strike. Likewise, ΔK 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 K_i

(CBOE 2016)

There are distinctive differences between the formula of VIX and the formula of Black-Scholes. VIX calculation is about weighted sum of option prices, while the Black-Scholes implied volatility is backed out of an option price. (CBOE 2016)

3.4. VIX futures and options

Due to the high demand of tradable products of the VIX index, on March 26, 2004, CBOE published futures on VIX index, which began trading on the new CBOE Futures Exchange (CFE). On February 24, 2006, VIX options were published and began trading on the CBOE. VIX options are one the most successful new listed options products in the recent history. In the first steps of both futures and options there was growth in volume and open interest from the 2006 calendar year to the first quarter of 2007; during this period the average daily volume of VIX options rose 63% to 38.239 contracts and the VIX options period-end open interest rose 42% to 987.579 contracts (Moran 2007). Open interest means the total number of derivatives contract that an investor has not closed and that have not expired (Hull 2012: 811).

Figure 7 indicates the rapid growth in volumes of VIX futures. The average daily volume in 2005 was $705.000 compared to the volume of $205.100.000 in 2015. After 2009 the average daily volume started to grow rapidly.

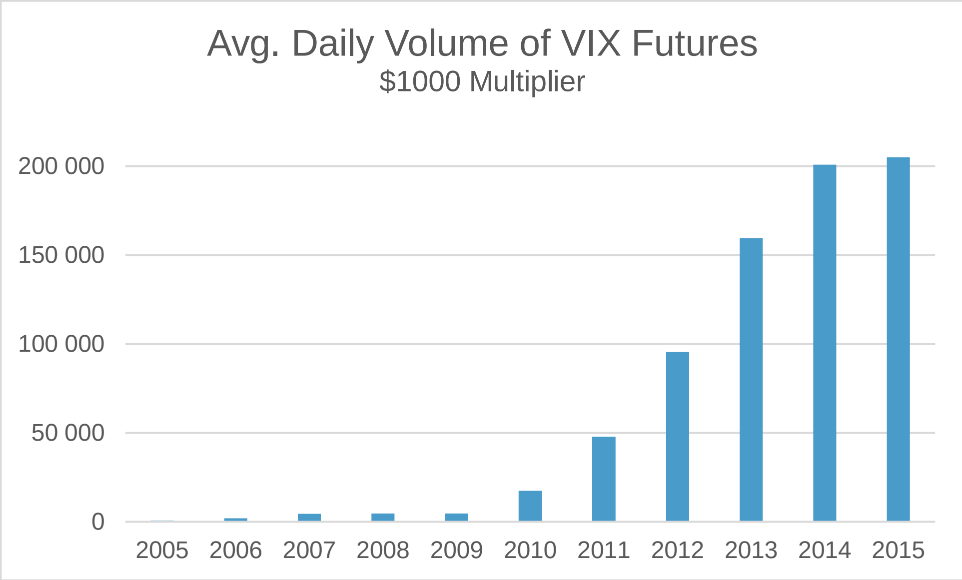

Figure 7: Average daily volumes of VIX futures. (CBOE 2016)

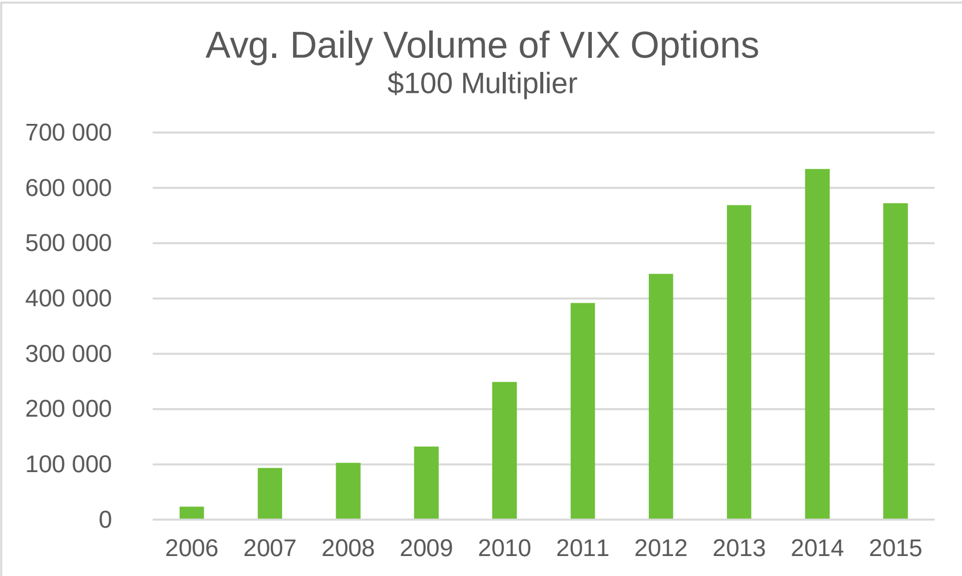

Figure 8: Average daily volumes of VIX options. (CBOE 2016)

The considerable distinction between the volumes of options and futures is that VIX futures have a contract multiplier of $1000, so if VIX is at 22, the notional value of futures is $22.000. At the same point, the notional value of options would be $2.200 (Moran 2007). As figure 8 shows, VIX options market has also grown rapidly from its early stages in 2006. It has grown from average daily volume of 2.400.000 dollars in 2006 to 57.200.000 dollars in 2015. The highest average daily volume, 63.400.000 dollars for VIX options, occurred in 2014.

4. SECTOR ROTATION AND STYLE ROTATION

Conventional sector rotation strategy is based on business cycles. The idea is to change the portfolio more towards industries that are expected to outperform other industries based on the state of the business cycle. Allocating between industry sectors over different stages of business cycles outperforms the market according to conventional market wisdom. However, following the popular belief and anticipating the business cycles perfectly, rotating between different industries generate at best only a 2.3% annual outperformance (Stangl, Jacobsen and Visaltanachoti 2009). Bodie, Kane and Marcus (2009) say that "...sector rotation, like any other form of market timing, will be successful only if one anticipates the next stage of the business cycle better than other investors". They also state in their book that the notion of sector rotation is "one way that many analysts think about the relationship between industry analysis and the business cycle".

Bodie et al. (2009) define the business cycle as a recurring pattern of recession and recovery. The transition points across cycles are called peak and troughs. Peak is the end of an expansion period and trough occurs at the bottom of recession. It might be expected that the performance of different industries may vary during different stages of the economy. At a trough, it might be expected that cyclical industries tend to outperform other industries due to the above-average sensitivity to the state of economy. In contrast to cyclical industries, defensive industries might be expected to outperform other industries as the economy enters a recession. Figure 9 below is a stylized depiction of the business cycle.

In this thesis the levels of VIX are used to indicate whether there are possibilities to generate higher returns by rotating between different industries. It is hypothesized that industries with lower correlations with VIX tend to perform better on periods of lower volatility.

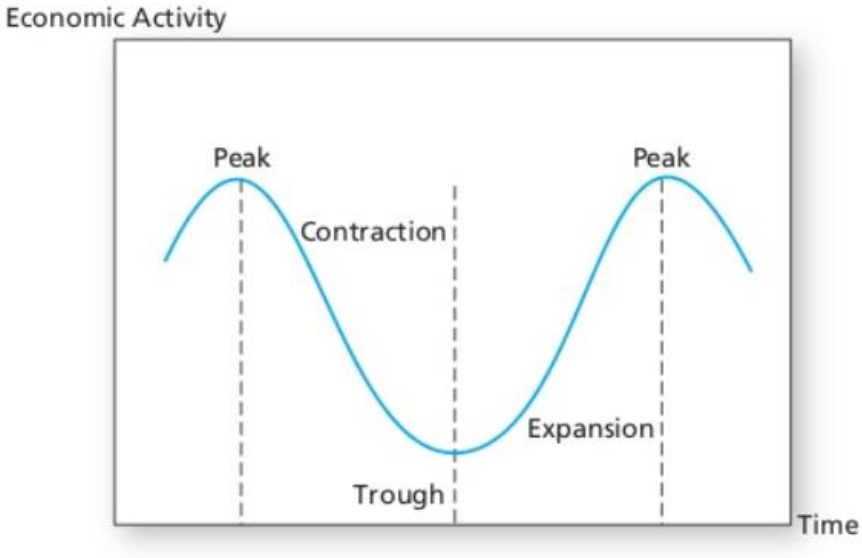

Figure 9. Business cycles. (Bodie, Kane & Marcus 2009)

Near the peak, the economy might be overheated and the inflation and interest rates may be high. At this point it would be a good time to invest in firms that are related to natural resource extraction and processing, such as minerals or petroleum. After the peak, when the economy contracts, defensive industries that are less sensitive to economic conditions might be the best performers. These industries are for example pharmaceuticals, food, and other necessities. When the economy approaches trough, lower inflation and interest rates favor financial firms. At the trough it might be a good idea to invest in capital goods industries such as equipment, transportation, or construction, because firms might be spending on purchases of new equipment to respond to expected increases in demand. Finally, in an expansion the economy starts growing fast. Cyclical industries such as consumer durables and luxury items could be most profitable in this stage. Also banks might as well, since the loan volume will increase and the rate of defaults is not that high. (Bodie, Kane & Marcus 2009)

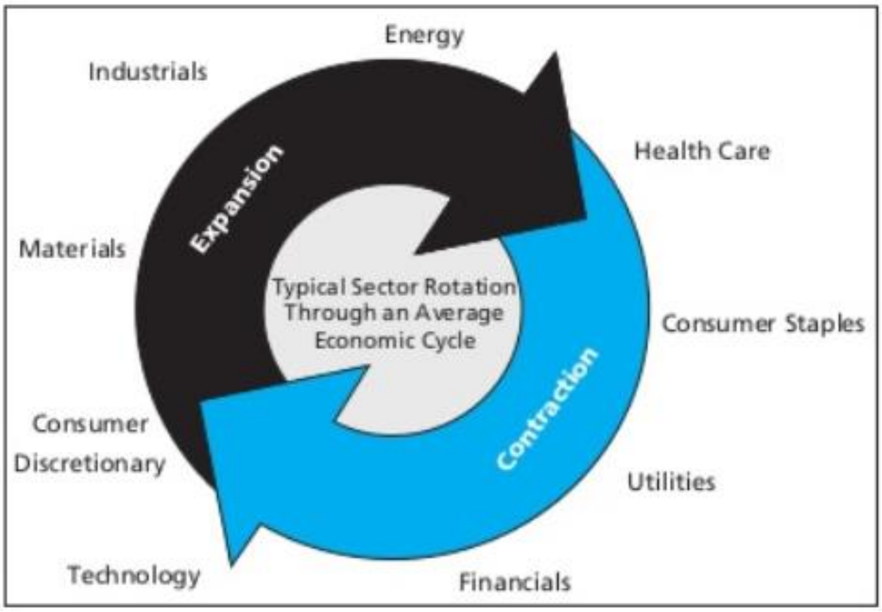

Figure 10. Sector rotation. (Bodie, Kane & Marcus 2009)

Below, Kiely and Prati (2009) find that style rebalancing significantly outperforms buy-and-hold approaches. Stangl et al. (2009) argue that in their base scenario different sectors do not significantly and systematically outperform other sectors and industries over the business cycle, at least not in the way that the conventional market wisdom suggests. Avramov and Wermers (2006) find a relation between mutual fund performance and industry allocation and business cycle proxies. Conover, Jensen, Johnson and Mercer (2008) state that sector rotation using monetary conditions may provide abnormal returns.

However, it is almost impossible to know when the economy is on its peak or trough. Hence, the idea in this paper is to examine when to use VIX levels as a market timer for sector rotation. In other words, it is examined that which industries are investable on low levels of VIX and which are investable on high levels of VIX. These results might give an idea for portfolio allocations, since the returns based on the ranking method used in this paper are always forward looking.

In addition to sector rotation, also style rotation is under examination. Fama and French (1993) describe three common risk factors for stocks in their paper. These three factors are an overall market factor and two factors related to the firm size and book-to-market. Later, Fama and French (2015) expanded their model to capture also profitability and investment patterns. Value stocks are stocks with high book-to-market ratio, while growth stocks have lower book-to-market ratio. Fama and French (1993) find that small capitalization stocks and high book-to-market stocks tend to have better returns than the returns expected by using Capital Asset Pricing Model. They argue that size factor (SMB) and value factor (HML), combined with the market risk premium, provide a satisfactory model to explain the cross-section of U.S. stock returns. For example, Kumar and Lee (2003) argue that the small firm effect might be based on the fluctuating investor sentiment. Petkova (2006) finds that the variation in SMB and HML portfolios can be modelled by using variables that capture the economic expectation. Baker and Wurgler (2006) study how investor sentiment affects on the cross-section of stock returns. They find that when the investor sentiment is low, the future returns are relatively high on smaller stocks, high volatility stocks, unprofitable stocks, non-dividend-paying stocks, extreme growth stocks and distressed stocks. In this paper, relatively high levels of VIX could be considered similar to low investor sentiment. When volatility is on its higher levels, it means that there is fear in the market.

Copeland and Copeland (1999) find that value stocks outperform (underperform) growth stocks when VIX goes up (down). Same pattern stands for large cap stocks versus small cap stocks. Large cap stocks outperform (underperform) small cap stocks when VIX goes up (down). On the contrary, Peltomäki and Äijö (2015) find that the returns to the value strategy are negatively related to increases in market volatility. Durand et al. (2011) use a four-factor model including Mkt-Rf, HML, SMB and UMD. They find that VIX drives the value growth premium, HML, and momentum premium, WML, in a way which is consistent with the theory of "flying to quality" (Abel 1988) when volatility is expected to rise. They also state that the market risk premium, Mkt-Rf, is negatively associated with the unexpected changes in market volatility. On the other hand, they do not find a significant relation between the size factor, SMB, and the market volatility. Smales (2016) finds that VIX drives the returns across firm size and value, and also across industry. He also states that small capitalization stocks, technology stocks, telecom stocks and firms that are more subjective to value are more sensitive to changes in investor sentiment.

In this paper the five factor returns are regressed on different levels of volatility in order to explain whether VIX drives the returns of the factor portfolios. Is volatility one of the drivers for the premiums? As Durand et al. (2011) find, VIX is a significant driver for HML and UMD premiums. Furthermore, unlike Copeland and Copeland (1999), Peltomäki and Äijö (2015) find that value premium is negatively associated with increased market volatility. This paper uses Fama-French five factors and implements them with Giot's (2005) methodology.

From now on, Mkt-Rf is used for the overall market factor, HML for book-to-market factor, SMB for size factor, RMW for profitability factor and CMA for the investment pattern. SMB stands for Small Minus Big, HML for High Minus Low, RMW for Robust Minus Weak and CMA for Conservative Minus Aggressive. Next chapter shows how these portfolios are constructed.

5. DATA

Motivation for this study comes from previous literature, where several researchers find that during turbulent times VIX is a useful diversifier, but during low volatility periods the benefits of volatility are eroded mainly due to the costs of rolling futures contracts. If the expected return on VIX futures is mainly negative, it is interesting to see, whether using VIX as a timing signal is possible to diversify between different equity industry classes in different times. Also possibilities for style rotation are under examination.

The data is collected from www.finance.yahoo.com for the volatility-based index, VIX, and the data used for S&P 500 is based on an exchange-traded fund SPY (Finance Yahoo 2016). Since S&P 500 itself is not tradable, SPY is used in order to create real portfolios Data for industry returns is obtained from Kenneth French's website (Kenneth French Data Library). These 10 different industries are Durables, Energy, Healthcare, Hi-Tech, Manufacturing, Non-durables, Others, Shops, Telecom and Utilities. All data is adjusted for splits and dividends. All returns are computed to logarithmic returns. Data for SPY, Fama-French 5 factors and 10 different industries starts from 29th January 1993. For VIX there is data starting 500 trading days prior 29th of January in order to define a rank number for VIX from the beginning of equity data. The last trading day for each of the components is 31st December 2015. The daily returns are under examination in this thesis.

Definitions for Fama-French 5 factors, Mkt-Rf, SMB, HML, RMW and CMA are as follows:

Mkt-Rf is the excess return on the market. The market return in this data is a value-weighted return of large amount 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:

(3) $SMB_{(B/M)}$ = 1/3 (Small Value + Small Neutral + Small Growth) – 1/3 (Big Value + Big Neutral + Big Growth

$SMB_{(OP)}$ = 1/3 (Small Robust + Small Neutral + Small Weak) – 1/3 (Big Robust + Big Neutral + Big Weak)

$SMB_{(INV)}$ = 1/3 (Small Conservative + Small Neutral + Small Aggressive) – 1/3 (Big Conservative + Big Neutral + Big Aggressive)

SMB = 1/3 ($SMB_{(B/M)}$ + $SMB_{(OP)}$ + $SMB_{(INV)}$),

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.

(4) HML = ½ (Small Value + Big Value) – ½ (Small Growth + 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.

(5) RMW = ½ (Small Robust + Big Robust) – ½ (Small Weak + Big Weak)

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

(6) CMA = ½ (Small Conservative + Big Conservative) – ½ (Small Aggressive + Big Aggressive).

(Kenneth French Data Library 2016).

6. METHODOLOGY

This thesis concentrates on whether high (low) levels of VIX are good buying (selling) signals for SPY, Fama-French five factors and 10 different industries. The methodology used in this thesis is based on Giot (2005). The holding periods are the same as Giot (2005) uses in order to be able to compare the results. Banerjee et al. (2007) find that the mean reversion of VIX is about 44.1 trading days and thus the holding periods of 1, 5, 20 and 60 days are admissible.

This study examines the effect of relative VIX levels as a timing indicator. The relative level of VIX means the recent history of VIX values. These relative values are used, since it is hard to determine absolute boundaries when VIX is high and when it is low. Also a simple correlation analysis between VIX and SPY, Fama-French factors and different industries is provided in the beginning of the next chapter. Correlations are calculated using Microsoft Excel’s correlation function using daily logarithmic returns. Long-short portfolios are also constructed based on the results of a ranking method.

6.1. VIX ranking system

In this study VIX levels are divided into 20 percentiles with a 500-day rolling method. This means that the estimation period for VIX is 500 days, T_0. T_0+1 gets a rank from 0 to 21 depending on how it is placed according the rolling method of VIX. Rank number 21 means that the observation is higher than any observation during the previous 500 days and rank number 0 means that the observation is lower than any other observation during the previous 500 days. This method is similar to Giot (2005), but here is added one rank number more, 0. Giot uses a two-year rolling method and in this paper there is a 500-day rolling method, which is almost similar. Giot finds that the results are similar with a one year rolling method.

The 500 days of VIX are divided into 20 percentiles. Table 1 is demonstrating the ranking. The first column shows the rank, the second column shows the corresponding percentile for each rank and the third column shows what the boundaries would be, if the whole sample history would have been used to determine the boundaries instead of the rolling method. This kind of rolling method for the ranking system means that the boundaries for percentiles do not change very quickly due to the fact that the next day has 499 same VIX values for estimation as the previous day and the day after that has 499 same values as the previous day and 498 same values as the day before the previous. But as Whaley (2009), Giot (2005), Fleming et al. (1995) and many others state, VIX is known for its rapid movements and thus there is a possibility for a different rank each day. The third column is additional information for the reader to demonstrate which values would be considered “low” and “high” in historical perspective. It is important to emphasize that these values do not represent the values of the rolling method. The boundaries in rolling method move over time.

Table 1. Ranks and historical boundaries for VIX based on percentiles.

Rank	Percentile	History of VIX
R0	Lower than previous 500 VIX values	
R1	0-5	11.47
R2	5-10	12.11
R3	10-15	12.67
R4	15-20	13.23
R5	20-25	13.89
R6	25-30	14.62
R7	30-35	15.45
R8	35-40	16.27
R9	40-45	17.11
R10	45-50	18.18
R11	50-55	19.22
R12	55-60	20.19
R13	60-65	21.19
R14	65-70	22.29
R15	70-75	23.54
R16	75-80	24.90
R17	80-85	26.65
R18	85-90	29.67
R19	90-95	34.97
R20	95-100	80.86
R21	Higher than previous 500 VIX values	

Using the whole sample to determine the boundaries, VIX would get rank 20, when values are between 34.97 and 80.86 and rank 1, when values are below 11.47. As we can see from the table, the differences between VIX values are not that high on lower ranks. Table 2 shows that between 29th January 1993 and 31st December 2015 the median value for

VIX is 18.18 and the average value 19.93. The lowest value, 9.31, occurred on 22nd December 1993 and the highest, 80.86, during the financial crisis, 20th November 2008.

Table 2. Historical statistics for VIX.

	VIX	Date
Min	9.31	22.12.1993
Max	80.86	20.11.2008
Mean	19.96	
Median	18.18	

6.2. Return calculation method for different ranks

The method used to calculate average returns for SPY, different industries and factor portfolios is similar to Giot (2005). The return data is regressed on 22 ranks, which are used as dummy variables. The ranks get a value of 0 or 1 depending on which rank VIX gets on a certain day. Only one rank can get a value of 1 and the others get a value of 0 on a certain day. The regression models used in this thesis are

$$r1d = \beta_0 D0_t + \beta_1 D1_t + \ldots + \beta_{21} D21_t + \varepsilon_t \tag{7}$$

$$r5d = \beta_0 D0_t + \beta_1 D1_t + \ldots + \beta_{21} D21_t + \varepsilon_t \tag{8}$$

$$r20d = \beta_0 D0_t + \beta_1 D1_t + \ldots + \beta_{21} D21_t + \varepsilon_t \tag{9}$$

$$r60d = \beta_0 D0_t + \beta_1 D1_t + \ldots + \beta_{21} D21_t + \varepsilon_t \tag{10}$$

Where r1d, r5d, r20d and r60d are 1-, 5-, 20- and 60-day returns for SPY, different industries and factor portfolios. It is important to emphasize that all of these returns are individual. This means that for example r1d stands for 16 different returns (SPY, 10 industries and five factors). D0, D1, D2,…, D20 and D21 represent the different dummy variables for ranks.

7. RESULTS AND DISCUSSION

The results part starts with a correlation analysis between VIX and different indices and factor portfolios. The correlations are calculated from daily returns from 29th January 1993 to 31st December 2015. Table 3 shows the statistics. The highest negative correlation is between VIX and the Mkt-Rf portfolio and the second highest between VIX and SPY (S&P 500). These results are in line with Fleming et al. (1995), Giot (2005), Whaley (2009) and others. Quite naturally, 10 different industries are somewhat in the same range between each other and in the same range as SPY. Manufacturing is most negatively correlated with VIX with a value of -0.697, while utilities seem to be correlating only -0.498 with VIX. RMW, CMA and HML are positively correlated with VIX. Mkt-Rf is in the same range with S&P 500, while RMW and CMA show correlation of 0.247 and 0.212. HML is only slightly positively correlated with VIX. SMB is slightly negatively correlated with VIX.

Table 3. Correlations between different indices and VIX from daily returns during 1993-2015.

Benchmark	Correlation with VIX
S&P 500	-0.727
Mkt-Rf	-0.735
SMB	-0.014
HML	0.043
RMW	0.247
CMA	0.212
Non-Durables	-0.621
Durables	-0.613
Manufacturing	-0.697
Energy	-0.529
Hi-Tech	-0.615
Telecom	-0.616
Shops	-0.645
Healthcare	-0.600
Utilities	-0.498
Other	-0.672

Figure 6 in chapter 3 shows the correlations between S&P 500 and VIX each year. Tables 4 and 5 show the same statistics for every index in the data.

Table 4. Correlations between different indices and VIX every year between 1993 and 2015.

Year	S&P 500	Mkt-Rf	SMB	HML	RMW	CMA	Non-Durables	Durables
1993	-0.50	-0.54	0.08	0.14	-0.08	0.20	-0.39	-0.39
1994	-0.69	-0.74	0.20	0.25	0.11	0.32	-0.58	-0.49
1995	-0.45	-0.49	0.01	0.26	0.22	0.21	-0.25	-0.25
1996	-0.69	-0.70	0.25	0.48	0.15	0.37	-0.57	-0.40
1997	-0.69	-0.72	0.42	0.48	-0.13	0.38	-0.61	-0.58
1998	-0.81	-0.82	0.33	0.58	0.14	0.53	-0.70	-0.67
1999	-0.76	-0.79	0.56	0.54	0.15	0.50	-0.60	-0.48
2000	-0.72	-0.77	0.12	0.54	0.43	0.51	-0.32	-0.43
2001	-0.81	-0.82	0.23	0.51	0.48	0.56	-0.41	-0.62
2002	-0.80	-0.82	0.38	0.27	0.35	0.16	-0.59	-0.69
2003	-0.63	-0.65	0.04	0.09	0.39	-0.24	-0.46	-0.53
2004	-0.80	-0.77	-0.42	0.07	0.44	-0.39	-0.55	-0.69
2005	-0.84	-0.82	-0.37	0.15	-0.03	0.14	-0.72	-0.63
2006	-0.85	-0.82	-0.48	0.22	0.12	0.16	-0.70	-0.69
2007	-0.88	-0.85	-0.20	-0.03	-0.14	0.17	-0.83	-0.75
2008	-0.85	-0.84	0.10	-0.31	0.18	0.29	-0.79	-0.76
2009	-0.76	-0.76	-0.27	-0.57	0.42	0.15	-0.67	-0.65
2010	-0.85	-0.85	-0.39	-0.60	0.47	-0.50	-0.79	-0.79
2011	-0.87	-0.87	-0.53	-0.26	0.67	-0.13	-0.84	-0.82
2012	-0.77	-0.76	-0.27	-0.13	0.36	0.19	-0.68	-0.62
2013	-0.83	-0.83	-0.21	-0.26	0.49	-0.06	-0.72	-0.69
2014	-0.85	-0.85	-0.16	0.19	0.31	0.27	-0.72	-0.74
2015	-0.88	-0.88	0.10	0.08	0.09	0.27	-0.80	-0.79

Table 4 shows correlation statistics more detailed than table 3. Interesting is that SMB and HML, which both were more or less non-correlating with VIX in the whole sample seem to be negatively correlated in eight out of ten (SMB) and seven out of ten (HML) years in the recent history. This recent negative correlation between VIX and SMB portfolio could be consistent with flight-to-quality (Abel 1988). When VIX goes up and the risk increases, investors are less willing to hold small stocks. However, for HML this same interpretation would mean that when the risk increases the investors are less willing to hold value stocks. On the other hand, RMW and CMA have been correlating with VIX quite randomly. RMW shows higher positive correlations in the recent years compared to the average, but CMA has no clear direction. There are years when the correlation is positive and years when it is negative, but these observations occur with no clear pattern. However, correlations are slightly positive for RMW and CMA. This also support the idea of flying to quality. As risk increases, investors are more willing to buy conservative stocks with good operating profitability.

For non-durables and durables, it can be seen that the correlations are becoming more negatively correlated when sample is closer this day. Older observations do not show as strong negative correlation as newer ones.

Table 5. Correlations between different indices and VIX every year between 1993 and 2015.

Year	Manufacturing	Energy	Hi-Tech	Telecom	Shops	Healthcare	Utilities	Other
1993	-0.39	-0.17	-0.50	-0.39	-0.40	-0.21	-0.35	-0.51
1994	-0.67	-0.49	-0.58	-0.59	-0.64	-0.57	-0.54	-0.70
1995	-0.40	-0.26	-0.37	-0.38	-0.42	-0.25	-0.15	-0.39
1996	-0.63	-0.38	-0.55	-0.51	-0.61	-0.59	-0.50	-0.65
1997	-0.70	-0.53	-0.61	-0.55	-0.64	-0.65	-0.52	-0.68
1998	-0.76	-0.47	-0.70	-0.69	-0.74	-0.68	-0.35	-0.77
1999	-0.63	-0.34	-0.64	-0.63	-0.68	-0.61	-0.36	-0.70
2000	-0.63	-0.13	-0.65	-0.59	-0.51	-0.45	-0.16	-0.64
2001	-0.73	-0.27	-0.70	-0.62	-0.67	-0.43	-0.21	-0.78
2002	-0.76	-0.68	-0.70	-0.74	-0.70	-0.66	-0.47	-0.79
2003	-0.63	-0.46	-0.60	-0.49	-0.58	-0.57	-0.53	-0.62
2004	-0.75	-0.41	-0.65	-0.61	-0.67	-0.62	-0.46	-0.72
2005	-0.80	-0.52	-0.71	-0.67	-0.70	-0.57	-0.62	-0.78
2006	-0.75	-0.45	-0.73	-0.70	-0.67	-0.68	-0.53	-0.79
2007	-0.83	-0.69	-0.80	-0.80	-0.78	-0.77	-0.68	-0.78
2008	-0.82	-0.70	-0.81	-0.80	-0.78	-0.79	-0.75	-0.79
2009	-0.71	-0.71	-0.71	-0.67	-0.65	-0.63	-0.60	-0.72
2010	-0.83	-0.77	-0.80	-0.78	-0.79	-0.76	-0.75	-0.82
2011	-0.85	-0.79	-0.83	-0.85	-0.83	-0.83	-0.78	-0.83
2012	-0.73	-0.65	-0.67	-0.71	-0.68	-0.70	-0.54	-0.74
2013	-0.80	-0.71	-0.69	-0.71	-0.75	-0.70	-0.61	-0.81
2014	-0.82	-0.61	-0.77	-0.71	-0.76	-0.68	-0.48	-0.82
2015	-0.82	-0.61	-0.83	-0.76	-0.82	-0.74	-0.54	-0.85

Table 5 continues to show the same pattern as table 4. Different industries become more negatively correlated as time goes by. From 2007 to 2015 all but one industry (utilities, 2014) has had higher negative correlation than the average correlation for each industry between 1993 and 2015. According to these three tables of correlations, it seems that no industry would support the hypothesis of profits in low levels of volatility. Correlation statistics for Fama-French factors are not so encouraging either, but there might be possibilities for sector and style rotation.

Tables 4 and 5 highlight that in 1990s the negative correlation between VIX and different stock indices have been less negatively correlated than in the recent years. 1990s is the period that Giot (2005) mostly examines in his paper. Guo and Wohar (2006) find in their paper that there is a clear structural change in VIX after 1997 and this might be the explanatory factor for higher negative correlations compared to the beginning of 1990s. Table 6 below presents the outcomes for buying SPY and holding it for different time periods. The ranks are as presented in the methodology part. Second column represents the number of VIX values between different rank numbers. 1d, 5d, 20d and 60d are the average returns for the time periods. The returns are reported in percentages. In addition, all the standard errors are Newey-West standard errors in order to take autocorrelation into account. If rank number is observed at time t, the returns start always from t+1 so it is a forward-looking measure. Furthermore, t-statistics tell whether the returns are statistically significantly different from zero.

Data in table 6 basically is a replication of Giot's paper with a longer time period. Giot (2005) finds that very low ranks result always into negative returns and very high ranks into positive returns. Also Giot states that there is no clear pattern for the middle ranks of VIX. Also while Giot has rank numbers from 1 to 21, in this paper there is a rank number 0 added in order to represent very low relative values of VIX. One gets rank 0, if the VIX value is below any VIX value during the past 500 days. This 500-day rolling method shows how high or low VIX is relative to its recent values. This method is similar to the one Giot (2005) uses in his paper. Giot uses a two-year rolling method, which is almost the same as the 500-day rolling method.

Table 6 below does not entirely support the findings of Giot (2005). The lowest ranks do lead into slightly negative returns apart from 60-day holding period, but these results are not statistically significantly different from zero. Also only the highest rank leads into significantly positive returns at 5% level, no matter what the holding period is. Interesting is that unlike Giot, it is found that rank numbers 7 and 10 lead into statistically significant returns at 5% significance level in every holding period. Rank number 7 represents the percentile above 0.30 and below 0.35 and 10 represents the percentile above 0.45 and below 0.5 as table 1 shows. However, high average returns for rank numbers 7 to 10 can be mostly explained by the fact that during the financial crisis from the end of 2007 until the beginning of 2009 there were no observations for rank numbers 0 to 10. During this period returns were highly negative. This anomaly also at least partially explains why the returns of lowest ranks were positive or just slightly negative. If the financial crisis period from December 2007 until the end of March 2009 were omitted from the data, the results for higher ranks would be interesting. For rank number 20 there are 456 observations and for rank number 21 there are 41 observations. A 60-day holding period would yield 5.85% and 7.91% for ranks 20 and 21. For a 20-day period corresponding values are 2.6% and

4.53%. However, on 5-day and 1-day holding periods rank number 21 yields slightly less than it yields when financial crisis is included, but rank number 20 yields around two times better, when financial crisis period is omitted. This suggests that even in extreme conditions rank number 21 shows positive returns on shorter time periods.

Table 6. SPY returns between different 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
R0	70	-0.077	0.062	-1.232	-0.008	0.157	-0.048	-0.049	0.398	-0.124	0.599	0.989	0.606
R1	627	-0.026	0.026	-1.006	-0.134	0.095	-1.406	-0.086	0.264	-0.325	0.430	0.512	0.840
R2	404	0.038	0.032	1.196	-0.025	0.114	-0.220	0.319	0.239	1.337	1.162	0.446	2.604 ***
R3	317	-0.026	0.036	-0.734	-0.069	0.109	-0.630	0.154	0.268	0.574	0.926	0.544	1.704 *
R4	314	-0.004	0.045	-0.084	0.155	0.129	1.201	0.408	0.323	1.265	1.431	0.639	2.239 **
R5	257	-0.016	0.054	-0.304	0.038	0.146	0.263	0.065	0.327	0.200	1.799	0.508	3.542 ***
R6	230	0.019	0.060	0.320	0.297	0.156	1.902 *	0.979	0.294	3.328 ***	1.689	0.534	3.163 ***
R7	213	0.144	0.057	2.516 **	0.451	0.144	3.141 ***	0.922	0.366	2.517 **	2.317	0.504	4.602 ***
R8	206	0.090	0.069	1.300	0.452	0.161	2.813 ***	0.742	0.398	1.864 *	2.703	0.586	4.609 ***
R9	195	0.040	0.065	0.608	0.255	0.173	1.476	1.202	0.362	3.320 ***	2.873	0.600	4.789 ***
R10	205	0.182	0.073	2.507 **	0.616	0.187	3.293 ***	1.353	0.413	3.274 ***	3.290	0.611	5.382 ***
R11	185	-0.011	0.069	-0.165	0.124	0.232	0.533	1.250	0.476	2.627 ***	2.700	0.998	2.705 ***
R12	189	-0.001	0.076	-0.008	-0.149	0.191	-0.780	0.443	0.476	0.930	0.664	1.247	0.533
R13	217	-0.033	0.071	-0.469	0.288	0.189	1.523	0.901	0.441	2.042 **	1.902	1.116	1.705 *
R14	228	0.061	0.087	0.697	0.040	0.197	0.202	0.776	0.392	1.978 **	0.655	1.139	0.575
R15	226	0.102	0.079	1.284	0.183	0.234	0.785	1.332	0.454	2.935 ***	2.326	0.809	2.876 ***
R16	235	-0.010	0.070	-0.147	0.129	0.215	0.602	1.451	0.510	2.845 ***	3.194	0.851	3.752 ***
R17	254	-0.025	0.088	-0.281	0.121	0.269	0.449	0.183	0.665	0.275	2.482	1.032	2.406 **
R18	294	-0.031	0.092	-0.342	-0.036	0.272	-0.133	-0.140	0.696	-0.201	2.372	1.030	2.304 **
R19	333	-0.009	0.084	-0.112	0.085	0.211	0.401	0.695	0.442	1.573	2.488	0.891	2.792 ***
R20	521	0.098	0.084	1.161	0.525	0.306	1.719 *	1.591	0.650	2.449 **	3.949	0.936	4.221 ***
R21	54	1.093	0.387	2.825 ***	2.469	0.753	3.278 ***	2.561	1.236	2.072 **	4.721	1.700	2.777 ***

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

From now on the significance levels in following tables are the same as in table 6. *** means significance at 1% level, ** at 5% level and * at 10% level. Table 7 shows the average returns for holding SPY for 1, 5, 20 and 60 days during 1993-2015. The average return is calculated in a way where a new position is taken every day, so there are 5774 observations in each category. The returns in the table below are in percentages.

Table 7. Average returns for SPY in different holding periods.

Holding period	Average return
1d	0.034
5d	0.168
20d	0.673
60d	2.008

On average, during this time period from 29th January 1993 to 31st December 2015, SPY has returned 0.034% on a daily basis. 5-day return is 0.168%, 20-day return 0.673% and 60-day return 2.008%. Based on tables 6 and 7, table 8 shows how different ranks return against the average returns of SPY on different holding periods. Table 8 represents the percentage of observations that are higher than the corresponding average return of SPY.

Table 8. Percentage of observations that are above the average corresponding returns of SPY.

Rank	#	1d	5d	20d	60d
R0	70	43 %	46 %	47 %	41 %
R1	627	50 %	47 %	46 %	48 %
R2	404	55 %	49 %	51 %	50 %
R3	317	49 %	49 %	50 %	49 %
R4	314	49 %	54 %	60 %	55 %
R5	257	52 %	54 %	48 %	55 %
R6	230	47 %	54 %	65 %	52 %
R7	213	58 %	61 %	65 %	58 %
R8	206	54 %	61 %	60 %	66 %
R9	195	51 %	57 %	60 %	67 %
R10	205	58 %	69 %	63 %	64 %
R11	185	51 %	56 %	58 %	64 %
R12	189	52 %	46 %	53 %	50 %
R13	217	47 %	58 %	53 %	58 %
R14	228	48 %	52 %	60 %	54 %
R15	226	55 %	55 %	63 %	57 %
R16	235	53 %	54 %	67 %	58 %
R17	254	49 %	51 %	53 %	55 %
R18	294	53 %	50 %	49 %	52 %
R19	333	49 %	49 %	52 %	58 %
R20	521	57 %	63 %	64 %	72 %
R21	54	61 %	72 %	72 %	83 %

Furthermore, table 8 shows that the highest ranks, 20 and 21, return above average more than 50% of the observations no matter what the holding period is. Above average return means that the return is higher than the average return of SPY during the whole sample. Notable is that for 60-day holding periods ranks 20 and 21 return above average 72% and 83% of their observations. On the other hand, lowest ranks 0 and 1 have difficulties in returning above average. Only 1-day return for rank 1 is slightly higher than average. However, this table alone does not tell the entire truth about the returns, because it simply does just show whether the return is above or below the average, but not the fact how much it is below or above the average.

Table 9. Above average returns.

Rank	1d	5d	20d	60d
R0	FALSE	FALSE	FALSE	FALSE
R1	FALSE	FALSE	FALSE	FALSE
R2	TRUE	FALSE	FALSE	FALSE
R3	FALSE	FALSE	FALSE	FALSE
R4	FALSE	FALSE	FALSE	FALSE
R5	FALSE	FALSE	FALSE	FALSE
R6	FALSE	TRUE	TRUE	FALSE
R7	TRUE	TRUE	TRUE	TRUE
R8	TRUE	TRUE	TRUE	TRUE
R9	TRUE	TRUE	TRUE	TRUE
R10	TRUE	TRUE	TRUE	TRUE
R11	FALSE	FALSE	TRUE	TRUE
R12	FALSE	FALSE	FALSE	FALSE
R13	FALSE	TRUE	TRUE	FALSE
R14	TRUE	FALSE	TRUE	FALSE
R15	TRUE	TRUE	TRUE	TRUE
R16	FALSE	FALSE	TRUE	TRUE
R17	FALSE	FALSE	FALSE	TRUE
R18	FALSE	FALSE	FALSE	TRUE
R19	FALSE	FALSE	TRUE	TRUE
R20	TRUE	TRUE	TRUE	TRUE
R21	TRUE	TRUE	TRUE	TRUE

Table 9 represents statistics whether average returns for different rank numbers in different holding periods are higher than the average return of SPY. “TRUE” indicates that returns are above average and “FALSE” that they are below average. Table 8 and table 9 combined are more informative than either of them individually.

As it can be seen, table 9 shows the same pattern as illustrated in table 8. Rank numbers 0 and 1 return less than average in every holding period and rank numbers 20 and 21 return more than average in every holding period. Actually, ranks from 0 to 5 have below average returns in all but one holding period (1-day return for rank 2). Interesting is that middle ranks from 7 to 10 beat the average in every holding period. However, as stated before, these results are at least partially explained by the fact that no observations were made for lower ranks from 0 to 10 during the financial crisis from the end of 2007 until the beginning of 2009. Ranks 15 to 19 are inconsistent on shorter holding periods, but all of them beat the average on a 60-day holding period.

7.1. Fama-French 5 factor results

After the results of SPY on different ranks, the same methodology is used for Fama-French 5 factors and 10 stock indices. It is interesting to see whether the results differ from the results of SPY. This chapter focuses on Fama-French factors. Table 10 shows the summary statistics for factors and VIX.

Table 10. Summary statistics.

	Mkt-RF	SMB	HML	RMW	CMA	ΔVIX
Mean	0.025	0.004	0.010	0.015	0.012	0.007
Median	0.070	0.020	0.000	0.010	0.000	-0.314
Maximum	10.751	4.430	4.688	4.421	2.499	49.601
Minimum	-9.376	-4.374	-4.312	-3.108	-6.102	-35.059
Std. Dev.	1.168	0.588	0.624	0.491	0.431	6.302

The data in table above is calculated using logarithmic daily returns between 29th January 1993 and 31st December 2015. Portfolios are constructed as presented in chapter 5. Between the five factors, not surprisingly, Mkt-RF exhibits highest mean return, median return, maximum return, minimum return and also the highest standard deviation. The average SMB risk premium is 0.004% on daily basis. For HML the premium is 0.010%, for RMW 0.015% and for CMA 0.012%. Standard deviation for HML is closest to Mkt-RF. Standard deviation for VIX is more than 5 times the standard deviation of Mkt-RF which reflects the nature of daily changes in VIX. Standard deviation of VIX is also more than 10 times more than the standard deviations of SMB, HML, RMW and CMA. These calculations are quite well in line with Durand et al. (2011). Main differences come from the return calculation method. Durand et al. use simple returns while in this paper is used logarithmic returns.

Table 11 represents the first factor, Mkt-Rf. Results from Mkt-Rf factor are supposed to be quite similar to the SPY results. Results in table 11 are quite steadily in line with the results of SPY. Rank number 21 is significant at 5% level in every holding period except for 20-day holding period. Rank numbers 7 and 10 are significant at all holding periods. None of the returns are significantly negative. Lower ranks tend to result in slightly negative return on shorter holding periods, but these results are not significantly different from zero. On a 60-day holding period all but two ranks ranks lead into positive return. Rank numbers 5, 6, 7, 8, 9, 10, 16, 20 and 21 are statistically significantly different from zero at least at 5% significance level.

Table 11. Mkt-Rf returns between different 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
R0	70	-0.071	0.063	-1.127	0.081	0.172	0.472	-0.081	0.418	-0.193	0.291	1.059	0.275
R1	627	-0.022	0.027	-0.795	-0.148	0.100	-1.478	-0.140	0.276	-0.508	0.113	0.559	0.203
R2	404	0.037	0.033	1.133	-0.001	0.118	-0.006	0.304	0.250	1.217	0.934	0.484	1.932 *
R3	317	-0.018	0.036	-0.509	-0.087	0.114	-0.765	0.038	0.283	0.134	0.633	0.580	1.092
R4	314	0.002	0.045	0.049	0.122	0.135	0.904	0.287	0.353	0.813	1.098	0.738	1.487
R5	257	-0.013	0.054	-0.237	-0.002	0.151	-0.015	-0.041	0.344	-0.118	1.487	0.581	2.561 **
R6	230	0.043	0.056	0.767	0.277	0.151	1.830 *	0.890	0.324	2.745 ***	1.305	0.592	2.203 **
R7	213	0.133	0.058	2.311 **	0.435	0.148	2.930 ***	0.823	0.391	2.105 **	2.001	0.540	3.708 ***
R8	206	0.048	0.068	0.704	0.418	0.167	2.504 **	0.548	0.427	1.283	2.186	0.635	3.443 ***
R9	195	0.048	0.064	0.748	0.248	0.167	1.482	1.181	0.372	3.178 ***	2.281	0.660	3.457 ***
R10	205	0.194	0.071	2.746 ***	0.601	0.195	3.080 ***	1.201	0.426	2.820 ***	2.737	0.669	4.090 ***
R11	185	-0.053	0.072	-0.737	0.030	0.245	0.123	0.955	0.493	1.938 *	1.918	1.042	1.841 *
R12	189	-0.009	0.076	-0.121	-0.224	0.198	-1.130	0.216	0.493	0.439	-0.285	1.308	-0.218
R13	217	-0.041	0.068	-0.611	0.242	0.190	1.271	0.694	0.442	1.570	1.138	1.151	0.989
R14	228	0.045	0.083	0.536	-0.022	0.205	-0.109	0.485	0.418	1.160	-0.264	1.158	-0.228
R15	226	0.105	0.080	1.311	0.093	0.244	0.382	0.989	0.477	2.074 **	1.415	0.867	1.633
R16	235	-0.032	0.069	-0.462	0.036	0.224	0.160	1.109	0.533	2.081 **	2.277	0.898	2.535 **
R17	254	-0.020	0.088	-0.226	0.030	0.269	0.111	-0.240	0.660	-0.363	1.499	1.076	1.393
R18	294	-0.064	0.090	-0.719	-0.085	0.273	-0.312	-0.472	0.695	-0.679	1.579	1.039	1.520
R19	333	-0.029	0.082	-0.354	-0.006	0.214	-0.027	0.255	0.466	0.546	1.471	0.882	1.667 *
R20	521	0.066	0.083	0.798	0.389	0.309	1.259	1.210	0.672	1.801 *	3.153	0.932	3.383 ***
R21	54	0.885	0.376	2.353 **	2.268	0.744	3.050 ***	2.143	1.253	1.710 *	3.850	1.672	2.303 **

Table 12 is more interesting, because it covers the data from SMB factor. Table 12 gives an idea of whether to allocate to small cap stocks or large cap stocks on different VIX levels. Flight-to-quality (Abel 1988) could support the idea that large stocks perform better, when the risk is higher, so SMB should exhibit negative return on higher ranks.

Table 12. SMB factor returns between different 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
R0	70	-0.027	0.046	-0.577	0.248	0.136	1.822 *	-0.213	0.348	-0.614	0.081	0.398	0.205
R1	627	0.040	0.019	2.157 **	0.075	0.069	1.091	0.324	0.189	1.712 *	0.467	0.286	1.633
R2	404	0.004	0.025	0.175	0.199	0.077	2.593 ***	0.634	0.191	3.321 ***	1.347	0.335	4.025 ***
R3	317	0.064	0.027	2.355 **	0.065	0.084	0.772	0.303	0.195	1.551	1.029	0.325	3.172 ***
R4	314	0.072	0.027	2.643 ***	0.182	0.100	1.826 *	0.417	0.265	1.572	1.138	0.593	1.920 *
R5	257	0.026	0.034	0.768	0.101	0.095	1.062	0.538	0.295	1.822 *	1.335	0.606	2.204 **
R6	230	0.068	0.043	1.570	0.085	0.130	0.655	0.714	0.358	1.994 **	1.225	0.538	2.277 **
R7	213	-0.009	0.034	-0.252	0.170	0.091	1.866 *	0.458	0.201	2.283 **	0.763	0.462	1.652 *
R8	206	-0.024	0.040	-0.605	0.195	0.118	1.652 *	0.293	0.301	0.974	0.377	0.503	0.750
R9	195	0.056	0.041	1.359	0.224	0.134	1.677 *	0.886	0.347	2.556 **	0.309	0.573	0.538
R10	205	0.060	0.040	1.508	0.183	0.103	1.773 *	0.361	0.303	1.191	0.146	0.539	0.271
R11	185	-0.014	0.059	-0.243	0.010	0.154	0.064	0.249	0.385	0.647	0.160	0.606	0.263
R12	189	0.024	0.044	0.554	0.079	0.137	0.576	0.208	0.307	0.677	-0.301	0.650	-0.464
R13	217	0.099	0.038	2.573 **	0.181	0.110	1.635	0.476	0.253	1.884 *	0.804	0.551	1.459
R14	228	-0.035	0.037	-0.927	0.026	0.111	0.231	0.079	0.244	0.324	0.083	0.585	0.141
R15	226	0.000	0.039	0.008	0.036	0.117	0.305	-0.197	0.209	-0.942	-0.092	0.533	-0.172
R16	235	-0.072	0.038	-1.875 *	-0.113	0.114	-0.994	-0.187	0.312	-0.599	-0.153	0.544	-0.281
R17	254	0.003	0.040	0.086	-0.123	0.131	-0.938	-0.655	0.320	-2.048 **	-0.778	0.594	-1.310
R18	294	-0.035	0.038	-0.922	-0.122	0.103	-1.189	-0.569	0.247	-2.301 **	-0.273	0.489	-0.557
R19	333	-0.023	0.037	-0.612	-0.060	0.125	-0.484	-0.453	0.250	-1.816 *	-0.960	0.457	-2.099 **
R20	521	-0.090	0.033	-2.685 ***	-0.451	0.124	-3.638 ***	-0.861	0.337	-2.557 **	-0.679	0.520	-1.307
R21	54	-0.309	0.134	-2.314 **	-0.434	0.285	-1.522	-1.364	0.687	-1.984 **	-2.023	0.885	-2.287 **

Table 12 shows that flight-to-quality effect indeed can be seen. Higher ranks tend to lead into negative returns, meaning that large cap stocks tend to perform better on higher levels of VIX. Thus, investors are leaning towards larger stocks when the risk gets higher. Rank number 21 is negatively significant at a 5% level on 1-day, 20-day and 60-day holding periods. Rank number 20 is negatively significant at a 5% level on 1-, 5- and 20-day holding periods. On 20-day holding period all ranks from 17 to 21 are negatively significant at least at a 10% significance level. For the lowest ranks 0 and 1 there is no clear pattern, but rank numbers 2 to 5 show significant positive returns quite consistently. It seems that for the longest holding period 4 out of 7 of the lowest ranks show significant positive return at a 5% significance level. These results support the idea, that on higher relative levels of VIX it might be reasonable to lean towards large cap stocks, while on lower levels small cap stocks seem to be more attractive. These results help to construct a long-short portfolio using different ranks as a signal for long or short positions. The results of this portfolio will be presented later in this paper.

The next table shows the same statistics for the third Fama-French factor, HML. According to flight-to-quality thinking, it might be reasonable to suggest that value stocks are more attractive in higher ranks. Thus it is reasonable to hypothesize that high book-to-market stocks, in other words value stocks, tend to perform better on higher levels of VIX, while low book-to-market stocks, so called growth stocks, perform better on lower levels of VIX. Copeland and Copeland (1999) find that value stocks outperform growth stocks, when VIX rises. Table 13 reveals that at least on longer holding periods the idea is not supported and is quite the opposite. Rank numbers 0, 1, 2 and 3 all show significant positive return at least at a 5% significance level on 20-day and 60-day holding periods, while rank number 20 and 21 are significantly negative at least at a 10% significance level on the same holding period. On shorter periods the results are co-directional, but not as strong as on longer holding periods. These findings are similar to Peltomäki and Äijö (2015), who find that the value premium is negatively associated with the increases in market volatility. One explanation for this kind of return behavior could be that when VIX is increasing investors are leaning towards value stocks. When VIX hits the highest ranks, value stocks could already be overpriced while growth stocks could be oversold. This leads into growth stocks to outperform value stocks on higher ranks and vice versa. The other explanation might be the beta of the portfolio.

Table 14 is the fourth factor, RMW. Results suggest that firms with higher operating profitability tend to perform better on higher levels of VIX. However, interesting point is that rank number 21 results in significant positive return at a 5% level only on a 60-day holding period, while rank numbers 19 and 20 are significantly positive at a 5% level on a 5-, 20- and 60-day holding periods. Rank number 1 is also significantly positive on a 60-day holding period. Thus these results are not so straightforward. However, there is a quite clear pattern for higher rank numbers being better at signaling positive returns for the RMW factor. On a 60-day holding period rank numbers 1, 8, 9, 10, 11, 12, 14, 18, 19, 20 and 21 are significant at least at a 5% significance level. This suggests that on lower VIX levels the difference of investing in high operating profitability firms or low operating profitability firms is not that big and significant. However, RMW factor is positive between all ranks on a 60-day holding period.

Table 13. HML factor returns between different 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
R0	70	0.028	0.038	0.727	0.037	0.124	0.302	0.851	0.274	3.105 ***	2.132	0.852	2.503 **
R1	627	0.055	0.018	3.133 ***	0.244	0.079	3.092 ***	0.941	0.218	4.316 ***	1.904	0.450	4.228 ***
R2	404	0.042	0.021	1.988 **	0.256	0.074	3.460 ***	0.625	0.174	3.591 ***	1.586	0.353	4.498 ***
R3	317	-0.029	0.024	-1.199	0.125	0.076	1.635	0.632	0.177	3.575 ***	1.357	0.359	3.784 ***
R4	314	0.030	0.027	1.096	0.094	0.094	1.008	0.331	0.186	1.780 *	0.887	0.413	2.151 **
R5	257	-0.034	0.028	-1.224	-0.069	0.087	-0.794	0.172	0.249	0.690	0.495	0.576	0.859
R6	230	0.004	0.031	0.117	0.006	0.092	0.068	-0.050	0.315	-0.160	0.130	0.550	0.237
R7	213	0.036	0.038	0.946	0.043	0.118	0.364	0.366	0.368	0.993	0.095	0.568	0.167
R8	206	0.003	0.039	0.071	0.169	0.124	1.363	0.638	0.356	1.790 *	0.819	0.611	1.341
R9	195	0.034	0.038	0.896	0.124	0.121	1.022	0.511	0.313	1.632	0.632	0.547	1.156
R10	205	0.037	0.036	1.037	0.115	0.118	0.979	0.085	0.271	0.312	0.038	0.525	0.072
R11	185	0.122	0.049	2.491 **	0.319	0.151	2.117 **	0.657	0.361	1.818 *	0.650	0.673	0.966
R12	189	-0.011	0.045	-0.233	0.105	0.154	0.682	0.355	0.385	0.920	0.452	0.597	0.758
R13	217	-0.006	0.038	-0.167	0.088	0.112	0.785	0.264	0.341	0.774	1.223	0.626	1.952 *
R14	228	0.012	0.042	0.286	-0.011	0.129	-0.087	-0.131	0.307	-0.427	0.265	0.588	0.450
R15	226	-0.012	0.047	-0.264	-0.022	0.129	-0.168	-0.097	0.242	-0.400	-0.202	0.547	-0.369
R16	235	0.038	0.040	0.964	0.087	0.139	0.629	0.167	0.334	0.501	0.431	0.479	0.900
R17	254	0.077	0.056	1.379	-0.030	0.178	-0.166	-0.057	0.338	-0.169	0.950	0.617	1.540
R18	294	-0.107	0.050	-2.165 **	-0.239	0.188	-1.274	-0.925	0.654	-1.415	0.641	0.859	0.746
R19	333	0.008	0.035	0.222	-0.035	0.104	-0.340	-0.068	0.251	-0.270	-0.058	0.723	-0.080
R20	521	-0.051	0.037	-1.396	-0.287	0.131	-2.189 **	-0.759	0.311	-2.440 **	-1.831	0.614	-2.984 ***
R21	54	-0.089	0.185	-0.479	0.029	0.262	0.110	-1.023	0.606	-1.689 *	-3.270	1.096	-2.983 ***

Table 14. RMW factor returns between different 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
R0	70	-0.045	0.035	-1.302	-0.069	0.148	-0.465	0.323	0.379	0.852	1.010	0.895	1.128
R1	627	0.005	0.019	0.242	0.068	0.082	0.832	0.228	0.216	1.053	1.177	0.451	2.608 ***
R2	404	0.022	0.021	1.030	0.019	0.074	0.261	0.185	0.185	0.997	0.578	0.414	1.395
R3	317	-0.009	0.024	-0.388	0.052	0.070	0.739	0.514	0.185	2.787 ***	0.739	0.428	1.727 *
R4	314	0.020	0.023	0.856	0.106	0.083	1.271	0.259	0.237	1.092	0.277	0.516	0.537
R5	257	0.002	0.031	0.059	0.114	0.097	1.181	0.358	0.298	1.199	0.576	0.722	0.798
R6	230	-0.021	0.033	-0.621	0.049	0.110	0.444	0.042	0.344	0.122	0.650	0.598	1.088
R7	213	0.045	0.031	1.443	0.030	0.103	0.292	0.357	0.275	1.300	0.627	0.562	1.115
R8	206	-0.037	0.038	-0.970	0.007	0.129	0.052	0.575	0.333	1.726 *	1.389	0.544	2.553 **
R9	195	-0.023	0.041	-0.576	-0.029	0.133	-0.216	-0.237	0.361	-0.657	1.175	0.565	2.078 **
R10	205	-0.041	0.033	-1.238	-0.041	0.111	-0.366	0.196	0.300	0.655	1.230	0.523	2.353 **
R11	185	0.066	0.056	1.169	0.027	0.149	0.184	0.471	0.355	1.326	1.402	0.608	2.304 **
R12	189	-0.001	0.038	-0.024	0.192	0.133	1.440	0.395	0.324	1.219	1.413	0.578	2.446 **
R13	217	0.052	0.036	1.418	0.032	0.113	0.287	0.125	0.282	0.442	0.886	0.532	1.666 *
R14	228	0.026	0.036	0.727	0.114	0.110	1.032	0.379	0.202	1.883 *	1.336	0.501	2.667 ***
R15	226	-0.025	0.033	-0.735	0.061	0.096	0.639	0.001	0.208	0.005	0.323	0.456	0.708
R16	235	0.117	0.036	3.238 ***	0.178	0.105	1.695 *	0.190	0.267	0.711	0.407	0.443	0.919
R17	254	0.022	0.040	0.559	0.048	0.100	0.480	0.318	0.200	1.587	0.599	0.506	1.185
R18	294	-0.001	0.028	-0.047	-0.014	0.098	-0.142	0.155	0.220	0.703	0.775	0.391	1.982 **
R19	333	0.007	0.025	0.284	0.154	0.073	2.118 **	0.473	0.205	2.312 **	1.419	0.352	4.032 ***
R20	521	0.043	0.026	1.685 *	0.224	0.102	2.209 **	0.602	0.247	2.442 **	1.228	0.400	3.074 ***
R21	54	0.121	0.093	1.298	-0.251	0.151	-1.666 *	0.577	0.574	1.006	1.799	0.853	2.108 **

Table 15 shows the statistic for the last Fama-French factor, CMA. The results suggest that conservative stocks perform better on lower levels of VIX. Rank numbers 1 and 4 are significantly positive at 5% level on every holding period. Rank numbers 2 and 3 are significantly positive at 5% level in all holding periods except at a 1-day holding period. Highest rank numbers result in negative returns, meaning that aggressive stocks perform better on higher levels of VIX, but only 5-day and 20-day holding periods for rank number 21 and 60-day holding period for rank number 20 are significantly negative at a 5% significance level. Better returns for aggressive stocks on higher levels can be explained by their higher betas. According to Banerjee, Doran & Peterson (2007) the mean reversion of VIX is around 44 trading days. Thus, when VIX is at its higher levels there is a tendency that VIX will fall in the near future closer to its mean values. Combined to its negative correlation with equities, this means that equity returns are positive. Aggressive stocks with higher beta tend to rise faster than conservative small beta stocks.

Overall the results from the Fama-French 5 factor statistics gives an idea for style rotation in investment strategies. An aggressive large cap growth stock with high operating profitability would be an ideal stock for higher VIX levels, while conservative small cap value stock with high operating profitability would suit better in low volatility environment. Of course this conclusion is very straightforward, but guides investors to choose best stocks in each situation.

Table 15. CMA factor returns between different 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
R0	70	0.058	0.032	1.820 *	-0.003	0.113	-0.026	0.268	0.300	0.894	1.020	0.775	1.317
R1	627	0.027	0.013	2.002 **	0.118	0.057	2.088 **	0.534	0.168	3.171 ***	1.423	0.411	3.460 ***
R2	404	0.012	0.016	0.753	0.161	0.059	2.710 ***	0.331	0.148	2.231 **	1.252	0.306	4.097 ***
R3	317	0.011	0.020	0.541	0.187	0.059	3.169 ***	0.595	0.165	3.613 ***	1.310	0.327	4.010 ***
R4	314	0.054	0.019	2.898 ***	0.185	0.066	2.810 ***	0.608	0.144	4.213 ***	1.535	0.337	4.548 ***
R5	257	0.008	0.024	0.326	0.064	0.074	0.868	0.520	0.176	2.954 ***	1.238	0.365	3.390 ***
R6	230	0.010	0.025	0.414	0.048	0.071	0.680	0.365	0.170	2.153 **	0.866	0.321	2.700 ***
R7	213	0.022	0.028	0.787	0.082	0.092	0.888	0.532	0.262	2.033 **	0.537	0.322	1.670 *
R8	206	0.028	0.030	0.942	0.175	0.084	2.097 **	0.719	0.222	3.235 ***	1.160	0.361	3.217 ***
R9	195	0.026	0.026	1.011	0.149	0.070	2.137 **	0.559	0.193	2.903 ***	1.066	0.315	3.387 ***
R10	205	0.009	0.025	0.335	0.067	0.078	0.858	0.201	0.164	1.229	0.802	0.315	2.542 **
R11	185	0.091	0.036	2.514 **	0.256	0.105	2.438 **	0.468	0.213	2.199 **	1.076	0.376	2.864 ***
R12	189	0.027	0.034	0.799	0.218	0.090	2.428 **	0.523	0.227	2.300 **	1.133	0.342	3.317 ***
R13	217	0.005	0.028	0.160	0.066	0.081	0.812	0.319	0.184	1.734 *	1.301	0.341	3.816 ***
R14	228	0.014	0.035	0.393	0.074	0.096	0.776	-0.024	0.175	-0.139	0.955	0.334	2.857 ***
R15	226	-0.040	0.032	-1.248	-0.001	0.082	-0.009	-0.005	0.177	-0.029	0.606	0.349	1.735 *
R16	235	0.046	0.030	1.540	0.049	0.097	0.506	-0.019	0.227	-0.081	0.320	0.336	0.950
R17	254	0.031	0.031	0.984	-0.042	0.075	-0.562	-0.037	0.183	-0.201	0.182	0.442	0.412
R18	294	-0.026	0.026	-1.015	-0.087	0.090	-0.960	-0.225	0.211	-1.067	-0.244	0.424	-0.575
R19	333	0.006	0.027	0.211	-0.035	0.087	-0.403	-0.032	0.193	-0.165	-0.043	0.372	-0.117
R20	521	-0.046	0.029	-1.577	-0.152	0.097	-1.568	-0.431	0.241	-1.791 *	-0.846	0.348	-2.430 **
R21	54	-0.062	0.093	-0.671	-0.578	0.178	-3.246 ***	-0.817	0.400	-2.042 **	-1.210	0.660	-1.833 *

Next empirical analysis shows how Fama-French 4 factor portfolios, constructed by using lowest and highest ranks, perform. Long-short portfolios are constructed for SMB, HML, RMW and CMA. In order to prevent overlapping holding periods, only 1-day returns are under examination. Since each day get only one rank number, this strategy shows no overlapping returns. For longer periods there might be for example five consecutive days of rank 21 and using longer holding periods the exposure would be more than 100%, if buying a position every time, the rank is 21.

For SMB, ranks 0 to 5 signal taking a long position in SMB portfolio. Ranks 16 to 21 signal taking a short position in SMB portfolio. For HML the same style is used. RMW portfolio is constructed using ranks 11 to 21 as signal for long position and ranks 0 to 10 as a signal for short position. CMA portfolio is long with ranks 0 to 10 and short with rank 11 to 21. “L” indicates long and “s” indicates short position. Portfolios are as follows:

$$SMB_{RANK} = lSMB_{LOW} + sSMB_{HIGH} \tag{11}$$

$$HML_{RANK} = lHML_{LOW} + sHML_{HIGH} \tag{12}$$

$$RMW_{RANK} = lRMW_{HIGH} + sRMW_{LOW} \tag{13}$$

$$CMA_{RANK} = lCMA_{LOW} + sCMA_{HIGH} \tag{14}$$

Table 16 shows the statistics for different portfolios. First column shows different portfolios. Bolded portfolios are the results from the long-short trading strategy. Second column shows average daily returns for each of these portfolios. For example, the average return for SMB_{HIGH} is -0.057, but in long-short portfolio SMB_{HIGH} is sold short, hence the return is positive. Third column shows number of observations. For SMB and HML the trading strategy covers 3680 days of 5774, which is approximately 64% of the days. Meaning that in 36% of the days there is no long or short position in SMB or HML. Fourth column shows sum of returns for sub-portfolios and also for the long-short portfolios (bolded). Fifth column shows returns for each of the factors during the whole sample. Last column tells whether the long-short strategy has outperformed or underperformed the conventional returns of Fama-French factors.

Table 16. Results from trading strategy between factor portfolios.

	Avg. Daily return	#	Sum, portfolios (%)	Sum, whole sample (%)	Excess return
SMB_{LOW}	0.037	1989	74.53		
SMB_{HIGH}	-0.057	1691	97.19		
SMB_{RANK}	**0.047**	**3680**	**171.72**	24.84	146.88
HML_{LOW}	0.023	1989	45.10		
HML_{HIGH}	-0.019	1691	31.59		
HML_{RANK}	**0.021**	**3680**	**76.69**	55.88	20.81
RMW_{HIGH}	0.032	2736	87.56		
RMW_{LOW}	-0.001	3038	3.42		
RMW_{RANK}	**0.016**	**5774**	**90.97**	84.14	6.84
CMA_{LOW}	0.022	3038	68.03		
CMA_{HIGH}	0.001	2736	-2.62		
CMA_{RANK}	**0.011**	**5774**	**65.41**	70.64	-5.23

Table 16 shows the outcome of the trading strategy. Three out of four strategies generate higher returns than the corresponding Fama-French portfolio. Extremely interesting are the results from the SMB_{RANK} portfolio. This strategy generates profit of 171.72% while conventional SMB portfolio has a return of 24.84%. The difference between these portfolios is remarkable 146.88 percentage points. This kind of result strongly suggests investing in large cap stocks in higher ranks of VIX since they clearly outperform small cap stocks. When VIX hits lowest ranks, it is time to switch investing in small cap stocks instead of large cap stocks. This kind of strategy does not necessarily generate high trading costs, since the rule for long position is that the rank must be from 0 to 5 and for short position from 16 to 21. The rank can be several consecutive days between those rank numbers and thus there is no need to sell or buy the position every day. The second long-short portfolio which outperform its peer is HML_{RANK}. This trading strategy generates 76.69% profit while conventional HML portfolio generates a return of 55.88%. The difference is 20.81 percentage points. This also suggests that it is reasonable to switch between value and growth stocks in different levels of VIX. The third outperforming portfolio is RMW_{RANK}. The difference between conventional RMW portfolio and RMW_{RANK} long-short portfolio is not that immense, but quite clear anyway. Conventional RMW portfolio has returned 84.14% from 1993 to 2015 while RMW_{RANK} returns 90.97%. Thus the difference is only 6.84 percentage points. The long-short strategy of the fourth factor, CMA, underperforms against the conventional CMA portfolio, but the underperformance is only 5.23 percentage points. CMA portfolio returns 70.64% while CMA_{RANK} generates 65.41%.

Overall, the results from SMB_{RANK} portfolio are quite groundbreaking. The trading strategy shows clearly when to invest in smaller stocks and when to larger stocks. These provided results suggest that VIX levels can indeed be used for style rotation at least between small and large stocks. Also HML_{RANK} shows promising results when to rotate between value and growth stocks. However, these results were not as clear as for SMB_{RANK}. Statistics from tables 12 and 13 for longer holding periods also support the idea of rotating between large and small cap stocks on different VIX levels. Also rotating between high book-to-market companies and low book-to-market companies for longer holding periods is supported. Results in table 15 for CMA factor show that rotating between aggressive and conservative stocks is also profitable.

7.2. Industry results

After having the results from SPY and Fama-French factors it is interesting to see how different industries perform on different levels of VIX. The hypothesis is that some industries provide high profits on the lowest levels of VIX. This means there are possibilities for successful sector rotation using different levels of VIX as an indicator.

Table 17 shows the data for the average 1-, 5-, 20- and 60-day returns for each industry. The data is shown in percentages. As we can see from the table, returns have been quite steady between different indices. The highest 60-day return is 2.62% for healthcare industry and the lowest 60-day return is 1.367% for durables industry. Next it is examined for each industry how these returns are distributed between different rank numbers.

Table 17. Average returns for different industries from 1993 to 2015.

Industry	1d	5d	20d	60d
Non-Durables	0.040	0.200	0.803	2.465
Durables	0.025	0.119	0.455	1.367
Manufacturing	0.041	0.203	0.797	2.419
Energy	0.037	0.180	0.695	2.082
Hi-Tech	0.040	0.195	0.778	2.332
Telecom	0.027	0.132	0.520	1.560
Shops	0.037	0.183	0.731	2.210
Healthcare	0.043	0.216	0.867	2.620
Utilities	0.032	0.158	0.627	1.908
Other	0.031	0.149	0.585	1.746

In order to avoid too much repetition, tables based on the ranking method for industries are represented in the appendix. For non-durables industry 60-day returns are significantly positive in all but two ranks. Rank numbers 20 and 21 generate the highest returns on a 60-day holding period, 3.707% and 4.42%. However, interesting is that rank 21 leads into significant returns at a 5% significance level only on 1-day and 60-day holding periods. Rank number 7 leads into significant positive returns in every holding period. 20-day and 60-day holding periods lead always into positive returns no matter what rank it is. On shorter holding periods different ranks lead into non-significant negative returns with no clear pattern. These results do not provide much help for sector rotation strategies.

Durables industry shows quite different statistics for highest ranks compared to previous results. Only a 1-day holding period for rank number 21 shows significant positive return at a 5% significance level. Interesting is that a 20-day return for rank number 21 is even negative, even though not significantly. A 60-day return is only 0.394%, which is the lowest return across industries for rank 21. On the other hand, also lowest rank numbers show negative returns across holding periods. However, these returns are significant at a 10% significance level at best. Middle ranks from 7 to 10 are strong and generate significant positive returns that are above the average. Rank number 0 leads into negative returns in all holding periods, yet none of those are significant at 5% significance level.

Next industry under examination is manufacturing. Again, rank number 21 does not show significant positive returns except for on a 1-day holding period. However, in every holding period the return is higher than the average return shown in table 15. Middle ranks from 7 to 10 continue their relatively steady performance. Those are significantly positive at a 5% significance level in all except on a 1-day holding period, where only rank numbers 7 and 10 are significant and 5-day holding period, where rank number 9 is only significant at a 10% level.

The results for energy industry are more in line with the results of SPY, when comparing the highest ranks. Rank number 21 shows significant positive returns in every holding period. Rank number 20 shows significant positive returns at least at a 5% significance level in 20-day and 60-day holding periods. Interesting is that on a 60-day holding period, also ranks from 0 to 2 are positively significant and above the average return shown in table 15. Rank number 0 generates 4.871% return compared to the average return 2.082%. Rank number 1 generates 2.615% returns and rank number 2 2.717% return. Energy industry is the first industry that shows signs of possible sector rotation strategy. However, the returns for lower ranks in shorter holding periods are inconsistent.

Next industry under research is hi-tech. Rank number 21 is significant at least at a 5% significance level in all but one holding period. On a 20-day holding period the results for rank number 21 are insignificant. Rank number 20 is also highly significant on longer holding periods. Actually, rank number 20 generates higher return on 60-day holding period than rank number 21. Lowest ranks experience quite steadily negative returns, but are significant only in one occasion. Another observation for hi-tech industry is that all ranks from 15 to 21 beat the average return in 20-day and 60-day holding periods. However, in only a 60-day holding period the results are significantly different from zero for all ranks from 15 to 21.

Next industry is telecom. Telecom industry has experienced the second lowest return among all ten industries from 1993 to 2015. Results for telecoms are quite interesting. Middle ranks from 7 to 10 show positive significant returns at a 5% significance level quite widely. The returns for rank number 1, 2 and 3 are narrowly above zero on a 60-day holding period, being 0.123%, 0.259% and 0.041%. Ranks from 15 to 21 all beat the average return on a 60-day holding period and all of the returns are significantly different from zero at least at a 10% significance level. Interesting is that rank number 21 generates rather high returns. On a 60-day holding period the return is 8.237%, on a 20-day holding period 3.621%, on a 5-day holding period 2.157% and on a 1-day holding period 0.902%. All of these returns are significant at a 1% significance level except for 1-day return, which is significant at a 5% level. These strong returns from highest ranks suggest that telecom industry should be included when forming a portfolio for high levels of VIX.

For shops industry rank number 21 shows significantly positive returns in all except for a 20-day holding period. For rank number 20 the returns are significant only on a 60-day holding period at a 5% significance level. Overall, ranks from 15 to 21 have quite good positive return on a 60-day holding period and returns are also significant at a 1% level except for rank number 15, which is significant at a 5% significance level. Middle ranks from 7 to 10 show positive and also significant returns quite steadily across holding periods. On a 60-day holding period all ranks from 5 to 11 are significant at a 1% significance level. Lowest ranks show negative insignificant returns on shorter holding periods. Only on a 1-day holding period rank number 0 show significant negative return at a 5% significance level.

Next industry under examination is healthcare industry. Healthcare industry is the best performer from 1993 to 2015 when looking at the returns in table 15. Both rank numbers, 20 and 21, have significant returns in all holding periods at least at a 5% level except for a 1-day holding period, where the returns are significant only at a 10% significance level. Also, rank number 7 is significant in all holding periods at a 1% significance level. However, rank 7 returns only slightly more than the average on a 20-day holding period and a little less on a 60-day holding period. Lowest ranks fail to beat the average return very consistently and some of the returns are negative, yet not significantly.

Last two industries are utilities and others. Rank number 21 is significant at a 1% level in longer holding periods and at a 10% level in shorter holding periods. Rank number 21 beats the average return in every period. But the most interesting part in the utility industry is that the lowest ranks lead into positive returns in longer holding periods. Every rank number from 0 to 10 are significant at least at a 5% level on a 60-day holding period. Rank number 1 and 2 are significant at least at a 10% level in all holding periods. The returns on a 60-day holding period are above average for every rank from 0 to 10 except for rank number 3. Actually, rank numbers 0, 1 and 2 beat the average return presented in table 15 in every holding period. These results suggest that utilities industry seems to be another industry that offers possibilities for sector rotation on different volatility levels.

Last industry is others industry. This industry covers categories which were not included in nine industries already presented. Rank number 21 is significant only in shorter holding periods at least at a 5% level, while rank number 20 shows no significance at a 5% significance level in any holding period. Results suggest that rank number 21 is rather good for shorter holding periods, but in longer periods there are better performing industries. Middle ranks from 7 to 10 show also strong significant and positive returns. Rank numbers 7 and 10 show again the strongest significance across holding periods and the returns are above average.

All in all, the greatest returns on a 60-day holding period for the highest ranks show telecom and healthcare industries. Also hi-tech industry shows high returns on highest volatility levels. On the other hand, there are two industries that show high returns on lowest volatility levels on a 60-day holding period. These two industries are energy and utilities. Also non-durables industry generates reasonable returns on lowest volatility levels.

To empirically demonstrate the previous results, the next step is to form a high volatility level portfolio and a low volatility level portfolio. An investment is made for 60 days to high volatility portfolio, when VIX hits ranks 19, 20 or 21 and to low volatility portfolio, when VIX hits ranks 0, 1 or 2. High volatility portfolio is constructed using telecom, healthcare and hi-tech industries equally weighted. Low volatility portfolio is constructed using energy, utilities and non-durables industries equally weighted as well. Interesting is that the best performers on lowest levels are energy and utilities, which are the two industries that were the least correlating with VIX. Ranks 0, 1, 2, 19, 20 and 21 represent 2009 days in the whole sample. If a 60-day position is taken 2009 times, it means that there is position for 120 540 days, while there are only around 5774 days in whole sample. 120 540 divided by 5774 is 20.88. 100% divided by 20.88 is around 4.8%. Thus, there is only 4.8% stake taken each day, when VIX gets rank 0, 1, 2, 19, 20 or 21. However, there still might be some periods, when the exposure is more than 100%, but taking only 4.8% position tries to prevent that. Nevertheless, if there are 60 consecutive values of 0, 1, 2, 19, 20 and/or 21, the maximum exposure is a little less than 290%. Investable portfolios are presented below. R60d represents the average equally weighted 60-day return between ranks 0, 1 and 2 for low volatility portfolio. For high volatility portfolio r60d represents an average equally weighted 60-day return between ranks 19, 20 and 21.

(15) Low Volatility = 1/3 (r60d Non-durables + r60d Energy + r60d Utilities)

(16) High Volatility = 1/3 (r60d Telecom + r60d Healthcare + r60d Hi-tech)

Table 18 shows the summary statistics for each of the portfolios, then the combined portfolio and also statistics for each component in these portfolios.

Table 18. Summary statistics for volatility based portfolios.

Portfolio	#	Avg. 60d return
High Volatility	908	4.472
Low Volatility	1101	2.630
High+Low	**2009**	**3.463**
Telecom	5774	1.560
Healthcare	5774	2.620
Hi-tech	5774	2.332
Non-durables	5774	2.465
Energy	5774	2.082
Utilities	5774	1.908

Table 18 shows that both high volatility and low volatility portfolios have higher average returns than their components individually. For the combined strategy there are 2009 observations with average 60-day return of 3.463%.

However, table 18 shows only average returns, but everyone is interested how a real and plausible portfolio would succeed. As stated previously, in order to prevent more than 290% exposure to this High + Low –strategy, only 4.8% stake is taken each day, when VIX hits certain ranks. 4.8% stake is taken on a low volatility portfolio (non-durables, energy and utilities combined) when VIX gets rank 0, 1 or 2. Another 4.8% stake is taken on a high volatility portfolio (telecom, healthcare and hi-tech combined), when VIX hits ranks 19, 20 or 21. The outcome of this strategy beats the return of every industry by a decent margin. The best performing industry has been healthcare, generating 250% profit from 1993 to 2015. However, newly presented High + Low –strategy generates 333% at the same time. This suggests that volatility can really be a signal for a sector rotation strategy. However, it is important to emphasize that the portfolio was constructed using historical performance on different VIX levels as guidance. These results do not necessarily mean that same portfolio constructed today with same parameters would be as successful.

All in all, with all these results provided using SPY, Fama-French factors and industry data, it is quite safe to state that the highest rank number, 21, is a considerably good indicator of future returns. On the other hand, the other extremity, rank number 0, does not show consistently significant results. To conclude, VIX seems to be a good signal for future returns.

8. CONCLUSIONS

The historical data show that VIX is becoming even more negatively correlated with equities as the time goes by. The correlation between VIX and S&P 500 has been almost -0.9 in the recent years. High levels of VIX combined to its rapid movements usually mean that VIX is going to come down from its higher levels somewhere in the near future. High negative correlation between VIX and equities indicate that when VIX is coming down, equities are going to the opposite direction. A ranking method for relative VIX levels is used in this paper following Giot's footsteps (2005), with minor adjustments. Results for S&P 500 are not quite the same as Giot finds in his shorter time period. It is true that the very highest levels of VIX do always lead into positive return, no matter the holding period is, but the lowest levels of VIX do not lead into negative returns consistently. Shorter holding periods tend to lead into negative returns, but these returns are not significantly different from zero.

The results show that especially size premium in equities is strongly driven by the levels of VIX. On higher levels of VIX, SMB portfolio generates negative returns. Many of these returns are significantly different from zero at a 5% significance level. On the other hand, on lower levels of VIX, SMB portfolio has positive and also significant returns across different holding periods. After these results, it is easy to argue that volatility and VIX can be indeed used for style rotation strategies. Also HMB factor shows encouraging results. Especially in longer holding periods it seems clear that on high volatility levels it is reasonable to invest in growth stocks while on lower levels the value premium is positive and value stocks are more attractive. These findings are not entirely in line with Copeland and Copeland (1999) who find that value stocks outperform growth stocks, when VIX rises. The results in this thesis are more in line with Peltomäki and Äijö (2015). However, volatility does not seem to be a significant factor driving the returns of RMW portfolio. On higher levels the premium is a bit higher, but these results are not as clear as for SMB and HML portfolios. A CMA portfolio also shows signs of style rotation possibilities. Aggressive stocks tend to perform better on higher VIX levels and conservative stocks outperform aggressive stocks on lower volatility levels. The first hypothesis is clearly proved right.

Sector rotation possibilities are also under consideration in this paper. All industries show high negative correlations with VIX and also these correlations are growing. The second hypothesis was that all industries lead into positive returns in every holding period on the highest VIX levels. This was the case for all except one industry: the returns of durables industry are negative on a 1-day holding period for rank number 20 and on 20-day period for rank number 21. Every other industry in every holding period lead into positive return with rank numbers 20 and 21.

The results also show that there indeed are possibilities for sector rotation when using volatility levels as an indicator. These results contribute to the previous literature. As far as concerned, similar study using levels of volatility signaling industry returns has not been examined. Comparing to VIX, utilities and energy industries are the two least correlating industries. These two industries also show high positive returns on lower levels of VIX in longer holding periods. Many industries do generate positive returns on a 60-day holding period in lower VIX levels, but not many of these returns are above average. Utilities and energy industry returns on a 60-day holding period are in lower levels of VIX above the average return. A simple trading strategy of Low volatility and High volatility portfolios show that sector rotation strategies are possible. The third hypothesis was that industries with lower correlation with VIX tend to perform better on lower volatility levels. This hypothesis is also proved right.

This thesis shows that the highest volatility levels, in other words rank numbers 20 and 21, are great at signaling positive future returns almost for every equity industry and for S&P 500. This fact should be taken into consideration in portfolio management. Especially for a passive investor this kind of information can be very useful. It seems that additional returns to traditional buy-and-hold strategy can be earned by timing the trades with VIX levels. A new contribution to the previous literature is that the returns of Fama-French five factor portfolios are significantly affected by the levels of volatility. The findings especially for HML factor are on the contrary to the previous literature. Copeland and Copeland (1999) find that value stocks outperform growth stocks, when volatility increases. However, their approach is slightly different, so these results are not completely comparable. It can be said that for an active investor VIX levels are useful in order to decide whether to buy value or growth stocks or is it time to buy small cap or large cap stocks. All in all, it can be said that relative VIX levels are a relatively good market timing signals.

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APPENDICES

Appendix 1: Non-durables industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.092	0.053	-1.759 *	-0.087	0.199	-0.435	0.417	0.442	0.943	2.393	0.789	3.035 ***
R1	627	0.011	0.022	0.495	-0.043	0.085	-0.511	0.257	0.236	1.090	2.305	0.461	5.003 ***
R2	404	0.024	0.030	0.790	0.015	0.101	0.146	0.330	0.241	1.369	2.048	0.394	5.192 ***
R3	317	-0.001	0.038	-0.029	0.120	0.110	1.093	0.696	0.255	2.729 ***	1.879	0.469	4.009 ***
R4	314	0.036	0.036	1.022	0.233	0.117	1.993 **	0.867	0.327	2.655 ***	2.133	0.602	3.541 ***
R5	257	0.013	0.045	0.277	0.193	0.120	1.607	0.670	0.317	2.112 **	2.540	0.556	4.572 ***
R6	230	0.028	0.054	0.518	0.300	0.138	2.168 **	0.971	0.299	3.245 ***	2.289	0.580	3.947 ***
R7	213	0.162	0.049	3.330 ***	0.535	0.105	5.112 ***	1.345	0.251	5.353 ***	2.602	0.510	5.097 ***
R8	206	0.024	0.047	0.512	0.509	0.123	4.149 ***	1.318	0.263	5.018 ***	3.374	0.501	6.736 ***
R9	195	0.030	0.060	0.496	0.301	0.159	1.892 *	1.374	0.349	3.942 ***	3.216	0.547	5.877 ***
R10	205	0.126	0.060	2.118 **	0.488	0.134	3.644 ***	1.258	0.313	4.016 ***	3.468	0.594	5.839 ***
R11	185	0.041	0.060	0.680	0.230	0.170	1.353	1.446	0.403	3.586 ***	2.980	0.777	3.834 ***
R12	189	0.013	0.059	0.221	-0.049	0.179	-0.273	0.635	0.339	1.872 *	1.348	0.977	1.380
R13	217	-0.004	0.057	-0.073	0.271	0.158	1.713 *	0.844	0.337	2.501 **	2.047	0.861	2.379 **
R14	228	0.134	0.065	2.063 **	0.213	0.162	1.311	0.980	0.357	2.747 ***	1.299	0.896	1.450
R15	226	0.056	0.062	0.909	0.081	0.185	0.435	1.117	0.373	2.991 ***	2.241	0.763	2.938 ***
R16	235	0.038	0.057	0.668	0.013	0.162	0.083	0.547	0.397	1.378	2.039	0.707	2.883 ***
R17	254	-0.013	0.075	-0.172	0.071	0.213	0.332	0.233	0.544	0.428	1.708	0.718	2.378 **
R18	294	-0.009	0.061	-0.144	0.101	0.184	0.548	0.179	0.520	0.345	2.458	0.723	3.397 ***
R19	333	0.020	0.062	0.323	0.198	0.158	1.256	0.827	0.365	2.269 **	2.709	0.578	4.683 ***
R20	521	0.065	0.063	1.031	0.434	0.229	1.898 *	1.311	0.540	2.427 **	3.707	0.684	5.421 ***
R21	54	0.626	0.314	1.993 **	1.301	0.682	1.908 *	1.806	1.101	1.640	4.420	1.423	3.106 ***

Appendix 2: Durables industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.210	0.108	-1.950 *	-0.179	0.369	-0.484	-1.280	0.691	-1.853 *	-2.128	1.992	-1.068
R1	627	0.031	0.039	0.790	-0.102	0.152	-0.668	0.104	0.451	0.230	-0.041	0.865	-0.047
R2	404	0.030	0.051	0.586	0.177	0.191	0.928	0.867	0.390	2.224 **	1.354	0.864	1.567
R3	317	0.044	0.060	0.721	0.027	0.174	0.155	0.607	0.439	1.382	1.402	0.910	1.540
R4	314	-0.027	0.064	-0.427	0.168	0.204	0.822	0.782	0.551	1.420	2.148	1.232	1.744 *
R5	257	-0.066	0.072	-0.911	-0.057	0.227	-0.248	0.365	0.523	0.698	2.488	0.944	2.637 ***
R6	230	0.122	0.089	1.374	0.411	0.208	1.975 **	1.586	0.510	3.110 ***	1.479	1.025	1.442
R7	213	0.163	0.081	2.023 **	0.510	0.203	2.511 **	1.285	0.484	2.652 ***	2.571	0.993	2.590 ***
R8	206	0.080	0.100	0.795	0.759	0.253	3.005 ***	1.114	0.627	1.778 *	3.316	1.097	3.023 ***
R9	195	0.108	0.087	1.248	0.464	0.272	1.705 *	1.361	0.602	2.261 **	3.144	1.123	2.800 ***
R10	205	0.237	0.092	2.573 **	0.952	0.288	3.305 ***	1.465	0.630	2.326 **	3.405	1.080	3.152 ***
R11	185	0.080	0.104	0.771	0.184	0.326	0.566	1.172	0.718	1.633	1.547	1.692	0.914
R12	189	-0.051	0.102	-0.495	-0.221	0.297	-0.744	0.561	0.787	0.713	-1.602	2.212	-0.724
R13	217	0.053	0.095	0.556	0.271	0.289	0.937	0.671	0.735	0.913	0.549	1.974	0.278
R14	228	-0.118	0.111	-1.059	-0.274	0.328	-0.836	0.402	0.688	0.584	-1.376	2.004	-0.687
R15	226	0.079	0.127	0.623	0.064	0.455	0.140	0.472	0.744	0.634	0.383	1.355	0.282
R16	235	0.018	0.096	0.192	0.192	0.356	0.539	1.523	1.133	1.344	2.751	1.601	1.718 *
R17	254	0.071	0.112	0.635	0.071	0.398	0.177	-0.935	1.038	-0.901	2.246	1.727	1.301
R18	294	-0.123	0.125	-0.983	-0.241	0.400	-0.602	-1.599	1.103	-1.450	2.818	1.920	1.468
R19	333	-0.077	0.096	-0.797	-0.333	0.307	-1.086	-0.377	0.654	-0.577	0.197	1.328	0.149
R20	521	-0.058	0.122	-0.478	0.034	0.454	0.074	0.367	1.109	0.331	1.679	1.429	1.174
R21	54	0.935	0.383	2.441 **	1.772	1.163	1.524	-0.885	2.487	-0.356	0.394	2.938	0.134

Appendix 3: Manufacturing industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.043	0.070	-0.612	0.182	0.204	0.892	0.037	0.509	0.073	1.496	1.067	1.403
R1	627	0.016	0.030	0.522	-0.028	0.113	-0.249	0.393	0.279	1.407	1.597	0.499	3.199 ***
R2	404	0.029	0.036	0.816	0.057	0.119	0.476	0.916	0.258	3.552 ***	2.547	0.489	5.205 ***
R3	317	-0.006	0.041	-0.139	-0.030	0.126	-0.238	0.697	0.280	2.492 **	2.266	0.544	4.164 ***
R4	314	0.046	0.047	0.972	0.295	0.137	2.145 **	0.802	0.395	2.029 **	2.432	0.816	2.982 ***
R5	257	-0.018	0.059	-0.306	0.103	0.161	0.640	0.535	0.371	1.443	2.575	0.649	3.966 ***
R6	230	0.085	0.065	1.312	0.442	0.174	2.546 **	1.477	0.398	3.711 ***	2.626	0.669	3.926 ***
R7	213	0.132	0.061	2.153 **	0.483	0.151	3.191 ***	1.327	0.322	4.118 ***	2.781	0.590	4.712 ***
R8	206	0.076	0.076	1.005	0.709	0.188	3.776 ***	1.164	0.481	2.419 **	3.708	0.752	4.931 ***
R9	195	0.067	0.071	0.946	0.375	0.194	1.934 *	1.363	0.474	2.876 ***	3.312	0.727	4.558 ***
R10	205	0.182	0.073	2.495 **	0.729	0.200	3.646 ***	1.490	0.465	3.201 ***	3.944	0.779	5.065 ***
R11	185	0.044	0.074	0.603	0.201	0.241	0.835	1.467	0.524	2.799 ***	3.042	1.188	2.560 **
R12	189	0.022	0.079	0.275	-0.041	0.231	-0.176	0.379	0.575	0.659	0.011	1.550	0.007
R13	217	0.041	0.068	0.609	0.378	0.200	1.886 *	0.809	0.502	1.611	2.148	1.335	1.610
R14	228	0.045	0.084	0.537	0.018	0.210	0.087	0.706	0.456	1.549	0.549	1.359	0.404
R15	226	0.096	0.089	1.087	0.181	0.290	0.626	1.290	0.555	2.325 **	1.806	0.984	1.835 *
R16	235	0.039	0.069	0.569	0.122	0.226	0.540	1.363	0.629	2.166 **	2.991	1.046	2.858 ***
R17	254	-0.008	0.084	-0.097	0.111	0.275	0.404	-0.274	0.714	-0.385	2.248	1.209	1.859 *
R18	294	-0.040	0.095	-0.417	-0.028	0.297	-0.094	-0.480	0.808	-0.594	2.510	1.256	1.999 **
R19	333	0.014	0.082	0.174	0.041	0.221	0.185	0.695	0.487	1.427	2.390	0.932	2.565 **
R20	521	0.000	0.086	-0.004	0.315	0.323	0.974	1.096	0.777	1.411	3.365	1.048	3.212 ***
R21	54	0.815	0.349	2.337 **	1.609	0.855	1.882 *	1.045	1.491	0.701	2.744	1.942	1.413

Appendix 4: Energy industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.116	0.121	-0.955	0.165	0.244	0.676	0.834	0.694	1.202	4.871	1.868	2.608 ***
R1	627	0.046	0.045	1.016	0.226	0.165	1.370	1.161	0.429	2.705 ***	2.615	0.771	3.394 ***
R2	404	0.110	0.057	1.943 *	0.286	0.162	1.767 *	1.166	0.410	2.844 ***	2.717	0.767	3.543 ***
R3	317	-0.036	0.057	-0.632	-0.028	0.170	-0.165	0.345	0.399	0.864	1.661	0.705	2.354 **
R4	314	0.079	0.065	1.216	0.192	0.183	1.047	0.438	0.507	0.865	1.945	0.747	2.604 ***
R5	257	-0.068	0.086	-0.793	-0.079	0.214	-0.368	-0.128	0.463	-0.276	1.756	0.789	2.225 **
R6	230	-0.010	0.082	-0.124	0.089	0.216	0.413	0.741	0.446	1.660 *	2.075	0.763	2.720 ***
R7	213	0.094	0.082	1.154	0.474	0.217	2.181 **	0.986	0.527	1.871 *	1.851	0.727	2.547 **
R8	206	-0.015	0.097	-0.154	0.599	0.247	2.420 **	0.426	0.577	0.738	3.190	0.793	4.022 ***
R9	195	-0.065	0.087	-0.747	0.196	0.246	0.795	1.272	0.535	2.380 **	3.413	0.760	4.492 ***
R10	205	0.179	0.092	1.944 *	0.381	0.254	1.499	0.950	0.508	1.871 *	3.610	0.864	4.179 ***
R11	185	-0.020	0.099	-0.199	-0.045	0.280	-0.160	0.935	0.484	1.931 *	1.701	1.121	1.517
R12	189	-0.046	0.114	-0.402	-0.129	0.305	-0.421	-0.005	0.654	-0.008	-1.208	1.455	-0.830
R13	217	0.070	0.089	0.783	0.291	0.233	1.248	0.401	0.556	0.721	1.183	1.203	0.984
R14	228	0.104	0.105	0.991	0.096	0.259	0.371	0.613	0.508	1.207	-0.453	1.282	-0.353
R15	226	0.002	0.110	0.021	0.059	0.307	0.191	1.171	0.705	1.660 *	1.134	1.294	0.877
R16	235	0.101	0.085	1.182	0.174	0.268	0.648	0.402	0.559	0.719	2.165	1.097	1.973 **
R17	254	0.054	0.087	0.617	-0.362	0.276	-1.314	-1.068	0.709	-1.507	0.628	1.304	0.482
R18	294	-0.055	0.106	-0.519	-0.196	0.334	-0.588	-0.786	0.729	-1.079	2.008	1.045	1.922 *
R19	333	0.009	0.101	0.094	-0.020	0.278	-0.073	0.525	0.472	1.112	2.155	0.868	2.481 **
R20	521	0.014	0.097	0.146	0.587	0.361	1.629	1.906	0.764	2.493 **	3.286	0.867	3.788 ***
R21	54	0.994	0.494	2.010 **	2.236	1.084	2.063 **	3.861	1.439	2.684 ***	4.372	1.753	2.494 **

Appendix 5: Hi-tech industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.042	0.090	-0.463	0.070	0.301	0.232	-0.861	0.736	-1.170	-1.644	1.726	-0.952
R1	627	-0.064	0.043	-1.480	-0.327	0.166	-1.968 **	-0.557	0.449	-1.241	-1.279	0.940	-1.361
R2	404	0.007	0.055	0.120	-0.111	0.203	-0.545	0.177	0.427	0.415	0.320	0.840	0.381
R3	317	0.042	0.063	0.669	-0.066	0.189	-0.347	-0.186	0.500	-0.372	0.434	0.988	0.439
R4	314	0.001	0.071	0.016	0.149	0.222	0.668	0.399	0.513	0.778	1.592	1.037	1.535
R5	257	0.004	0.082	0.050	0.021	0.240	0.088	-0.336	0.593	-0.566	2.077	1.153	1.802 *
R6	230	0.082	0.092	0.896	0.392	0.253	1.548	1.444	0.604	2.390 **	2.700	1.076	2.510 **
R7	213	0.083	0.094	0.891	0.451	0.288	1.563	0.685	0.817	0.838	3.232	1.047	3.087 ***
R8	206	0.053	0.111	0.478	0.267	0.285	0.936	0.148	0.779	0.190	2.511	1.167	2.152 **
R9	195	0.071	0.101	0.699	0.256	0.266	0.963	1.368	0.597	2.291 **	3.574	1.151	3.105 ***
R10	205	0.244	0.098	2.475 **	0.694	0.296	2.345 **	1.698	0.673	2.522 **	4.101	1.120	3.661 ***
R11	185	-0.133	0.133	-1.001	0.060	0.392	0.152	1.159	0.769	1.507	3.081	1.532	2.012 **
R12	189	0.046	0.127	0.361	-0.277	0.308	-0.901	0.323	0.794	0.407	0.657	1.720	0.382
R13	217	-0.004	0.105	-0.035	0.417	0.310	1.345	1.337	0.686	1.948 *	2.480	1.532	1.619
R14	228	-0.036	0.129	-0.279	0.114	0.328	0.346	1.224	0.697	1.756 *	1.127	1.552	0.727
R15	226	0.246	0.125	1.965 **	0.418	0.326	1.285	1.515	0.650	2.330 **	3.248	1.197	2.714 ***
R16	235	-0.152	0.119	-1.282	0.193	0.362	0.533	2.064	0.822	2.510 **	4.363	1.200	3.635 ***
R17	254	0.036	0.129	0.277	0.431	0.349	1.234	0.819	0.911	0.899	3.288	1.647	1.996 **
R18	294	0.053	0.118	0.452	0.258	0.346	0.746	0.839	0.800	1.048	3.484	1.332	2.616 ***
R19	333	-0.010	0.118	-0.088	0.207	0.315	0.659	0.980	0.760	1.289	3.547	1.331	2.666 ***
R20	521	0.138	0.111	1.240	0.577	0.399	1.445	2.172	0.912	2.382 **	6.011	1.460	4.118 ***
R21	54	1.027	0.401	2.565 **	2.553	0.731	3.494 ***	2.590	1.611	1.607	5.431	2.767	1.963 **

Appendix 6: Telecom industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.017	0.076	-0.224	0.129	0.186	0.695	0.252	0.526	0.480	1.026	1.338	0.767
R1	627	-0.057	0.036	-1.574	-0.267	0.136	-1.973 **	-0.433	0.380	-1.139	0.123	0.741	0.165
R2	404	0.044	0.037	1.208	0.044	0.125	0.355	-0.172	0.329	-0.524	0.259	0.651	0.398
R3	317	0.023	0.041	0.561	-0.010	0.129	-0.078	-0.076	0.340	-0.225	0.041	0.731	0.056
R4	314	0.035	0.054	0.642	0.217	0.163	1.331	0.647	0.346	1.866 *	1.115	0.695	1.605
R5	257	-0.014	0.069	-0.206	0.158	0.174	0.911	0.337	0.391	0.862	0.797	0.752	1.059
R6	230	0.025	0.066	0.378	0.288	0.167	1.726 *	1.057	0.335	3.156 ***	0.796	0.749	1.064
R7	213	0.181	0.062	2.925 ***	0.455	0.178	2.553 **	0.879	0.452	1.947 *	1.945	0.731	2.660 ***
R8	206	0.129	0.078	1.659 *	0.613	0.194	3.163 ***	1.092	0.475	2.298 **	2.304	0.828	2.783 ***
R9	195	-0.054	0.083	-0.644	0.193	0.220	0.875	1.412	0.446	3.164 ***	2.292	0.860	2.665 ***
R10	205	0.227	0.086	2.635 ***	0.521	0.226	2.305 **	1.324	0.521	2.539 **	2.184	0.839	2.602 ***
R11	185	-0.065	0.081	-0.800	-0.045	0.296	-0.152	1.030	0.628	1.641	1.671	1.238	1.350
R12	189	-0.038	0.084	-0.450	-0.252	0.208	-1.207	0.397	0.606	0.656	0.381	1.478	0.258
R13	217	-0.166	0.084	-1.986 **	0.131	0.231	0.568	0.642	0.521	1.232	0.626	1.263	0.495
R14	228	0.078	0.092	0.851	-0.200	0.268	-0.745	0.489	0.552	0.887	-0.586	1.150	-0.510
R15	226	0.084	0.094	0.885	-0.123	0.280	-0.440	0.788	0.539	1.463	1.752	0.933	1.877 *
R16	235	0.007	0.076	0.093	0.042	0.220	0.192	0.962	0.568	1.693 *	2.312	0.895	2.582 ***
R17	254	-0.014	0.105	-0.133	-0.075	0.312	-0.241	-0.645	0.738	-0.874	2.207	1.259	1.752 *
R18	294	-0.065	0.089	-0.738	0.062	0.265	0.234	-0.502	0.748	-0.671	2.267	1.095	2.070 **
R19	333	0.037	0.086	0.426	0.269	0.255	1.057	0.577	0.537	1.074	2.737	1.158	2.363 **
R20	521	0.060	0.091	0.656	0.474	0.344	1.379	1.647	0.699	2.357 **	4.441	1.060	4.189 ***
R21	54	0.902	0.417	2.165 **	2.157	0.797	2.706 ***	3.621	1.268	2.857 ***	8.237	1.884	4.371 ***

Appendix 7: Shops industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	-0.142	0.069	-2.064 **	-0.060	0.204	-0.296	0.596	0.342	1.742 *	0.735	1.016	0.724
R1	627	-0.032	0.030	-1.060	-0.208	0.118	-1.772 *	-0.103	0.277	-0.372	0.779	0.540	1.442
R2	404	0.039	0.039	0.982	0.032	0.128	0.249	0.504	0.276	1.826 *	1.618	0.456	3.552 ***
R3	317	-0.031	0.041	-0.744	-0.053	0.130	-0.411	0.271	0.315	0.862	0.866	0.537	1.614
R4	314	-0.003	0.049	-0.070	0.213	0.151	1.416	0.388	0.374	1.037	1.661	0.777	2.137 **
R5	257	0.007	0.060	0.126	0.112	0.150	0.749	0.348	0.363	0.959	2.168	0.594	3.648 ***
R6	230	0.043	0.069	0.620	0.326	0.182	1.788 *	1.125	0.388	2.900 ***	1.750	0.604	2.898 ***
R7	213	0.143	0.060	2.387 **	0.348	0.146	2.380 **	1.082	0.362	2.987 ***	2.888	0.542	5.325 ***
R8	206	0.090	0.067	1.361	0.600	0.169	3.559 ***	1.189	0.381	3.119 ***	3.247	0.558	5.821 ***
R9	195	0.096	0.074	1.296	0.265	0.223	1.187	0.901	0.442	2.039 **	2.658	0.635	4.186 ***
R10	205	0.120	0.074	1.621	0.592	0.183	3.232 ***	1.190	0.438	2.719 ***	3.215	0.632	5.088 ***
R11	185	-0.032	0.083	-0.382	0.106	0.256	0.416	1.207	0.523	2.307 **	2.938	0.945	3.109 ***
R12	189	0.090	0.088	1.017	0.011	0.223	0.051	0.602	0.446	1.349	0.596	1.150	0.518
R13	217	-0.017	0.073	-0.237	0.166	0.197	0.841	0.599	0.452	1.328	1.170	1.024	1.143
R14	228	0.111	0.088	1.271	-0.042	0.211	-0.197	0.613	0.438	1.399	0.175	0.986	0.177
R15	226	0.090	0.081	1.111	0.194	0.212	0.916	1.180	0.447	2.638 ***	1.768	0.750	2.358 **
R16	235	0.036	0.075	0.474	0.148	0.246	0.600	1.793	0.522	3.437 ***	2.704	0.915	2.954 ***
R17	254	0.024	0.081	0.300	0.349	0.267	1.306	0.943	0.640	1.474	3.158	1.033	3.057 ***
R18	294	-0.058	0.083	-0.699	0.124	0.225	0.552	0.279	0.639	0.436	3.146	0.926	3.397 ***
R19	333	-0.036	0.080	-0.449	0.124	0.219	0.565	0.599	0.489	1.226	2.729	0.843	3.236 ***
R20	521	0.091	0.083	1.096	0.465	0.304	1.527	1.262	0.679	1.859 *	4.665	0.926	5.038 ***
R21	54	0.908	0.381	2.385 **	2.181	0.923	2.363 **	2.128	1.453	1.464	5.553	1.593	3.487 ***

Appendix 8: Healthcare industry results on different ranks.

Rank	#	1d	std.error	t-stat		5d	std.error	t-stat		20d	std.error	t-stat		60d	std.error	t-stat	
R0	70	-0.061	0.092	-0.661		0.205	0.243	0.843		0.437	0.565	0.772		1.913	1.025	1.866	*
R1	627	-0.025	0.033	-0.775		-0.091	0.113	-0.802		-0.143	0.326	-0.437		1.370	0.624	2.195	**
R2	404	0.035	0.042	0.832		-0.076	0.137	-0.556		0.051	0.296	0.174		1.537	0.521	2.951	***
R3	317	-0.011	0.047	-0.234		-0.012	0.137	-0.090		0.206	0.321	0.642		1.259	0.733	1.719	*
R4	314	-0.005	0.054	-0.094		0.245	0.149	1.645	*	0.636	0.344	1.850	*	1.689	0.622	2.714	***
R5	257	0.009	0.061	0.140		0.173	0.163	1.061		0.897	0.386	2.321	**	2.998	0.481	6.236	***
R6	230	0.014	0.060	0.225		0.337	0.161	2.100	**	1.373	0.322	4.265	***	2.238	0.644	3.477	***
R7	213	0.189	0.066	2.860	***	0.528	0.151	3.498	***	1.091	0.347	3.142	***	2.463	0.632	3.898	***
R8	206	0.036	0.067	0.542		0.259	0.193	1.342		0.707	0.380	1.861	*	2.603	0.605	4.303	***
R9	195	0.083	0.080	1.031		0.258	0.212	1.218		1.271	0.406	3.132	***	3.305	0.654	5.058	***
R10	205	0.144	0.072	1.992	**	0.307	0.191	1.606		1.012	0.388	2.609	***	3.447	0.585	5.895	***
R11	185	0.057	0.087	0.652		0.346	0.211	1.640		1.605	0.433	3.704	***	4.054	0.797	5.085	***
R12	189	0.039	0.076	0.515		0.183	0.184	0.993		1.000	0.438	2.284	**	2.375	1.040	2.283	**
R13	217	0.013	0.069	0.181		0.297	0.183	1.628		1.047	0.396	2.646	***	2.662	0.945	2.816	***
R14	228	0.153	0.084	1.819	*	0.336	0.193	1.746	*	1.075	0.416	2.582	***	2.600	0.907	2.865	***
R15	226	0.073	0.069	1.071		0.298	0.208	1.437		2.032	0.388	5.238	***	3.409	0.765	4.454	***
R16	235	0.030	0.082	0.365		0.037	0.212	0.177		1.174	0.469	2.504	**	3.170	0.707	4.482	***
R17	254	-0.045	0.078	-0.573		0.184	0.243	0.755		0.712	0.598	1.192		2.396	0.864	2.773	***
R18	294	0.048	0.069	0.694		0.065	0.228	0.284		0.563	0.575	0.978		1.669	0.817	2.042	**
R19	333	-0.044	0.073	-0.594		0.093	0.218	0.427		0.988	0.420	2.353	**	2.760	0.709	3.891	***
R20	521	0.116	0.067	1.734	*	0.611	0.246	2.486	**	1.662	0.566	2.936	***	5.009	0.703	7.124	***
R21	54	0.651	0.337	1.933	*	2.193	0.614	3.572	***	3.047	1.040	2.931	***	6.965	1.382	5.040	***

Appendix 9: Utilities industry results on different ranks.

Rank	#	1d	std.error	t-stat	5d	std.error	t-stat	20d	std.error	t-stat	60d	std.error	t-stat
R0	70	0.035	0.067	0.521	0.243	0.173	1.405	1.024	0.468	2.187 **	4.155	0.826	5.033 ***
R1	627	0.063	0.026	2.470 **	0.242	0.102	2.367 **	1.065	0.312	3.413 ***	2.994	0.591	5.066 ***
R2	404	0.092	0.038	2.422 **	0.241	0.136	1.768 *	0.663	0.321	2.065 **	2.479	0.538	4.604 ***
R3	317	-0.021	0.042	-0.501	0.045	0.126	0.354	0.329	0.282	1.167	1.228	0.602	2.041 **
R4	314	-0.022	0.043	-0.502	0.097	0.129	0.753	0.615	0.382	1.612	1.973	0.586	3.365 ***
R5	257	-0.083	0.054	-1.547	0.025	0.148	0.169	0.303	0.318	0.953	2.426	0.529	4.583 ***
R6	230	0.038	0.060	0.630	0.158	0.154	1.025	0.663	0.347	1.909 *	2.173	0.613	3.546 ***
R7	213	0.098	0.061	1.606	0.470	0.155	3.032 ***	0.981	0.316	3.104 ***	2.675	0.548	4.880 ***
R8	206	-0.021	0.054	-0.383	0.249	0.154	1.613	0.568	0.340	1.671 *	2.938	0.536	5.486 ***
R9	195	-0.001	0.063	-0.013	0.050	0.188	0.268	1.062	0.410	2.592 ***	2.355	0.611	3.856 ***
R10	205	0.158	0.062	2.554 **	0.317	0.177	1.790 *	0.691	0.393	1.760 *	2.469	0.546	4.522 ***
R11	185	-0.026	0.068	-0.377	-0.097	0.188	-0.517	0.964	0.446	2.160 **	1.191	0.831	1.433
R12	189	0.000	0.069	0.001	0.012	0.172	0.070	0.703	0.429	1.638	0.541	1.126	0.480
R13	217	-0.041	0.053	-0.760	0.282	0.164	1.718 *	0.890	0.406	2.196 **	1.315	0.987	1.332
R14	228	0.080	0.073	1.102	0.052	0.204	0.257	0.592	0.447	1.325	0.088	1.027	0.086
R15	226	0.090	0.070	1.281	0.203	0.203	1.000	0.944	0.398	2.372 **	1.772	1.012	1.752 *
R16	235	0.068	0.072	0.949	0.077	0.213	0.363	0.166	0.458	0.363	1.957	0.843	2.322 **
R17	254	-0.003	0.071	-0.040	-0.160	0.241	-0.664	-1.258	0.687	-1.831 *	0.101	1.016	0.100
R18	294	-0.062	0.083	-0.755	-0.072	0.257	-0.281	-0.541	0.698	-0.774	0.662	0.910	0.728
R19	333	0.037	0.066	0.559	0.094	0.211	0.445	0.473	0.358	1.322	1.410	0.806	1.748 *
R20	521	0.015	0.071	0.213	0.324	0.264	1.224	1.270	0.550	2.307 **	2.154	0.738	2.918 ***
R21	54	0.740	0.419	1.765 *	1.362	0.719	1.895 *	3.268	1.041	3.138 ***	5.112	1.212	4.218 ***

Appendix 10: Others industry results on different ranks.

Rank	#	1d	std.error	t-stat		5d	std.error	t-stat		20d	std.error	t-stat		60d	std.error	t-stat	
R0	70	-0.088	0.067	-1.314		0.025	0.177	0.140		0.209	0.454	0.460		0.759	1.097	0.691	
R1	627	-0.005	0.031	-0.170		-0.060	0.111	-0.541		0.249	0.313	0.796		0.919	0.568	1.617	
R2	404	0.059	0.040	1.481		0.062	0.138	0.451		0.589	0.289	2.041	••	1.777	0.555	3.202	•••
R3	317	-0.079	0.042	-1.862	•	-0.109	0.131	-0.831		0.223	0.304	0.734		1.310	0.610	2.147	••
R4	314	-0.006	0.050	-0.129		0.108	0.153	0.708		0.265	0.402	0.659		1.368	0.943	1.450	
R5	257	-0.013	0.064	-0.195		-0.143	0.176	-0.811		-0.156	0.374	-0.417		1.865	0.639	2.919	•••
R6	230	0.055	0.065	0.847		0.418	0.186	2.248	••	0.872	0.363	2.399	••	1.253	0.693	1.808	•
R7	213	0.174	0.065	2.681	•••	0.520	0.160	3.257	•••	0.869	0.384	2.266	••	1.977	0.646	3.059	•••
R8	206	0.072	0.078	0.919		0.477	0.197	2.424	••	0.767	0.480	1.599		2.530	0.739	3.422	•••
R9	195	0.122	0.073	1.680	•	0.400	0.210	1.903	•	1.477	0.465	3.178	•••	2.633	0.723	3.642	•••
R10	205	0.233	0.091	2.555	••	0.775	0.235	3.302	•••	1.368	0.492	2.782	•••	2.970	0.766	3.876	•••
R11	185	0.022	0.081	0.266		0.239	0.256	0.934		1.509	0.580	2.604	•••	2.715	1.224	2.218	••
R12	189	-0.028	0.093	-0.299		-0.138	0.251	-0.552		0.572	0.586	0.976		0.022	1.481	0.015	
R13	217	-0.045	0.081	-0.557		0.284	0.225	1.260		0.961	0.557	1.726	•	1.722	1.358	1.269	
R14	228	0.059	0.093	0.629		-0.025	0.232	-0.107		0.620	0.465	1.333		-0.123	1.405	-0.088	
R15	226	0.129	0.098	1.315		0.047	0.321	0.146		1.217	0.591	2.059	••	1.602	0.999	1.604	
R16	235	-0.016	0.082	-0.191		0.141	0.281	0.500		1.615	0.671	2.406	••	3.073	1.127	2.727	•••
R17	254	0.003	0.115	0.022		0.031	0.364	0.084		0.028	0.802	0.034		2.711	1.222	2.218	••
R18	294	-0.162	0.125	-1.295		-0.286	0.422	-0.677		-1.002	1.108	-0.905		2.171	1.600	1.357	
R19	333	-0.074	0.101	-0.727		-0.091	0.261	-0.349		0.004	0.578	0.008		1.282	1.288	0.995	
R20	521	0.082	0.104	0.792		0.345	0.395	0.875		1.012	0.828	1.223		2.386	1.301	1.834	•
R21	54	1.058	0.436	2.428	••	3.260	0.835	3.906	•••	2.017	1.557	1.296		2.305	2.476	0.931	