Volatility and stock market returns
CAN VOLATILITY PREDICT STOCK MARKET RETURNS?

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Abstract

This study examines the relation between volatility and stock market index return in the US and Germany and if volatility can be used as trade signal for investors. This study uses the VIX as proxy for volatility and the returns of the stock market indices of the S&P500 and the DAX. Consistent with theoretic predictions, volatility is negatively related to stock market returns. In case of extreme movements of the VIX (volatility index) can be used as trade indicator. However, there is no supporting evidence that a change in the VIX affects stock market returns.
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1. Introduction

The financial crisis of 2007-2008 also known as the Global Financial Crisis is considered by many economists to have been the worst financial crisis since the Great Depression of the 1930’s and therefore has been subject for many analyses and papers. So have Theo Kocken and Terry Jones by making the documentary ‘Boom Bust Boom’ (2014), where they are trying to analyze the causation and identifying economic indicators or signs, which could have predicted the Global Financial Crisis. In their analysis Kocken and Jones are reintroducing the Financial Instability Hypothesis invented by Hyman Minsky (1975, 1982, 1986, 1992), whose theory had fallen into oblivion. The theory argues that financial market fragility belongs in a normal life cycle of an economy and speculative investment bubbles are endogenous to financial markets and therefore financial crises are a normal function of the capitalistic economy. Times of economic expansion and protracted periods of prosperity lead to greater risk acceptance and therefore the behavior of excessive risk taking, rises. In addition during this periods of prosperity governments are likely to loosening regulations. According to Minsky combining this phenomenon with excessive risk taking leads to bubbles, which eventually will burst and bring the economy into recession or even depression. Kocken and Jones argue that in times of economic expansion and periods of prosperity the volatility of stock markets, measured by the VIX, is minimized. Therefore, they plea that if the VIX hits its lowest levels and thus a period of low implied volatility will lead to a market crash. This implicates that Kocken and Jones argues that the fall of the VIX implies negative future stock returns.

However, this is contradicted by the Asymmetric Volatility Phenomenon that is, negative (positive) returns are generally associated with upward (downward) revisions of the volatility. This empirical phenomenon is often referred to as asymmetric volatility (Schwert (1989), and Nelson (1991); Engle and Ng (1993); Zakoian (1994), Bekaert and Wu (2000) and Wu (2001). However, this study is trying to determine whether it also works the other way around, thus that upward (downward) revisions of the volatility can predict negative (positive) returns and therefore
it could be used as a trade signal for investors. Therefore, this study asks itself the question whether a low volatility implies negative stock market returns and therefore testing the hypothesis of Kocken and Jones. The second question that will be asked in this research is whether a relative rate of change in the volatility index can signal if returns are either positive or negative.

Obtaining the data of the stock market indices of the US and Germany, by using the respectively the S&P500 and Deutscher Aktienindex (DAX) and their corresponding volatility index (VIX), allows me to do a regression analysis of the VIX over the respective indices.

Considering the outcomes of regression analysis, we can conclude that there clearly exists an inverse relationship between the level of the VIX and stock market return of the S&P500, which is statistically significant. However, it only will be recognizable and of valuable input for investors if the magnitude of the leap in the VIX is rather unrealistic and therefore it is difficult to use it as a direct trade indicator. This means that the hypothesis of Kocken and Jones is theoretically correct, however this situation will hardly occur in practice. In addition, this study cannot provide evidence that the rate of change in the VIX has a significant effect on stock market returns and therefore is not a useful tool for investors to directly use it as a trade signal.

The remainder of the paper is organized as follows. Section 2 briefly reviews the related literature. Section 3 describes the data, methodology and provides a summary statistics for the used data of the indices and its corresponding volatility index. Section 4 discusses empirical results for the two main hypotheses. Section 5 concludes the paper and section 6 discusses the limitations of this research and provides recommendations for future research.
2. Theory and background

In Theo Kocken and Terry Jones’s documentary movie “Boom Bust Boom” (2014) Jones and Kocken, using puppetry and talking heads, trying to popularize the work of Minsky, an US economist who died in 1996 but whose name has become associated with the Lehman Brothers Crash. Paul Mason in the Guardian (22nd of March, 2015) and the New Yorker (4th of February, 2008) have labelled it as the “Minsky moment”.

2.1 Financial Instability Hypothesis

Hyman Minsky, an American economist, a professor of economics at Washington University in St. Louis, proposed a theory linking financial market fragility, in the normal life cycle of an economy, with speculative investment bubbles endogenous to financial markets which is called the Financial Instability Hypothesis (FIH). Minsky (1975, 1982, 1986, 1992), argues that financial traumas occur as a normal function in a capitalistic economy. The normal functioning of the economy with a robust financial situation is both tranquil and on the whole successful. However, tranquility and success (stability) are not self-sustaining states of the economy. So, stability leads to more optimism and therefore more borrowing in stocks and assets. This leads to a transformation over time of an initially robust financial structure into a fragile structure. After a deep depression governments impose regulations on the financial world. There follows a time of stability but consequently this stability breathes overconfidence, which lead to financial euphoria during which time politicians relax financial regulations. This then lead to excessive borrowing and this phenomenon in combination with financial euphoria creates bubbles. So, stable and booming markets creates blindness for increasing risks.

Furthermore, according to Mulligan (2013) Hyman Minsky has labelled firms in three categories:

1. The “hedge borrower” who can generate sufficient cash flow to pay both the interest payments and the principal
2. The “speculative borrower” needs to borrow so much that their cash flow cover interest payments but he is not able to repay the principal
3. The “Ponzi borrower” needs to borrow so much they cannot even cover interest on their debt; only increasing asset prices can keep the Ponzi borrower afloat

In The Financial Instability Hypothesis (FIH) “protracted periods of prosperity lead endogenously either to progressive acceptance of greater risk on the part of firms, or a mistaken under-evaluation of the market risk to which firms are exposed (Mulligan, 2013)”. As the expansion phase of the business cycle continues, more-leveraged firms expose the financial sector to greater risk. Therefore, the actual risk-adjusted returns are lowered as the economy becomes more dominated by speculative and Ponzi borrowers. Firms can either increase their leverage with additional borrowing as well as by failing to meet sales/earnings to explain their current degree of leverage. Higher degrees of leverage can be considered as normal during a period of expansion. This induces that the restrictions on lending and borrowing become more and more neglected. If the use of Ponzi is general enough in the financial system and once Ponzi borrowers reach a level of indebtedness where they can no longer borrow increasing amounts based on fixed collateral, they are forced to sell assets in order to pay interest. This means that asset prices stop increasing due to an oversupply of assets and even the speculative borrower can no longer refinance the principal or cover the interest payments. As with a line of dominoes, collapse of the speculative borrowers can then bring down even hedge borrowers, who are unable to find loans despite the apparent soundness of the underlying investments. The resulting debt deflation causes a financial crisis and liquidity shortage.

Based on Minsky’s Financial Instability Hypothesis, Kocken and Jones argues that periods of low volatility predict market crashes. Based upon their assumption that during a period of economic expansion will be followed by loosening financial regulation and increase the behavior of excessive risk taking. During this period they argue that the volatility on stock markets decreases
and induce higher stock market returns. Kocken and Jones refer to the fact that the market traded price of risk (VIX) declines to very low levels during periods where stock markets go sky high. Approaching the crash of 2008 the price of risk (VIX) was historically as its lowest level.

2.2 Asymmetric volatility phenomenon

The relationship between stock price and its volatility has long interested financial researchers. Innovation in market volatility affect investors’ investment choices either by changing their forecast of future market performance or by changing the trade-off between risk and return. The multifactor models of Merton (1973) and Ross (1976) imply that risk premiums are related to the conditional covariance between asset returns and changes in state variables that affect investors’ time-varying investment choices. In the models of Campbell (1993, 1996), investors are concerned with market returns and changes in the expectation of future market returns. Chen (2002) extends the models to incorporate investors’ concern with aggregate future volatility risk. They show that investors want to hedge against changes in market volatility because increasing volatility represents less investment opportunities. Risk-averse investors demand stocks that hedge against this risk. Periods of high volatility also tend to coincide with downward market movements (French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992). They argue that firm's sensitivity to innovations in market volatility is a priced risk factor in the cross-section of stock returns.

Ang et al. (2006) and Loudon and Rai (2007) assume a symmetric relation between innovation in market volatility and stock returns. Nevertheless, there is growing literature documenting that returns and conditional variance of next period’s returns are negatively correlated. That is, negative (positive) returns are generally associated with upward (downward) revisions of the volatility. This empirical phenomenon is often referred to as asymmetric volatility (Schwert (1989), and Nelson (1991); Engle and Ng (1993); Zakoian (1994), Bekaert and Wu (2000) and Wu (2001). The presence of asymmetric volatility is most apparent during stock market
crashes when a large decline in stock is associated with a significant increase in market volatility. Delisle et al. (2011) and Van Ahn Mai et al (2015) agree with this view however they argue that it does not work the other way around. They conclude that the rise of the VIX is negatively related to future returns, but there is no relation between the fall of the VIX and future returns. They conclude that ‘VIX innovations are a priced risk factor only when VIX rises, and not when it declines’ (Delisle et al. 2011).

Concluding, Kocken and Jones (2014) suggesting, based on Minsky’s Financial Instability Hypothesis that in case the market price of risk (VIX) hits its lowest levels and thus a period of low implied volatility will lead to a market crash. This implicates that Kocken and Jones argues that the fall of the VIX implies negative future stock returns. The asymmetric volatility phenomenon (AVP), however states that the rise of the VIX is negatively related to future returns, yet there is no relation between the fall of the VIX and future returns. This study will examine if there is a relationship between the decline of the market price of risk and negative stock market returns. As consequence, if it turns out after conducting the research that the hypothesis of Kocken and Jones is correct it means that investors and portfolio managers in equity markets will have a new tool to position and manage their portfolios. For example, when the level of the VIX will be considerably low it could be an indicator for portfolio managers to go short or sell their long positions.
3. Sample and variable definitions

3.1. Data

The collected data consists of two samples of international stock markets indices and the corresponding index of the VIX composed by the CBOE. In order to create an international representing dataset, the sample contains the prices of the Standard & Poor’s 500 (S&P500) index from 1st of January 1990 to 29th of July 2016. The daily data (with at least one call and one put option) on the S&P500 were available consistently available from 1990 (this principle is used for the complete dataset). This data is necessary to construct the VIX. The S&P500 is a market index based on the market capitalizations of 500 large companies having common stock listed on the NYSE or NASDAQ. Furthermore, to extend and diversify, the dataset contains the prices of the Deutscher Aktienindex (DAX), which is a stock market index consisting of the 30 major German companies on the Frankfurt Stock Exchange, from 1st of January 1992 to 29th of July 2016. In addition, the daily data of the VIX for the DAX is collected in the same period of time.

The used indices are total return indices which means that all cash distributions (mostly in the form dividends) are reinvested in addition to tracking the components’ price movements. The data is obtained from Bloomberg.

3.2. Variables

As proxy for volatility the VIX (implied market volatility) is used. The implied volatility index is the trade mark of Chicago board options exchange and is introduced in 1993\(^1\) and is in 2003 modified. The new methodology is model-free forward-looking based on S&P 500 index options, and it is the markets’ expectation of the future market volatility over 30 day horizon (Whaley, 1993).

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\(^1\) At a January 1993 news conference, Prof. Whaley provided his recommendations, and subsequently, the CBOE has computed VIX on a real-time basis. Based on the history of index option prices, Prof. Whaley computed daily VIX levels in a data series commencing January 1986, available on the CBOE website. (Whaley, 1993)
The VIX is implied by the current prices of S&P 500 (or other indices) index options and represents expected future market volatility over the next 30 calendar days.

Therefore, the implied volatility index is the measure of expected volatility for the near future, it is estimated out of the trading prices of the options written on equity index and Whaley (2000, 2008) argues that the VIX can be considered as ‘investor fear gauge’.

In order to analyze whether the volatility index can predict future stock market returns, this study uses the relative change (ΔVIX) as well as the absolute value of the VIX. To measure the changes in the VIX the daily relative change of the absolute value is used. This is computed by using log returns (choosing log returns will be explained more extensively later this paragraph) of the value of the VIX ($V_t$) on a specific moment in time ($t$).

$$\Delta VIX_t = \log \left( \frac{V_t}{V_{t-1}} \right)$$

Besides using the logarithm function for the relative change of the VIX, this study also uses the function to compute stock market return ($r_i$) for a specific stock market index ($i$) at a given moment in time ($t$).

$$r_{i,t} = \log \left( \frac{P_t}{P_{t-1}} \right)$$

where $P_{t,t}$ refers to the price on day $t$

Using the logarithm function allows this study to measure all variables in a comparable metric, thus enabling the analysis of variables despite originating from price series.

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2 The VIX index is constructed so that it represents the implied volatility of a synthetic at-the-money option contract on the S&P500 index that has a maturity of 1 month. It is constructed from eight S&P500 index puts and calls and takes into account the American features of the option contracts, discrete cash dividends, and microstructure frictions such as bid–ask spreads (see Whaley (2000) for further details)
3.3. *Empirical model and methodology*

The aforementioned empirical phenomenon of asymmetric volatility (Schwert (1989), and Nelson (1991); Engle and Ng (1993); Zakoian (1994), Bekaert and Wu (2000) and Wu (2001), is that returns and conditional variance of next period’s returns are negatively correlated. That is, negative returns are generally associated with upward revisions of the volatility. Delisle et al. (2011) and Van Ahn Mai et al (2015) agree with this view however they argue that it does not work the other way around. They conclude that the rise of the VIX is negatively related to future returns, but there is no relation between the fall of the VIX and future returns. They conclude that VIX innovations are a priced risk factor only when VIX rises, and not when it declines’ (Delisle et al. 2011). Kocken and Jones (2014) suggesting, based on Minsky’s Financial Instability Hypothesis, that in case the market price of risk (VIX) hits its lowest levels and thus a period of low implied volatility will lead to a market crash. This implicates that Kocken and Jones argues that the fall of the VIX imply negative future stock returns. To examine if there is a relationship between the declining of the market price in of risk in absolute terms and a stock market returns, this study regresses stock market returns on the absolute value of the VIX, \( \beta VIX_{t-1} \):

\[
r_{i,t} = \alpha + \beta VIX_{t-1} + \epsilon_{i,t}
\]

The model contains a lag variable \( VIX_{t-1} \) since this regression equation is used to examine if stock market returns can be predicted by values of the VIX (volatility) in the past period.

In order to test whether volatility has predictive power over stock market returns, this study measures the stock market index sensitivity to changes in the VIX (\( \Delta VIX \)). To obtain the sensitivity measure, \( \beta_{\Delta VIXi} \), daily stock returns are regressed on changes of the VIX:

\[
r_{i,t} = \alpha + \beta_{\Delta VIXi} \Delta VIX_{t} + \epsilon_{i,t}
\]
3.4. Descriptive statistics

3.4.1. S&P500

Table 1 provides summary statistics for all the observed stock market indices and the behavior of its variables, which consist of SPX (S&P500), the VIX (absolute value), stock market return, \( R_{i,t} \), and the relative change \( \Delta VIX \) (dVIX in the table). The mean of the S&P500 has a price level of 1.0905,04 and a standard deviation of 477,2207. The lowest price of the index is 295,46 and the highest level is 2.175,03 in a period from January 1990 until July 2016.

Table 1 Summary statistics S&P500 and VIX

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>St. dev.</th>
<th>min</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>S&amp;P500</td>
<td>6696</td>
<td>1090.504</td>
<td>477,2207</td>
<td>295.46</td>
<td>669.04</td>
<td>1133.71</td>
<td>1366.96</td>
<td>2175.03</td>
</tr>
<tr>
<td>VIX</td>
<td>6696</td>
<td>19.7658</td>
<td>7.8704</td>
<td>9.31</td>
<td>14.08</td>
<td>17.92</td>
<td>23.16</td>
<td>80.86</td>
</tr>
<tr>
<td>Return</td>
<td>6696</td>
<td>0.0268%</td>
<td>1.1324%</td>
<td>-9.4695%</td>
<td>-0.4681%</td>
<td>0.0532%</td>
<td>0.5663%</td>
<td>10.9572%</td>
</tr>
<tr>
<td>( \Delta VIX )</td>
<td>6696</td>
<td>-0.0039%</td>
<td>6.3218%</td>
<td>-35.0588%</td>
<td>-3.6368%</td>
<td>-0.3324%</td>
<td>3.1906%</td>
<td>49.6008%</td>
</tr>
</tbody>
</table>

The variable VIX has a mean of 19.7658 with a standard deviation of 7.8704. Over its entire history the median daily closing level of VIX is 17.92 (which is close to the observations of Whaley, 1993 and 2000) where the highest absolute value in the sample (end of month data) is 80.86\(^3\). However, since the lowest value of the VIX is 9.31 (the values could even be 0 or 100 in extreme conditions) it is hard to say anything about the behavior of the VIX. Thus, to indicate the

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\(^3\) The highest value observed of the VIX was 80.86 on 20 November 2008. If intraday values are taking into account the all-time highest value of the VIX was 89.53 reached on 24 October 2008 (data obtained from Bloomberg). According to Whaley (2008) the VIX even exceeded a level of 100 during the October 19, 1987 market crash.
normal behavior of the VIX I consider the history of the VIX. The history of the VIX will be only described in perspective of the American stock market. This is because the VIX of the S&P500 has the largest number of observations and the longest time span. Furthermore, describing the history has the purpose to demonstrate specific patterns of the VIX and therefore it would be unnecessary to extensively describe the volatility of the DAX. In addition to that international equity market returns have become more and more correlated and therefore other indices should demonstrate similar behavior (Berben and Jansen, 2005).

*Figure 1*
Daily VIX and S&P500. This figure plots the daily levels of VIX and S&P500 from 1 January 1990 through 29 July 2016
Seeing Figure 1 it’s interesting to see that the VIX spikes upward frequently. The first spike upward occurred when Iraq invaded Kuwait. This was followed by the attack on Iraq by the United Nations forces, which corresponds to the second spike upward in early 1991 (Walsh, 1993). In October 1997 and in October 1998 two sharp spikes are observed from figure 1. The October 1997 occurred following a stock market sell-off (see figure 2) that was caused by the economic crisis in Asia (SEC, 1998) and is considered as a ‘mini-crash’. The observed spike around October 1998 was caused by ‘a currency crisis occurred in Russia on August 17, 1998 and led to devaluation of the ruble and the default on public and private debt’ (Chiodo and Owyang, 1998). The spike around March 2000 was induced by the dot-com bubble. The 9/11 attack on the Twin Towers, which caused global stock markets to drop sharply, directly caused the VIX to spike in 2001 and indirectly caused the spike in 2002 due to economic effects after the attack (Makinen, 2002). After a period where the VIX became relatively stable and even hits its lowest value the Lehmann crash followed, which explains the spike around 2008. The European sovereign debt crisis, where the European and the IMF activated a €45 billion bailout for the Greece’ government, induced the spike around April 2010 (CNN, 28th of April, 2010). The volatility of stock markets continued, explaining the spike around August 2011, due to fears of contagion of the European Sovereign debt crisis to Spain, Italy and even France. The last steep rise of VIX occurred around July 2015, where the Chinese surprisingly devaluated the Yuan, which caused stock markets to decline and increase the volatility. To conclude, figure 1 demonstrates that when markets become nervous the volatility rises. Most of the time peaks of the VIX coincide with big events, such as war other crises followed by a sharp decline of stock markets, however ‘in aftermath of each spike, the VIX returns to more normal levels’ (Whaley, 2008).

Returning to the descriptive statistics a daily return of 0.0268% can be observed with a standard deviation of 1.1342%. Using the following calculation \([(0.0268+1)^{365}-1]\) gives an annualized return of 11.407%. Over the period January 1986 through October 2008, the mean daily returns of the S&P500 were 0.0266% (Whaley, 2008), which aligns with our reported data. The
largest performance of S&P500 on daily basis in the dataset is 10,9572% and the biggest turn downwards is -9,4696% with a median, 50th percentile, of 0,0532%.

Lastly, Table 1 reports descriptive statistics of the ΔVIX, which has a mean of -0,004%, which means that the average daily change in the VIX is with the aforementioned percentage. Considering the standard deviation of 6,3218%, a maximum ΔVIX of 49,6008%, minimum of -35,0589% and even the 25th and 75th percentile of respectively -3,6368% and 3,1906% allows this study to conclude that the price movements of the VIX can be very inconsistent with enormous fluctuations.

3.4.2. DAX

Secondly, this study briefly discusses the summary statistics of the DAX and its corresponding volatility. From 1st of January 1992 to 29th of July 2016 the mean value of DAX is 5.365,5244 and has a standard deviation of 2.501,339. The peak value of the DAX in the sample period is 12.374,73 and bottomed out at a level of 1.420,3.

Table 2 Summary statistics DAX and VIX

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>mean</th>
<th>St. dev.</th>
<th>min</th>
<th>p25</th>
<th>p50</th>
<th>p75</th>
<th>max</th>
</tr>
</thead>
<tbody>
<tr>
<td>DAX</td>
<td>6219</td>
<td>5365,524</td>
<td>2501,339</td>
<td>1420,3</td>
<td>3376,2</td>
<td>5297,35</td>
<td>6966,15</td>
<td>12374,73</td>
</tr>
<tr>
<td>VIX</td>
<td>6219</td>
<td>21,5582</td>
<td>8,4644</td>
<td>9,36</td>
<td>15,595</td>
<td>19,65</td>
<td>24,88</td>
<td>74</td>
</tr>
<tr>
<td>Return</td>
<td>6219</td>
<td>0,0298%</td>
<td>1,4488%</td>
<td>-8,8745%</td>
<td>-0,6737%</td>
<td>0,0955%</td>
<td>0,7787%</td>
<td>10,7975%</td>
</tr>
<tr>
<td>ΔVIX</td>
<td>6219</td>
<td>0,0054%</td>
<td>4,8871%</td>
<td>-27,0342%</td>
<td>-2,8137%</td>
<td>-0,1476%</td>
<td>2,4017%</td>
<td>31,44%</td>
</tr>
</tbody>
</table>

The mean of the absolute value of the VIX is 21,5583 and has a standard deviation of 8,4645. The highest value of the VIX throughout the dataset is 74 and has a minimum of 9,36. The computed returns of the DAX has a daily average of 0,0298% with a standard deviation of 1,4488%. Using
the following calculation \[ ((0,0298+1)^{365} - 1) \]
gives an annualized return of 11.502\%. The performance of the DAX is slightly higher than the performance of the S&P500, which can partly be explained by including the year 1990 and 1991 in the dataset for the S&P500. Those years, as mentioned before, were mostly negative due to the invasion in Kuwait among other things. Besides the higher return for the DAX is associated with higher risk considering the standard deviation. This observation is emphasized by the descriptive statistics of the VIX, which has a higher mean (21,5583) and higher standard deviation of 8,4645. Despite that, the maximum value of the VIX, which is 74, is less extreme than the VIX composed by put and call options of the S&P500. In addition, this observation is confirmed by the descriptive statistics of the ΔVIX considering the daily change average change of 0,0059\% with a smaller standard deviation, which is 4,8871\%, than the S&P500. Also, the minimum (-27,03420\%) and maximum (3.44\%) and the 25\textsuperscript{th} and 75\textsuperscript{th} percentile, which are respectively -2.8137\% and 2.4017\% are smaller deviations from the mean than the descriptive statistics of the ΔVIX\textsubscript{S&P500}. 
4. Empirical Results

In this section the results of this research are being discussed. This section contains an analysis of the relationship between the volatility, measured by the VIX, and stock market returns. Firstly, the analysis will be concentrated on the stock market of United States by using the S&P500 stock market index and its corresponding volatility index. Subsequently, the analysis will shift from the S&P500 to another stock market index, which is the Deutscher Aktien Index (DAX). The effect of volatility on stock market returns and whether volatility can be used to predict future returns will be analyzed in both relative as well as absolute terms.

4.1 Volatility index and stock market returns

In the first part of the discussion I will analyze if there exists a relationship between the VIX and the stock market returns. The following model will be tested:

\[ r_{i,t} = \alpha + \beta VIX_{t-1} + \epsilon_{i,t} \]

According to the asymmetric value phenomenon it should be the case that negative (positive) returns are generally associated with upward (downward) revisions of the volatility and therefore a negative (positive) returns induce high (low) levels of the VIX. However, this model will tests if it works also the other way around, so that a high (low) level of the VIX can predict negative (positive) returns and therefore it can be used as trade indicator for investors.

4.1.1 S&P500

Firstly, we will analyze the effect of the absolute value of the VIX on stock market returns. Seeing the output of the regression analysis (Table 3) we can conclude that the VIX and the returns of the S&P500 has a negative relationship with a \( \beta \) coefficient of -0.0127 and \( \alpha \) (intercept) coefficient of 0.278. This gives the following model for the S&P500:

\[ R_{i,t} = 0.278 -0.0127VIX_{i,t-1} + \epsilon_{i,t} \]
Considering the regression output we can conclude that the level of the VIX has a statistically significant effect on stock market returns of the S&P500 at a 1% level. The precision of the estimate should allow this study to round off only on one decimal. Considering for example the standard error of the intercept would justify only the 2 (in case of the intercept) in the estimation. However, for convenient reasons calculations that leads to a result with decimals, the amount arrived is rounded off to four decimals.

Table 3

**OLS–S&P500 index returns and VIX**

This table presents OLS regression results. The dependent variable is the S&P500 return index. The independent variable concerns the volatility index (VIX). Variables are the S&P500 return index and the volatility index. The standard errors are presented in parenthesis. The data are 6,696 daily observations. The table report the regression results for the sampling period 1st January 1990 to 29th July 2016.

<table>
<thead>
<tr>
<th>S&amp;P500 index returns</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.0127***</td>
</tr>
<tr>
<td></td>
<td>(0.00175)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.278***</td>
</tr>
<tr>
<td></td>
<td>(0.0373)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,696</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

Because I analyze a time series model with a large sample size (N = 6696) there is a probability that the model exhibit heteroscedasticity. Executing the Breusch-Pagan/Cook-Weisberg test allows this study to identify problems of heteroscedasticity. Given a Chi-square of 6835.23 and a very small p-value (see Table 4) we reject the null hypothesis and I can conclude that the model suffers from heteroscedasticity. The existence of heteroscedasticity can invalidate statistical tests of significance. Using heteroscedasticity-consistent standard error estimator (Eick-Huber-White standard error) allows the fitting of the model that does contain heteroscedastic residuals. However, taking heteroscedasticity into account the level of the VIX still has a significant effect on stock market index returns of the S&P500 at a 1% level.
Robustness check by using Eick-Huber-White standard error estimator. Variables are the S&P500 return index and the volatility index. The standard errors are presented in parenthesis. The data are 6,696 daily observations. The table report the regression results for the sampling period 1st January 1990 to 29th July 2016.

<table>
<thead>
<tr>
<th>S&amp;P500 index returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
</tr>
<tr>
<td>-0.0127***</td>
</tr>
<tr>
<td>(0.00419)</td>
</tr>
<tr>
<td>Intercept</td>
</tr>
<tr>
<td>0.278***</td>
</tr>
<tr>
<td>(0.0753)</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>6,696</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
<tr>
<td>0.008</td>
</tr>
<tr>
<td>Breusch-Pagan / Cook-Weisberg test (Chi-square)</td>
</tr>
<tr>
<td>6835.23***</td>
</tr>
</tbody>
</table>

Besides that, the model is serial through time, which means that the sample consists of day to day data, which make the residuals vulnerable to autocorrelation. Autocorrelation can create problems that tends to bias standard errors of the regression coefficients downwards which consequently inflates the T-test statistics coefficients upwards.

The output of the Breusch-Godfrey LM test has a large Chi-square value of 25.887 (Table 5) and a p-value, which is very small therefore we reject the null hypothesis and can draw the conclusion that the model suffers from autocorrelation. Using the rule of thumb (see equation below) allows this study to use a lag of 14.

\[
m = 0.75 \times T^{1/3}
\]

where M refers number of lag and T to number of observations.

This means that realizations of the returns are correlated with themselves either positively or negatively at t-1. This phenomenon is a common problem in case of analyzing returns. In case of high volatility returns tend to cluster during these periods and consecutive returns show the behavior that they move in one direction, which leads to positive autocorrelation. For example
in times of crises returns fall and keep on falling. Or a 5% decline of an index, which is slightly offset by a 3% rise on the next day, which leads to negative autocorrelation. To overcome this problem of serial autocorrelation and heteroscedasticity this study estimates the variance-covariance matrix by using the Newey-West covariance matrix estimator. This allows the model to use both heteroscedasticity and autocorrelation consistent standard errors. However, considering Table 5 the previous conclusions does not change.

Table 5

Newey-West OLS – S&P500 index returns and VIX

To overcome the problem of serial autocorrelation by using Newey-West variance covariance matrix. Variables are the S&P500 return index and the volatility index. The standard errors are presented in parenthesis. The data are 6,696 daily observations. The table report the regression results for the sampling period 1st January 1990 to 29th July 2016.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P500 index returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.0127***</td>
</tr>
<tr>
<td></td>
<td>(0.00419)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.278***</td>
</tr>
<tr>
<td></td>
<td>(0.0753)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,696</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.008</td>
</tr>
<tr>
<td>Breusch-Godfrey LM</td>
<td>25.887***</td>
</tr>
<tr>
<td>Lag</td>
<td>14</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.10

The estimated slope coefficient is negative and significant and clearly reflects the inverse relationship between the level of the VIX and stock market return of the S&P500. Firstly, this study will focus on a rather extreme movement of the VIX as input for the testing whether the model is also for valuable input for investors and thus economically significant. Later in this section the analysis extends to more realistic changes on daily basis in the VIX.

By looking at Table 6 it can be seen that the descriptive statistics are used as input. Taking a closer look to the descriptive statistics the highest level of the VIX obtained in the sample is
The lowest value of the VIX within the sample has a value of 9,31. In extreme conditions it could be possible that the VIX could fall from 80,86 points to 9,31 points (or vice versa). Despite that this scenario is not likely to occur, this study will use this extreme situation to demonstrate the effect of a change in the VIX on the returns of the S&P500. From Table 6 it can be concluded that if the VIX falls from 80,86 to 9,31, thus the VIX falls by 71,55 the return of the VIX will increase by 1,1867%. However, it is also possible to approach this from the other way around and see what the effect is if volatility increases and the effect on the returns of the S&P500. In case the VIX rises from its lowest value in the sample to the peak value the return of the S&P500 is -0,6307%.

Table 6  
This table presents and tests whether the model is economically significant using hypothetical movements of the VIX.

<table>
<thead>
<tr>
<th>Movement</th>
<th>$\beta \text{VIX}_t-1$</th>
<th>Model</th>
<th>$R_{i,t}$</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX falls from maximum value to minimum value volatility ↓ → hypothesis: $R_{i,t}$ ↑</td>
<td>Max_S&amp;P500 (80.86) → Min_S&amp;P500 (9.31) = -71.55 -0.0127 * -71.55 = 0.9087</td>
<td>0.278% + 0.9087%</td>
<td>1,1867%</td>
<td>Economically significant → conjecture is true, however rather extreme movement of VIX</td>
</tr>
<tr>
<td>VIX rises from minimum value to maximum value volatility ↑ → hypothesis: $R_{i,t}$ ↓</td>
<td>Min_S&amp;P500 (9.31) → Max_S&amp;P500 (80.86) = 71.55 -0.0127 * 71.55 = -0.9087</td>
<td>0.278% - 0.9087%</td>
<td>-0.6307%</td>
<td>Economically significant → conjecture is true, however rather extreme movement of VIX</td>
</tr>
<tr>
<td>VIX falls from 75th percentile to 25th percentile is sample volatility ↓ → hypothesis: $R_{i,t}$ ↑</td>
<td>p75_S&amp;P500 (23.16) → p25_S&amp;P500 (14.08) = -9.08 -0.0127 * -9.08 = 0.1153</td>
<td>0.278% + 0.1153%</td>
<td>0.3933%</td>
<td>Economically significant → conjecture is true, however still unrealistic movement of VIX</td>
</tr>
<tr>
<td>VIX rises from 25th percentile to 75th percentile is sample volatility ↑ → hypothesis: $R_{i,t}$ ↓</td>
<td>p25_S&amp;P500 (14.08) → p75_S&amp;P500 (23.16) = 9.08 -0.0127 * 9.08 = -0.1153</td>
<td>0.278% - 0.1153%</td>
<td>0.1627%</td>
<td>Economically significant → conjecture is true, however still unrealistic movement of VIX</td>
</tr>
</tbody>
</table>

In extreme conditions it can be concluded that there is also an economic significant effect on the returns of the S&P500. Given the extreme conditions and the unlikeliness of this movement of the VIX it is hard to value these results. Therefore, this study will deviate from the extreme
movements to more realistic changes in the VIX. Considering the difference between 25\textsuperscript{th} percentile and the 75\textsuperscript{th} percentile displayed in the descriptive statistics is a more realistic change in the VIX. Thus, if the VIX falls from 23.16 (75\textsuperscript{th} percentile) to 14.08 (25\textsuperscript{th} percentile) the effect on returns of the S&P500 is 0.3933\%. However, if volatility increases, thus the VIX rises from 14.08 to 23.16, the effect on returns of the S&P500 will still have a positive performance of 0.1627\%, however it deviates strongly from the intercept and it can be seen that the return is decreasing in case the VIX rises.

Despite the previous fluctuation is more realistic than the one which is used as starting point, it still is a rather large price movement. Considering the first two rows of Table 7 it can be seen that if the VIX rises or falls by one point the returns of the S&P500 will be respectively 0.2907\% and 0.2653\%. By taking a more likely movement of the VIX the return of the index is less affected and is almost not worth mentioning.

Table 7
This table presents and tests whether the model is economically significant using more realistic movements of the VIX

<table>
<thead>
<tr>
<th>Movement</th>
<th>( \beta_{\text{VIX}_{t-1}} )</th>
<th>Model</th>
<th>( R_{i,t} )</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX falls by 1 point volatility ↓ ( \rightarrow ) hypothesis: ( R_{i,t} ) ↑</td>
<td>(-0.0127 \times (-1) = 0.0127)</td>
<td>0.278% + 0.0127%</td>
<td>0.2907%</td>
<td>Economically insignificant ( \rightarrow ) conjecture does not hold by using realistic movement of VIX</td>
</tr>
<tr>
<td>VIX rises by 1 point volatility ↑ ( \rightarrow ) hypothesis: ( R_{i,t} ) ↓</td>
<td>(-0.0127 \times 1 = 0.0127)</td>
<td>0.278% - 0.0127%</td>
<td>0.2653%</td>
<td>Economically insignificant ( \rightarrow ) conjecture does not hold by using realistic movement of VIX</td>
</tr>
<tr>
<td>VIX falls by approximation of daily change by equaling mean of VIX with ( \Delta \text{VIX} ) volatility ↓ ( \rightarrow ) hypothesis: ( R_{i,t} ) ↑</td>
<td>( \mu_{\text{S&amp;P500}} \text{VIX} \times \mu_{\text{S&amp;P500}} \Delta \text{VIX} ) ( 19.7658 \times (-0.0039%) = -0.0008)</td>
<td>0.278% + 0.0008%</td>
<td>0.2788%</td>
<td>Economically insignificant ( \rightarrow ) conjecture does not hold in case of expected daily change of the VIX</td>
</tr>
<tr>
<td>VIX falls by approximation of daily change by equaling mean of VIX with ( \Delta \text{VIX} ) volatility ↑ ( \rightarrow ) hypothesis: ( R_{i,t} ) ↓</td>
<td>( \mu_{\text{S&amp;P500}} \text{VIX} \times \mu_{\text{S&amp;P500}} \Delta \text{VIX} ) ( 19.7658 \times 0.0039% = -0.0008)</td>
<td>0.278% - 0.0008%</td>
<td>0.2772%</td>
<td>Economically insignificant ( \rightarrow ) conjecture does not hold in case of expected daily change of the VIX</td>
</tr>
</tbody>
</table>
In addition, by analyzing the data on daily basis also the relative change of the VIX (ΔVIX) is compiled. By taking the mean of the relative change of the VIX on daily basis and equaling it with the mean of the VIX we can approximate the absolute daily change of the VIX, which gives a realistic input to test whether the model is a valuable tool for investors. Implementing this result into the obtained equation in case the daily change of the VIX is either increasing or decreasing with -0.0008%, gives the following results of 0.2788% and 0.2772%, which can be read out of the last two rows of Table 7. Considering the results it allows me to draw the conclusion that the absolute value of the VIX does not have an economically significant effect on the stock market returns of the S&P500 and therefore should not be used as a direct trade signal.

So, when the magnitude of the innovation in the VIX becomes smaller the effect on index returns also becomes smaller. So, already a statistical significant relationship has been established, however the inverse relationship between the VIX and the S&P500 only becomes economically significant if the either the downward or upward movement of the VIX is rather extreme. Moreover, the model does not have much explanatory power considering an R-squared of 0.008 in every regression.

4.1.2 DAX

Doing a regression analysis of the volatility of the Deutscher Aktien index (DAX) on the return of the stock market index this study discovers a negative relationship with a β-coefficient of −0.0152 and α-coefficient of 0.358. This results in the following model for the DAX:

\[ R_{i,t} = 0.358 - 0.0152VIX_{i,t-1} + \epsilon_{i,t} \]

Considering output of the OLS regression in Table 7 I can conclude that the level of the VIX has a statistically significant effect on stock market returns of the DAX at a 1% level.
Table 7

OLS - DAX index returns and VIX

This table presents OLS regression results. The dependent variable is the DAX return index. The independent variable concerns the volatility index (VIX). The standard errors are presented in parenthesis. The data are 6,620 daily observations. The table report the regression results for the sampling period 1st January 1992 to 29th July 2016.

<table>
<thead>
<tr>
<th>DAX index returns</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.0152***</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.358***</td>
</tr>
<tr>
<td></td>
<td>(0.0501)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,220</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.01

Because this study already has established problems of heteroscedasticity by analyzing the daily returns of the S&P500, there is a probability that the model exhibit heteroscedasticity. Executing the Breusch-Pagan/Cook-Weisberg test allows this study to identify problems of heteroscedasticity. Given a Chi-square of 3845.20 and a very small p-value (see Table 8) we reject the null hypothesis and can conclude that the model suffers from heteroscedasticity. Using heteroscedasticity-consistent standard error estimator (Eick-Huber-White standard error) allows the fitting of the model that does contain heteroscedastic residuals. However, taking heteroscedasticity into account the level of the VIX still has a significant effect on stock market index returns of the DAX at a 1% level. The analysis of the S&P500 showed problems of autocorrelation however using a Newey-West variance covariance estimator did not alter the drawn conclusions and autocorrelation is very common for time series analysis. Therefore, the Newey-West OLS regression is not applied to the DAX analysis and autocorrelation is assumed.

The estimated slope coefficient is negative and statistically significant and again reflects the inverse relationship between volatility and the stock market return of the DAX. The output of the model, which now focuses on the German stock market index, is showing many similarities with the results of regressing the VIX on the S&P500 despite the fact that magnitude of the β.
coefficient is larger and has a higher intercept. The previous analysis of the S&P500 extensively proved that the model is only economically significant if the VIX showed rather extreme fluctuations either downward or upward.

Table 8
**OLS (Robustness) – DAX index returns and VIX**
Robustness check by using Eick-Huber-White standard error estimator. Variables are the DAX return index and the volatility index. The standard errors are presented in parenthesis. The data are 6,620 daily observations. The table reports the regression results for the sampling period 1st January 1992 to 29th July 2016

<table>
<thead>
<tr>
<th>z</th>
<th>DAX index returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX</td>
<td>-0.0152*** (0.00395)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.358*** (0.0755)</td>
</tr>
<tr>
<td>Observations</td>
<td>6.696</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.008</td>
</tr>
<tr>
<td>Breusch-Pagan / Cook-Weisberg test (Chi-square)</td>
<td>6835.23***</td>
</tr>
</tbody>
</table>

This observation also applies to the case of the volatility on the German stock market looking at Table 9. In the analysis of the S&P500 the conclusion was drawn that the model was only significant in case the VIX made an unrealistic price movement. Considering that the magnitude of the model specified on the DAX is larger than the model of the S&P500 and therefore this conclusion can also be applied to the effect of the VIX on the returns of the DAX. This statement is verified by the following calculation in case the VIX drops from the peak value (74) to the nadir (9.36) and vice versa, which creates either a positive or negative leap of 64.64 and results in returns of 1.3405% and -0.6245%. Also the difference between the 25th percentile and 75th percentile is elaborated in Table 9.
This table presents and tests whether the model is economically significant using hypothetical movements of the VIX.

To implement a more realistic value of the change of the VIX in absolute terms this study uses the same procedure as with the S&P500 and is summarized in table 10. By taking the mean of the relative change of the VIX on daily basis and equaling it with the mean of the VIX I can approximate the absolute daily change of the VIX, which gives a realistic input to test whether the model is economically significant and also a change of 1 in the VIX is used as input.

From all the calculations which are made in Table 9 and 10 the inverse relationship is demonstrated however the results are rather small and moreover applying the model to another stock market index, namely the DAX, does not change the previous drawn conclusions.
4.2. Change in volatility (ΔVIX) and stock market returns

In the previous section this study established that there exists an inverse relationship between the level of the VIX and stock market returns, however it only will be recognizable and of valuable input for investors if the magnitude of the leap in the VIX is unrealistic. Therefore, this study examines in the next section if the daily relative change of the VIX has an effect on stock market returns. The fact that the VIX spikes during periods of market turmoil has been established in section 3 and therefore it has become known as the ‘investor fear gauge’ (Whaley, 2008). According to Whaley (2008) two forces are at play. If expected market volatility increases (decreases), investors demand higher (lower) rates of return on stocks, so stock prices fall (rise). This suggest the relation between the rate of change in the VIX should be proportional to the rate of return on the S&P500. In Whaley’ research (2008) he demonstrated the relation between the

Table 10
This table presents and tests whether the model is economically significant using more realistic movements of the VIX.

<table>
<thead>
<tr>
<th>Movement</th>
<th>( \beta_{VIX_{t-1}} )</th>
<th>Model</th>
<th>( R_{t,t} )</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>VIX falls by 1 point volatility ↓ hypothesis: ( R_{t,t} ) ↑</td>
<td>-0.0152 \times (-1) = 0.0152</td>
<td>0.358% + 0.0152%</td>
<td>0.3732%</td>
<td>Economically insignificant → conjecture does not hold by using realistic movement of VIX</td>
</tr>
<tr>
<td>VIX rises by 1 point volatility ↑ hypothesis: ( R_{t,t} ) ↓</td>
<td>-0.0152 \times 1 = 0.0152</td>
<td>0.358% - 0.0152%</td>
<td>0.3428%</td>
<td>Economically insignificant → conjecture does not hold by using realistic movement of VIX</td>
</tr>
<tr>
<td>VIX falls by approximation of daily change by equaling mean of VIX with ( \Delta VIX ) volatility ↓ hypothesis: ( R_{t,t} ) ↑</td>
<td>( \mu_{DAX} VIX \times \mu_{DAX} \Delta VIX ) 21,5583 \times (-0.0054%) = -0.000012 \times -0.0012 = 0.00002</td>
<td>0.358% + 0.00002%</td>
<td>0.3502%</td>
<td>Economically insignificant → conjecture does not hold in case of expected daily change of the VIX</td>
</tr>
<tr>
<td>VIX falls by approximation of daily change by equaling mean of VIX with ( \Delta VIX ) volatility ↑ hypothesis: ( R_{t,t} ) ↓</td>
<td>( \mu_{DAX} VIX \times \mu_{DAX} \Delta VIX ) 21,5583 \times 0.0054% = 0.0012 \times 0.0012 = 0.00002</td>
<td>0.358% - 0.00008%</td>
<td>0.35798%</td>
<td>Economically insignificant → conjecture does not hold in case of expected daily change of the VIX</td>
</tr>
</tbody>
</table>
rates of change in the VIX and the S&P500 is asymmetric, which was both statistically and economically significant, however ‘VIX is more a barometer of investors’ fear of the downside than it is a barometer of investors’ excitement (or greed) in a market rally’ (Whaley, 2008). However, this study is interested if the rate of change in the VIX has an effect on stock market returns and therefore investors could use the change of rate in the VIX as trade signal. To see whether this relationship exists, the following model is used:

\[ r_{i,t} = \alpha + \beta_{\Delta VIX} \Delta VIX_t + \varepsilon_{i,t} \]

4.2.1 S&P500

The relative daily change in the VIX of the S&P500 has been regressed over the returns of the same index. From the output the following model can be constructed:

\[ r_{i,t} = 0.0269 + 0.0028 \Delta VIX_t + \varepsilon_{i,t} \]

Considering the model a positive relationship has been established between \( \Delta VIX \) and stock market returns. However, interpreting the p-value of the regression analysis the null hypothesis cannot be rejected and therefore the \( \Delta VIX \) has not a statistically significant effect on stock market returns. On this basis I can conclude that the daily change in the VIX does not predict either negative or positive stock market returns and therefore the \( \Delta VIX \) should not be directly used as a trade signal. Moreover, taking into consideration that the previous analysis of the absolute value of the VIX had problems of heteroscedasticity and autocorrelation this time series analysis also should have the same problem, which makes the test statistics even less significant and therefore the positive relationship is less effective.
Table 11

**OLS–S&P500 index returns and ΔVIX**

This table presents OLS regression results. The dependent variable is the DAX return index. The independent variable concerns the ΔVIX. Standard errors are presented in parenthesis. The data are 6,696 daily observations. The table report the regression results for the sampling period 1st January 1990 to 29th July 2016.

<table>
<thead>
<tr>
<th>S&amp;P500 index returns</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔVIX</td>
<td>0.0028</td>
</tr>
<tr>
<td></td>
<td>(0.0022)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.0269*</td>
</tr>
<tr>
<td></td>
<td>(0.0138)</td>
</tr>
<tr>
<td>Observations</td>
<td>6.696</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.01

4.2.2 **DAX**

The previous regression also included the analysis of the DAX. In this section also the ΔVIX of the DAX will be analyzed to see whether I can draw the same conclusion, which has been made in the analysis of the S&P500. Doing a regression of the daily change of the VIX over the returns of the stock market index gives the following output:

\[ r_{i,t} = 0.0297 + 0.005ΔVIX_t + \varepsilon_{i,t} \]

Again the relationship is positive although it is not statistically significant, which again allows me to draw the conclusion that the ΔVIX cannot predict either negative or positive stock market returns and therefore should not be used as direct trade signal by investors. As observed with the analysis made in section 4.1, where the impact of the model of the DAX was greater than the S&P500, this model exhibits the same result.
Table 12

**OLS– DAX index returns and ΔVIX**

This table presents OLS regression results. The dependent variable is the DAX return index. The independent variable concerns the ΔVIX. Standard errors are presented in parenthesis. The data are 6,619 daily observations. The table report the regression results for the sampling period 1st January 1992 to 29th July 2016.

<table>
<thead>
<tr>
<th></th>
<th>S&amp;P500 index returns</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔVIX</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.0038)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.0297*</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
</tr>
<tr>
<td>Observations</td>
<td>6.219</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.000</td>
</tr>
</tbody>
</table>

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.01
5. Conclusion

Considering the analyses in section 4, I can conclude that there clearly exists an inverse relationship between the levels of the VIX stock market return of the S&P500. The inverse relationship is statistically significant even when heteroscedasticity and autocorrelation into consideration, however it will only be recognizable and of valuable input for investors if the magnitude of the leap in the VIX is rather unrealistic and therefore is difficult to use it as a direct trade indicator. This means that the hypothesis of Kocken and Jones is theoretically correct, however this situation will hardly occur in practice. Moreover, the model does not have much explanatory power. In addition, this study cannot provide evidence that the rate of change in the VIX has a significant effect on stock market returns and therefore is not a useful tool for investors to directly use it as a trade signal.
6. Limitations and recommendations for future research

6.1 Limitations

Throughout the analysis already a number of limitations of this study has been mentioned. First, because this study has performed a time series analysis with a large sample size there is a probability that the two models will display problems of heteroscedasticity and autocorrelation. The first model concerning the analysis of the VIX over stock market returns both problems have been addressed, however they did not alter the conclusions and they are common in time series analysis.

Second, since stock market returns has been analyzed, there exists many variables and factors that could be considered as leading economic indicators, such as the CCI (consumer confidence index) and could be used as predictive power of stock market returns. Because those variables are not included in the analysis due to simplification the model will probably display problems of the omitted variable bias.

In addition to this, both models are likely to exhibit problems of endogeneity, because one or more explanatory variables could be jointly determined with the stock market returns and volatility. An example of such explanatory variable could be an US 10-year government bond yield (or Germany in case of analyzing the DAX). From a theoretical point of view this could be argued because in case the economy hits a period of temporary economic decline and stock markets are facing negative returns consequently volatility rises. If panic enters on financial markets investors flee to safe havens. Investment opportunities, which are considered as safe havens consists of gold, other precious metals and both short-term and long-term bonds. Considering that investors increase their investments in government bonds during times of economic downturn or crises, consequently means that the price of government bonds increases and the interest rates decreases. To overcome and address this problem future studies can use the 10-year government bond yield as instrumental variable estimator.
Lastly, there could be case of reverse causality seeing that literature (Schwert (1989), and Nelson (1991); Engle and Ng (1993); Zakoian (1994), Bekaert and Wu (2000) and Wu (2001) documented that returns and conditional variance of next period’s returns are negatively correlated. That is, negative (positive) returns are generally associated with upward (downward) revisions of the volatility.

6.2 Recommendations for future research

The evidence available for the effect of the VIX over stock market returns could be further analyzed. Using the VIX among others economic leading indicators could such be used, such as the yield curve, to construct a model that has explanatory power over stock market returns and consequently could be used as a predictive tool for investors to manage their portfolios. In addition, the hypothesis of Kocken and Jones (2014) could be further tested by identifying market crashes and testing whether volatility is low in periods before an actual market downturn.
6. References


Jones, B., Kocken T. (Producers), & Jones, B. (Director). (2014). Boom Bust Boom [Motion Picture]. United Kingdom: Bill and Ben Productions


