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The VIX Puzzle

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Preface

This work marks the end of a two-year master in Financial Economics at the Norwegian University of Technology and Science. We would like to thank our supervisor Knut Anton Mork for valuable guidance and for providing us with useful suggestions and feedback. We would also like to thank Elisabeth Lio Rosvold for proofreading this thesis, your input is greatly appreciated. This thesis is a joint product completed by Sara Hovda Ottesen and Liv Lio Rosvold. Any errors or shortcomings are of our own doing.

Trondheim, June 2018.

Abstract

The CBOE volatility index, VIX, represents the market's expected volatility over the next 30 days, and is supposed to increase when uncertainty rises. Over the last years, this index has remained at historically low levels, despite a considerable increase in geopolitical tension. This phenomenon is referred to as the *VIX Puzzle* and is the basis of this work. We examine how realized volatility and stock index correlation on the S&P 500 affect the VIX, and to what extent they can contribute in explaining the depressed levels. This is done by using ordinary least squares (OLS) with Newey West robust standard errors. According to our results, realized volatility exhibits a positive, but weak effect. We conclude that low realized volatility can explain a low VIX to some degree. Further, we observe a positive relation between stock index correlation and movements in the VIX. This result is not statistically significant, and its contribution to the puzzle is weak. In our analyses we also examine and discuss the relation between economic policy uncertainty and the VIX. We find a positive, but small, relationship and confirm the *VIX puzzle* in our data. As a second contribution to this thesis, we question how well the VIX suits its purpose. By running a simple regression we suggest that the VIX is a biased estimator of future realized volatility. In light of existing literature, we discuss whether the role of the index has changed, as it now may seem like the emergence of VIX derivatives drives the market. In conclusion we question how well the index truly reflects future volatility. In particular, we stress that the trading of VIX derivatives may reduce the role of the index as a reliable measure of future volatility. We consider this an important aspect of the VIX, seeing that it is widely recognized as precisely this.

Sammendrag

Volatilitetsindeksen VIX representerer markedets forventede volatilitet over de kommende 30 dager, og er ment å stige når usikkerhet øker. De siste årene har denne indeksen forblitt på historiske lave nivåer, til tross for en betraktelig økning i geopolitisk spenning. Dette fenomenet omtales som *VIX-gåten* og er utgangspunktet for denne oppgaven. Vi undersøker hvordan indekskorrelasjon og realisert volatilitet på S&P 500 påvirker VIX, og i hvilken grad de kan bidra i forklaringen på indeksens lave nivå. Til dette benyttes minste kvadraters metode (MKM) med robuste standardavvik av typen Newey West. Vi finner at realisert volatilitet viser en positiv, men svak effekt. Det konkluderes med at lav realisert volatilitet til en viss grad kan forklare en lav VIX. Videre viser resultatene en positiv relasjon mellom indekskorrelasjon og VIX. Effekten er imidlertid ikke statistisk signifikant, og dens bidrag til gåten er begrenset. I regresjonsanalysen undersøker og diskuterer vi også effekten av politisk usikkerhet. Vi finner en positiv, men svak, sammenheng, og bekrefter *VIX-gåten* i våre data. Som et ekstra bidrag i dette arbeidet, stiller vi spørsmål ved hele indeksens formål. Gjennom en enkel regresjon konkluderer vi med at VIX er en skjev estimator av fremtidig realisert volatilitet. Basert på dette, og i lys av tidligere litteratur, diskuterer vi om indeksen ikke lenger fungerer som den skal. Mens VIX vanligvis tenkes på som avledet av markedet, har det oppstått produkter omkring selve indeksen, som nå ser ut til å ha drevet markedet. Vår konklusjon er først og fremst at vi stiller spørsmål ved hele indeksens formål. Spesielt med tanke på at handelen knyttet til den, muligens har bidratt til å redusere dens rolle som troverdig indikator av fremtidig volatilitet. Vi ser på dette som et viktig aspekt ved VIX-indeksen, da den er bredt anerkjent som nettopp dette.

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1 Introduction

The Chicago Board Options Exchange's Volatility Index, the VIX, is constructed so as to reflect the market's expectations of future volatility on the S&P 500 stock index. The VIX is derived from put and call options on the S&P 500, and there is today global acceptance of the index being the ultimate barometer for investor sentiment (Asensio, 2013). The underlying logic is that the price of options will increase if the market expects larger stock market movements in the nearby future (Sentana, 2016). A higher reading on the VIX is thus associated with expectations of higher market turbulence. Low levels indicate expectations of low future volatility, and hence represents a more uncritical and complacent market (Fernandes, Medeiros and Scharth, 2013). In other words, this index is expected to rise when uncertainty increases.

The starting point of our work, is that increased political tension over the last few years, has in fact not translated into a rise in the VIX. According to Pastor and Veronesi (2013), political uncertainty should have a strong influence on market volatility. Political statements contain information about what the government intend to do in the future. Market participants respond and act based on such signals, which further will affect stock price movements. The response is stronger when the uncertainty of the political signals is larger (Pastor and Veronesi, 2013). Following the US presidential election of November 2016, one has observed the opposite; markets have not responded to increased political uncertainty, and the VIX has remained at historically low levels (Barletta, Santucci de Magistris and Sloth, 2017). This is by many referred to as the *VIX Puzzle* and is the basis of this thesis. Daily data from January 1990 until February 2018, show that the average value of the VIX is 19.35. Since 2016, however, the index has been stable around 10, which is a level not observed since the months preceding the financial crisis. Combined with high political uncertainty, these low levels have led to both worry and wonder in the financial world.

The purpose of this thesis is to closer examine the VIX Puzzle, using two different approaches:

1. By questioning both the ability of the VIX to predict future volatility, as well as its role as a reliable measure of market risk.

2. By examining how realized volatility and stock index correlation affect the index, as well as examining to what degree political uncertainty in fact does influence the VIX index. The latter is done in order to confirm the puzzle.

The first question is addressed using our own empirical research as well as discussing it in the light of existing literature. In a discussion regarding the puzzle, we find it reasonable to question how well the volatility index in fact suits its purpose. Can the answer simply be that the VIX no longer works as intended? The empirical research includes a simple regression and graphical analyses, in order to test the ability of the VIX to predict future volatility. Earlier literature is used to discuss volatility derivatives, and how the massive growth of this market may have contributed to reducing the reliability of the VIX as a measure of market risk. We seek to answer the second question empirically, using a regression model.

The basis of this thesis was the low VIX levels observed throughout 2017. In February 2018 the VIX left these low levels and spiked following the sudden market drop on US stock exchanges. Does this mean that the puzzle got solved, or that there never was a puzzle to begin with? We think not. The return of the volatility to the financial markets, does not change the fact that the VIX has been extremely low despite a nervous period. The jump in the index only actualized our work even more. Due to the enormous attention towards the market of VIX derivatives and an increasing number of analysts claiming that this market exacerbated the market turmoil, we found the question regarding the reduced reliability of the VIX as both interesting and very relevant.

The rest of this thesis is organized as follows: chapter 2 starts off with a closer look at the main components of the VIX, the calculation of the index, as well as a short introduction to VIX derivatives. In chapter 3 we present existing literature concerning the VIX. A description of our data set is given in chapter 4, including a thorough inspection of the VIX time series properties. In chapter 5 we present the methodologies used in order to test our hypothesis, hereunder both econometric frameworks and graphical analyses. In chapter 6 the main findings from our analyses are discussed. We start off by approaching the question regarding the ability of the VIX to predict future volatility. This is done by running a simple regression using the realized volatility as the dependent variable and VIX as the explanatory variable. From here we move on to examine what influences the index. Using a regression model we test and discuss whether the effect of realized volatility and stock index correlation can explain the low levels of the VIX. In this model we also study the effect of political uncertainty on the VIX. We test and discuss the robustness of our model in chapter 7. In chapter 8 we extend our model with a discussion about what happened in February 2018. We address the increasing market of VIX derivatives and return to the discussion about how well the VIX works as an indicator of future risk. Chapter 9 provides concluding remarks.

2 The CBOE Volatility Index

The Chicago Board Option Exchange (CBOE) publishes several indices of implied volatility. The most popular index is the SPX VIX, which is derived from a wide range of puts and calls on the S&P 500 Index (SPX). It is a measure of the market's expectation of future volatility over a 30 day horizon, and is by many considered the premier benchmark for U.S. stock market volatility (CBOE, 2018). The index is by many referred to as the ”fear gauge”. The intuition behind the VIX is that the demand for portfolio insurance will increase if one expects the future to be more volatile. A low VIX suggests that there are many people willing to sell insurance policies against a market downturn, and few people willing to buy protection against it (Macintosh, 2017). In this chapter, we go through the important components of the VIX, as well as the derivation of the index (see section 2.4).

2.1 S&P 500

The Standard and Poor's 500 Index is a market capitalization-weighted stock index containing 500 of the largest companies in the U.S. It covers approximately 80 % of available market capitalization, and is today widely regarded as the best single gauge of large-cap companies (Standard and Poor's, 2018). The index was developed with a base level of 10.

The companies included are selected by the S&P Index Committee. The index is thus actively managed by a team of analysts and economists at Standard and Poor's. In order to assure that the index displays an accurate picture of the stock market, the committee uses guidelines for stock selection (Blitzer, 2014). Options on the S&P 500 are the most actively-traded index options in the U.S. (Whaley, 2009). As the CBOE Volatility Index is based on these option prices, it is reasonable to consider the VIX as representative of the entire U.S. market as well.

2.2 Options

An option is a contract that offers the buyer the right, but not the obligation, to buy (call) or sell (put) a financial asset at an agreed-upon price at a specific date (McDonald, 2013). The buyer is in control of the option, deciding whether to buy/sell. Therefore the buyer of an option must pay the seller a premium that compensates the seller for being at a disadvantage at expiration (McDonald, 2013). Due to their features, options are used as a hedging instrument to reduce the potential risk associated with the underlying asset.

There are numerous option pricing methods, among which the most widely used is the Black-Scholes option pricing formula. This was developed by Fisher Black and Myron Scholes in 1973 (McDonald, 2013). The idea is that the stock price and the derivative price are both affected by the same underlying source of uncertainty, namely stock price movements (McDonald, 2013). The formula uses risk-neutral valuation, making it independent of investors' risk preferences (McDonald, 2013). This is an advantage, and eases the pricing of options. The two standard Black and Scholes pricing formulas valuate a European Put and a European Call

$$C = SN(d_1) - Ke^{-rt}N(d_2) \tag{1}$$

$$P = Ke^{-rt}N(-d_2) - SN(-d_1) \tag{2}$$

$$d_1 = \frac{ln(S_0/K) + (r - \delta + \frac{1}{2}\sigma^2)T}{\sigma\sqrt{T}} \tag{3}$$

$$d_2 = d_1 - \sigma\sqrt{T} \tag{4}$$

C = Price of the call
P = Price of the put
S = Current price of the stock
K = Strike price of the option
$N(x)$ = Cumulative normal distribution function
r = Continuously compounded risk-free interest rate
σ = Volatility of the stock
δ = Dividend yield on the stock
T = Time to expiration

Initially, the VIX index was based on the Black and Scholes formula. After an update in 2003 the index no longer depends on this framework, making it a model free index. In section 2.4 the updated version of the index is derived.

2.3 Volatility

In order to make sound investment decisions, it is critical for investors to have a sense of the expected risk associated with each investment. This means finding a way to quantify potential losses. In financial markets, volatility is widely accepted as a practical measure of uncertainty and risk (Marra, 2015). The volatility of a stock is a measure of uncertainty about the returns of the stock (Hull, 2009). More specifically, one measures how much the asset return fluctuates around its mean. The most straightforward way to measure volatility, is calculating the standard deviation of historical returns over a particular period of time (Marra, 2015). This is called realized volatility, and is defined by the following formula:

$$\sigma^2 = \sqrt{\frac{252}{n-1}\sum {r^2}_i} \tag{5}$$

Realized volatility, σ^2, depends on the number of observations, n, and the square of the stock return, r_i^2. In order to transform the volatility into an annualized measure we use the number of trading days, which normally is set to 252 (Hull, 2009). The return of the stock is given in equation 6, where $S_{i,t}$ is the stock price at time t.

$$r_i = \ln \frac{S_{i,t}}{S_{i,t-1}} \tag{6}$$

What is important to investors, is being able to predict future levels of volatility. Whereas historical volatilities are backward looking, implied volatilities are forward looking (Hull, 2009). Implied volatility can be derived using option market prices, and is regarded as an expectation of the actual market volatility. The implied volatility of an option is the volatility of the underlying instrument which, when substituted into an option pricing model, will return a theoretical value equal to the current market price of the option (Hull, 2009). By using interpolation and equation 1-4, one can obtain an expression for the implied volatility. The VIX is a measure of volatility implied by option prices on the S&P 500. When agents expect a more volatile market, option prices rise, and this will drive the implied volatility up (Sentana, 2016).

2.3.1 The Statistical Nature of Volatility

Being able to forecast future levels of volatility is one of the most important goals when allocating risk and participating in financial markets (Marra, 2015). While most financial variables remain largely unpredictable, volatility has some stylized characteristics that makes the prediction of its future values quite effective (Marra, 2015). Some of these are volatility clustering and mean reversion.

Volatility Clustering. There is a delay in the reversion of asset returns back to mean levels. This means that there is a tendency of large changes in financial returns being followed by large changes, and small changes being followed by small changes (McDonald, 2013). This tendency is called volatility clustering, and Engel and Patten (2000) report numerous studies in which there has been reported evidence of such behaviour. Clustering suggests that past volatility can be indicative of future volatility, and enhance the forecasting performance (Marra, 2015).

Mean Reversion. In periods with lower volatility, investors tend to reduce their expectations of future volatility (Marra, 2015). They become less risk averse and adjust their market positions accordingly. Lower expectations, make investors become more sensitive to new information, resulting in a larger reaction function and higher volatility. Conversely, in periods of higher levels of volatility, investors increase their expectations of volatility and become less sensitive to new information (Marra, 2015). This will result in decreased volatility in subsequent periods. When volatility is high, it will be pulled back down to its long-run mean, and vice versa when volatility is low (Whaley, 2009). This is another property of volatility – the tendency of reverting to its mean over time. The half-life of volatility is defined as the time it takes to move halfway back to the long-run mean following a deviation from it (Engel and Patten, 2000). According to Marra (2015), the half-life of realized volatility is 15-16 weeks, while the half-life of implied volatility is about 11 weeks (Marra, 2015). Thus, the reversion of implied volatility back to the long-term average takes less time relative to realized volatility, and is hence said to be accelerated (Marra, 2015). The VIX is also asymmetric, meaning that lower levels of implied volatility seem to last longer and to be more stable than elevated levels. Knowing that volatility tends to be both mean reverting and clustering, can increase the ability of volatility forecasting (Marra, 2015).

2.4 Derivation of the VIX

CBOE launched the VIX Index in 1993, and presented a new and updated version ten years later, in 2003. The index was revised in order to reflect a new way of measuring expected volatility, making it a model free estimator (Fernandes, Medeiros and Scharth, 2013). In other words, the VIX no longer depends on the Black-Scholes-Merton option pricing framework, but is rather calculated as a variance swap on the underlying S&P 500. A variance swap is a forward contract on future realized variance (Hull, 2009). The revised formula is based on the fact that the variance rate of an asset between time 0 and time T can be replicated using a portfolio of put and call options. Hence, the VIX is now extracted directly from option prices (Jiang and Tian, 2007).

Two important changes were implemented in 2003. The index went from being based on options on the S&P 100 (OEX) to options on the much bigger S&P 500. In addition, while the original-formula index used only at-the-money strikes, the new formula now includes a much broader range of strike prices Whaley (2009).

The model free estimator of the implied volatility used to calculate the VIX reads[1]:

$$\sigma^2 = \frac{2}{T} \sum \frac{\Delta K_i}{K_i^2} e^{RT} Q(K_i) - \frac{1}{T} \left[\frac{F}{K_0} - 1 \right]^2 \tag{7}$$

T $=$ Time to expiration

F $=$ Forward index level desired from index option prices

K_0 $=$ First strike below F

K_i $=$ Strike price of the i_{th} out-of-the-money option

ΔK_i $=$ Interval between strike prices - half the difference between the strike on either side of K_i

R $=$ Risk-free interest rate to expiration

$Q(K_I)$ $=$ Price of an option with strike K_i

Each option is weighted by the inverse of the square of its strike price (CBOE, 2018). This ensures that options with lower strike prices are given a higher weight, making up for the fact that options are more sensitive to changes in volatility as their strike prices increase (Steadman,

[1]See appendix A for the detailed derivation of the VIX.

2014). Calls and puts are included up to the point where two consecutive strike prices are found to have zero bid prices(Ahoniemi, 2006).

Formula 7 is applied to so-called near-term and next-term options, with maturities of T_1 and T_2, respectively. This yields an expression for both σ_1^2 and σ_2^2, components which are published by CBOE under ticker symbols "VIN" and "VIF". Near-term options always have more than 23 days to maturity while next-term options always have less than 37 days to maturity, ensuring a constant average of 30 days. The single VIX number then stems from calculating the 30-day weighted average of σ_1^2 and σ_2^2, taking the square root of that value and multiplying by 100 (CBOE, 2018):

$$VIX = 100\sqrt{\left(T_1\sigma_i^2\left[\frac{N_{T2} - N_{30}}{N_{T2} - N_{T1}}\right] + T_2\sigma_2^2\left[\frac{N_{30} - N_{T1}}{N_{T2} - N_{T1}}\right]\right)\frac{N_{365}}{N_{30}}} \tag{8}$$

N_{T1} $=$ number of minutes to settlement of the near-term of options

N_{T2} $=$ number of minutes to settlement of the next-term of options

N_{T30} $=$ number of minutes in 30 days

N_{T365} $=$ number of minutes in a 365-day year

2.5 VIX Derivatives

The VIX is not a tradable asset and the replication of its spot value is both difficult and costly. Direct exposure to it is thus principally achieved through the trading of financial assets that are linked to the index – the VIX derivatives (Mencia and Sentana, 2013). When introduced in 1993, one of the purposes of the VIX was to provide an index on which investors could buy future and option contracts on volatility (Whaley, 2009). A future contract is an agreement on buying or selling an asset or commodity at a specific time in the future, to an agreed-upon price (McDonald, 2013). A future contract on an index includes only a cash delivery dependent on the value of the index when the contract matures. The CBOE launched futures on the VIX index in 2004 and VIX options in 2006. These products offer a way to gain exposure to the future level of the VIX, enabling investors to trade volatility, independent on the direction of the stock price movements (CBOE, 2018). In 2009 the first exchange traded product (ETP) linked to VIX was constructed.

ETPs are products based on VIX futures and allow retail investors to put wagers on volatility. In practice they work as a normal mutual fund, but can be traded directly from a brokerage account (Sentana, 2016).

The trading of volatility have grown tremendously over the years and is today a highly active market. By 2017 there were more than 40 different ETPs linked to the VIX available for retail investors. According to Sentana (2016), the trading of VIX-related products represented in the summer of 2016 more than 4 % of total volume trade on US exchanges (Sentana, 2016). An important aspect of this growth is the observed shift in the trading from large investment banks to ordinary retail investors (Barton, 2018). One of the many ETPs was the XIV, an exchange traded note constructed to mirror the inverse performance of the VIX. This fund, issued by Credit Suisse, delivered a -1x exposure to first- and second-month VIX futures[2] (ETF, 2018). Going long in the XIV, is equivalent to bet on the markets to remain calm.

[2] More specifically, it follows the S&P VIX Short-Term Futures Index.

3 Existing Literature

Research on the VIX index is vast, with several papers covering the index and its properties. A popular topic amongst researches has been the predictive power of the VIX, implementing the index in econometric models in attempt to forecast future levels. Another well covered topic has been examining the relation between the VIX and its derivatives. However, there are not many papers covering what have affected the historical levels of the VIX. Nevertheless, earlier literature provides useful information for our thesis, and this chapter surveys some of it.

3.1 VIX as a Forecast of Future Implied Volatility

A common effort has been forecasting implied volatility by looking at the VIX index and its past levels. The first aim of these papers has been to find the best econometric model in forecasting future levels of the VIX index. Ahoniemi (2006) finds that the best model, an ARIMA(1,1,1), predicts the direction of the change for over 60 percent of the trading days (Ahoniemi, 2006). Ahoniemi (2006) modeled six different models and concluded that the inclusion of GARCH terms did not improve forecast. Fernandes, Medeiros and Scharth (2013) examine the time series properties of the VIX, concluding that a pure HAR model is the best due to the persistent nature of the index. In order to predict the future, they investigate the causal effects of different macro variables (Fernandes, Medeiros and Scharth, 2013).

The papers differ in their conclusion, and no clear answer is given as to what econometric model works best when forecasting the VIX. It is important to separate our study from these papers. While their goal has been forecasting the VIX and examine whether useful forecasts could be made when modeling the index, our study goes beyond this literature to study the VIX puzzle, particularly in 2017. We aim to discover how some particular explanatory variables influence the VIX index. Yet, several of these earlier papers have provided us with great information regarding both the time series properties of the VIX, and also some noteworthy explanatory variables.

3.2 The VIX Puzzle

There are several studies covering political uncertainty and its influence on the risk levels of financial assets. Pastor and Veronesi (2013) develop a model in which they find that stock market volatility responds to political uncertainty. This relation is confirmed in the paper by Goodell and Vähämaa (2012). They focus on the effect of the uncertainty related to US presidential elections on market fluctuations. According to their empirical findings, option-implied stock market volatility is affected by the political uncertainty around US presidential elections. Kelly, Pastor and Veronesi (2016) give support to this relation when they report that political uncertainty is priced into the option market. Caldara and Iacoviello (2018) have developed an index measuring geopolitical risks, called the GPR index. They find that higher GPR leads to a decline in the real activity and lower stock returns for a short period. Investors carefully consider geopolitical risks when investment decisions are made, and rank geopolitical risk ahead of economic policy uncertainty (Caldara and Iacoviello, 2018). They also conclude that geopolitical threats lead to elevated levels of uncertainty, which in turn induce a persistent decline in investments.

In recent years volatility and political uncertainty seem to have become disconnected phenomena. This is in literature referred to as the *VIX Puzzle* and summarizes the concern that the market volatility does not fully embrace the overall riskiness in the financial world (Barletta, Santucci de Magistris and Sloth, 2017). Barletta, Santucci de Magistris and Sloth (2017) confirm this puzzle in their study of hedging strategies. Pastor and Veronesi (2017) justify the VIX Puzzle by referring to their own model and paper from 2013. Their theory suggests that volatility and uncertainty should indeed correlate, but only given a certain precision of the political signals. They explain the VIX puzzle by the fact that ever since the presidential election in November 2016, political signals have become considerably less precise (Pastor and Veronesi, 2017).

3.3 Stock Market Correlation and Volatility

When the correlation between stocks is low, they move independently of one another. This will dampen total movements in a stock index, even if the stocks fluctuate individually. The correlation coefficient between stocks can be considered as a measure of common risk shared by stocks that does not depend on their individual volatility (Berk and DeMarzo, 2013).

Loretan and English (2000) evaluate correlation breakdowns during periods of market volatility. They argue that during periods of high volatility, correlation amongst asset prices can differ from those seen in a more quiet market. Quarters in which volatility is high, are usually quarters in which correlation is high as well, confirming a relationship between volatility on the stock market and correlation between assets. They conclude that supervisors of financial institutions should be aware of this link between volatilities and correlation when evaluating a firm's risk management, especially when using value at risk (VAR) models (Loretan and English, 2000).

Mandy Xu, Director of Equity Derivatives Strategy in Credit Suisse, posited in a report that sector correlation on the S&P 500 index has been at an all time low throughout 2017 (Xu, 2018). The last time sector correlation was observed at these levels was in 2000, right before the burst of the dot com bubble. In an article published by Financial Times, Xu says that the record breakdown in sector correlation explains why the VIX has been so stable at low levels, despite the fact that the underlying sectors are moving (Rennison, 2017). Our thesis further investigates this statement, and examine whether correlation between the stocks included in the S&P 500 and the index itself, might have contributed to the low VIX levels.

3.4 VIX and Risk Management

In addition to examine how some specific factors influence the VIX, we also question how well the index actually suits the purpose of being an indicator of future volatility. Jiang and Tian (2007) show that the VIX may underestimate the true volatility by as much as 198 index basis points or overestimate it by as much as 79 index basis points. The econometric analysis carried out by Berger, Dew-Becker and Giglio (2017), reveals that it is the realized volatility that seems to have a significant impact on the real economy, and not uncertainty about the future. In other words, they suggest that the level of the VIX has little or no impact on the real economy, and that its relevance as a risk management tool thus is limited. Bongiovanni, De Vicentiis and Isaia (2016), evaluate the predictive power of the index, by organizing the paper around two research questions. The first one is based on historical data, from which they conclude that the VIX is a biased estimator, but that it contains strong information regarding future realized volatility. The second method is to compute a Value at Risk (VaR) to examine the performance of the VIX, where they find the VIX to be less effective (Bongiovanni, De Vicentiis and Isaia, 2016)

Corrado and Miller (2005) asses the forecast quality of the VIX index by comparing two econometric methods. They compare the results from an OLS regression with the results from an instrument variable regression. Both univariate and multivariate regression analyses are examined. They find that using instrument variables does not improve the regression results compared to OLS in the multivariate case. Thus, the standard OLS provides useful regression output when trying to evaluate the forecast quality of the VIX index. They also find that the VIX index yields an upward biased volatility forecast, but compared to using historical volatility, the VIX index is more efficient (Corrado and Miller, 2005). Another interesting observation by Corrado and Miller (2005), is that the inclusion of realized volatility as an explanatory variable only provide a trivial result to the R-squared. Thus, its explanatory power concerning movements in the VIX is small. This will be further examined in our thesis by testing the hypothesis that low realized volatility on S&P 500 explains the low VIX levels. We also consider the possibility of VIX not being a good predictor of future realized volatility.

What does it mean if the VIX index does not work as a true predictor of future volatility, but continues to be considered one? Gennaioli, Shleifer and Vishny (2011) study the market of shadow banking preceding the financial crisis of 2007–2009. They explain how neglecting tail risks can create financial fragility and lead to recession. This can be seen in relation to Hyman Minsky's hypothesis of financial instability (Minsky, 1992). Minsky (1992) claimed that periods of low volatility will lead market participants into a false perception of risk, resulting in overleverage and increased vulnerability to recessions. Barletta, Santucci de Magistris and Sloth (2017) make a distinction between low volatility and high volatility regimes, and claim that during periods of subdued volatility, the use of volatility as the only measure of uncertainty can lead to dangerous investment decisions. In an article published by Forbes, Friesen (2017) suggests that the low realized volatility is one of the reasons we observe low implied volatility. He states that investors have little fear of the future due to a very favorable past (Friesen, 2017). This could be an example of neglecting risk, where investors look backwards.

3.5 VIX and its Derivatives

Following the introduction of VIX futures in 2004, several research papers have covered the topic of VIX derivatives. Some papers seek to discover the best valuation method for VIX derivatives, while others study the relation between VIX and its derivatives. Sentana (2016) argues, that even though these new types of assets offer additional hedging and investment opportunities, correct use of them requires reliable valuation models. Mencia and Sentana (2013) asses the VIX derivatives valuations and investigate the possibility of mispricing. They find that some of the valuation methods used on the VIX derivatives do not account for the strong presence of heteroskedasticity nor the presence of autocorrelation. Thus the possibility of mispricing is high.

Shu and Zhang (2010) study the relationship between the VIX index and the VIX futures. They examine whether the VIX futures contracts could have some price discovery function, meaning that futures prices lead spot VIX. When using an Error Correction Model (ECM), they find this to be true to some extent. However, when using a modified Baek and Brick nonlinear Granger test, they find that VIX and VIX futures react simultaneously to new information. They stress the importance of further investigating whether VIX and VIX futures are predictable by one another. Though the VIX futures do have some price discovery function, they conclude that, due to the unstable predictive power, the futures market is still information efficient (Shu and Zhang, 2010). Nossman and Wilhelmsson (2008) argue that the futures contract price is an upward-biased estimate of future levels of the VIX index, claiming that models including a risk premium is more successful in predicting the direction of change in the VIX index. They find that the inclusion of a negative risk premium predicts the direction of change correctly in 73 percent of the time in the one day ahead forecast. The test is implemented by examining whether information from the term structure of volatility futures can predict future changes in implied volatility (Nossman and Wilhelmsson, 2008).

The papers by Nossman and Wilhelmsson (2008) and Shu and Zhang (2010) are of interest because we wish to examine whether the market correction in February was driven by the VIX derivatives. Our thesis discusses the possibility that the trade of VIX futures leads to changes in the VIX index.

4 Data

The first aim of this thesis is to investigate why the VIX has been stable at low levels. We seek to find out what factors have affected the VIX index by examining some various independent explanatory variables, with focus on realized volatility, stock index correlation and economic policy uncertainty. This chapter takes a closer look at the data included in our analysis. The data is reported daily, from 02.Jan.1990–28.Feb.2018. As the stock exchange is closed on weekdays and public holidays, these days have been omitted from the dataset. Thus, a year in this dataset is approximately 252 days. The data is collected from Yahoo Finance (YahooFinance, 2018*a*) and Macrobond. Descriptive statistics and characteristics of the VIX index will be presented, along with some description of the independent variables included in the regression analysis.

4.1 Descriptive Statistics of VIX

The level of the VIX index changes every second and historical data is reported in open, close, high and low values. These values can differ substantially from one another as the index can fluctuate during the opening hours. A jump will be reflected in the high values, while a fall will be reflected in the low values. In our analysis, we use the closing values. The VIX index time series is collected from Yahoo Finance (YahooFinance, 2018*b*). The data set for daily VIX index levels starts in January 1990 and ends in February 2018, and contains 7096 observations. Table 1 presents the descriptive statistics of the VIX index.

Table 1: Descriptive statistics VIX index 1990-2018

Variable	**Mean**	**Std.dev**	**Min**	**Max**	**Skewness**	**Kurtosis**	**Observations**
VIX	19.354	7.8725	9.14	80.86	2.0788	7.5745	7096

We observe large variation in the data, with a minimum value of 9.14 and a maximum value of 80.86. The standard deviation is low at 7.85. We also observe some excess kurtosis and a positive skew.

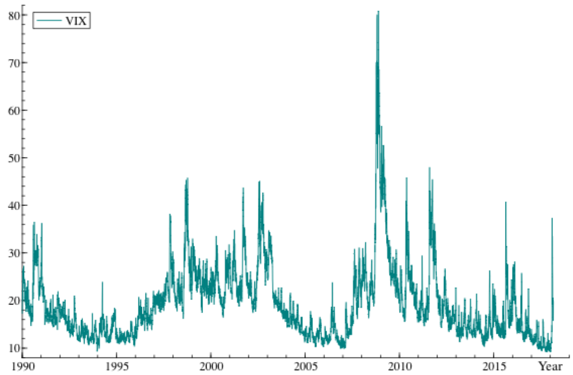

Figure 1: Daily VIX level, 02.01.1990 - 28.02.2018

Figure 1 plots the daily VIX levels from January 1990 - February 2018. There is no clear pattern but we observe the large variation in the index. The index swings around short periods with high volatility, and longer periods with low volatility. The highest peaks occur in periods in which there have been market setbacks. The highest peak, around 2008-2009, was the global financial crisis following the Lehman Brothers collapse in September 2008.

The Augmented Dickey-Fuller test (ADF) rejects the null hypothesis of a unit root at the 1% level. Thus, there is no indication of a unit root in the VIX series. Figure 2 shows the autocorrelation function (ACF) and the partial autocorrelation function (PACF) using 20 lags. The green bars represent the ACF while the red bars represent the PACF. We observe that the ACF exhibits a positive autocorrelation and strong dependence between current and past values of the VIX. This indicates a high degree of persistence, suggesting that the series is non-stationary. Further, we look at the PACF. This is helpful in determining the order of the auto regressive (AR) process. The PACF immediately decays to zero after lag 1, which suggests that the VIX follows an AR(1) process. Figure 3 plots the distribution of the VIX. We observe a clear skew to the right and some excess kurtosis. The red line represents the smoothed distribution of the VIX index, while the blue line represents the normal distribution reference. Normality of the index was tested using Shapiro-Wilk and Shapiro-Francia. Both rejected the hypothesis of normality at the 5 % significance level. Thus, by both visual inspection and numerical testing, we can conclude the the data is not normally distributed. This is not surprising seeing that normality cannot be expected for a series that do not take on negative values.

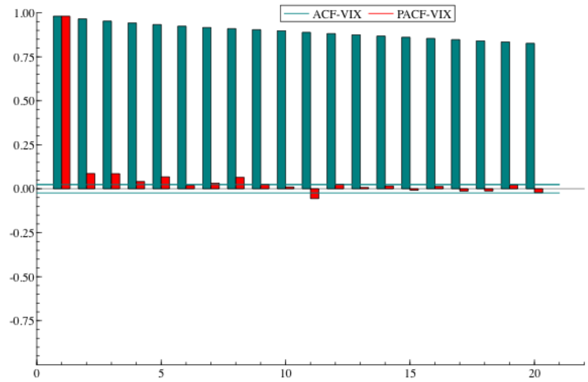

Figure 2: ACF and PACF: daily VIX level

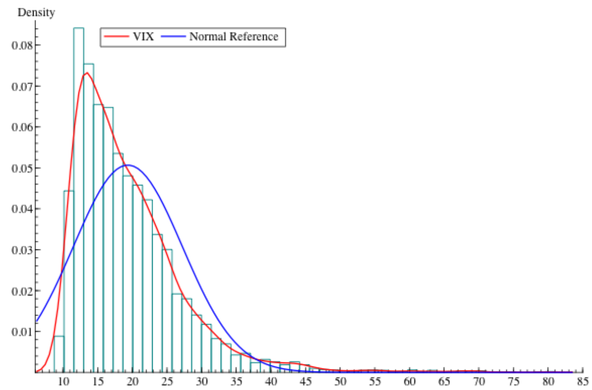

Figure 3: Density: daily VIX level

Due to the indication of non-normality and non-stationarity, the data should be both differenced and log-transformed. The differencing accounts for non-stationarity, while the log-transformation helps dealing with the skewness. This new variable, called RVIX, is now a growth rate rather than an index level. Figure 4 plots the VIX in first difference. The series oscillates around a long-term mean, providing strong indications of stationarity. Looking at figure 5, the ACF and PACF help us ascertain this indication. We observe that the non-stationarity in the original variable is no longer present. Figure 6 plots the distribution of RVIX. The distribution is less skewed and has slightly less excess kurtosis, with values of 0.89257 and 6.9463 respectively. The change in kurtosis is insignificant, but the decrease in skew is helpful when further modeling.

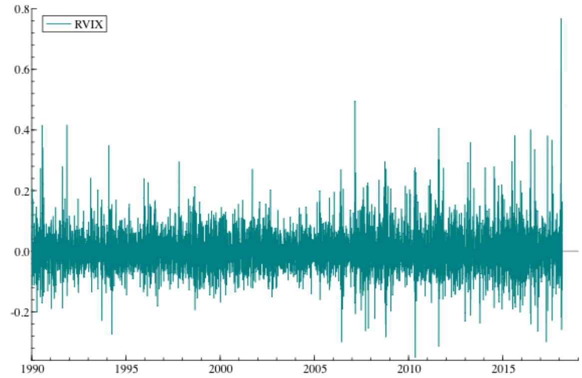

Figure 4: VIX first differences

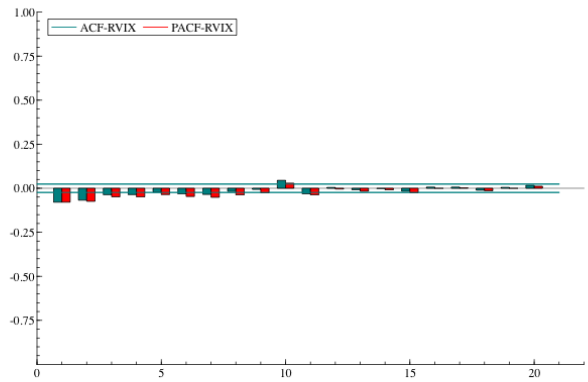

Figure 5: ACF and PACF: first differences of log-transformed VIX

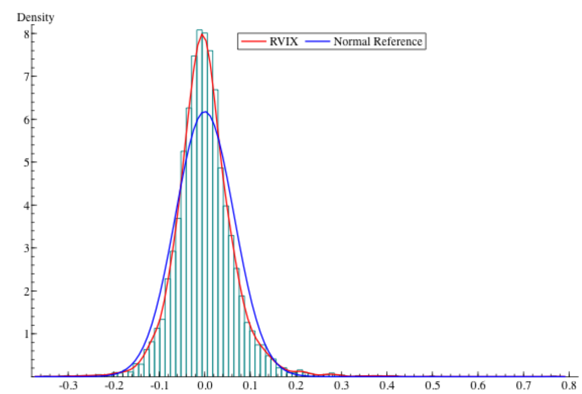

Figure 6: Density: first difference of log-transformed VIX

4.2 Financial Data

To understand why the levels of the VIX has been abnormally low throughout 2017, we want to examine what outside factors influence the VIX. Data for the S&P 500 index was collected from Yahoo Finance (YahooFinance, 2018*a*). Data for the MSCI EAFE Index, the U.S. Dollar Index (DXY) and VIX futures were collected from Macrobond while the Economic Policy Uncertainty Index (EPU) was collected from policyuncertainty.com (Baker, Bloom and Davis, 2016).

4.2.1 Data Description

In our analysis we have included data that may have an impact on the VIX index. The choice of explanatory variables has been inspired by both earlier research and more recent articles. Some variables are included as control variables, while some are included for further investigation. The data are reported on a daily basis, from January 1990 to February 2018. The following variables are included in the analysis. See Appendix B for descriptive statistics.

Realized Volatility[3]. The VIX index reflects expected future volatility on the S&P 500 index, implied by option prices. We want to test to what degree low realized volatility translates into low implied volatility. We expect realized volatility to affect the market's expectations about future volatility positively. For the time period 1990–2018, we have computed the realized volatility for every day, representing the volatility on the S&P 500 over the previous 30 days. This variable is also used when discussing the predictive power of the VIX.

Stock Index Correlation[4] . Low average index correlation suggests that the individual stocks move more independently, causing the total movements in the index to be dampened (Berk and DeMarzo, 2013). Small movements in the S&P 500 index indicate low volatility in the market, and so we expect a positive relation between index correlation and the VIX. As a proxy for the total S&P 500 index, we have used the 55 largest stocks, measured by market-cap. These make up for about 50 % of the total market value of the S&P 500. The variable is derived by calculating the daily average rolling correlation between each of these stocks and the index

[3]Realized volatility is calculated using equation 5.

[4]See Appendix C for calculation, as well as an overview of the 55 companies.

itself. A common problem when using index data, is that stocks are included and excluded at different times, causing the composition of the index to vary. We argue that the average correlation achieved by using 55 companies, is a sufficient proxy for the total average index correlation.

EPU Index. When uncertainty rises, the VIX index is expected to rise as well. According to Pastor and Veronesi (2017), political uncertainty has a strong influence on market volatility. A rise in uncertainty should induce more market turmoil (Caldara and Iacoviello, 2018). The Economic Policy Uncertainty Index (EPU) seeks to capture the overall political uncertainty in the U.S. The index is developed by Baker, Bloom and Davis (2016), and is based upon the following three components: Newspaper coverage of economic policy uncertainty, number of federal tax code provisions and disagreement among economic forecasters. The index is normalized by setting the mean equal to 100 (Baker, Bloom and Davis, 2016). Thus, an index number above 100 reflects higher political uncertainty than normal, while an index level below 100 points to lower political uncertainty than normal. The relationship between the EPU index and the VIX should be positive.

VIX Futures. Investment exposure to the VIX index is only achieved through the trading of its derivatives (Asensio, 2013). These are financial instruments that will pay off based on the future level of the underlying VIX. The most actively traded derivative is VIX futures, upon which the popular ETPs are based. After being launched on the CBOE in 2004, the demand for VIX futures has grown rapidly. Shu and Zhang (2010) find that the prices of VIX futures do have predictive ability on the VIX. Some claim that this highly active derivative market now also influences the stock market. Among these are Bloomberg, calling the market drop in February 2018 a *VIX event* (Keene, Ferro and Fox, 2018). As an extension of our model, we include daily trading volume of VIX futures. This is done in order to examine this claimed relation. The data is collected from Macrobond and is available from March 2004. We expect a positive relation between the trading volume of VIX futures and the VIX.

S&P 500 Return. Seeing that the VIX index represents expected volatility on the S&P 500 over the next 30 days, there should be a clear relationship between these two. If market volatility is expected to increase, investors will demand a higher premium on stocks, and so the stock price will fall (Whaley, 2009). In addition, a fall in the market may increase investors' demand for hedging strategies in order to reduce further losses. We expect the relation to be inverse, as confirmed in earlier studies (Fernandes, Medeiros and Scharth, 2013). The data is from the period January 1990 to February 2018.

S&P 500 Trading Volume. This variable reflects the total trading volume of all 500 stocks included in the S&P 500 index. The S&P 500 trading volume is included because a high trading volume may indicate panic selling. This could be connected to increased implied volatility (Ahoniemi, 2006). Thus, we expect an increase in the trading volume to be followed by an increase in the VIX. The variable is measured in percentage change.

U.S. Dollar Index. The U.S. Dollar Index (DXY) measures the value of the U.S. Dollar relative to some foreign currencies. When the dollar strengthens compared to the other currencies the index moves upward. Strengthening of a currency happens when the demand for that currency increases. This variable is included as a control variable in order to reflect some of the macroeconomic conditions (Fernandes, Medeiros and Scharth, 2013). The expected relationship between DXY and the VIX index is that an increase in DXY will lead to a decrease in VIX.

MSCI EAFE Index. The MSCI EAFE index represents large- and mid-cap equities in 21 developed countries in Europe, Australasia and the Far East. When looking at the historical levels of the VIX, it seems to fluctuate much more in the case of larger global events. This suggests that bigger events in the global economy may have an impact on investors' belief about the future volatility on the American stock market. This explanatory variable is thus supposed to capture tendencies in the global economy, and works as a control variable. An increase in MSCI EAFE index should lead to a decrease in the VIX.

5 Methodology

This chapter provides an insight to how our research questions can be solved empirically. First, we describe how to evaluate the VIX index' ability to predict future volatility. Then, we take a closer look at the statistical properties of volatility. At the end of the chapter our econometric model is presented.

5.1 VIX as a Predictor of Realized Volatility

Before running the main regression with VIX as the dependent variable, we start off by examining its historical forecasting power. The VIX is widely accepted as an indicator of future volatility in the stock market (Asensio, 2013). But how well has it actually performed as a predictor? We examine this in two different ways. First, we run a simple regression with realized volatility ($Rvol$) as the dependent variable. Secondly, we compute the expected monthly range of S&P 500 returns implied by the VIX, and then analyse how often the realized monthly return has ended up within the predicted intervals.

5.1.1 Simple Regression

VIX is, by definition, a measure of the market's expectations of volatility over the next 30 days. Hence, we must compute the realized volatility over a 30-day period, and then compare this number with the level of the VIX at beginning of that same period. We run a simple regression with $Rvol$ as a dependent variable and the level of the VIX as the only explanatory variable.

$$Rvol_t = \alpha + \beta VIX_{t-30} + \epsilon_t \tag{9}$$

The volatility implied by the VIX tends to exceed the subsequent realized volatility of the S&P 500, on average (Pedersen and Rennison, 2012). This may be due to the fact that investors are willing to pay for their portfolio insurance, ensuring that options trade at a premium (Whaley, 2009). We expect this premium to end up in the constant term, which further implies that the α-coefficient should have a negative sign.

In order to conclude that VIX is a good predictor of future realized volatility, we want to keep the hypothesis of β = 1. The rejection of this hypothesis will suggest that VIX is an imprecise predictor of volatility.

5.1.2 Probability Intervals

Another way to examine the performance of the VIX, is to compute what we have called probability intervals. This method is inspired by Whaley (2009)[5]. This methodology makes use of the fact that the volatility implied by VIX represents the likely range of possible stock index levels that the market expects.

From the cumulative standard normal density function, we know that a random drawn number has a 50 % chance of being within 0,6745 standard deviations of 0 and a 75 % (95 %) chance of being within 1.1504 (1.9600) standard deviations of 0 (McDonald, 2013). If we assume that the VIX is at 20, chances are 50-50 that the return on the S&P 500 over the next 30 day-period, will be up or down by 3.9 %. For the same VIX-level, there is a 75 % (95 %) chance that the 30-day stock return will be +- 6.5 % (11 %). These expected ranges are computed using the following relations:

Expected range at 50 % = 0,1947 * VIX
Expected range at 75 % = 0.3321 * VIX
Expected range at 95 % = 0.5658 * VIX

VIX is an annualized measure, and hence we convert the number into a monthly value by scaling the coefficients by the square root of 12[6] (Steadman, 2014).

We have recorded the level of the VIX at the beginning of each month, 339 observations in total. Based on these numbers and by using the three formulas above, we computed the 50 %, 75 % and 95 % expected ranges. Further, we calculated the realized volatility for these 339 months and examined how many times the realized volatility fell outside the different ranges.

[5]One of the developers behind the CBOE VIX Index.

[6](0,6745/$\sqrt{12} = 0.1947$) $(1.1504/\sqrt{12} = 0.3321)$ $(1.9600/\sqrt{12} = 0.5658)$.

5.2 Statistical Properties of Volatility

There are some specific statistical features linked to volatility which improve the ability to forecast its future levels compared to other financial assets (Marra, 2015). As described in section 2.3.1, these features are, among others, volatility clustering and mean reversion. We discuss whether these properties can provide some useful insight to the VIX puzzle. We emphasize that these analyses are done by visual inspections using graphs, and are not tested in a model.

5.2.1 Volatility Clustering

As mentioned in section 2.3.1, volatility clustering is the tendency of high volatility days to be followed by high volatility days (McDonald, 2013). Such an effect suggests that past values are indicative of future values. Clustering behavior leads to persistence, and could in this case contribute to the explanation of why VIX has been at depressed levels for such a long period. Clustering effects are also relevant in the discussion about the ability of the index to predict future levels of realized volatility. In order to reveal a possible clustering effect of the VIX, we have plotted the current month's volatility against the previous month's volatility.

5.2.2 Mean Reversion

Just as a clustering effect leads to persistence, the presence of mean reversion indicates an anti-persistent behavior. As described in section 2.3.1, the presence of mean reversion indicates that there is a normal level of the VIX to which the index eventually will revert (Engel and Patten, 2000). What is important to us, is whether this reversion back to the long-term average is less pronounced in periods of low volatility. According to Marra (2015), the mean reversion of implied volatility is indeed asymmetric. Lower levels of implied volatility seem to last much longer and to be more stable than elevated levels.

In order to capture this effect of the VIX index, we have studied weekly observations from January 1990 to August 2017[7]. We started with the 10 % highest and lowest closing values, and

[7]Lower observations were observed after August 2017, but were left out as we needed to study how they developed over the subsequent 24 weeks.

examined the path of the average value of these observations over the subsequent 24 weeks. The results are presented in figure 8.

5.3 Econometric Method

The aim of this work is not to forecast future VIX levels, but to examine its history. To investigate the relationship between VIX and realized volatility, stock index correlation and political uncertainty, we use an Ordinary Least Squares (OLS) regression. We present our model specification in this section, results in chapter 6, while econometric obstacles will be discussed in chapter 7.

5.3.1 Ordinary Least Squares with Newey West Standard Errors

As our data suffers from both serial correlation and heteroskedasticity, we use the Newey West robust errors. These standard errors are calculated conditional on a choice of maximum lag, computed from a distributed lag of the OLS residuals (Wooldridge, 2015). Newey and West (1986) argue that the maximum lag should be a function of the number of observations, setting the lag length equal to $T^{1/4}$, where T is the number of observations in the model (Newey and West, 1986).

Our estimated model is an autoregressive (AR) model. This is because we include a lagged value of the dependent variable, Y_t, as a control. To better determine what happens first, it would be reasonable to include lagged values of the explanatory variables. This can also help avoid potential problems linked to feedback effects (Wooldridge, 2015). However, as we operate with data from financial markets, we argue that information from a lagged value will be too delayed. Investors react immediately to new information, and so we use contemporaneous data.

$$RVIX_t = \beta_0 + \beta_1 Rvol_t + \beta_2 Corr_t + \beta_3 EPU_t + \beta_4 RVIX_{t-1} + \beta_5 S\&PRet_t + \beta_6 S\&PVol_t + \beta_7 MSCI_t + \beta_8 DXY_t + \epsilon_t \quad (10)$$

The reason for including a lagged value of the $RVIX$ is the high degree of persistence. We have argued that the level of the VIX yesterday will affect the level of the VIX today. By including one lag we capture the effect of yesterday's change in the VIX on today's change. The $S\&PRet$ reflects the percentage return of the S&P 500 index. The $S\&PVolume$ reflects the daily percentage change in S&P 500 volume. $Rvol$ represents the percentage change in realized volatility, as it has been differenced and logged. As realized volatility and the VIX index have the same dimensions they should also have the same time series characteristics. DXY, the dollar exchange rate, is also calculated as a percentage daily change, and the same goes for the $MSCI$, the MSCI EAFE index. The $MSCI$ reflects information that will be available to US investors before the local markets open for trading (Ahoniemi, 2006). EPU reflects the daily percentage change in the Economic Policy Uncertainty index, as it has been differenced and logged. The correlation coefficient, $Corr$, is in first difference, and so it reflects the daily change in correlation.

In addition, we include the daily change in the trading volume of VIX futures, together with its first lag. The lagged value is included in order to account for the fact that the CBOE operates with extended opening hours for the trading of VIX-linked derivatives (CBOE, 2018). ETPs are rebalanced every day in the after-market time periods, in order to manage to deliver the promised daily return. What effect this rebalancing may have, will come clear only the following trading day. Thus, we find it reasonable to assume that there may be a delayed effect. VIX futures became available in March 2004[8], and so this variable appears only in model 5, 6 and 7. These results from these variables will be presented in section 7, and the effects will be discussed in section 8.

[8]This is why Fut and Fut_1 do not appear in equation 10.

6 Results

In this chapter, we present and discuss our main findings. First we address the VIX as a predictor by discussing the results from the simple regression and the statistical nature of the VIX. Then we test our hypotheses about realized volatility, index correlation and political uncertainty, discussing to what extent these can contribute in explaining the low VIX levels.

6.1 VIX as a Predictor of Realized Volatility

As the VIX is regarded an indicator of future volatility, it is important to address its historical forecasting power. In the following we go through the results of our simple regression and the probability intervals.

6.1.1 Simple Regression

The first step in our analysis was running a simple regression with realized volatility as the dependent variable. The result from this regression is presented in table 2.

Table 2: Regression Output: Simple Regression

	Model 1
VIX	0.855***
	(0.0155)
Constant	-0.0103***
	(0.00270)
Observations	7096
R-Squared	0.562

Standard errors in parantheses

*** $p<0.001$, ** $p<0.05$, * $p<0.01$.

Implied volatility derived from option prices tends to exceed realized volatility due to a risk premium (Whaley, 2009). We expected this effect to be captured by the constant term, and thus to observe the α-term having a negative sign. As reported in table 2, our simple regression confirms this expectation, with α = -0.0103, being statistically significant at the 1 % level.

Further, we observe that the VIX has a positive effect on realized volatility. Hence, an increase in the volatility index will be followed by an increase in realized volatility. The estimated β-coefficient of the VIX is 0.855. This result is statistically significant at the 1 % level, and the null hypothesis of $\beta = 0$ is rejected[9]. Based on such a large coefficient value, one could argue that VIX is a good predictor of realized volatility. However, in this case, we find it important to distinguish between a "good" predictor and a "correct" predictor. As described in section 5.1.1, if VIX is to be considered a reliable measure of future volatility, then we should expect a β-coefficient equal to 1. We compute a Wald test in STATA. With a p-value of 0.0000, the hypothesis $\beta = 1$ is rejected at the 1 % significance level. Thus, the VIX is a biased predictor. This raises some questions about how well the VIX actually suits its purpose. Bongiovanni, De Vicentiis and Isaia (2016) address and comment on the inability of the VIX to correctly capture extreme market moves. Our regression, though very simple, supports their conclusion. The VIX being a biased predictor of the future is also confirmed by Jiang and Tian (2007), Bongiovanni, De Vicentiis and Isaia (2016) and Corrado and Miller (2005).

6.1.2 Probability Intervals

The results from our calculations with probability intervals are presented in table 3. For comparison, we have examined four different time ranges. For the entire period as a whole (1990–2018), we have computed 339 monthly returns on the S&P 500. Looking at the table, we see that 63.4 % of the returns fell inside the 50 %-range predicted by the VIX. 92.9 % fell inside the 75 %-range and 98.8 % fell inside the 95 %-range. From the other three periods we read similar results. We notice that in the period 2014-2018, the monthly returns on S&P 500 ended inside the 95 %-range every time. These numbers are in line with the calculations of Whaley (2009).

A first reading of these results might indicate that the VIX is a good predictor of what is to come. But we must not forget what these ranges actually measure, a VIX level of 20 indicates that there is a 95 % chance that the realized return on S&P 500 the next month will be up or down by 11 %. If the stock index then ends up moving only 1.5 %, this procedure will still

[9] Hence the *** in table 2.

suggest that the prediction of the VIX was correct. But that does not necessarily make it a good prediction. At least, not a very precise one. In fact, the implied ranges are not very informative when evaluating the accuracy and precision of the VIX and its indications about the future. What we observe is that the estimated ranges are quite wide relative to the actual return. The reason for this may be related to the risk premium mentioned in the previous section. Options trade at a premium because investors are willing to pay more for their portfolio insurance (Whaley, 2009). This causes the VIX index to almost always exceed the actual realized volatility on S&P 500.

In conclusion, this procedure provides some information about the ability of the VIX to forecast future movements, but is not very helpful when examining its accuracy. At the most we can say that the probability intervals reveal that VIX works *reasonably* well as a measure of risk regarding future realized volatility.

Table 3: Probability intervals for different time periods

Time Period	**50%-range**	**75%-range**	**95%-range**
1990–2018	63.3 %	92.9 %	98.8 %
2000–2006	65.5 %	92.8 %	100 %
2007–2013	66.7 %	91.7 %	98.8 %
2014–2018	66.7 %	91.16 %	100 %

6.2 Statistical Properties

In the following we address the clustering effect and mean reversion of the VIX. This is done by visual inspections of graphs.

6.2.1 Volatility Clustering

Figure 7 displays the results from plotting the current level of the VIX (VIX_t) against the level of the VIX one month ago (VIX_{t-30}). As expected, there is a clear, linear relationship between recent and current levels of implied volatility. This linear relationship is indicative of VIX exhibiting clustering behavior, and thus confirms the tendency of implied volatility to be persistent.

We find this to be quite an important element in our discussion regarding the ability of the VIX to forecast the future. The tendency of large (small) changes being indicative of further large (small) changes, strengthens the argument about VIX not reflecting more than the current level of market volatility. Such behavior would suggest that whenever VIX turns out to be correct in its forecasting of future realized volatility, it can partly be explained by the clustering phenomenon. As our figure indicates; the implied volatility over the next 30 days tends to be more or less the same as the volatility implied for the previous 30 days.

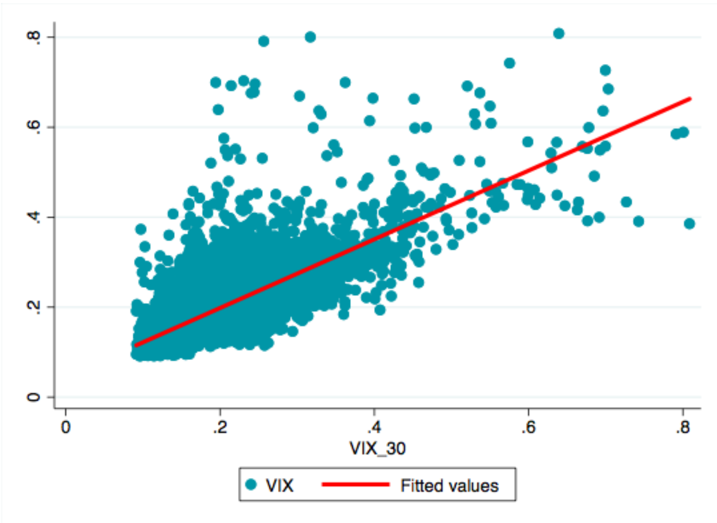

Figure 7: Clustering of the VIX

As stated by Bongiovanni, De Vicentiis and Isaia (2016), the VIX has not succeeded in predicting any of the larger market corrections. This may simply be due to fact the financial markets in the periods preceding these drops, were calm and stable. And in calm periods, the VIX will tell us that the future will be calm as well. In the year preceding the financial crisis, the average realized volatility on the S&P 500 was only at 8.2 % - a level considerably below the long-term mean of about 15 %.

6.2.2 Mean Reversion

Figure 8 exhibits the mean reversion of the VIX Index. The grey line represents the long-term average of 19.17[10]. The red and blue lines are derived by studying weekly closing values of the VIX, starting from January 1990 to August 2017. From this we extracted the 10 % highest and 10% lowest values[11], and studied how the VIX developed from these extreme values over the subsequent weeks. More precisely, we examined the VIX-level after 4, 8, 12, 16, 20 and 24 weeks, and computed the average values. We found that the mean of the 10 % highest weekly observations was 36.47, and that the average value of these observations four weeks later was 33.02. The rest of the average values is given in table 4. The red line in figure 8 is derived from these. The path of the 10 % lowest values are represented by the blue line and given in table 4.

Table 4: Development of top and bottom deciles over 24 weeks

Weeks after observation	**10 % highest**	**10 % lowest**
0	36.47	11.10
4	33.02	12.27
8	29.93	12.62
12	27.39	12.83
16	26.26	12.96
20	24.93	12.62
24	24.03	13.16

As expected, it seems that the mean reversion of the VIX is asymmetric. Lower levels of the index move towards the grey line at a lower pace. Put another way, the VIX declines with a greater magnitude when at elevated levels. This confirms what has been observed in the recent years; depressed levels of the volatility index are more stable and persistent than higher levels. From a visual inspection of the movements in the VIX (see figure 1), we see that the index periodically makes large jumps, but that it also falls back down rather quickly.

This statistical feature of volatility, that we now have proven to be applicable to VIX, cannot contribute to the explanation of *why* the volatility index has been so low. It is only an observable

[10] When using daily data, the long-term average is 19.35.

[11] The top and bottom deciles are in total 290 observations.

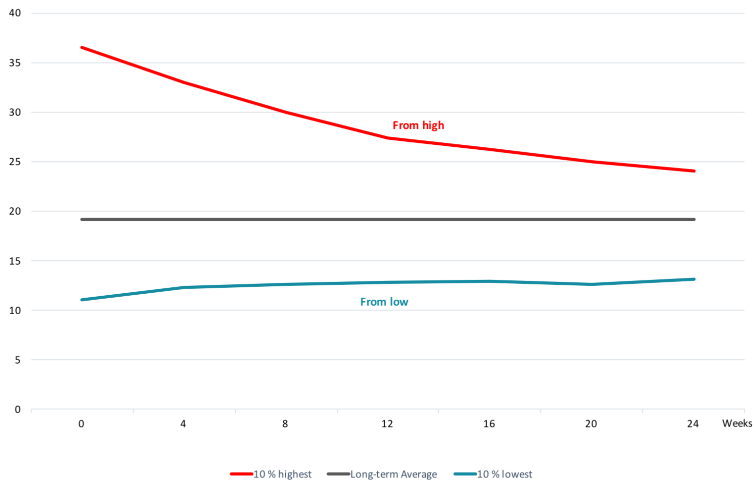

Figure 8: Asymmetric mean reversion of VIX level

phenomenon which hardly can serve as a causal explanation of anything. In fact, in a mean reverting time series, a decrease tends to be followed by an increase (Engel and Patten, 2000). This is only a statistical feature which tell us that the VIX eventually will return to its normal levels. During times of calm and stable markets, investors tend to reduce their expectations of future volatility. They become less risk averse, which consequently makes them more sensitive to new information (Marra, 2015). This will lead to an increase in the amplitude of returns and more volatility. Conversely, in periods of market turmoil and larger price fluctuations, investors will prepare themselves on more volatility and adjust their positions accordingly. This will make them less reactive to new incoming signals and lead to lower volatility in subsequent periods (Marra, 2015). Hence, depressed levels of the VIX will eventually go back up, but it may take some time.

6.3 Empirical Regression Analysis and Discussion

In the following we present our results from the regression analysis. First we discuss the impact of realized volatility, $Rvol$. Then we address the effect from average stock index correlation, $Corr$, before discussing the relationship between the VIX and Economic Policy Uncertainty, EPU. Ultimately, we present the control variables included, and a short review of their impact on the VIX index. Table 5 displays the result of our OLS regression with Newey West standard errors.

Table 5: Regression output equation 10

	Model 2
	(1990-2018)
Rvol	0.145***
	(0.0246)
Corr	0.865
	(0.637)
EPU	0.00286***
	(0.000824)
RVIX_1	-0.0970***
	(0.0106)
S&PRet	-3.847***
	(0.151)
S&PVolume	0.019***
	(0.00313)
MSCI	-0,437***
	(0.0797)
DXY	-0.432***
	(0.141)
Constant	0.00112**
	(0.000495)
Observations	7091
R-Squared	0.5245
Adj R-Squared	0.5240

Standard errors in parantheses

*** p<0.001, ** p<0.05, * p<0.01.

6.3.1 Realized Volatility

In 2017 the average realized volatility of the S&P 500 was low at 0,07. The last time realized volatility was observed at similar levels were in 1995 and 2006. Based on Minsky's hypothesis regarding financial instability, and the statement of Friesen (2017) that low realized volatility is one of the reasons for low observed implied volatility, we test whether realized volatility can contribute in explaining the low VIX levels.

From the results, we see that $Rvol$ has a positive effect on the VIX, and is statistically significant at the 1% level. This implies that an increase in realized volatility can be followed by an increase in the VIX Index. This is in line with Engel and Patten (2000) who claim that volatility exhibits persistence, and that shocks to volatility today will influence the expectations of future volatility (Engel and Patten, 2000). Low levels of volatility may therefore lead investors to have little fear of the future because of a promising past (Friesen, 2017). Gennaioli, Shleifer and Vishny (2011) argue that a few bad news will not change the investors' mind set because of the good state still being representative (Gennaioli, Shleifer and Vishny, 2011).

Periods of low volatility will induce market participants to take on more risk (Danielsson, Valenzuela and Zer, 2015), because abnormally low levels of volatility may not be representative for the total riskiness of the market (Barletta, Santucci de Magistris and Sloth, 2017). Thus, when investors make investment decisions solely based on the low volatility and a favorable past, the danger of neglecting tail risk increases. Minsky (1992) argues that during periods of financial stability, the market participants become complacent, and points out that stability will eventually lead to instability. Based on this, the positive relationship between realized volatility and the market's expectations about future volatility, is expected.

However, the effect of realized volatility is surprisingly small. By looking at figure 9, we would expect a stronger relationship between the two. The graph displays realized volatility and the VIX index over the period 2007–2010[12]. We observe that they fluctuate in the same periods, and that the VIX seems to jump right after a spike in realized volatility.

Both the results from our regression analysis and the graphical inspection confirm the positive

[12] We have chosen a short interval in order to display a clear picture of how the two indexes move together.

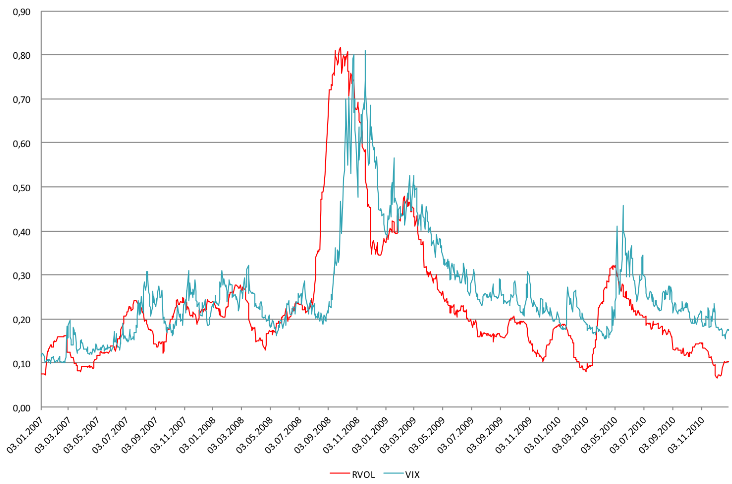

Figure 9: Daily VIX level and daily realized volatility, 03.01.2007–31.12.2010

relationship between realized volatility and the VIX index. Our results confirm the findings of Engel and Patten (2000) and the statement of Friesen (2017). However, the effect is smaller than what we expected. We also find that the inclusion of $Rvol$ only provides a trivial increase in the R-squared, confirming the observation done by Corrado and Miller (2005). The small effect may be due to noise when using daily data. This will be examined in the robustness chapter.

6.3.2 Stock Index Correlation

The correlation between a stock and the S&P 500 index indicates to what extent the stock and the index move in the same direction. In this section we discuss the effect of average stock index correlation on the movements in the VIX. From table 5 we observe that the coefficient $Corr$ has a positive effect on $RVIX$, but that this effect is not statistically significant.

The overall riskiness of a stock can be divided into idiosyncratic and systematic risk. The former represents the risk that is specific to a single company, and hence is diversifiable, while the latter represents the risk that all companies are exposed to (Berk and DeMarzo, 2013). The more systematic risk the stocks on the S&P 500 consist of, the more the stocks will move together, and the larger will the total fluctuations of the index be. Low stock correlation will, on the other hand, cause the individual stocks to dampen each other's movements, reducing the total fluctuations of the index. In the case of small movements in the S&P 500, investors will not gain so much from buying options on it. As the level of the VIX depends on option prices on the S&P 500, lower demand will lead to lower VIX (CBOE, 2018). According to our model, a decrease in average stock index correlation is associated with a decrease in the VIX.

In table 6 we have plotted the average stock index correlations for different time periods. We observe that the average correlation for 2017 and the start of 2018 is below the average value for the period as a whole ($0.4751 < 0.5341$). This is also a period in which the VIX has been abnormally low. Correspondingly, the period with the highest average correlation coincides with the period in which we find the highest recorded VIX-levels. That is, during the global financial crisis (2008–2009).

Table 6: Average stock index correlation calculated for different time periods

Period	**Average Stock Index Correlation**
1990-2018	0.5341
1990-1999	0.4795
2000-2006	0.4829
2007-2010	0.6275
2008-2009	**0.6758**
2011-2014	0.6296
2015-2018	0.5814
2017-2018	**0.4751**

These low levels of stock correlation observed in the recent months, have not occurred since 2001 and 2006, the years preceding the Dotcom bubble burst and the financial crisis, respectively. Mandy Xu stated that the low volatility observed throughout 2017, was indeed a result of the low sector correlation on the S&P 500, which also was at historical low levels during 2017 (Rennison, 2017). Figure 10 displays the monthly average stock index correlation, represented by the red line, and the VIX, represented by the blue line, over the time period January 1990–February 2018. It seems that the two variables covary to some extent, and that spikes in the VIX coincide with elevated levels of the average correlation. This can then be seen as supportive to our empirical results that reveals a positive relationship between stock index correlation and the VIX Index. However, as this result was nonsignificant, it is only valid for our sample.

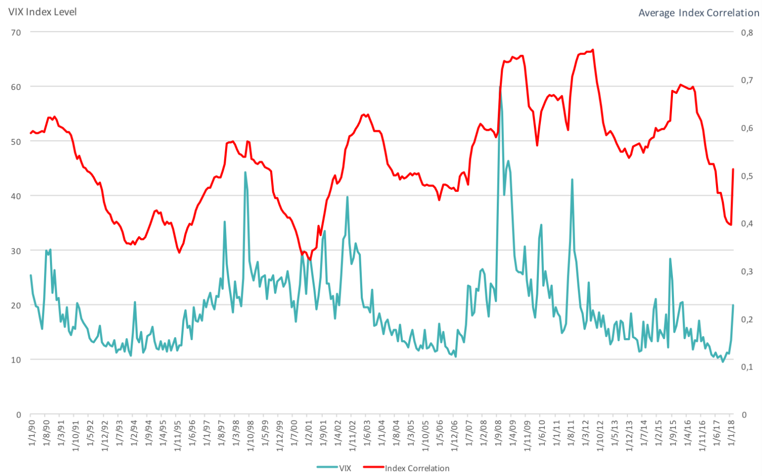

Figure 10: Monthly stock index correlation and monthly VIX level, Jan 1990–Feb 2018

6.3.3 Political Uncertainty

The regression shows that the economic policy uncertainty index (EPU) has a statistically significant positive effect on the VIX index at the 1 % level. This result is in line with existing literature claiming that if uncertainty increases, volatility should increase (Pastor and Veronesi, 2012). As the estimated coefficient is very small, the effect of the EPU on the VIX is rather weak. Baker, Bloom and Davis (2016) find a correlation coefficient of 0.58 between the VIX index and EPU when looking at monthly data (Baker, Bloom and Davis, 2016). This suggests that we should have seen a more powerful relation between the two indexes. When looking at daily data, we find the correlation to be 0.33. Daily data usually hold more noise, and could explain why we observe a smaller effect. A graphical inspection, see figure 11, suggests that the two indexes covary to a great extent, but also reveals that the gap between them has increased since 2016.

Pastor and Veronesi (2013) argue that market volatility is an increasing function of political uncertainty and the precision of political signals (Pastor and Veronesi, 2013). Thus, they argue that if signal precision is low, volatility can be low even if uncertainty is high. They claim that investors have become sceptical that announcements from politicians will have much to do with their future political actions. Especially in 2017, there has been a series of contradictory political signals (Pastor and Veronesi, 2017).

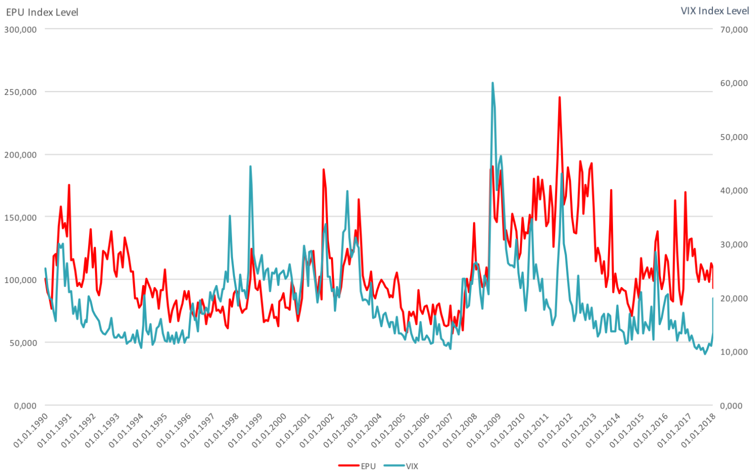

Figure 11: Monthly VIX level and monthly EPU index, Jan 1990 - Feb 2018

As mentioned in chapter 3, Caldara and Iacoviello (2018) have developed an index measuring geopolitical risk (GPR). They state that high geopolitical risk should induce a fall in the stock market and a decline in the real economy, and claim that over 75 % of investors are worried about geopolitical risk (Caldara and Iacoviello, 2018). High uncertainty suggests volatile markets, which should be captured by the VIX. We test whether the use of GPR, reveals a stronger relationship between uncertainty and the VIX. The effect was small and insignificant, and there was no clear relationship between the two indexes.

As uncertainty can be troublesome to measure, the way the EPU index is constructed, may be another reason for why we observe a small effect. In addition, some of the papers written about this topic use monthly data rather than daily, which could have an impact on the result. The elevated levels of the EPU Index observed recently, have not translated into higher readings on the VIX, despite the positive relation found in our analysis. In this case, we find the argument of Pastor and Veronesi (2013) about signal precision to be both interesting and relevant.

6.3.4 Controls and Summary

We notice that the model reports a R^2 of 0.5245. This tells us that the included variables explain 52.45 % of the total variation of RVIX. The first lag of the differenced VIX, $RVIX\_1$, has a negative impact on $RVIX$. This is not surprising as the VIX *level* has a positive, but less than unity, autocorrelation, as shown in section 4.1. The negative effect of $RVIX\_1$ confirms, in other words, that yesterday's *level* of the VIX has a positive impact on today's level. We observe that the S&P 500 index and the VIX index have an inverse relationship. If the return on S&P 500 index increases the VIX index will decrease. We also notice that the effect between the two is strong. This result is not surprising, as the inverse relationship between the two is well documented in earlier studies (Fernandes, Medeiros and Scharth, 2013).

According to our model, the trading volume of the S&P 500 and the VIX exhibit a positive relationship. Increased trading volume on the S&P 500 can be an indication of panic selling (Ahoniemi, 2006). The positive relationship between the index and the trading volume is therefore as expected. The DXY index is included to capture some of the macroeconomic aspects of the U.S. economy (Fernandes, Medeiros and Scharth, 2013). We observe an inverse relationship between the DXY and the VIX, which is expected as the DXY will increase when the business cycle is in a boom. The MSCI EAFE incorporates information from the global financial markets. We observe that a rise in the return of the MSCI index is associated with decreasing returns of the VIX. This suggests that movements in the global economy impact the U.S. markets. The effect from all the control variables included are statistically significant at the 1 % level.

We find a positive effect from both $Rvol$ and $Corr$ on the VIX. Seeing that both realized volatility and average stock index correlation have been at low levels lately, the depressed levels of the VIX, may be explained by this. Despite increased uncertainty, it may be that investors weigh these factors more than political signals. In particular if they consider the signal precision to be low. A favorable past of low realized volatility make investors believe that future realized volatility will be low as well (Friesen, 2017). Low correlation on the S&P 500 may dampen the effect from political tension, as it may affect companies differently. However, our results reveal small point estimates, and so we cannot conclude that these variables alone help explain the *VIX Puzzle.*

7 Robustness

In this chapter we examine and discuss the robustness of our model. First, we address obstacles when modeling time series, and how they where solved, before the results from running our model in different time periods are deliberated. Ultimately, we discuss the results from running our model using monthly data compared to that of using daily data.

7.1 Time Series Characteristics

Economic time series contain some stylized features and properties that can lead to serious violations of the underlying model assumptions. This section will discuss some of these violations, and how they were solved. Test results are provided in Appendix D.

If standard inference tests are to be valid, stationarity is a requirement. A time series is stationary if the mean, variance and autocorrelation are constant over time (Enders, 2015). As discussed in chapter 4, the VIX does not have the properties of a stationary time series, which is also the case for some of the included explanatory variables.[13]. The solution to this problem was to differentiate these variables. As seen in figure 4 in chapter 4, differentiating of the VIX led to stationarity.

For the estimated parameters to be Best Linear Unbiased Estimator (BLUE), constant variance is required. If this is not the case, the model suffers from heteroskedasticity. In the presence of heteroskedasticity, the estimators will still be consistent and unbiased, but the variance of the estimators will be biased. As the standard deviation of the predictors is solely based on the variance, the t-statistics will no longer follow a t-distribution and standard inference tests will not be valid (Wooldridge, 2015). Presence of heteroskedasticity was tested using Breusch-Pagan and ARCH-LM. These tests rejected the null hypothesis of constant variance at the 5 % significance level, hence our model suffers from heteroskedasticity. This problem was accounted for using robust standard errors. The robust regression adjusts the standard errors so that the t-statistics become valid.

[13] We ran an Augmented Dickey-Fuller (ADF) test for all variables, in order to reveal any presence of a unit root, see Appendix D.

Autocorrelation in the residuals will also cause bias in the estimated standard errors. Positive autocorrelation will lead OLS to underestimate the variance of the estimated parameters, and consequently the t-statistics to be too high (Wooldridge, 2015). This will increase the chances of mistakenly rejecting a null hypothesis that is in fact true. The Durbin Alternative test and Breusch Godfrey test for higher order autocorrelation both rejected the null hypothesis of no autocorrelation. This indicates that the residuals in the standard OLS regression are autocorrelated. This was also accounted for using robust standard errors. The Newey-West standard errors are robust to both serial correlation and heteroscedasticity, ensuring that standard inference tests are valid (Newey and West, 1986).

A more complicated problem is the possibility of misspecification, a problem that could lead to biased and inconsistent estimators. A common misspecification problem is when important explanatory variables are omitted, leading to omitted variable bias (Wooldridge, 2015). This problem is more difficult to correct as it can be hard to discover what variables that might be omitted, and often there is no clear solution. The Ramsey RESET test for omitted variables test was run, and the null hypothesis of no omitted variables was rejected. This indicates that our model is misspecified in some way. When modelling, there is always a possibility that more lags should be included, or that some important variable is omitted. We tested whether the inclusion of several lags could improve our results, but this was not the case.

Multicollinearity amongst the explanatory variables, indicates that some of the included variables capture the same effect. The presence of multicollinearity, will not lead to biasedness and inconsistency, but the standard errors will become larger, yielding the results uninteresting and harder to interpret (Wooldridge, 2015). We compute the variance inflation factor (VIF) and conclude that there seems to be no problem of multicollinearity in our data.

Based on the previous discussion, our model, given in equation 10, is estimated using a standard OLS with Newey-West robust standard errors. This method guarantees that the variance-covariance matrix is positive definite (Newey and West, 1986). The estimated standard errors are now consistent, and the standard inference tests are valid as the t-statistics will be correct. However, it is important to be aware that using robust standard errors does not remove the autocorrelation or heteroscedasticity. The use of this method only accounts for these limitations, making it a next best solution. From this, we argue that our econometric framework has some flaws, but is nonetheless valid for examining relations between variables.

7.2 Simultaneity and IV Method

In order to obtain unbiased and consistent coefficients, exogeneity is required (Wooldridge, 2015). That is, no correlation between the error term, u_t, and the independent variable, x_t, included in the regression model:

$$Cov(x_t, u_t) = 0$$

The violation of this assumption will cause an endogeneity problem, a problem that can arise due to omitted variables, measurement errors or simultaneity (Wooldridge, 2015). Simultaneity occurs when the dependent variable and one or more of the independent variables, are jointly determined (Wooldridge, 2015).

In our main regression model, we test whether realized volatility has a significant effect on VIX. However, based on the definition of VIX, together with earlier discussions in this thesis, we should also expect the opposite effect. That is, a feedback from VIX to $Rvol$. As long as the VIX can predict any part of realized volatility, simultaneity may be present, even if the VIX is a poor predictor. In their study of volatility forecasting, Granger and Poon (2003) find that option implied volatility contains a substantial amount of information about future realized volatility.

Simultaneity can be solved using the method of instrumental variables, henceforth the IV method. This involves replacing the endogenous variable, x_t, with an instrument, z_t, that is assumed to satisfy the following assumptions:

$(i) Cov(z_t, u_t) = 0$
$(ii) Cov(z_t, x_t) \neq 0$

As an instrument, we use the realized volatility of the Dow Jones Industrial Average Index (DJIA). Just like the S&P 500, this index is widely regarded as a good proxy for US market movements. In order to determine its relevance, we used the two-stage least square approach

(2SLS). First step includes estimating the relationship between the endogenous variable and the instrument, controlling for the other independent variables (Wooldridge, 2015).

$$Rvol = \beta_1 Corr + ... + \beta_n RvolDOW \tag{11}$$

If the null hypothesis of β_n = 0 is rejected by a large margin, the relevance criteria (ii) is met. With a correlation coefficient of 0.9877, and a rejection of the null hypothesis at the 1 % level, we argue that $RvolDOW$ is a strong instrument. The endogenous variable ($Rvol$) is then replaced with the predicted value ($\widehat{Rvol}$) from equation 11.

$$RVIX = \beta_1 Corr + ... + \beta_n \widehat{Rvol} \tag{12}$$

In STATA we compute the IV estimator by using the command for 2SLS, where we find that the use of $RvolDow$ as an instrument to yield statistically significant results [14]. We perform the Durbin-Wu-Hausman test for endogeneity in order to determine whether the IV method is indeed necessary. According to this test, we cannot reject the null hypothesis of exogeneity.

As an alternative instrument, we also test $Rvol$ lagged by 30 days. Using this as an instrument, the Durbin-Wu-Hausman test suggests that we have an endogeneity problem. However, we find this instrument to be weaker than that of $RvolDOW$. With a correlation coefficient between $Rvol$ and $Rvol\_30$ of -0.40, combined with the results from the IV estimation, we consider $Rvol\_30$ to be a weak instrument. In the event of the instrumental variable being a weak instrument, the result of the endogeneity test might not be valid. Because we find $Rvol\_30$ to be a weak instrument, we use the results from the Durbin-Wu-Hausman test with $RvolDOW$ as an instrument. And, thus, we argue that our model does not suffer from simultaneity, suggesting that IV estimation is superfluous. The results from the IV estimation given in Appendix E give support to our model.

[14]See appendix E for results from IV estimation.

7.3 Results from Alternative Estimations

We now present the results from three alternative estimations. First, we estimate our model using multiple time periods in order to check whether the effects differ over time. Then, we test whether the use of lagged explanatory variables reveal different results compared to contemporaneous data. Ultimately, we use monthly data to test whether noise in the daily data affects the results.

7.3.1 Multiple Time Periods

To check whether the included explanatory variables have affected the VIX index differently over time, equation 10 was estimated with different time spans for various time periods. This was also done to examine whether VIX futures contributed to the rise of the VIX in February 2018. The impact of the futures contracts will be discussed in chapter 8.

We have looked at five different intervals, in which the number of observations varies. The time periods estimated are 1990–1999, 2000–2006, 2007–2010. 2011–2014 and 2015–2018, and the results from these estimations are given in table 7. The first period incorporates the strong economic growth in the 1990's and the rise of the tech bubble. The second period captures the Dotcom burst, and is also the period leading up to the financial crisis. The third period reflects the financial frisis, the fourth the aftermath of the crisis, as well as the European Debt Crisis. The last period captures what has affected the VIX in the most recent years.

Realized volatility has a statistically significant effect on the VIX in each of the time periods, although the size of the effect varies. The results reveal a surprisingly small effect, as we expected a greater impact. Still, based on these results, we argue that past levels of volatility will affect expectations about future volatility, positively. The low observed realized volatility might have contributed to the low VIX levels as argued by Friesen (2017), though in a small manner.

Looking at the average stock index correlation, the estimated coefficient has only had a statistical significant effect on the VIX level in the period 1990–1999. For the succeeding time periods we observe a positive effect, but not a significant one. These estimations confirm the results we found in our main model. We also notice that the size of the effect has decreased over the intervals. However, we notice in Model 7, that the point estimate is much larger, and the

Table 7: Regression output from multiple time periods

	Model 3 (1990–1999)	**Model 4** (2000–2006)	**Model 5** (2007–2010)	**Model 6** (2011–2014)	**Model 7** (2015–2018)
Rvol	0.0874***	0.0940***	0.228***	0.0979***	0.135**
	(0.0290)	(0.0279)	(0.0754)	(0.0356)	(0.0571)
Corr	1.929**	0.648	0.159	0.0664	1.517
	(0.812)	(0.710)	(0.776)	(0.495)	(1.128)
EPU	0.00362***	0.000835	-0.00131	0.00370	0.00183
	(0.00122)	(0.00110)	(0.00272)	(0.00303)	(0.00284)
RVIX_1	-0.128***	-0.0688***	-0.116***	-0.0764**	-0.0689**
	(0.0196)	(0.0172)	(0.0261)	(0.0298)	(0.0337)
S&PRet	-3.931***	-3.360***	-2.917***	-6.047***	-7.962***
	(0.170)	(0.129)	(0.219)	(0.333)	(0.506)
S&PVolume	0.0137***	0.0106**	0.0332***	0.0221**	0.0173
	(0.00398)	(0.00471)	(0.00884)	(0.00862)	(0.00109)
MSCI	-0.472***	-0.235*	-0.435***	0.0257	-0.287
	(0.123)	(0.123)	(0.168)	(0.221)	(0.422)
DXY	-0.390*	-0.0468	-0.532*	-0.813**	-0.787*
	(0.199)	(0.196)	(0.301)	(0.411)	(0.443)
Fut	-	-	0.00234	0.00325	-0.00358
			(0.00263)	(0.00271)	(0.00274)
Fut_1	-	-	0.00288	0.00101	-0.00430*
			(0.00223)	(0.00261)	(0.00234)
Constant	0.00253***	-0.000526	-8.71e-05	0.00314**	0.00286*
	(0.00081)	(0.000781)	(0.00129)	(0.00126)	(0.00170)
Observations	2525	1757	1005	1003	795
R-Squared	0.4410	0.5628	0.6217	0.6725	0.6791
Adj R-Squared	0.4392	0.5608	0.6183	0.6692	0.6750

Standard errors in parantheses. *** p<0.001, ** p<0.05, * p<0.01.

standard error smaller. Still, it is not significantly different from zero on the 5% level.

Regarding the EPU index, we observe the same as for the stock index correlation. The estimated coefficient has only had a statistical significant effect on the VIX in the period of 1990–1999. The effect is positive but, as discussed in section 6.3.3, relatively small. For the remaining time periods, no significant effect is detected. Unexpectedly, we also find a negative effect in the period 2007–2010. Considering these results, we cannot conclude that the EPU Index influences the VIX in a notable manner. If the EPU Index is indeed a reliable measure of uncertainty, our results confirm the *VIX Puzzle*.

How powerful effect the control variables have on the VIX, vary. The return on the S&P 500 index has had a stronger effect in the most recent periods, and is statistical significant at the 1 % level. The impacts of DXY, $MSCI$ and the $S\&Pvol$ oscillate in how powerful they have been, and for some of the intervals the results are not statistical significant. We also notice that the size of the effect of $RVIX\_1$, varies between periods, but is significant in all the models estimated.

Regarding the development of the R^2, we observe this to be greater as the time periods become shorter and more recent. This can be due to fewer degrees of freedom, and thus, less total variation to explain (Wooldridge, 2015). The adjusted R^2 accounts for the number of included explanatory variables, and the number of observations. We observe an increase in both. They take on values between 0.55 and 0.68, except for the interval 1990-1999 where R^2 is lower. The results from estimating over multiple time periods are in line with the results from Model 2.

7.3.2 Lagged Explanatory Variables

In order to better determine what happens first it would be reasonable to include lagged values of the explanatory variables. As discussed, market participants react immediately to new information, and we argue that information from a lagged value will be too delayed. However, we still find it interesting to examine whether the use of past values yield similar effects as contemporaneous data. All explanatory variables are lagged by one day, making it an autoregressive distributed lag model. Table 8 presents the results from estimating equation 13. As information from $MSCI$ is known prior to the opening of the U.S. stock markets, this variable is not lagged.

$$RVIX_t = \beta_0 + \beta_1 Rvol_{t-1} + \beta_2 Corr_{t-1} + \beta_3 EPU_{t-1} + \beta_4 RVIX_{t-1} + \beta_5 S\&PRet_{t-1} + \beta_6 S\&PVol_{t-1} + \beta_7 MSCI_t + \beta_8 DXY_{t-1} + \epsilon_t \quad (13)$$

Table 8: Regression output lagged explanatory variables

	Model 8
	(1990-2018)
Rvol_1	-0.0201
	(0.0227)
Corr_1	-0.765
	(0.612)
EPU_1	-0.000384
	(0.00108)
RVIX_1	-0.0646***
	(0.0219)
S&PRet_1	1.044***
	(0.110)
S&PVolume_1	-0.0109***
	(0.00364)
MSCI	-2.559***
	(0.108)
DXY_1	-0.505***
	(0.149)
Constant	-6.30e-05
	(0.000599)
Observations	7091
R-Squared	0.1603
Adj R-Squared	0.1594

Standard errors in parantheses

*** p<0.001, ** p<0.05, * p<0.01.

We notice that all the estimated coefficients, except the DXY, now have the opposite sign than that of using contemporaneous values. This is by Ahoniemi (2006) explained by the statistical feature of VIX as mean reverting. A rise in the S&P 500 during day T, will lead to a lower VIX this same day, as we confirmed in Model 2. Thus, in day $T + 1$ the VIX is expected to rise (Ahoniemi, 2006). Further, we observe that the point estimates are smaller and that the effects from realized volatility and political uncertainty no longer are statistically significant. In addition, both R^2 and adjusted R^2 take on considerably lower values. Based on this, we argue that lagged explanatory variables contain delayed information as investors tend to react immediately.

7.3.3 Monthly Data

When using daily data, the information is likely to be exposed to noise. That is, large daily variations in some of the explanatory variables. By looking at monthly data, some of this noise may disappear. In addition, some of the explanatory variables included do not experience large daily variation, and the use of monthly data could make it easier to capture systematic changes and trends. Table 9 presents the results from the OLS robust regression using monthly data from January 1990 to February 2018.

We observe that the results are quite similar to those obtained using daily data. Realized volatility has a less powerful effect, but is still statistically significant at the 5% level. Regarding the stock index correlation, the use of monthly data yields a smaller point estimate. This effect is still not statistically significant. Economic policy uncertainty seems to have a more powerful effect than that of daily data. However the effect is still trivial, and the estimated coefficient is no longer statistical significant. These resultat give support to our model. In addition, the use of monthly data may not be appropriate as we have already argued that investors react immediately.

In this chapter, the robustness of the model has been discussed and tested. This has been done by addressing possible obstacles when dealing with time series and by estimating equation 10 for different time intervals, with lagged explanatory variables and by using monthly data. From these results, we argue that the econometric framework is appropriate, but that it is difficult to capture what factors influence the VIX.

Table 9: Regression output using monthly data

	Model 9
	(1990–2018)
Rvol	-0.0568**
	(0.0284)
Corr	0.262
	(0.518)
EPU	0.0499
	(0.0349)
RVIX_1	-0.304***
	(0.0509)
S&PRet	-2.561***
	(0.295)
S&PVolume	0.258***
	(0.0480)
MSCI	-0.355
	(0.211)
DXY	-1.062*
	(0.609)
Constant	0.0144**
	(0.00720)
Observations	336
R-Squared	0.5313
Adj R-Squared	0.5198

Standard errors in parantheses

*** p<0.001, ** p<0.05, * p<0.01.

8 Extension: The VIX Spike in February 2018

Before addressing the effects from Fut and Fut_1 in our regression analyses, we briefly go through what happened in February 2018, when VIX suddenly left its historically low levels. From there, we continue our analysis by taking a closer look at the effect of the VIX futures trading volume. We discuss to what extent the market of VIX-derivatives might have exacerbated the stock market correction. We round off the section with a brief discussion regarding the warning signs that an increasing number of analysts tell us to be aware of.

8.1 Stock Market Correction in February 2018

On February 2nd 2018, the US Labor Department reported a surprisingly large jump in average hourly earnings (Cox, 2018). With concerns over rising inflation, combined with the Federal Reserve indicating a more aggressive increase in the interest rates, this marked the starting point of a stock rally ending in all the major stock indexes experiencing their steepest drops in a long time. The Dow Jones Index fell 2.54 % in one day, and by February 8th, it was down 8.88 %. During the same week, S&P 500 was down by 8.54 %, taking its biggest dive in two years.

Even though the market recovered rather quickly, the event in early February represented an important shift regarding the VIX; volatility now seems to be back in the market. As the S&P 500 started to fall, the volatility index made its biggest one-day jump, when closing at 37 on February 5th. This represents a percentage rise of 116 % compared to the preceding trading day[15]. Figure 12 exhibits a graphical view of the extreme surge, showing daily closing values of VIX over the time period January 2017 – February 2018. The red line represents the long-term average. The days of low-volatility markets appear to be over for now, with the VIX being back at its normal levels[16], oscillating around the long-term mean of 20 and being seemingly much more sensitive to events in the market.

Despite this being an expected and also, by many, a desired stock market correction, analysts and market watchers differ in their opinions about what was the reason for the decline. Especially

[15] On February 6th 2018 the VIX reached an intra day value of 50, the highest since August 2015.
[16] As of March 2018.

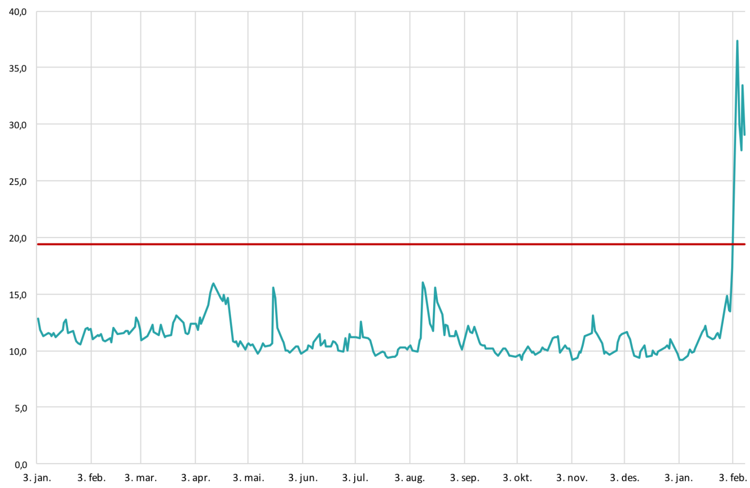

Figure 12: Daily VIX level, 03.01.17–09.02.18

concerning why the market reacted so strongly. As confirmed both in our empirical analysis and earlier papers, there is a clear inverse relation between the S&P 500 and the VIX Fernandes, Medeiros and Scharth (2013). An increase in the VIX is hence to be expected in the event of a stock market fall. In February we observed that the VIX reacted only after the sudden change on the S&P 500, and not in advance. As mentioned in section 6.2.1, what the VIX indicates will happen in the future, seems first and foremost to be related to what is happening in the market as we speak. If the market experiences some major movements today, the VIX will tell us that the next 30 days will be volatile, as well.

There is an increasing number of analysts claiming that no matter the reason for the decline in February, it was worsened due to the enormous trading of VIX futures (Keene, Ferro and Fox, 2018) and (Wiggelsworth, 2018*b*). When the VIX started to rise, the backers of inverse VIX-derivaties, such as the XIV, were forced to buy a large number of future contracts in a very short amount of time (Keene, Ferro and Fox, 2018). This active trading led to an increase in the VIX, which further increased the demand for futures contracts even more, and so we got a spiraling effect (Keene, Ferro and Fox, 2018). The extreme spike in the volatility index caused the XIV to implode, losing about 94 % of its value in one day and causing large losses for investors. A few days later, Credit Suisse announced the redemption of the product and February 20th to be the last day of XIV-trading (Franck, 2018). Figure 13 shows the daily values of XIV from 2013 until February 2018, with the sharp drop reflecting the dramatic crash on February 5th.

Figure 13: Daily value XIV, 15.02.2013–16.02.2018

(source: www.ETF.com)

8.2 Results from the Econometric Analyses

To empirically examine this relation between VIX and the trading of VIX futures, we add to our existing regression analysis the effect of a change in the volume today and yesterday, Fut and Fut_1. The time periods represented by Model 2, 3 and 4 exceed the life span of VIX futures, and so the effects from these appear only in Model 5, 6 and 7. As the effect of volume is likely to be nonlinear, we included the square of the variable, but the inclusion of $Futures^2$ did not improve our results. As it appears in table 7, the effects of both Fut and Fut_1 are very small, and alternates between being positive and negative. A statistical significant relationship is only found for the lagged value in the most recent period. In this period the effect is also reported as negative, which contradicts our expectations.

Although available since 2004, the trading activity linked to VIX futures has blossomed in the most recent years (Wiggelsworth, 2018a). This becomes evident in Figure 14 which exhibits the weekly trading volume since the launch in April 2004. It is only recently, with the trading activity reaching much higher levels, that its influence on the VIX and the stock market has become a topic for discussion. This opens up for the possibility that we may not have enough data in order for our model to reveal clear evidence for our hypotheses. In addition, we notice a considerable large daily variation in the trading volume, which also might affect our results.

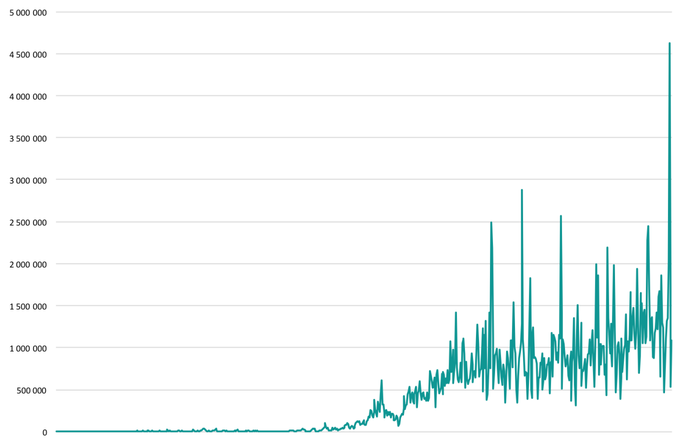

Figure 14: Weekly trading volume of VIX futures, Jan 17–Feb 18

8.3 VIX Derivatives and the VIX as a Reliable Measure of Future Volatility

The small, and also negative, effects reported in our regression, give little support to the hypothesis of the trading volume of VIX futures influencing the movements in VIX. Despite that, we find this discussion relevant and important. If these financial assets, whose values are dependent on the VIX, are truly contributing to the movements in the VIX itself – what impact will this have on its role as a reliable measure of market risk? We are talking about a possible feedback loop that markets and investors should be aware of in the future. An increasing number of analysts claim that this is what happened in February (Keene, Ferro and Fox, 2018). The market correction escalated as a result of the volatility market, and this *VIX-event* might have been nothing but a taste of what we will witness more of in the future (Wiggelsworth, 2018*b*). In the following we address the possible effect of the trading of VIX derivatives in the light of previous literature.

Gennaioli, Shleifer and Vishny (2011) address the shadow banking system and how securitization, when combined with aggregate neglecting tail risks, can cause a fragile financial system and lead to recession. Gennaioli, Shleifer and Vishny (2011) refer to securitization as the way banks create new financial instruments to be sold to investors, by pooling their loans together. Neglecting tail risks means neglecting the worst case scenario as likely to happen, leading intermediaries to treat a downturn in the economy as the worst possible state and to adjust their promised returns to investors accordingly (Gennaioli, Shleifer and Vishny, 2011).

The system of securitization grew exponentially prior to the financial crisis (Chernenko, Hanson and Sunderam, 2014). The products sold to investors were called Collateral Debt Obligations (CDOs), and contributed eventually to the subprime mortgage crisis 2007-2009. The problem, according to Gennaioli, Shleifer and Vishny (2011), was not the securitization system itself, but when combined with neglecting tail risks. Correspondingly, some claim that the VIX itself is not a problem, but the fact that it can be traded (Russell, 2018). The VIX-derivatives have been introduced as a way of diversifying portfolios and reducing the aggregate risk of investors. And yet, it was these products that ended up creating even more risk and causing large suffers in February.

In November 2017, the British financial journalist John Plender wrote an article about the so-called volatility paradox; the fact that low volatility makes market participants do things that render the financial system more fragile and vulnerable to crisis (Plender, 2017). He explains the pervasive search for yield as one of the reasons to why such a paradox can occur (Plender, 2017). What the market experienced in February may be explained as a result of precisely this. ETPs are complex products, yet popular as they have proven to be very lucrative (Keene, Ferro and Fox, 2018). This combination of complex products and over-optimistic investors not considering it probable to see volatility returning to the market in the nearby future, proved to be unfortunate.

The volatility paradox explained by Plender (2017), is in line with the already mentioned hypothesis about financial instability. Periods of subdued volatility and improved welfare, can lead investors to take on more risk and, hence, create more instability (Minsky, 1992). The shadow banking system led to a more vulnerable system, and so may the VIX ETPs. The downturn in February could have been a normal, and also a healthy, reversal of the stock markets. But due the ETPs triggering an enormous automated trading of VIX futures, it turned into a terrifying slide instead (Wiggelsworth, 2018*b*).

Returning to our question above, what impact will it have if these VIX ETPs are truly contributing to the movements in the VIX itself? Does an answer to the puzzle simply lie in the increased trading linked to it? Paradoxically, as the attention towards the VIX has been increasing, its role as an indicator of volatility may have been decreased. As the market starts turning downwards and the VIX rises, the inverse ETPs will automatically buy VIX futures, and hence cause the VIX to spike even more (Wiggelsworth, 2018*a*). A rise in this index is interpreted as a warning sign, and so people will continue their sell-off. Due to this feedback loop, the interpretation of the VIX becomes harder. It may be that the VIX now works better as an arena for trading and betting on volatility, and not much more than that. In that case, we find the economist Charles Goodhart's (quoted in Wiggelsworth, 2018*b*) famous saying about how observing some phenomenon actually changes their nature, to be highly relevant: "when a measure becomes a target, it ceases to be a good measure".

9 Conclusion

The starting point of this thesis was the *VIX Puzzle* – the fact that increased geopolitical tensions in the most recent years have seemingly not translated into higher readings on the VIX index. The aim of this thesis was to examine what factors influence the VIX index and whether these factors could help clarify the reasons for these historically low levels. Finally, we also question the ability of the VIX to predict future volatility and its role as a reliable measure of market risk.

We investigated how well the VIX works as a predictor of future volatility. This was done by running a simple OLS regression with realized volatility as the dependent variable and VIX as the only explanatory variable. In addition, we computed probability intervals and performed graphical analysis. The results from both the simple regression and the probability intervals, suggest that the VIX works to some extent, but that its precision is poor.

From here, we moved on to an empirical analysis to investigate what factors may influence the VIX index. This was done by running a standard OLS with Newey West robust standard errors. The first aim of this regression analysis was to examine whether stock index correlation and low realized volatility contribute in explaining the low VIX levels. We also wanted to check how, and if, uncertainty regarding economic policy affect the VIX. The robustness of our model was tested by estimating the model in different time periods and by using monthly data.

In our analysis we found a positive relation between realized volatility and the VIX. This suggests that periods of low volatility might contribute to low VIX levels. The effect was statistically significant in all estimated models, but the size of the effect was small. We also found a positive effect from stock index correlation, suggesting that small movements in the S&P 500 are associated with a low VIX. We thus argue, that low stock index correlation affect the VIX to some degree. However, the result is only valid for our sample. As for the economic policy uncertainty, we found a positive relationship between the EPU index and the VIX. The effect was small and we confirm that high uncertainty has not translated into high volatility. Based on our empirical results, we argue that it is hard to determine what, and how, different factors influence the VIX.

We end this thesis with a discussion of the VIX jump in February, and tested whether extensive trade of VIX futures contributed to this spike. None of the models supported our hypothesis that the marked of VIX derivatives influence the movements in the VIX index. As this marked has blossomed only recently, we stress that lack of data may render it too early to discover such a relationship in an empirical model. We think that this would be an interesting topic for further research. We also question whether the index today works best as an arena for trading and betting on volatility, rather than a measure of future risk. If this is true, the VIX index can be considered a case of Goodharts law, holding that, when the measure becomes a target, it may loose the properties that made it good a measure originally (Goodhart, 1975).

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Appendices

A Derivation of the VIX Formula

Suppose that a stock price follows the process

$$\frac{dS}{S} = (r-q)dt + \sigma dz \tag{14}$$

in a risk-neutral world where σ is itself stochastic. From Ito's lemma:

$$dlnS = (r - q - \frac{\sigma^2}{2})dt + \sigma dz \tag{15}$$

$$\frac{\sigma^2}{2}dt = (r-q)dt + \sigma dz - dlnS \tag{16}$$

By subtracting these two equations, we obtain:

$$\frac{1}{2}\sigma^2 dt = \frac{dS}{S} - dlnS \tag{17}$$

Integrating between time 0 and time T, the realized average variance rate, $\overline{V}$, between time 0 and time T is given by

$$\frac{1}{2}\overline{V}T = \int \frac{dS}{S} - ln\frac{S_t}{S_0} \tag{18}$$

Taking expectations in a risk-neutral world:

$$\hat{E}(\overline{V}) = \frac{2}{T}\ln\frac{F_0}{S_0} - \frac{2}{T}\hat{E}\Big[ln\frac{S_T}{S_0}\Big] \tag{19}$$

Where F_0 is the forward price of the asset for a contract expiring at time T.

Now, consider:

$$\int_{K=0}^{S^*} \frac{1}{K^2} max(K - S_T, 0)dk \tag{20}$$

for some value S^* of S. When $S^* < S_T$ this integral is zero. When $S^* > S_T$ it is

$$\int_{K=S_T}^{S^*} \frac{1}{K^2}(K - S_T) = ln\frac{S*}{S_T} + \frac{S_T}{S*} - 1 \tag{21}$$

Consider next:

$$\int_{K=S^*}^{\infty} \frac{1}{K^2} max(S_T - K, 0)dk \tag{22}$$

When $S^* > S_T$ this integral is zero. When $S^* < S_T$ it is

$$\int_{K=S_T}^{S^*} \frac{1}{K^2}(S_T - K) = ln\frac{S*}{S_T} + \frac{S_T}{S*} - 1 \tag{23}$$

From these results it follows that

$$\int_{K=0}^{S^*} \frac{1}{K^2} max(K - S_T, 0)dk + \int_{K=S^*}^{\infty} \frac{1}{K^2} max(S_T - K, 0)dk = ln\frac{S*}{S_T} + \frac{S_T}{S*} - 1 \tag{24}$$

for all values of S^* so that

$$ln\frac{S_T}{S^*} = \frac{S_T}{S*} - 1 - \int_{K=0}^{S^*} \frac{1}{K^2} max(K - S_T, 0)dk - \int_{K=S^*}^{\infty} \frac{1}{K^2} max(S_T - K, 0)dk \tag{25}$$

This shows that a variable that pays off lnS_T can be replicated using options. This result can be used in conjunction with equation (16) to provide a replicating portfolio for $\overline{V}$.

Taking expectations in a risk-neutral world in equation (22):

$$\hat{E}\left[ln\frac{S_T}{S^*}\right] = \frac{F_0}{S*} - 1 - \int_{K=0}^{S^*} \frac{1}{K^2} e^{RT} p(K)dk - \int_{K=S^*}^{\infty} \frac{1}{K^2} e^{RT} c(K)dk \tag{26}$$

Where $c(K)$ and $p(K)$ are the prices of European call and put options with strike price K and maturity T and R is the risk-free interest rate for a maturity of T.

Combining equation (a) and (b) and noting that:

$$\hat{E}\left[ln\frac{S_T}{S_0}\right] = ln\frac{S^*}{S_0} + \hat{E}\left[ln\frac{S_T}{S^*}\right] \tag{27}$$

we get the following equation:

$$\hat{E}(\overline{V}) = \frac{2}{T}\ln\frac{F_0}{S^*} - \frac{2}{T}\left[\frac{F_0}{S^*-1}\right] + \frac{2}{T}\left[\int_{K=0}^{S^*}\frac{1}{K^2}e^{RT}P(K)dK + \int_{K=S^*}^{\infty}\frac{1}{K^2}e^{RT}C(K)dK\right] \tag{28}$$

We set S^* equal to the frist strike price below F_0 and then approximate the integrals as

$$\int_{K=0}^{S^*}\frac{1}{K^2}e^{RT}P(K)dK + \int_{K=S^*}^{\infty}\frac{1}{K^2}e^{RT}C(K)dK = \sum_{i=1}^{n}\frac{\Delta K}{K_i^2}e^{RT}Q(K_i) \tag{29}$$

where

$$\Delta K_i = 0,5[K_{i+1} - K_{i-1}] \qquad for \quad 2 < i < n-1 \tag{30}$$

In equation (25), the ln function can be approximated by the first two terms in a series expansion:

$$ln\frac{F_0}{S^*} = \left[\frac{F_0}{S^*} - 1\right] - \frac{1}{2}\left[\frac{F_0}{S^*} - 1\right]^2 \tag{31}$$

Substituting this into eq (25)

$$\hat{E}(\overline{V}) = \frac{2}{T}\left[\left(\frac{F_0}{S^*} - 1\right) - \frac{1}{2}\left(\frac{F_0}{S^*} - 1\right)^2\right] - \frac{2}{T}\left[\frac{F_0}{S^*} - 1\right] + \frac{2}{T}\left[\sum_{i=1}^{n}\frac{\Delta K}{K_i^2}e^{RT}Q(K_i)\right] \tag{32}$$

Which reduces to:

$$\hat{E}(\overline{V}) = \frac{2}{T}\sum_{i=1}^{n}\frac{\Delta K}{K_i^2}e^{RT}Q(K_i) - \frac{1}{T}\left[\frac{F_0}{S^*} - 1\right]^2 \tag{33}$$

This is the formula used in the VIX calculation.

B Descriptive Statistics: Explanatory Variables 1990-2018

Table 10: Descriptive statistics: explanatory variables 1990-2018

	Mean	Std.dev	Min	Max	Obs
S&P Return	0.00028	0.01109	-0.09470	0.10957	7095
S&P Volume	2,10E+09	1,77E+09	1,50E+07	1,15E+10	7094
Realized Volatility	0.15487	0.08965	0.03883	0.81579	7095
MSCI Return	0.00009	0.01074	-0.08814	0.08212	7096
DXY Index	90.63711	10.32034	71.329	120.9	7093
Correlation	0.53407	0.10680	0.31714	0.76291	7096
EPU Index	96.96882	67.06129	3.32	719.07	7096
Futures Volume	38654.26	52564.63	0	506362	3499

C Average Stock Index Correlation

In order to compute the average stock index correlation, we used the command $CORREL$ in Excel. This command makes use of the following formula:

$$Corr(X,Y) = \frac{\sum (x-\overline{x})(y-\overline{y})}{\sqrt{\sum (x-\overline{x})^2 \sum (y-\overline{y})^2}}$$

Where X represents the return of the S&P 500, and Y represents the return of a single stock. $\overline{X}$ and $\overline{Y}$ are the sample means. We calculated the daily rolling correlation between S&P 500 and each stock, from which we further computed the average correlation.

Table 11: 55 Largest companies in the S&P 500, February 2018

Ticker Symbol	Company	Weight	Ticker Symbol	Company	Weight
AAPL	Apple Inc.	3.589	PEP	PepsiCo Inc.	0.707
MSFT	Microsoft Corporation	3.039	DIS	Walt Disney Company	0.696
AMZN	Amazon.com Inc.	2.394	PM	Philip Morris International Inc.	0.700
FB	Facebook Inc. Class A	1.876	MA	Mastercard Incorporated Class A	0.687
JPM	JP Morgan Chase & Co.	1.706	MRK	Merck & Co. Inc.	0.671
BRK-B	Berkshire Hathaway Inc. Class B	1.685	WMN	Walmart Inc.	0.650
JNJ	Johnson & Johnson	1.555	ORCL	Oracle Corporation	0.650
XOM	Exxon Mobil Corporation	1.435	NVDA	NVIDIA Corporation	0.628
GOOG	Alphabet Inc. Class C	1.400	MMM	3M Company	0.599
GOOGL	Alphabet Inc. Class A	1.393	GE	General Electric Company	0.579
BAC	Bank of America Corporation	1.315	IBM	International Business Machines Corp.	0.577
WFC	Wells Fargo & Company	1.112	MCD	McDonald's Corporation	0.573
T	AT&T Inc.	0.989	AMGN	Amgen Inc.	0.564
CVX	Chevron Corporation	0.963	MO	Altria Group Inc.	0.547
HD	Home Depot Inc.	0.961	HON	Honeywell International Inc.	0.503
UNH	UnitedHealth Group Incorporated	0.957	NFLX	Netflix Inc.	0.482
V	Visa Inc. Class A	0.943	MDT	Medtronic plc	0.481
INTC	Intel Corporation	0.919	GILD	Gilead Sciences Inc.	0.463
PG	Procter & Gamble Company	0.910	BMY	Bristol-Myers Squibb Company	0.458
PFE	Pfizer Inc.	0.910	UNP	Union Pacific Corporation	0.448
VZ	Verizon Communications Inc.	0.909	TXN	Texas Instruments Incorporated	0.443
CSCO	Cisco Systems Inc.	0.873	ABT	Abbott Laboratories	0.440
C	Citigroup Inc.	0.871	AVGO	Boradcom Limited	0.428
BA	Boeing Company	0.832	ACN	Accenture Plc Class A	0.425
CMCSA	Comcast Corporation Class A	0.804	QCOM	QUALCOMM Incorporated	0.421
ABBV	AbbVie Inc.	0.793	UTX	United Technologies Corporation	0.415
KO	Coca-Cola Company	0.739	ADBE	Adobe Systems Incorporated	0.414
DWDP	DowDuPont Inc.	0.726			

D Test results

Table 12: Results from the Augmented Dickey-Fuller test

	Test Statistic	P-Value
VIX	-8.334	0.0000
S&PRet	-77.836	0.0000
S&PVolume	-9.685	0.0000
Rvol	-1.671	0.4461
MSCI	-66.322	0.0000
DXY	-2.417	0.1370
Corr	-0.966	0.7655
EPU	-40.813	0.0000
Fut	-14.465	0.0000

1% Critical Value $= -3.430$, 5% Critical Value $= -2.860$,

10% Critical Value $= -2.570$

Table 13: Test results omitted variable

	F-Statistic	P-value
Ramsey RESET	81.11	0.0000

Table 14: Test results autocorrelation and heteroskedacticity

Test	**Chi2**	**P-value**
Durbin's Alt – Autocorrelation	58.723	0.0000
Breusch-Godfrey LM – Autocorrelation	3.774	0.0521
LM (ARCH) – Heteroskedasticity	138.291	0.0000
Breusch-Pagan – Heteroskedasticity	369.21	0.0000

Table 15: Variance inflation factor (VIF) test results

	VIF	**1/VIF**
MSCI	1.59	0.627315
S&PRet	1.30	0.767359
DXY	1.16	0.860480
RVIX_1	1.15	0.873072
Rvol	1.14	0.875496
Corr	1.14	0.876618
S&PVolume	1.02	0.981447
EPU	1.00	0.996679
Mean VIF	1.19	

E IV Estimation

Table 16: Regression output IV method with realized volatility Instrumented

	Model 10 RvolDOW =Instrument	**Model 11** Rvol_30 =Instrument
Rvol	0.155***	-0.0104
	(0.0246)	(0.0281)
Corr	0.799	1.873*
	(0.707)	(0.821)
EPU	0.00285***	0.0036***
	(0.000786)	(0.000803)
RVIX_1	-0.0969***	-0.0974***
	(0.0122)	(0.0127)
S&PReturn	-3.844***	-3.886***
	(0.0996)	(0.104)
S&PVolume	0.0188***	0.0223***
	(0.00299)	(0.00323)
MSCI	-0.437***	-0.450***
	(0.0804)	(0.0824)
DXY	-0.431***	-0.454***
	(0.124)	(0.127)
Constant	0.00112**	0.00117**
	(0.000531)	(0.000541)
Observations	7091	7061
R-Squared	0.524	0.513

Standard errors in parantheses

*** $p<0.001$, ** $p<0.05$, * $p<0.01$.

Table 17: Test results Durbin-Wu-Hausman endogeneity test

Instrument Variable	**Chi2**	**P-value**
Rvol_30	21.5378	0.0000
RvolDOW	2.0841	0.1488

$H0$: All variables are exogenous