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Understanding Uncertainties

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Abstract

This thesis investigates the relationship between macroeconomic uncertainty and stock market volatility. The study focuses particularly on how uncertainty about the macroeconomic factor expected future GDP growth influences variation in stock prices. Our results indicate that increased macroeconomic uncertainty generate volatility in the stock market for an extended period of time. Furthermore, an analysis of the volume of trade on the S&P 500 index shows that the market responds to increased stock market volatility.

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We wish to thank our supervisor Alessandro Graniero at BI Norwegian Business School for contributing with an inspiring topic and literature, and for the guidance during our research.

1. Introduction

This thesis investigates the relationship between macroeconomic uncertainty and stock market volatility, and how volume of trade is affected by changes in our measures of uncertainty and volatility. Our focus is on US financial markets and US macroeconomic factors generally, and the S&P 500 and US forecasted Gross Domestic product, GDP growth specifically.

Uncertainty has no precise definition and has a multitude of dimensions. It is a term that reflects ambivalence in the minds of all market participants about possible future outcomes. Uncertainty, as a broad concept, include unpredictability over the path of both micro- and macroeconomic phenomena like the growth rate of a specific firm, or the growth of GDP. A general and accepted definition of uncertainty is a situation which involves imperfect and/or lack of information necessary for the prediction of future events (Knight, 1921).

Bloom (2009) shows that uncertainty appears to dramatically increase after major economic and political shocks. This is well illustrated by figure 1 (the economic policy uncertainty index), where events like Brexit and the Euro crisis are associated with a high level of uncertainty. The economic policy uncertainty index consists of three components. The first component is newspaper coverage of policy related economic uncertainty. The second component reflects the number of tax code provisions set to expire in future years, and the last component is disagreement among economic forecasters. Current levels of economic policy uncertainty are at a historically high level. Since the financial crisis in 2008, the economic policy uncertainty index has averaged almost twice the level of the past 20 or so years. Most of this macroeconomic uncertainty can be related to a changing political landscape and political tension between governments (Economic Policy Uncertainty, 2018). Bloom (2014) has later showed that good macroeconomic news has a rather gradual effect on macroeconomic uncertainty, while bad news act as shocks to the market, generating uncertainty.

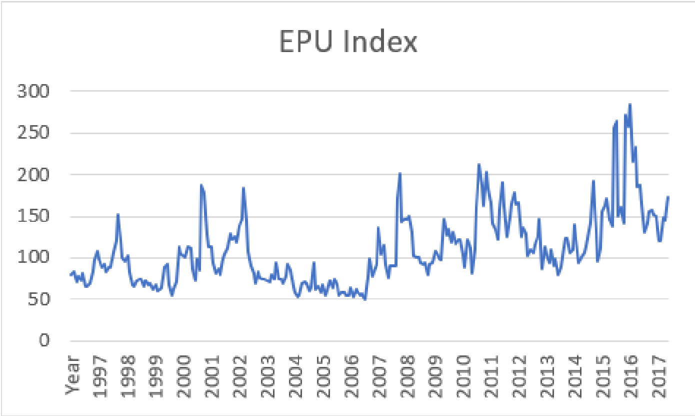


Figure 1: The Economic Policy Uncertainty Index (Economic Policy Uncertainty, 2018).

An important and interesting question for investors, analysts, finance students and other market participants is how the increasing macroeconomic uncertainty translates into the stock market. Every trade carries the risk of both failure and success, and with less volatility, the risk of both is lower. To understand the riskiness of our investments, we must be aware of the underlying reasons for volatility in the value of our assets. As illustrated by figure 2, volatility varies significantly over time. Periods that are associated with higher volatility are typically related to drops in the market or political events, i.e. the tech-bubble collapse, the financial crisis and the Euro Crisis.

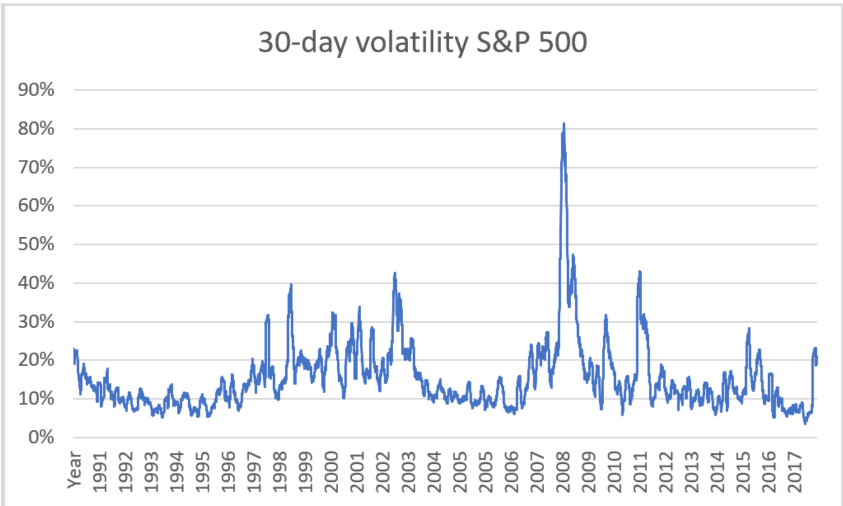


Figure 2: *30-day historical volatility S&P 500 (annualized).*

Financial institutions' inability to accurately understand the riskiness of their investments is partially what caused the financial crisis in 2008. In the aftermath, Knight's (1921) idea about risk, "Knightian uncertainty", has gained increased attention. According to Knight, risk applies to situations where we do not know the outcome, but the range of outcomes can be described by a probability distribution. "True uncertainty" on the other hand, applies to situations where we do not have the knowledge to come up with a probability distribution for the range of outcomes.

With Knight's distinction of risk and uncertainty, we acknowledge that uncertainty has different dimensions. Our measure of macroeconomic uncertainty is disagreement among analysts trying to predict next periods GDP growth. There is an infinite number of factors influencing the GDP growth of the US economy, and it is impossible for analysts to come up with a probability distribution for the next period's GDP growth. A high degree of uncertainty does not necessarily increase the chance of sudden changes in the underlying value. Hence, disagreement fits Knight's definition of "true uncertainty". Stock market volatility have different characteristics and resembles something in the direction of what Knight calls risk. A higher volatility means that the security's value can potentially be spread out over a larger range of values. This means that a highly volatile stock is more prone to the risk of sudden large changes in value.

Previous research has deployed several measures of macroeconomic uncertainty to try and explain the behaviour of stock markets. One measure that we find particularly interesting is disagreement among forecasters in the Survey of Professional Forecasters. Each forecaster in the survey have unique biases in their forecasts, and the level of disagreement varies significantly over time. Schwert (1989) and Davis & Kutan (2003) all agree on an insignificant relation between macro uncertainty and the stock market, using time series models. However, Arnold and Vrugt (2008) argue that a dispersion-based model, which uses analyst disagreement as proxy for uncertainty, is better suited to investigate such a relation.

We are interested in, and intend to investigate, the different dimensions uncertainty can take in financial markets and the macroeconomy. More precisely, how uncertainty influences volatility and economic decisions.

Existing literature on the relationship between macroeconomic uncertainty and the stock markets focus mostly on how returns are affected by uncertainty. How uncertainty translates into stock market volatility is a relatively untouched topic over the last decades. However, Bloom (2014) has brought some new life to this topic. Literature on the opposite relation, how stock market uncertainty affect volatility in macroeconomic factors, is almost non-existent. This is one of the additional questions we want to answer in this thesis.

Another topic we will investigate is the response of market participants to increased macroeconomic uncertainty and stock market volatility. As we will see, previous literature disagrees on the relationship between volume of trade and uncertainty/volatility. While Varian (1985) argue that trading volume goes up with uncertainty, Pfleiderer (1984) claimed that the relationship is opposite. We argue that the disagreement may originate from a market response that is dependent on the state of an economy, and that the results therefore are reliant on sample period.

The remaining part of the thesis is divided into five main sections. In section 2 we will present a literature review, where we will discuss existing evidence and previous research on the field. In section 3 we give a description of the data used in our research, where the data is extracted from and a description of the variables we employ. The following two sections are organized based on research topics. In section 4, we present our methodology for the topics; “Macroeconomic uncertainty and volatility in stock markets”, “stock market uncertainty and macroeconomic volatility” and “volume of trade”. Similarly, in section 5 we present descriptive statistics and findings relevant to answer the research questions within each topic, before we give an analysis of the results. In the final part of the thesis we present concluding remarks and propositions for future research.

2. Literature Review

2.1 Measuring Uncertainty

How to measure uncertainty is highly debated in the literature. As there is no optimal theoretical approach to measures of uncertainty, every new author claims to have found the best way of capturing uncertainty. Using Frank Knight´s (1921) definition of uncertainty; “people’s inability to forecast the likelihood of events happening”, Bloom (2014) further elaborates uncertainty as the inability to assign probability distributions to unforeseen events.

Bloom (2009) finds empirical evidence that there is a countercyclical relationship between uncertainty in macro activities and stock market volatility. He introduces a framework to analyse the impact of shocks that cause uncertainty. Through simulation, he finds that uncertainty shocks lead to a reduction in investment and hiring among firms. Further, due to the reduced economic activity, an overshoot in employment, productivity and output follows. The result is recessions followed by recoveries. When comparing the results from the simulated models with vector autoregression on real data, Bloom found that the results are similar, i.e. uncertainty shocks do have an impact on economic stability, and might cause recessions.

Kyle Jurado, Sydney C. Ludvigson and Serena Ng (2015) identifies time-varying macroeconomic uncertainty outside the established proxies and methods. They found that the established proxies of uncertainty reflect more than uncertainty, such as stock market volatility. However, the paper discovers a close link between uncertainty and changes in real activity in macroeconomics factors, and that macro uncertainty is robustly counter-cyclical. This is in line with the findings from Bloom (2009).

Contrary to economic data, some authors have tried to capture uncertainty from other sources. Baker, Bloom and David (2016) construct a measure of uncertainty based on newspaper coverage, called the economic policy uncertainty index (EPU index). The index is based on a search for keywords related to economic policy uncertainty; uncertainty of *who* will make new policies, uncertainty about *what* new policies are being incorporated, and lastly *when* the policies are being enforced. The index is intended to incorporate both direct economic uncertainty, like for example volatile inflation rates, and indirect economic uncertainty such as wars. They found that their index worked as a proxy for change in economic policy uncertainty. The index had large spikes during times of political uncertainty, such as 9/11, the Gulf war and the 2008 financial crisis. The authors conclude that higher economic policy uncertainty results in a higher stock market volatility.

Both Baker et al. (2016) and Alexopoulos and Cohen (2009) find empirical evidence between stock market volatility and macro level uncertainty with data gathered from newspapers. In addition, both papers find evidence that periods of high uncertainty are followed by periods of lower productivity in the economy.

Arnold and Vrugt (2008) used dispersion in economic forecasts from the Survey of Professional Forecasters (SPF) to determine the level of uncertainty in the economy. The paper finds a strong link between the dispersion in forecast and the stock market volatility in the US. However, the authors only find evidence for this up to 1996, where the authors speculate that technology driven sectors may be an additional driver of volatility in the US stock market. Nevertheless, they indicate that investors may improve their forecasts of the market volatility by using dispersions in the SPF. Giordani and Söderlind (2002) also find evidence that the SPF is a better proxy of uncertainty than what literature have previously thought.

Beber, Brandt and Luisi (2015) created a technique to extract daily macroeconomic news from data released at different times and frequencies. Their measure of uncertainty consists of data on different macroeconomic news and disagreement among professional forecasters Their findings indicate that the technique stipulates a more authentic forecast about shifts in future economic factors than previous methods. The authors are able to forecast on a daily basis instead of quarterly like the SPF. Beber et al. (2015) find that this new measure is highly correlated with the SPF. Thus, the method makes it possible to measure the state of the economy and level of uncertainty at a higher frequency than previous methods. This measure of uncertainty can explain a large fraction of the volatility that occurs in financial markets. While economists seem to be fairly successful in predicting downturns in the economy, the authors find more disagreement about recoveries. This serves as an explanation to economist disagreement during recessions.

We see from previous literature that the measurement of uncertainty has no definitive answer. From the use of simple volatility measures (Bloom (2009)), and newspaper coverage (Baker et al. (2016), Alexopoulos and Cohen (2008)) to disagreement among professional forecasters (Arnold and Vrugt (2008),Giordani and Söderlind (2002)). All methods and uncertainty measures have been proven empirically to have significance in explaining volatility in the stock market.

2.2 Implementation of Macro News

In line with the market efficiency hypothesis, a model of stock pricing is dependent only on the sum of expected future dividends, discounted by the relevant discount rate, and the available information set.

$$(1) \qquad P_t = E\left(\sum_{t=1}^{\infty} \frac{d_{t+\tau}}{1+r_{t+\tau}} |\Omega_t\right)$$

Where P_t is the price of the stock at time t, $d_{t+\tau}$ is the dividend paid at time $t+\tau$, $r_{t+\tau}$ is the stochastic discount factor for cash flows at time $t+\tau$ and Ω_t represents the information set available at time t.

New information is equal to the difference between Ω_t and Ω_{t-1}. Under the assumption of rationality and market efficiency, expected news in t+1 and previous news are already incorporated in Ω_t. As a result, only information which deviated from the expectation can distinguish Ω_{t+1} from Ω_t. Under the assumption of rational expectations and the efficient market hypothesis, stock markets respond only to the new information distinguishing Ω_{t+1} from Ω_t.

The finance literature struggle to show a strong relationship between stock prices and news. This indicates that the assumption of rationality among investors is violated, or that trading patterns are largely influenced by private information. Based on these evidences, Shiller (1980) argue that the efficient market hypothesis is at best an academic model and that it struggles to explain market behaviour. Later, Cutler, Poterba and Summers (1989) and Roll (1988), to name a few, have backed up on Shiller's claim.

Applying a vector autoregressive model and using news about macroeconomic performance as a proxy for new information, Cutler, Poterba and Summers (1989) find that their news proxy can only explain about one third of the variance in stock prices. Stock markets may move as response to information not incorporated in the vector autoregressive model. The authors therefore investigate stock returns related to major news events like wars, terrorist attacks, the presidency and so forth. What they found is that while such news affect the stock market, it is implausible that they cover all the abnormal returns that cannot be traced to macroeconomic innovations.

2.3 Private and Public Signals

According to Scherbina (2003) all analysts receive a public signal (news) about next period's expected value of a macroeconomic variable. Additionally, each analyst also receives a private signal (priors), which is independent of the public signal. To come up with a minimum variance forecast of the macroeconomic variable, each analyst combines the public signal and their private signal. Uncertainty in prior information will lead to higher dispersion in the forecasts of macroeconomic variables, and the forecasts as a whole will be less viable as predictors.

Kozeniaukas, Orlik and Veldkamp (2014) claim that when uncertainty is high, analysts have unreliable priors and they therefore weight more on the heterogenous public signals. The more analysts trust their priors, the more dispersion they generate in forecasts. Kozeniaukas states that analysts will incorporate an increased weight on the public signal when they are doubtful. In contrast, when they are confident, the emphasis is on their own beliefs. This means that confident analysts will generate dispersion in the forecasts.

2.4 Signals and Trading Volume

Varian (1985) proved that the volume of trade is determined by equation (2);

(2) $$T = \sum_{i=1}^{n} \frac{\alpha\theta|\nu_i - \bar{\nu}|}{2}$$

Where ν_i is each agent's prior belief, $\bar{\nu}$ is the mean of all analysts' priors, α is a risk tolerance and θ is prior precision, how well they forecasted in the previous period. Varian concluded that when keeping all other factors equal, the volume of trade must increase when the disagreement among investors increase. However, Pfleiderer (1984) came to the opposite conclusion, claiming that volume is declining with higher variance of the idiosyncratic risk.

2.5 Stock Market Responses Dependent on Economic States

McQueen and Roley (1993) show that when allowing for different states (expansion/recession) of the economy, they find evidence of a relationship between stock prices and macroeconomic news. They also found that the impact (whether it's positive or negative) of macroeconomic news is dependent on the state of the economy. More specifically, during expansions, positive shocks to real economic activity led to lower stock returns. This effect is caused by a larger increase in the relevant discount rate relative to the expected future cash flow in equation (1). Interestingly, the same positive shocks in real economic activity led to higher stock returns during recessions. According to McQueen and Roley, the stock market interprets these news as a sign of recovery when being released during recessions.

Similarly, Hu and Li (1998) examines the S&P500, the Dow Jones and the Russel indices in the period 1980-1996 to see if stock market reaction to macroeconomic news is dependent on business cycles. Similar to McQueen and Roley (1993), they found strong evidence that stock market reactions to macroeconomic news is conditional on economic states. By examining several indices consisting of different stocks (small cap and large cap), Hu and Li (1998) also present evidence for different reactions to macroeconomic news by small cap stocks and large cap stocks.

2.6 Uncertainty and Investor Activities

Bloom (2014) discusses the increased risk premia from investors when uncertainty is high. Making investments under uncertainty of future macroeconomic states, increases the risk of the investment. Fajgelbaum, Schaal and Taschereau-Dumouchel (2017) find that increased uncertainty leads to a lower activity level in the economy, which leads to lower information sharing between participants. Thus, uncertainty contributes to more uncertainty, simply because information sharing is reduced during times of low activity in the market.

3. Data

In this section we are going to provide arguments for the choice of data that we have made. We had two important decisions to make before starting the analysis. Which index and what macro variable are we going to use for our study?

We considered several of the leading indices in the United States such as the Nasdaq, Dow Jones and NYSE as our proxy for the stock market. However, for our purpose it is important to find the index that includes firms that are representative of the US economy. Our decision was that the Standard & Poor´s 500 index (figure 3) would be the best index for our analysis. Consisting of the 500 largest publicly traded firms in the country weighted by their market value, it is a widely used measure of the US equity market.

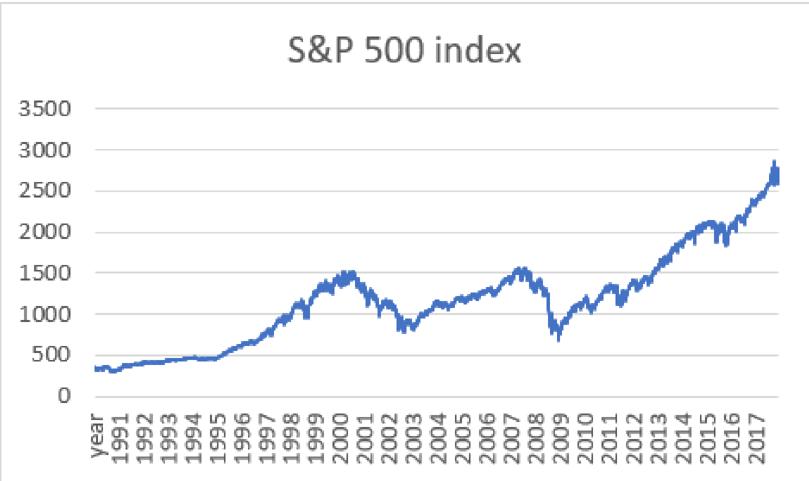


Figure 3: *S&P 500 index, 1990-2018.*

To find the uncertainty for the equity market, we use the expected future realized variance of the S&P 500 as a proxy (Bekaert, Hoerova and Lo Duca (2010)). We use 3 month realized variance of the daily stock market returns on the S&P 500 to correspond the quarterly announcement of the GDP growth. The 3-month realized variance is the sum of the squared returns, using data from 1990 to 2018.

To measure uncertainty in the macroeconomy, we use analyst dispersion among forecasters in the Survey of Professional Forecasters (SPF). The SPF has been in existence since the early 1970´s and is operated by the Federal Reserve Bank of

Philadelphia. They ask professional forecasters to give their best estimates of future macroeconomic variables. For our analysis, we are going to use forecasts about GDP growth in particular, and following a large literature in economics and finance. Our measure of uncertainty will be disagreement (standard deviation) about GDP growth forecasts.

The survey of professional forecasters consists of respectable professionals that are screened in order to provide the best possible forecasts. The forecasters are in close proximity to the decision makers in the US economy. Laster, Bennett and Geoum (1999) argues that the professional forecasters may have an agenda to not give their best estimates. If the forecasters give a highly risky answer that turns out to be true, they will gain more personally from that then if they give a conservative answer that becomes reality. However, the argument from Laster et al. (1999) is assuming that the answers are public, and the SPF is anonymous. Thus, we have no reason to believe they have a personal agenda.

Giordani and Söderlind (2002) argues that the evaluation of candidates before they become forecasters goes a long way in protecting against ridiculous answers, and that the forecasters are close to important decision makers. In our data sample we have included all data for the analysis, including the outliers. According to Giordani and Söderlind (2002), analyst dispersion is a good measure since you can easily recognize the contribution of singular agents.

3.1 Biases

There are biases that we have to take into consideration during the analysis. The first one is the small-sample bias. With a limited number of observations, there is a chance that the observations will deviate from the true population mean. In accordance with the central limit theorem, an infinite number of observations will distribute to the true mean and be normally distributed. With the limited amount of observations, we are likely to experience fat tails, and possibly a deviation from the true population mean.

Another bias to consider is the behavioural bias. As stated above, it is possible that the participants in the SPF have their own motivations for deviating from what they consider the true estimate. It is not possible to review the answers; thus, we make the assumption that all participants have answered truthfully.

4. Methodology

4.1 The Impact of Macroeconomic Uncertainty on Stock Market Volatility

To measure the impact of macroeconomic uncertainty on stock market volatility we will base our methodology on the work done by Hamilton and Lin (1996). First, we need to determine whether daily returns on the S&P 500 have time varying volatility. As can be seen from the plot of daily returns (figure 5, p.20), there seems to be volatility clustering in the data. That means; periods of high volatility are likely to be followed by periods of high volatility, while periods of low volatility are likely to be followed by periods of low volatility. Hence, we might have to apply a GARCH (1,1) framework to capture this feature of daily returns on the S&P 500. The GARCH (1,1) framework, introduced by Engle (1982), can accommodate volatility clustering, which almost every asset price series exhibits. As can be seen from the correlogram of squared returns (appendix 1), we have serial autocorrelation in the residuals, and we therefore estimate the volatility of stock returns as follows:

(3) $$R_t = c + \alpha R_{t-1} + \varepsilon_t \rightarrow \ \varepsilon_t \sim N(0, \sigma_t^2)$$

(4) $$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Equation (3) is an AR (1) model on daily returns on the S&P 500, where R_t is the return of the S&P 500, c is a constant and ε_t represents the residuals. Equation (4) is the variance equation, where σ_t^2 is the variance at time t, ω is the unconditional variance, ε_{t-1}^2 is news about volatility from the previous period, measured as the lag of the squared residual from the AR (1) model (the ARCH term), and σ_{t-1}^2 is the variance from the previous period (the GARCH term). Variance of the S&P 500 is measured daily.

We are interested in investigating how macroeconomic uncertainty, in the form of standard deviation of analyst forecasts, affect the conditional variance of stock returns. To test this, we run a regression where conditional variance is the dependent variable, while analyst dispersion is the independent variable, as shown in equation (5).

(5) $$\sigma_t^2 = \alpha + \beta_1 (Analyst\ dispersion)_t + \mu$$

A GARCH framework assumes that agents predict this period's variance by forming a weighted average of a long-term average (constant), the forecasted variance from last period (the GARCH term), and information about volatility observed in the previous period (the ARCH term). This means that reactions in the GARCH model may be lagged by one period, which is why we will run equation (5) using σ_{t+1}^2 as the dependent variable as well. Also, to study if variance in returns are persistent in the period after the release of uncertainty news, we will run several regressions with experimental variables up to σ_{t+x}^2. Analyst dispersion is the disagreement among forecasters at time t, where time t is the release date of the SPF forecasts.

4.2 Asset Uncertainty's Impact on Macroeconomic Volatility

To identify if uncertainty in stock markets causes volatility in macroeconomic factors, we will use a similar approach as described in section 4.1. First we will run an AR(1) model (equation 6) on GDP growth, and a GARCH variance equation (equation 7) where the ARCH term is the squared residuals from our AR(1) model.

(6) $$\Delta GDP_t = c + \beta(\Delta GDP)_{t-1} + \varepsilon_t \rightarrow \ \varepsilon_t \sim N(0, \sigma_t^2)$$

(7) $$\sigma_t^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

In this framework, ΔGDP is the growth in GDP from quarter t-1 to quarter t, and the GARCH model behaves similarly as previously described. We intend to study how volatility in macroeconomic factors are affected by uncertainty in the stock market, and run the following regression:

(8) $$\sigma_t^2 = \alpha + \beta_1 (RVAR)_t + \mu$$

In our test regression (equation 8), RVAR is the realized three-month variance on the S&P 500 and is calculated as the sum of squared returns. RVAR represents a proxy for uncertainty in stock markets while the variance of GDP growth represents macroeconomic volatility.

4.3 Causality

To examine whether there is a lead-lag relationship between macroeconomic uncertainty and stock market volatility we first employ a vector autoregressive model. In equation 9, RVAR represents stock market volatility, while AD (analyst dispersion) represents macroeconomic uncertainty. Both Akaike and Schwarz information criterion suggest we use one lag, as shown in appendix 9. Hence, the model looks as follows:

(9) $$\begin{bmatrix} RVAR_t \\ AD_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \beta_{2,1} & \beta_{2,2} \end{bmatrix} \begin{bmatrix} RVAR_{t-1} \\ AD_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{RVAR,t} \\ \varepsilon_{AD,t} \end{bmatrix}$$

After the model is employed we use a Granger causality test to test for a potential lead-lag relationship. Granger (1969) introduced the concept of Granger-causality. The idea is that if the variance of X predicted using all available information, U, is less than the variance of X predicted using all information except variable Y, then we can claim that Y is causing X. This effect is denoted Y→X and it is formally shown in equation (10). By performing a Granger causality test, we hope to reveal if past values of RVAR can be used to predict AD or vice versa.

(10) $$\sigma^2(X|U) < \sigma^2(X|\overline{U-Y})$$

4.4 Volume of Trade

To study the repercussions of increased volatility and uncertainty, we will look at how volume of trade is affected. We know that investors utilize both public signals and prior beliefs as a source of information when making their decisions. In uncertain times, market participants will differ in interpretations of signals and this should affect trading volume. Varian (1985) and Pfleiderer (1984) disagree if volume increases or decreases with uncertainty, but researchers generally agree that volume is affected by uncertainty. Karpoff (1986) claim that trading opportunities arise because market participants revise their demand price when new information arrives. We want to investigate how volume of trade is affected by both macro uncertainty and stock market volatility. To investigate this effect, we run the following regressions:

(11) $$\Delta Volume\ of\ trade = \alpha + (Analyst\ dispersion)_t + \mu$$

(12) $$\Delta Volume\ of\ trade = \alpha + \sigma_t^2 + \mu$$

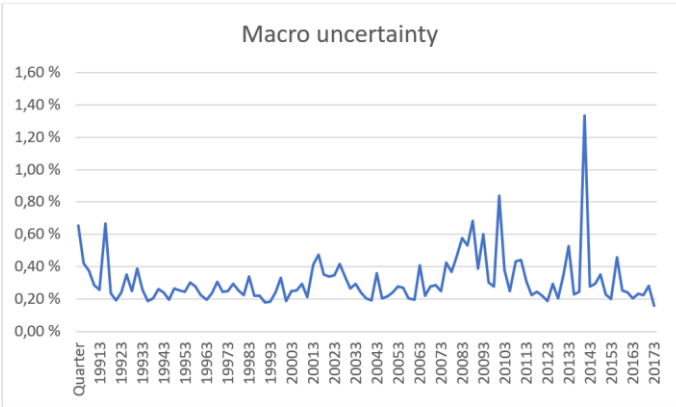
Where $\Delta Volume\ of\ trade$ is the absolute change in trading volume on the S&P 500 from day t-1 to day t, analyst dispersion is disagreement among forecasters and σ_t^2 is the variance of the S&P 500, modelled with our GARCH (1,1) framework. We use the change of trading volume to obtain a stationary measure of how trading volume is affected. Additionally, we use the absolute value as we know that the literature disagrees on how volume is affected by increased uncertainty. It is also reasonable to believe that market participants behave differently depending on the perception of the state of an economy (Kozeniauskas et al. 2014). By using the absolute value of change in trading volume, we obtain a measure that is non-dependent on the state of the economy, and hence zero out the possible effect of perceived recessions.

5. Results

In this section we will present descriptive statistics, findings and an analysis of our results. The impact of macroeconomic uncertainty on volatility in stock markets is the first results that will be discussed, before we go on and interpret the opposite relation, namely how volatility in the macroeconomy affects stock market uncertainty and causality effects between macroeconomic uncertainty and stock market volatility. Towards the end, we will see how both macroeconomic uncertainty and stock market volatility influence the volume of trade.

5.1 Macro Uncertainty's Impact on Volatility in Stock Markets

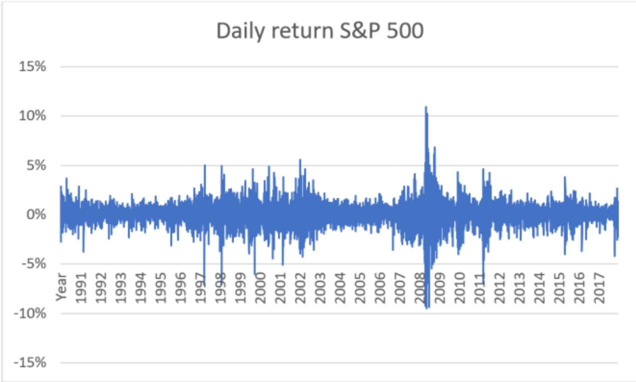
The standard deviation of GDP growth forecasts is our preferred measure of uncertainty. In previous literature, a level measure is also frequently used, but the standard deviation covaries more with other typical measures of uncertainty (Bloom 2014). Summary statistics of our uncertainty measure is available in appendix 2. The standard deviation of forecasts has a long right tail due to some outliers in the dataset. This is also visible in figure 4 with the maximum value taking place in 2014. Apart from that, uncertainty seems to be high in periods of economic turmoil, such as the financial crisis and the around the tech-bubble collapse. The average number of respondents to the survey of professional forecasters in the period from 1990 to 2018 is 52. However, the number of observations is the same in most studies involving macroeconomic data.



Summary statistics macro uncertainty	
Sample period	1990Q4-2017Q4
Observations	109
Mean	0,003132
Median	0,002598
Max	0,013342
Min	0,001589
Std. Dev.	0,001560
Skewness	3,377326
Kurtosis	19,48157

Figure 4: *Macro uncertainty (Standard deviation of GDP change forecasts)*

As previously outlined, our proxy for volatility in stock markets will be the volatility of daily returns on the S&P 500. Complete summary statistics on daily returns of the S&P 500 is available in appendix 3. As is the case in most financial time series, the S&P 500 index shows volatility clustering which is clearly visible in figure 5.



Summary statistics daily return S&P 500	
Sample period	01.10.1990-09.04.2018
Observations	6934
Mean	0,000309
Median	0,000510
Max	0,109572
Min	-0,094695
Std. Dev.	0,011138
Skewness	-0,262702
Kurtosis	11,98765

Figure 5: *Summary statistic daily return on the S&P 500*

As a result of this volatility clustering, we have modelled volatility on the S&P 500 using a GARCH framework as described under the methodology section. Figure 6 provides a first glance at the relationship between uncertainty about GDP growth and stock market volatility. The visual inspection shows that the two time-series move in similar fashion (covary).

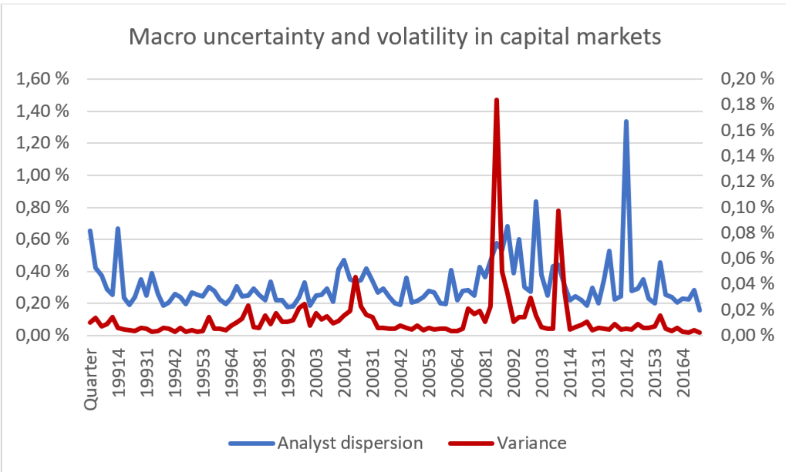


Figure 6: *Analyst dispersion and GARCH modelled variance of S&P 500*

Following the methodology previously described in section 4.1, we now provide a more rigorous analysis on how macroeconomic uncertainty impacts volatility in stock markets. Table 1 presents the regression results. The findings show that there is significance on a 1%-level that macro uncertainty impacts stock market volatility with a positive coefficient of 0,034. We also witness that news about macro uncertainty cause volatility in stock markets that is persistent for quite some time. Figure 7 shows the p-value of analyst dispersion with regressions using variance measures from t up to t+50, with the solid horizontal lines being normal significance levels; 1 %, 5 % and 10 %.

Macro uncertainty's impact on stock market volatility				
	β(AD)	P-value (AD)	R-squared	Std. Error (AD)
Variance t	0,034	0,006***	0,068	0,012
Variance t+1	0,031	0,007***	0,066	0,011
Variance t+2	0,031	0,004***	0,074	0,011
Variance t+3	0,032	0,006***	0,069	0,011
Variance t+4	0,032	0,010***	0,061	0,012
Variance t+5	0,033	0,013**	0,056	0,013
Variance t+6	0,034	0,013**	0,056	0,013
Variance t+7	0,031	0,016**	0,053	0,013
Variance t+8	0,030	0,018**	0,051	0,013
Variance t+9	0,028	0,017**	0,052	0,011
Variance t+10	0,031	0,030**	0,044	0,014
Variance t+15	0,023	0,044**	0,037	0,011
Variance t+20	0,020	0,041**	0,038	0,010
Variance t+25	0,019	0,031**	0,043	0,009
Variance t+30	0,016	0,045**	0,037	0,008
Variance t+50	0,023	0,108	0,024	0,014
Variance t+260	0,006	0,593	0,002	0,019

Table 1*: Regression results: Analyst dispersion's impact on the volatility of S&P 500.*

$\sigma^2_{t+x} = \alpha + \beta_1(Analyst\ dispersion)_t + \mu.$

,,*** represent significance levels on 10 %, 5 % and 1%, respectively.*

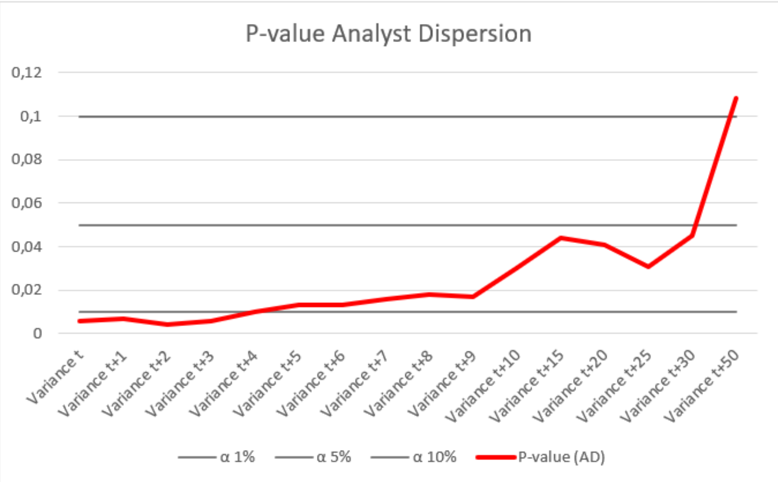


Figure 7*: P-value of analyst dispersion from regression;*

$\sigma^2_{t+x} = \alpha + \beta_1(Analyst\ dispersion)_t + \mu$

Figure 7 shows that, with a significance level of 1 %, news about macro uncertainty cause changes in volatility on the S&P 500 for t up to t+4. Also, on a 5 % significance level we can say that news about macro uncertainty cause changes in volatility for 30 days. First when we look at the impact after 50 days, we fail to find significance on the 10 % level. Considering that all coefficients in table 1 are positive, this means that news about macro uncertainty cause increased volatility in stock markets for an extended period of time. Based on our prior beliefs, the persistency of volatility following uncertainty news is somewhat surprising, as we expected the stock market to adjust quickly to the new information. However, it underlines the importance of macroeconomic uncertainty´s role as an influencer of the stock market's volatility.

As briefly mentioned above, all coefficients in table 1 are positive. This means that an increase in analyst dispersion will lead to increased volatility for a period of time. The coefficients for the immediate days after the release of macro uncertainty news vary between 0,030 and 0,034, which means that if analyst dispersion increases by one, volatility on the S&P 500 increases by roughly 3%. Both the coefficients and the R squared estimates are declining with time, which means that the explanatory power of analyst dispersion on volatility in stock markets is decreasing over time, just as one would expect.

Previous literature offers various possible explanations for this relationship. Baker et al. (2016) claimed that uncertainty about future economic states is influential on a firm's decision to invest in new projects. Increased uncertainty lead firms to rethink their investment strategies, which again cause confusion among investors and volatility in the stock market. Fajgelbaum et al. (2017), on the other hand, would have explained our findings with risk aversion among investors. They claim that increased uncertainty leads to lower activity and thus less information sharing between market participants. As each participant possesses less information about the market's valuation of the stock market, stock prices become more volatile. However, we will later discuss how trade volume and macroeconomic uncertainty are related and see that the latter might be a fragile argument.

5.2 Macroeconomic Volatility and Stock Market Uncertainty

To see if the relationship between macro- and microeconomic variables (GDP-growth volatility and stock market uncertainty) are mutually dependent, we test if uncertainty in the stock markets affect the volatility of GDP-growth. We now use

3-month realized variance as the measure of uncertainty in the stock market, and GARCH-modelling of the GDP-growth as the measure of volatility. Since changes in GDP have volatility clustering, as seen in figure 8, we use the GARCH framework to model volatility. Summary statistics of GDP growth and stock market uncertainty can be found in appendix 6 and 7, respectively. From figure 9 we see that the uncertainty in the capital markets increased significantly during the financial crisis, and in figure 8 we see that GDP decreased significantly in the same period. In addition, we notice that uncertainty in stock markets are higher during times of financial difficulty. There is an increase in realized variance both during the dot-com bubble in the early 2000 and in the beginning of the European Sovereign Debt Crisis in 2011. During the same time periods, except 2011, it is a counter-cyclical pattern for the GDP-growth. Since the observations are only done quarterly, the data is prone to have large tails due to a small amount of observations.

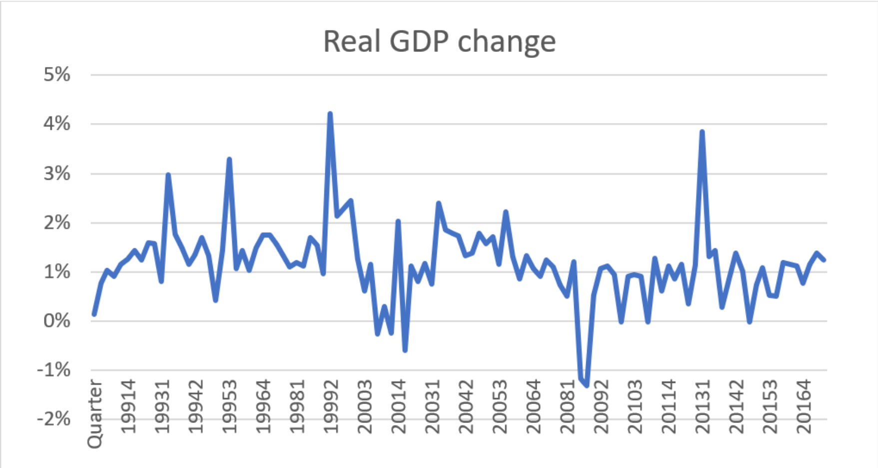


Figure 8: *Real GDP change.*

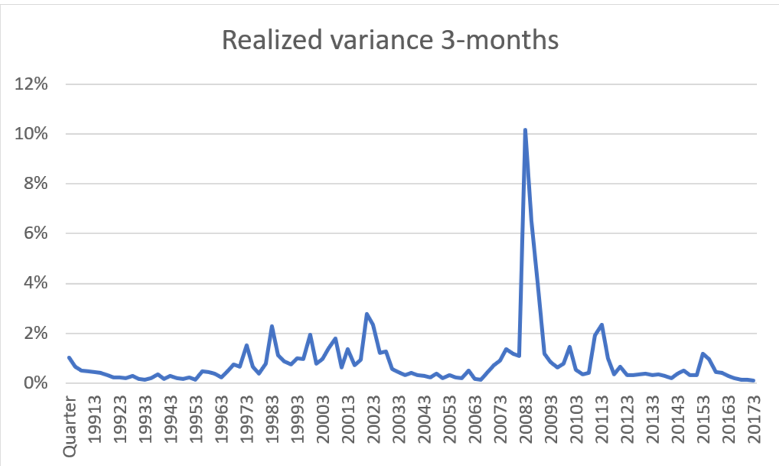


Figure 9: *Realized 3-month variance for the S&P 500.*

In figure 10, we see clear peaks of macroeconomic volatility during times of financial difficulty. Interestingly the volatility is starting to increase several years before the events, and sharply drop after the events are over.

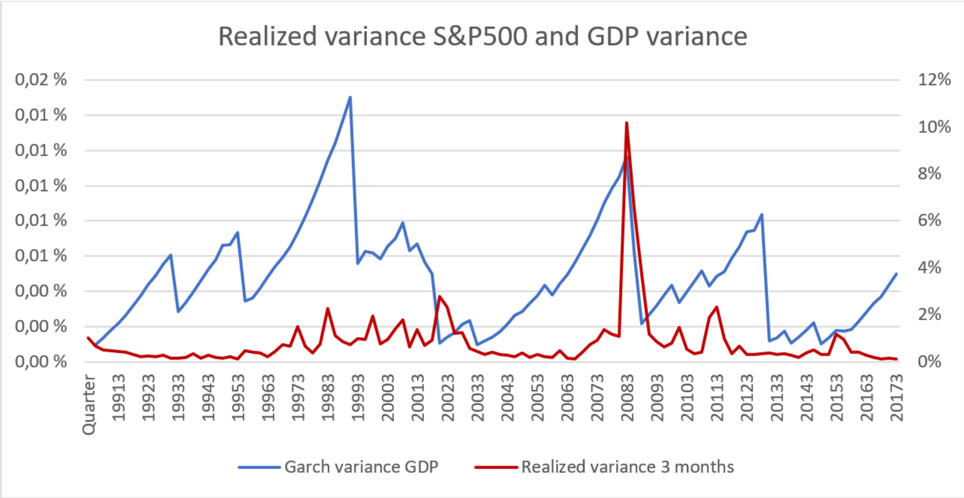


Figure 10: *GARCH modelled variance GDP and realized 3-month variance of S&P 500*

From the regression in table 2, we find significant results that uncertainty in the stock markets will influence the volatility of the GDP growth on a 1%-level. The coefficient from the realized variance is positive, so we can draw the conclusion that higher uncertainty in the stock market will result in higher volatility for the GDP growth. One possible explanation of this phenomenon is that the S&P 500 is represented by the biggest companies in the United States. It is possible that the size of these companies is large enough to affect the GDP-output of the country.

Macroeconomic volatility				
	β	P-value	R-squared	Std. Error
RVAR 3 month	0,0006	0,007***	0,066	0,0002

Table 2: *Regression output Macroeconomic Volatility.*

$\sigma_t^2 = \alpha + \beta_1 (RVAR)_t + \mu$

*,**,*** *represent significance levels on 10 %, 5 % and 1 %, respectively.*

The findings are interesting and in line with our expectations. The GDP is the gross production output of a country and is dependent on the firms´ willingness to grow and invest. When there is uncertainty, the firms will operate with investment decisions as a real option (Bernanke 1993). If they invest, they lose their option, but if they delayed their investment they still have the option. Thus, investment decisions will be delayed, and create less output in the economy. The test is in many ways the same as the previous test of macroeconomic uncertainty and stock market volatility, and this test shows that it is mutual dependence between the two variables. The uncertainty for firms can come from many sources, such as energy-prices (Sadorsky, 1999). When uncertainty is high, firms may not be able to predict the future cost of commodities. To help ease this problem, businesses use derivatives, like for example the aviation industry uses derivatives to control their fuel cost. Hamilton (2003) shows that changes in oil prices will have a forecasting effect on the GDP growth. Thus, interlinking variables that affect both uncertainty for firms and the GDP growth could play a contributing factor for the relationship between the stock market uncertainty and the GDP volatility.

5.3 Causality

To further investigate the relationship between macroeconomic uncertainty and stock market volatility we tested for Granger causality between analyst dispersion about GDP growth forecasts and 3-month realized variance in the stock market. For the Granger-causality test, we chose 3-month realized variance as a proxy for volatility as the observation length corresponds to the observations from the SPF. To be able to test for causality, we first ran a VAR model (results available in appendix 8) and checked the optimal lag length using Akaike and Schwarz selection criterion (available in appendix 9).

From table 3 we see that there is significance on a 5%-level that 3-month realized variance Granger-causes analyst dispersion. This means that if realized variance is high over a three-month period prior to the release of macroeconomic uncertainty news, analyst dispersion is likely going to be high as well. To our surprise we do not find evidence that analyst dispersion Granger causes 3-month realized variance. We saw in figure 7 that analyst dispersion impacts stock market volatility for an extended period of time, and we expected this to be backed up by the Granger causality test. However, it seems as analyst dispersion cannot be used to predict the stock market volatility for the next three months as a whole, presumably because we use a quarterly measure of uncertainty. Had we employed a daily measure of uncertainty and tested this with a daily measure of volatility, we would probably achieve a different result, as previously indicated in figure 7.

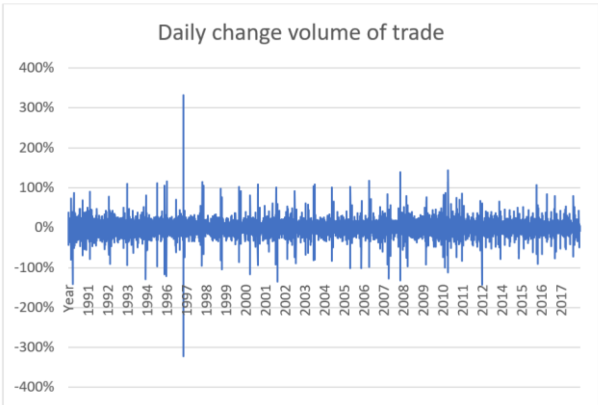
Granger Causality Test	
	RVAR AD
AD t-1 (p-value)	0,702
RVAR t-1 (p-value)	0,011**

Table 3: *VAR Granger Causality/Block Exogeneity Wald Tests.*

*,**,*** *represent significance levels on 10 %, 5 % and 1 %, respectively.*

5.4 Volume of Trade

We have already witnessed that an increase in analyst dispersion leads to an increase in stock market volatility. However, uncertainty also leads to changes in the volume of trade.



Summary statistics absolute change of trading volume		
	Full sample	SPF release dates
Sample period	01.10.1990-09.04.2018	1990Q4-2017Q4
Interval	Daily	Quarterly
Observations	6934	109
Mean	0,129	0,103
Median	0,091	0,090
Max	3,315	0,426
Min	0,000	0,007
Std. Dev.	0,151	0,084
Skewness	5,396	1,348
Kurtosis	69,790	5,211

Figure 11: *Summary statistics daily change volume of trade on the S&P 500.*

We clearly see that the number of daily trades on the S&P 500 during the last 28 years have several spikes. When matching the daily number of trades with the release dates of the survey of professional forecasters, a total number of four observations are defined as outliers. Without any obvious explanation, the number of trades increased by more than 60% from the day before during those trading days. As these outliers are clearly not associated with our measure of macro uncertainty or stock market volatility, we have removed the observations from our dataset. The table in figure 11 shows summary statistics of the absolute change in volume of trade, while the plot shows daily change. From the table, we notice that the mean is significantly higher than the median, which suggests we have a long right tail. In the full sample statistics, outliers are not removed which explains why the mean is much higher for this sample, while the median is comparable to that of the limited sample. Full summary statistics, including a histogram, is available in appendix 4 and 5.

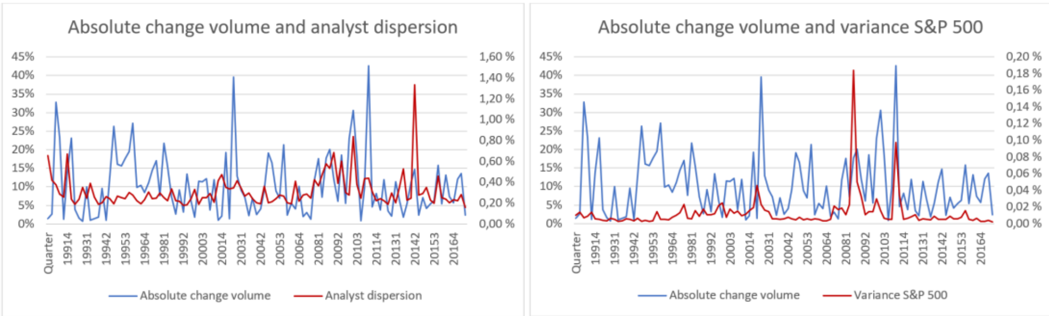


Figure 12*: Absolute change in volume of trade paired with analyst dispersion and variance of the S&P 500, respectively.*

From figure 12 we notice that the absolute change in volume of trade seems to fluctuate with both analyst dispersion and stock market volatility, and that the correlation seems to be positive. This is confirmed by table 4, which shows our regression results. Both coefficients are positive and significant on respectively 5% and 1% significance levels. If we run the same regression without taking the absolute value of change in trading volume, we do not obtain significant results. According to Nimark (2013), trivial events catch more interest in uncertain times, whilst they would be unimportant in a normal state of the economy. This phenomenon will lead to increased uncertainty in periods of distressed markets. Similarly, we know that market participants interpret news differently in periods of financial distress. If this is the case, then the effect from periods of recessions may cancel out the effect from expansions and vice versa. This issue may be the reason why we do not find significance without taking the absolute value of change in volume. Alternatively, this issue could be solved by including a dummy variable for recessions, but using NBER recession dates as dummy did not change the results for our data.

Absolute change volume of trade				
	β	P-value	R-squared	Std. Error
Analyst dispersion	10,439	0,042**	0,038	5,076
Stock market volatility	110,043	0,005***	0,072	38,234

Table 4: *Regression results: Analyst dispersion and stock market volatility on absolute change volume of trade.*

$\Delta Volume\ of\ trade = \alpha + (Analyst\ dispersion)_t + \mu$

and

$\Delta Volume\ of\ trade = \alpha + \sigma^2_{S\&P500,t} + \mu.$

*,**,*** *represent significance levels on 10 %, 5 % and 1 %, respectively.*

Our findings suggest that volume of trade is affected by both macroeconomic uncertainty and stock market volatility. However, the effect seems to be dependent on the state of the overall economy. This is in line with previous research, where we have seen that Varian (1985) and Pfleiderer (1984) disagrees about the relationship between uncertainty and volume of trade. When controlling for recessions using NBER recession dates we expected to isolate the effect of economic states. However, it seems like market participants disagree on the perceived state of the economy, which may serve as an explanation as to why we struggle to find a definitive relationship between volume of trade and macroeconomic uncertainty and/or stock market volatility.

6. Conclusion

The results presented in this thesis show evidence that uncertainty about future GDP growth will affect the volatility of the stock market. Even more interesting; macroeconomic uncertainty affects volatility of the stock market for an extended period of time after the initial uncertainty news is revealed. We used the standard deviation of analyst forecasts of next periods GDP as proxy for uncertainty, while the S&P 500 index served as our proxy for the stock market.

Additionally, we find mutual dependence between macro and micro variables. Meaning that uncertainty in the stock market has an impact on the volatility of GDP growth. We mention that the S&P 500 index may accommodate values substantial enough to affect the gross domestic product of USA. Furthermore, using a vector autoregressive model we find that stock market volatility granger causes macroeconomic uncertainty, while the opposite relation is not present in our data. This means that past values of stock market volatility can be used to help predict values of macroeconomic uncertainty. Based on the persistence of volatility after an uncertainty shock, we have reason to believe that the opposite relation, that past values of stock market volatility can be used to predict macroeconomic uncertainty, could be proved using a daily measure of macroeconomic uncertainty.

Lastly, we present evidence that both stock market volatility and macroeconomic uncertainty affect the absolute change in trading volume. This means that market participants adjust their trading strategy based on both volatility and uncertainty. Our research indicates that the changes in volume is dependent on the perceived state of the economy. Both coefficients in our regressions are positive, indicating that trading volume becomes more volatile as stock market volatility and macroeconomic uncertainty rises.

6.1 Suggestions to Future Reasearch

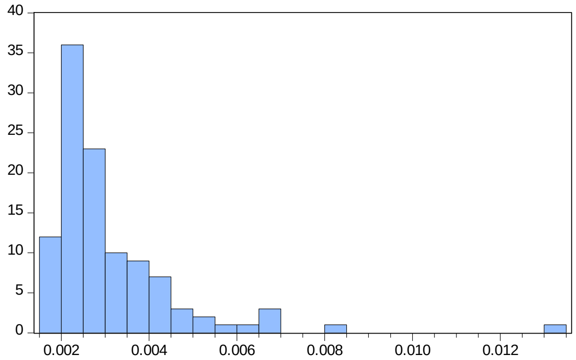
In this thesis we use GDP growth as the sole macroeconomic factor. It could be interesting to see if the results hold on other popular measures of uncertainty such as a level measure of professional forecasters, the VIX and/or the EPU. Using monetary measures like GDP growth, which are published quarterly, also present a challenge in building a rich dataset. Even with an extensive sample period, the number of observations will be relatively modest. Using a daily measure of macroeconomic uncertainty would probably lead to different results, and would be particularly interesting in the VAR model and Granger causality test. A daily measure of uncertainty would also make it easier to control for economic states in the regression for trading volume. A single quarter may include several perceived states of an economy and it is different to control for in a regression. As proxy for capital market we use the S&P 500 index. While this is viewed as a good representation of the American stock market, it could be interesting to see if the effects of macroeconomic uncertainty are persistent across indices as well, also those consisting of small cap companies.

7. Appendix

Sample: 1/02/1990 4/09/2018
Included observations: 7123

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.216	0.216	331.81	0.000
		2	0.364	0.333	1275.1	0.000
		3	0.196	0.085	1550.3	0.000
		4	0.287	0.153	2136.4	0.000
		5	0.318	0.217	2859.2	0.000
		6	0.286	0.120	3442.6	0.000
		7	0.296	0.108	4068.0	0.000
		8	0.223	0.030	4422.4	0.000
		9	0.277	0.079	4970.4	0.000
		10	0.256	0.070	5439.4	0.000
		11	0.344	0.151	6284.3	0.000
		12	0.265	0.059	6784.4	0.000
		13	0.209	-0.049	7096.0	0.000
		14	0.136	-0.113	7228.0	0.000
		15	0.209	0.000	7538.8	0.000
		16	0.241	0.051	7955.1	0.000
		17	0.246	0.038	8388.4	0.000
		18	0.230	0.034	8767.4	0.000
		19	0.179	-0.000	8997.6	0.000
		20	0.209	0.026	9310.7	0.000
		21	0.238	0.072	9714.7	0.000
		22	0.181	-0.046	9948.4	0.000
		23	0.236	0.039	10348.	0.000
		24	0.148	-0.011	10503.	0.000
		25	0.169	-0.007	10707.	0.000
		26	0.157	-0.005	10884.	0.000
		27	0.258	0.092	11360.	0.000
		28	0.225	0.043	11722.	0.000
		29	0.187	-0.015	11972.	0.000
		30	0.149	-0.029	12132.	0.000
		31	0.147	-0.014	12287.	0.000
		32	0.222	0.054	12640.	0.000
		33	0.153	-0.027	12807.	0.000
		34	0.237	0.066	13208.	0.000
		35	0.110	-0.034	13295.	0.000
		36	0.153	-0.041	13462.	0.000

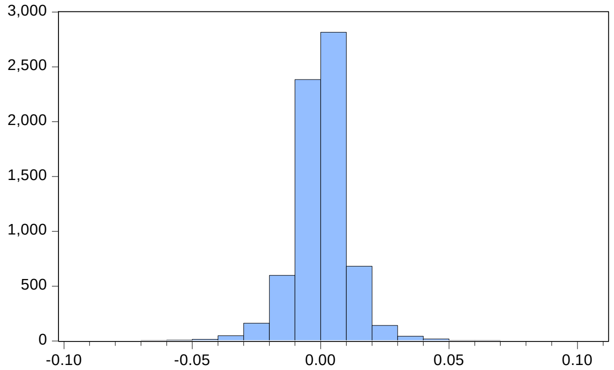
Appendix 1: *Correlogram squared returns of S&P 500*



Series: STD_DEV_ENDRING__LN_
Sample 1990Q4 2017Q4
Observations 109

Mean	0.003132
Median	0.002598
Maximum	0.013342
Minimum	0.001589
Std. Dev.	0.001560
Skewness	3.377326
Kurtosis	19.48157
Jarque-Bera	1440.923
Probability	0.000000

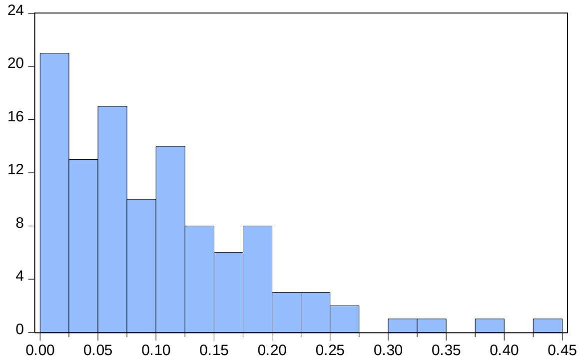
Appendix 2: *Summary statistics Analyst dispersion (Uncertainty measure).*



Series: DAILY_RETURN
Sample 10/01/1990 4/09/2018
Observations 6934

Mean	0.000309
Median	0.000510
Maximum	0.109572
Minimum	-0.094695
Std. Dev.	0.011138
Skewness	-0.262702
Kurtosis	11.98765
Jarque-Bera	23417.83
Probability	0.000000

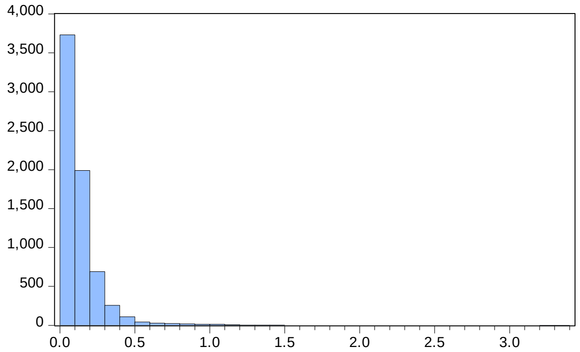
Appendix 3: *Summary statistics daily return S&P 500.*



Series: ABSOLUTE_CHANGE_VOLUME
Sample 1990Q4 2017Q4
Observations 109

Mean	0.102927
Median	0.089554
Maximum	0.425667
Minimum	0.007286
Std. Dev.	0.083523
Skewness	1.347818
Kurtosis	5.210856
Jarque-Bera	55.20097
Probability	0.000000

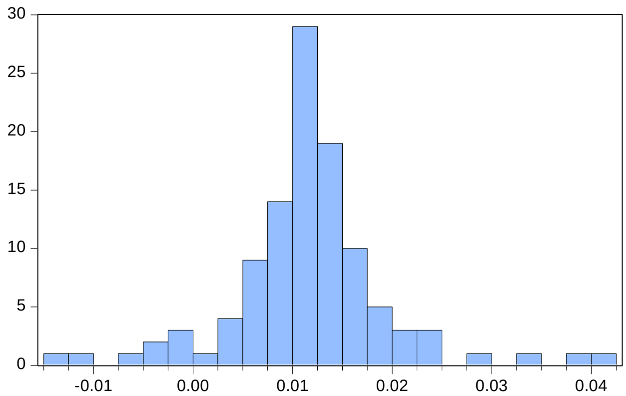
Appendix 4: *Summary statistics absolute daily change volume of trade. SPF dates.*



Series: ABSOLUTE_CHANGE_VOLUME
Sample 10/01/1990 4/09/2018
Observations 6934

Mean	0.128516
Median	0.091172
Maximum	3.314901
Minimum	0.000000
Std. Dev.	0.151453
Skewness	5.396194
Kurtosis	69.79017
Jarque-Bera	1322488.
Probability	0.000000

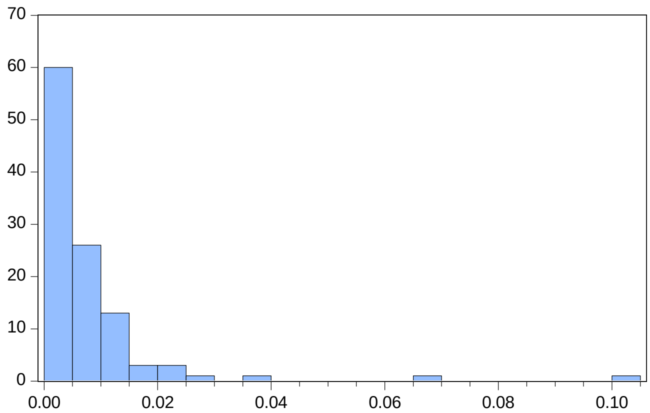
Appendix 5: *Summary statistics absolute daily change volume of trade. Full sample.*



Series: REAL_GDP_CHANGE
Sample 1990Q4 2017Q4
Observations 109

Mean	0.011704
Median	0.011522
Maximum	0.042225
Minimum	-0.013163
Std. Dev.	0.007919
Skewness	0.439916
Kurtosis	6.550079
Jarque-Bera	60.75462
Probability	0.000000

Appendix 6: *Summary statistics GDP growth*



Series: RVAR_3_MONTH
Sample 1990Q4 2017Q4
Observations 109

Mean	0.008185
Median	0.004339
Maximum	0.101745
Minimum	0.001028
Std. Dev.	0.012292
Skewness	5.216246
Kurtosis	36.13905
Jarque-Bera	5481.944
Probability	0.000000

Appendix 7: *Summary statistics 3-month realized variance S&P 500.*

Vector Autoregressive Model		
	RVAR	AD
RVAR t-1	0,577	0,031
	(0,083)	(0,012)
	[6,927]	[2,531]
AD t-1	0,252	0,071
	(0,658)	(0,097)
	[0,383]	[0,736]
C	0,003	0,003
	(0,002)	(0)
	[1,192]	[8,118]
Adj. R-squared	0,331	0,061
F-stat	27,509	4,478

Appendix 8: *Vector Autoregressive model.*

VAR Lag Order Selection Criteria
Endogenous variables: RVAR_3_MONTH STD__DEV_ENDRING__LN_
Exogenous variables: C
Date: 06/19/18 Time: 17:59
Sample: 1990Q4 2017Q4
Included observations: 105

Lag	LogL	LR	FPE	AIC	SC	HQ
0	848.0602	NA	3.44e-10	-16.11543	-16.06488	-16.09495
1	870.9712	44.51287	2.40e-10*	-16.47564*	-16.32399*	-16.41419*
2	872.6589	3.214660	2.51e-10	-16.43160	-16.17884	-16.32918
3	878.2680	10.47023*	2.43e-10	-16.46225	-16.10839	-16.31886
4	879.3404	1.960957	2.57e-10	-16.40648	-15.95152	-16.22212

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Appendix 9: *VAR Lag order selection criterion.*

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