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-Master Thesis-

Does macro uncertainty affect stock markets?

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Contents

Abstract

This thesis concerns the topic of uncertainty and its application to economics. Uncertainty is a situation which involves imperfect and/or lack of information necessary for the prediction of future events. In this study, we are in particular concerned with macroeconomic uncertainty and it's relation to the stock price variations in the US financial markets. Our results indicate that the macroeconomic uncertainty is dependent on the stock market's interpretation of macroeconomic news. We also find that macro uncertainty is positively related to the volume of trade and the stock price volatility. It is suggested that an aggregate measure of cross-sectional analyst dispersion, could serve as a proxy for macro uncertainty.

Acknowledgements

We wish to thank our supervisor Professor Dagfinn Rime at BI Norwegian Business School for contributing us with the exciting topic, providing rich datasets and guidance during our research.

Introduction

The aim of this research is to investigate how different levels of macroeconomic uncertainty affect the uncertainty of analyst forecasts and hence influence the stock prices in the US financial markets.

In our analysis, we use two different measures of analyst dispersion and two well-known uncertainty proxies for macro uncertainty. We create a measure of aggregate uncertainty, based on a cross-section of analyst dispersion which allows us to observe how it relates to widely employed uncertainty indices such as the VIX Implied Volatility Index and the Economic Policy Uncertainty (EPU) Index.

Our results indicate that variables from the categories of Industrial Production and Labor follow Bayesian probability updating, whereby stock prices and uncertainty levels are directly related, i.e. prices show larger variations when uncertainty is high, compared to smaller variations when uncertainty is low. In addition, our results show that analyst dispersion is positively correlated with both the volume of trade and volatility of the stock market.

The thesis is divided into 5 sections. In the first section, we describe our motivation for investigating the topic of this Thesis. In the second section, we present a literature review, sectioned into three parts: Uncertainty Proxies, analyst dispersion and uncertainty linked to macro news, trade volume and volatility. In the third section, we present the theoretical foundation and our methodology in detail. In the fourth section, we examine our datasets and perform a comparison of our chosen uncertainty indices to;

1. Extract the effects of macro uncertainty on stock markets by three different variables:
   a) Impact of news
   b) Volume of trade
   c) Volatility of stock price
2. Build an aggregate uncertainty measure based on cross-sectional analyst dispersion and evaluates it against known uncertainty indices.

In the fifth section, we present our conclusions based on the main findings of our analysis and propose future research questions.

Motivation

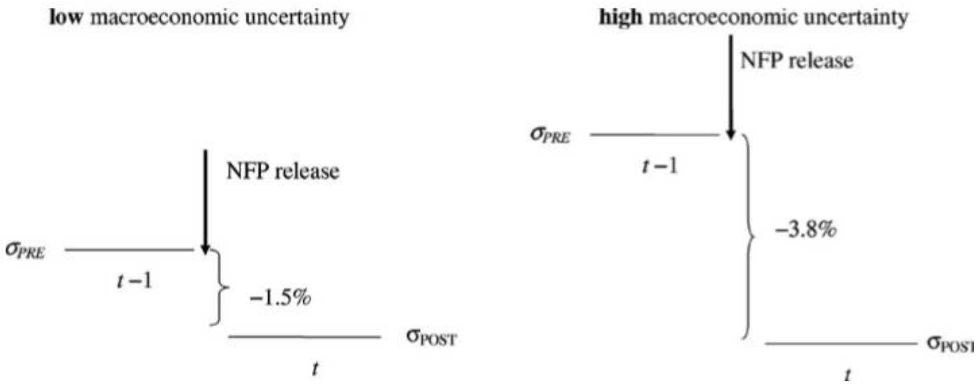


Figure 1: The theoretical impact of macro shocks on the volatility (Beber et al 2014)

Uncertainty is a situation which involves imperfect and/or lack of information necessary for the prediction of future events. In order to infer future behavior in the dynamic analysis of sequential data, Bayes theorem is an important technique in mathematical statistics and when it is applied iteratively, it defines the procedure termed as Bayesian updating which is widely used and computationally convenient.

Since future predictions and shocks affect financial assets, the importance of uncertainty has an impact on all intermediaries in financial markets. Beber et al (2014) proposed a modern, state-of-the-art model to measure uncertainty and the state of the economy. We see in Figure 1 that there is a significant impact of shocks on the uncertainty itself, but how does the macro uncertainty affect the stock market?

In particular, institutional and private investors would be interested in incorporating the results of thesis like this in their planning of future strategies. If analyst dispersion is highly related to the impact of macro news on stock prices, investors can trade on stock movements by employing information on analyst dispersion in the forecasts of macroeconomic variables, since it is postulated that if analyst dispersion is high, it will be most likely followed by a large stock movement when macro news is released.

Historically, there have been many measures of uncertainty e.g. stock volatility, implied volatility of options and newspaper articles. One measure we find particularly interesting is the forecaster disagreement on macroeconomic announcements. Research shows that all analysts have different biases and we see that analyst disagreement varies significantly over time and we will also extract and demonstrate the impact of this dispersion over time in this thesis.

Schwert (1989), Davis and Kutan (2003) and Chan et al. (1998), agree on the insignificant relation between macro uncertainty and stock markets, using time series models. Arnold and Vrugt (2008) argue that time-series analysis does not capture the macroeconomic uncertainty as well as a dispersion based model, which uses analyst disagreement as an uncertainty measure.

Another great source of motivation for this thesis is the topic of “Brexit”, where Great Britain has been involved in a referendum on extending their ongoing membership in the European Union. Based on previous research by Baker et al (2015), we expect the Economic Uncertainty Policy Index to reflect the uncertainty in the market moving towards the date of the referendum. Thus we have the opportunity to see uncertainty being outplayed in practice while we examine the theoretical background. Bloom (2009) found that uncertainty appears to dramatically increase after major economic and political shocks. The “Brexit” is a potential shock of this kind and according to the work by Bloom (2009); we are likely to see a major increase in uncertainty.

According to Bayesian update analysis, the news is expected to have a larger impact when uncertainty is high, and that is a result that we anticipate from our research. If this is confirmed, in the period leading up to the “Brexit” we should observe an increase in uncertainty, news will have larger impacts and an increasing amount of macro news will be significant for Great Britain and all stock markets affected by the UK.

As we demonstrate in Figure 2Figure 3 there is, as expected, a large increase in the uncertainty of the S&P500, explained by the VIX index, in the weeks leading up to the referendum. The sharp increase in uncertainty of the US stock markets is explained by the investments US companies have made in the UK and usage of Great Britain as a trading hub with the rest of the EU. From the increase in the VIX index and the spike in the US EPU index, it is expected that the outcome of the “Brexit” will affect the markets on US soil. The US stock market was not, in contrast to the political uncertainty, at an “all time high” uncertainty state, possibly explained by the media aspect of the EPU index. The relationship between high uncertainty measured by the EPU index and the VIX index, as seen during the default of Lehman Brothers and the debt ceiling dispute, is absent in the period surrounding the referendum.

In the weeks following the decision of the UK to leave the European Union, we observe that the volatility of the S&P500 has returned to a normal state. This indicates, and somewhat confirms our hypothesis, that at periods of high uncertainty, the markets react increasingly to macroeconomic news. According to a survey from Wall Street Journal, US equity analysts have made no significant adjustments to their projections for growth in the US economy. This in addition to the interest rate decision by the FED to keep the interest rate unchanged has fueled the economy and helped to decrease the uncertainty in the markets.

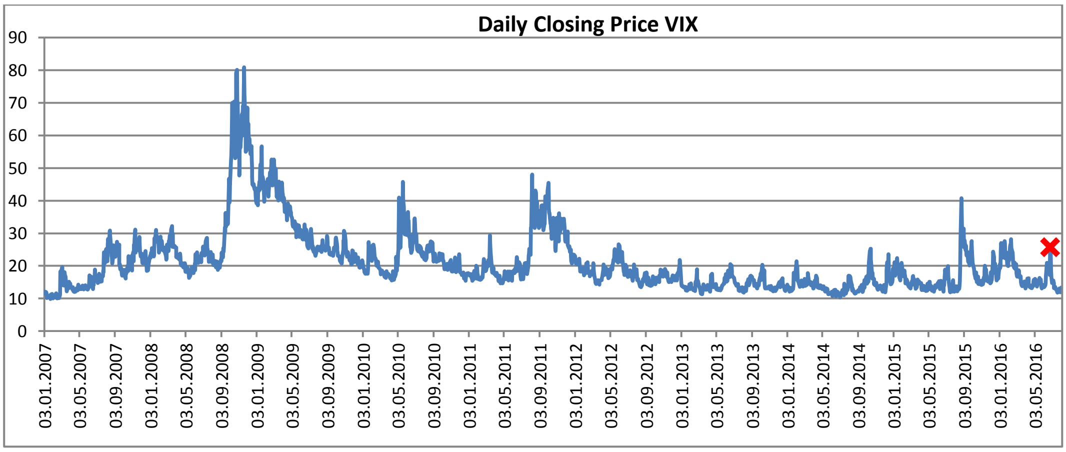


Figure 2: Daily closing prices of the VIX index. The red cross marks 24.06.2016, where the announcement of Great Britain leaving the EU was released.

Figure 3: Monthly Economic Policy Uncertainty Index. Where "P" is the slowdown in China, "N" is the Debt Ceiling dispute, "J" is the default of Lehman Brothers, "H" is the 2nd Gulf War and "G" 9/11. The last peak in the figure is the time surrounding "Brexit". Collected from http://www.policyuncertainty.com/

On the other hand, we also need to consider market imperfections when explaining the economic impacts of news. Shiller (1980) found that stock prices were too volatile to only be determined by expectations of future dividend, giving birth to "behavioral finance". According to behavioral finance, investors can over and under react to news, which is then followed by a correction from the market. The phenomenon of herding, which is when the entire market follows the same direction as a reaction to certain news, is also present in the markets. When the market tends to copy experienced investors in order to make the same profits as those investors have made in the past, it is called the "copycat". We are likely to witness these behavioral finance effects in the time surrounding the date of the "Brexit".

Literature Review

Uncertainty Measures

Knight (1921) early defined the concept of risk as: “a known probability distribution over a set of events” and also defined uncertainty as: “people's’ inability to forecast the likelihood of events happening”. In our economic days, a common measure or proxy of the degree of uncertainty in the finance industry is the volatility of the stock market. The volatility of the S&P 500 Index is an example which is frequently used due to its simplicity. When data series of the financial markets become more volatile, it becomes harder to forecast the future states of the economy (Bloom 2014) and this is a major disadvantage for the investors, who rely on accurate predictions.

A different proxy for uncertainty is the implied volatility of options is reflected in the VIX Implied Volatility Index. Option contracts have six different variables: the time to maturity, the spot price of the underlying asset, the strike price, the risk-free rate, dividends and the implied volatility. Since market prices of options are observable, the implied volatility of the options can be calculated using the other four. The most used and widely accepted measure of general uncertainty in the economy is the historical volatility. In contrast to this, Fleming (1998) argues that with a correction for certain biases, conditional volatility can be a better estimator for predicting uncertainty of the stock market.

Research by Campbell et al., (2001) reports that cross-firm stock-return variation is almost 50 percent higher in times of economic recessions compared to times of economic booms. One explanation of increased variance in recessions, where negative shocks have an increased impact on the volatility rather than a corresponding positive shock in a booming period, is the leverage effect. The leverage effect is a concept that describes the increase of debt in the economy during troubled times, which also lead to an increase in stock return volatility. However, Schwert (1989) revealed that only 10% of the volatility increase in recessions is due to the leverage effect, therefore this cannot be the only explanation.

Scherbina (2003) elaborates on the possibility that predictions and forecasts about future macroeconomic shocks are subject to conflict of interest, rather than being pure proxies for future uncertainty. Consequently, it is difficult to map the analyst's subjective expectations about macroeconomic variables, since they tend to have a systematic bias, as will be discussed in the next chapter.

Alexopoulos and Cohen (2009) used another proxy, namely the "Main Street" measure. This metric is based on the number of New York Times articles that contains uncertainty and the economy tropics. Comparing this to a classical measure of uncertainty in finance as the volatility of the stock index, the "Main Street" is extensively more volatile. Furthermore, the "Main Street" measure has longer downturns and prolonged rebounds than the market index. This supports the idea that the "Main Street" measure is a more comprehensive measure of total volatility in the economy rather than the stock index exclusively. However, this measure is also biased with journalist incentives and therefore less suitable for trading. Baker et al (2012) applied the same methodology from the ten biggest newspapers in the US and found that 51% increase in selected combination of words during recessions, consistent with Alexopoulos and Cohen (2009) study. The Economic Policy Uncertainty (EPU) Index was constructed as a result of the Baker et al paper. The EPU-Index has since 2012 been a frequently used uncertainty index, complementing the VIX.

Bachmann et al (2010) showed that forecaster disagreement is significantly higher in economic downturn periods. In these periods, analysts and forecast experts from different types of institutions and organizations, display more dispersed opinions and their forecasts reflect higher uncertainty, compared to economically booming periods. Therefore, this paper illustrates that forecaster disagreement can be seen as a proxy for macro uncertainty.

Scotti (2013) introduced a methodology of index construction in order to capture market surprise and analyst uncertainty whenever macroeconomic news is released. In that study, she constructs one surprise and one uncertainty index and applies them to five different economies to examine if there is worldwide consistency. These indexes measure the degree of optimism and pessimism about the economy when the news is released. Positive figures from the surprise index indicate that the expectations have been higher than consensus and the agents were pessimistic about the macroeconomic situation. The correlation between the two indexes was found to be negative; hence the study concludes that negative news actually increases volatility.

There has also been argued that one can use the size of forecast errors to measure uncertainty. Scotti (2013) and Jurado et al (2013) concluded that the magnitude of forecast errors varies in economic cycles, emphasizing the rise of uncertainty in recessions.

More recently, Beber et al (2014) proposed a modern, state-of-the-art model to measure uncertainty and the state of the economy. They proposed a simple, cross-sectional technique to extract factors from economic news released at different times and frequencies. They provided a methodology for the aggregated level of the economy and uncertainty, based on principal components analysis, and a categorization of different news. This was proven as an accurate measure of both, the state of the economy and the general uncertainty level.

Forecast dispersion may also be used as a proxy for macroeconomic uncertainty according to Orlik and Veldkamp (2015), whereby the measure is regarded as "model-free". The forecast is determined as the difference between the macroeconomic variable and noise $y_{t+1} = E[y_{t+1}] + \varepsilon_t$. Furthermore, the dispersion which reflects the analysts private signals is measured as the average squared difference between the true value and the average forecast: $\frac{1}{N}\sum e_t^2$. The results show that using forecast dispersion to measure macroeconomic uncertainty will not be able to capture all the variation in uncertainty measures.

Another method to measure uncertainty is the mean-squared forecast error model (Orlik and Veldkamp, 2015). This model is capturing both the private and common errors, since the MSE is squared difference between the forecast and the real value of the input:

$$MSE = \sqrt{\frac{1}{N}\sum (E[y_{t+1}] - y_{t+1})^2}$$

Analyst dispersion as an Uncertainty Proxy

An important part when assessing the impact of analyst uncertainty on macroeconomic shocks is the role of macro-analysts. Professional forecasters are employees that hold qualified skills and experience in interpreting information and utilizing it to infer economic forecasts.

According to Laster et al (1999), there are two types of users that utilize economic forecasts, namely intensive and occasional users. The intensive users have a high demand for accurate forecasts because they utilize them to create value in the short and long-term horizon, using a variety of financial contracts and assets. Hence, poor forecasts will eventually lead to ineffective usage of recourses and increased risk for financial losses. On the contrary, the occasional users are not that dependent on pin-point accuracy in forecasts provided, since they rather search for long-term trends and are limited in their use of advanced financial markets. According to the same study, the analysts´ bonus is defined by their ability to support to the firm´s investors in investment decisions and to what degree they are able to facilitate growth in the client base of the firm. The analysts´ reputation is based on the accuracy of their forecast, how the investors perceive their recommendations and to what extent they are benefiting from following the forecaster's recommendation. The study also concludes that if all forecasters have similar data, intentions and seek to have the highest accuracy of future states, their projections will cluster around the consensus.
Following Schuh (2001), the traditional forecaster has the goal to produce the most accurate and unbiased forecast with uncorrelated forecast errors. His assumption is that all forecasters use all new information available to get the most correct forecast possible.

Batchelor (2007) elaborates that there are three possibilities for deviations between the forecasted value and true value of financial assets. The first possibility is that the forecaster lacks the skill to properly utilize all information available at any given time. The second reason might be that the analyst possesses the proper skill to comprehend the signals, but lacks sufficient information to get correct results. The last possibility of deviation is that the forecaster both have the required skill and data, but consequently introducing a “rational bias”. Since analysts are not directly compensated from the investors, but from their employer, their perception about new information is not consistent with the true value. As this rational bias is important, we will further elaborate on it.

Other research by McNees (1978) finds little support that macroeconomic forecasts, such as GNP, Inflation, and Unemployment from professional analysts are completely efficient and unbiased. Ito (1990) finds evidence that FX forecasts are systematically biased in projections that are in favor of the analysts´ firm.
It is suggested that it is not only the analysts' bonus schemes that are causing the bias, forecasts can also be used as an instrument to rationalize and gaining power in politics and government institutions. An example of this behavior is published by Heinemann (2005), that shows forecasts of economic growth in Germany have been constantly optimistic during the last decades and is, in fact, allowing the German government to make unrealistic high spending plans.

Another interesting behavioral pattern of forecasters has been proposed by Ehrbeck and Waldeman (1996), who argue that forecasters that lack proper skill and knowledge try to mirror respected and powerful forecasters. This can also be connected to the phenomenon of "Herding", that explains why forecasters continuously overestimate the accuracy of other forecasters and lead to clustering of forecasts.

Uncertainty linked to macro news, trade volume and volatility

In the years after the groundbreaking research by Treynor (1961) and Fama et al., (1969), it is a common belief that asset prices are sensitive to changes in macroeconomics, also consistent with the "Capital Asset Pricing Model".

This is also in agreement to Ross (1979) who confirmed the theory of the "Arbitrage Pricing Model" whereby asset returns are determined by exposures to macroeconomic factors and are not in conflict with the theory of market efficiency.

However, previous research showed little evidence of actual effects of macroeconomic news on stock prices, except monetary news. Pearce and Roley (1985) compiled survey data from 1977-82 and found that consumer price index, unemployment, and industrial production has weak links with returns on stock, on the other hand, monetary information was found to be significant. Schwert (1981) found evidence of weak links between stock prices and inflation using data from 1958-78. Cutler et al., (1989) applied VAR models to measure news on macroeconomic time series from 1871-1986. Their conclusion was that less than one-third of the monthly variance in stock returns could be explained by macroeconomic events.

McQueen and Roley (1993) used data from S&P 500 in the ten year period 1977-88 to show that both the effect and sign of macroeconomic news on stock returns were, in fact, dependent on the state of the economy. In particular, they revealed that in booming economic periods, positive shocks to the real activity led to lower stock returns. Simultaneously, in recessions, the same positive shocks in the real activity led to higher stock returns. Along the same lines, Hu and Li (1998) used data from the S&P 500, the Dow Jones and the Russel Indexes from 1980-1996 to see if the effect of macroeconomic news on stock prices were dependent on the state of the economy. They found strong evidence that the impact macroeconomic shocks have on prices is varying through stages in the business cycle. However, they also stressed the importance of distinguishing variables in association with business stages. This means that different variables respond differently to business cycles (Bloom et al 2014).

Kozeniauskas et al (2014) describe macroeconomic shocks as two factors, “macroeconomic”- and “higher-order uncertainty”. The first factor, “macroeconomic uncertainty” is perceived to being less predictive than the “higher-order uncertainty”, due to the complexity of its nature. The authors measure “higher-order uncertainty” as the deviation between the outcome of a macroeconomic parameter in the next period and its value this period, conditioned on the information that is available this period. They find a strong relation between higher-order uncertainty and macro uncertainty.

Beber et al (2014) based their data on 43 distinct U.S. macroeconomic announcements during the years of 1997-2011. They used in excess of 8000 announcements over 3,800 business days to extract daily factors from economic news released at different times and frequencies, using a simple cross-sectional technique. While doing this, they also show that forecasters tend to agree on downturns, but could not forecast recoveries in the economy with the same accuracy. In turn, this may perhaps be an explanation of why forecasters disagree in recessions.

Theory and Methodology

Analyst uncertainty – Bayesian Update method

The Bayesian Update mathematical procedure of inference is based on Bayes' Theorem (Bayes 1764) and comprises the theoretical basis of our Thesis. As applied to economic inference and forecasting and the uncertainties depending on the individual analyst, following Scherbina (2003), all analysts and investors receive a public signal (news) about next period's expected value of a macroeconomic announcement that is normally distributed. Each analyst also receives a private signal (priors), independent of the public signal. The analyst then combines the private and public signal to come up with a minimum variance forecast. If uncertainty occurs in the prior information, it will lead to higher volatility in the expectations of the macroeconomic variables and be a less viable predictor.

Given Bayes theorem, where P(E) and P(H) are events and $P(E) \neq 0$

$$P(H|E) = \frac{P(E|H) \times P(H)}{P(E)}$$

According to Bayes theorem, the posterior is a result of the prior and the compatibility of observed evidence. A prior is the probability distribution of an uncertain quantity that expresses a belief about the given quantity before some evidence/data is taken into account. In our paper, analyst dispersion serves as prior and data on the macro news are the observed evidence.

Hence, under the assumption of the normal distribution, the analysts' expectation of an asset's price can be written as:

$$E(P) = \gamma V + (1 - \gamma)s$$

Where γ is the analyst "confidence" in own prediction, V is the private signal, and s is the value of the public signal. The term of "confidence", γ, can again be written as

$$\gamma = \frac{1/\sigma_v^2}{1/\sigma_v^2 + 1/\sigma_s^2}$$

Here, σ_v^2 is the variance of the private signal and σ_s^2 is the variance of the public signal. The variance of the forecast σ_v^2 is the focus of this paper. From the model above, we see that if the variance in the public signal increases and the confidence of the forecaster decreases, this will result in an increase in weight of the public signal.

Kozeniauskas et al (2014) state that "When uncertainty is high, agents tend to have imprecise prior beliefs and they weight more on their heterogeneous public signals. With more weights in their beliefs (priors), heterogeneous signals generate more dispersion in forecasts". Analysts will, when doubtful about their own predictability, incorporate an increased weight of the public signals into their forecast, in contrast to when confident, where they increase the emphasis on their own beliefs.

Implementation of macro news

The classical model of a stock price expresses that the price is only dependent on the sum of its discounted expected future dividends, given the information set available.

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

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

The new information for each period is the difference between Ω_t and Ω_{t-1}. On any given time, the expected news in t+1 and all previous economic announcements are already part of Q_t. Under the assumption of market efficiency and rational investors and expectations, stock prices should solely respond and adjust immediately to new information. As stock prices are known to follow a random walk and announcements shocks are uncorrelated over time, it is possible to combine daily prices with macroeconomic events to extract the effects of a macro announcement.

The macroeconomic news will affect stock prices if the new information set changes the expectation of either the discount rate or the future cash flow, or both. Cash flows respond to both real and nominal economic forces and changes in e.g. inflation will influence nominal cash flows and nominal interests.

Market Response Conditional on States of Uncertainty

Initial model for effects on stock indices to macro surprises

Our methodology will follow in the same direction as Li and Hu (1998), but we will in contrast to their work condition the responses on analyst uncertainty rather than economic states. The methodology is a standard least squares approach with robust standard errors. To estimate the effect of new macroeconomic information on assets, we use the daily changes of the log of stock prices as the dependent variable. First, we formulate a model for the effect of the macroeconomic news on a stock index:

$$P_t S = \alpha + X_t^u b + v_t$$

Where P_tS is the change of the logarithmic stock price index from the close of business day t-1 to t. X_t^u describes the vector of news. A standardized news X is defined as

$$X = \frac{x_{act} - E(x)}{Stdev\ of\ sample}$$

Where x_{act} is the macro announcement and E(x) is the expected macro announcement. If the assumption of market efficiency is valid, only new information should be important, meaning that the value of news itself is of less importance compared to the news subtracted expectations. We define the expected macro announcement as the median of forecasted values by the analysts. The median is chosen instead of the average value due to less sensitivity to outliers and since we do not assume normality in analysts forecast it is accepted as a better measure.

Model for effects conditional upon analysts' uncertainty

The model of a conditional response to macroeconomic news given analysts' uncertainty is specified as:

$$P_tS = \alpha + \sum_i D_i X_t^u b_i + v_t$$

Where P_tS is the change of the logarithmic stock price index from the close of business day t-1 to t. X_t^u describes the vector of news and D_i is the dummy for a given economic state. To estimate responses that are conditional upon analysts' expectations, we classify the uncertainty in levels using both the standard deviation of the total forecast and a HighLow measure. The HighLow measure is the difference between the most optimistic forecast and the most pessimistic forecast. The HighLow measure is also a measure of analysts' dispersion like the standard deviation. However, it will be more sensitive to outliers and extremes than the standard deviation.

We will divide the datasets into quartiles, based on the level of uncertainty provided by each separate uncertainty measure. In addition to the standard deviation and the HighLow measure, we will also classify by more known uncertainty indices, namely the VIX Index and the Economic Policy Uncertainty Index, for comparison reasons. The lowest 25% will be classified as "Low" uncertainty; the highest 25% of the data will be classified as "High" uncertainty. The two mid quartiles will be classified as "Medium". We then mark the calendar for different uncertainty levels and allow us to condition the impact of macro news on stock prices, given the model above.

Volume of Trade

After extensive mathematics, Varian (1985) proved that overall trade volume (T) is determined by

$$T = \sum_{i=1}^{n} a\theta \left| v_i - \bar{v} \right| /$$

Where v_i is each agent's prior beliefs, $\bar{v}$ is the mean of all analysts' priors, a is risk tolerance and θ is prior precision.

Following this model, overall trade clearly depends on differences of opinion. Holding all other variables equal, an increase in dispersion of opinions measured as the deviation of the priors will increase the total trade. Varian continues to argue that the deviation only depends on the respective confidence in prior beliefs and not on the actual value of information in the priors.

Our hypothesis is that an increase in analysts' dispersion should lead to an increase in the volume of trade.

As shown in research by Bloom (2009) and Kozeniauskas et al (2014), financial crisis will lead to an increase in uncertainty and therefore affect the volume of trade. To control for financial distress in our regression, we create dummy variables for the "Subprime Crisis" in 2008-2009 and the burst of the "IT Bubble" in early 2000's.

For comparison reasons, in addition to using our basis analysts' dispersion measures of Stdev and HighLow, we will also determine the same regression using the uncertainty measures of the VIX and the EPU Index.

The model we employ is defined as:

$$Volume\ of\ trade = Analysts\ dispersion + D_1 + D_2$$

The D_1 and D_2 are dummy variables for the "Subprime Crisis" and the "IT bubble" respectively.

Price Volatility

Using time series, Schwert (1989), Davis and Kutan (2003) and Chan et al. (1998) all agree on insignificance between macro uncertainty and stock markets. However, Arnold and Vrugt (2008) argue that time-series analysis does not capture the macroeconomic uncertainty as good as a dispersion based model that uses analyst disagreement as an uncertainty measure.

According to Bayesian updating method, analysts utilize both signals and priors as sources of information when making their forecasts. Hence, in an uncertain macroeconomic state, analysts will differ in interpretations of signals, and thereby generating dispersion in their predictions. The relation illustrates that higher order and macroeconomic uncertainty are closely related and is well documented in Bloom (2009) and Kozeniauskas et al (2014).

To test if this also affects our dataset, we will conduct testing on whether the Stdev and HighLow measures have a significant relation with the variation on the VIX and the Economic Policy Uncertainty Index. Our hypothesis, based on the previous research, will be that the uncertainty measures are positively and significantly moving together.

Following the methodology in Kozeniauskas et al (2014), our model becomes:

$$Volatility\ of\ stock\ prices = Analysts\ dispersion + D_1 + D_2$$

Where D_1 and D_2 are the dummy variables for subprime crisis and IT bubble, respectively. The reason for including these dummy variables follows the same line of argument as in the previous section.

Aggregate Uncertainty

We will create an aggregate uncertainty measure based on cross-sectional news and analyst forecast, following the main steps of the suggested technique by Beber et al (2014). However, we will adjust the technique to some extent in order to let it be within the scope of our thesis. Furthermore, an elaboration on how we intend to build the model is in the next section. It also seems appropriate to explain why a full Principal Component Analysis is not the best choice.

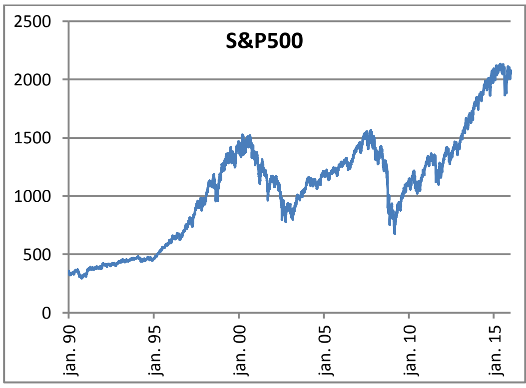
To extract a set of factors from the cross-section of macro news releases in several different categories, typically highly correlated, a full Principal Components Analysis (PCA) is the obvious choice. However, with a complete PCA method, one obtains factors that are mechanically orthogonal, where the dimensions of the news flow are probably highly correlated. For example, the industrial production and the inflation are both low in a recession and high in an expansion of the economy and thus, orthogonalization make it almost impossible to extract the economic interpretation of higher order factors.

Instead, we let the data speak for itself. We use the categorization of Inflation, Industrial Production, Labor, GDP, and Trade Balance and obtain correlation matrices $\boldsymbol{\Omega}_i$ on each category i. First, we extract the first principal component C_i of each category and use it as weights. Moving on, we then create two time-series on a monthly basis. The first time series is the sum of weight C_i multiplied with the respective news in each category i. This is to create an aggregate news measure for the level of the economy. The second time series is the sum of the same weight C_i multiplied with the corresponding standard deviation of the analyst forecast to create an aggregate uncertainty measure.

Data

Stock Market Benchmark

As we are investigating the uncertainty impact on the US stock market, we sought to use the best proxy for the US economy. After evaluating different opportunities as the Russell3000, Dow Jones Industrial Average (DJIA), NYSE composite and other indices, we concluded that the Standard & Poor´s 500 index is reflecting the US stock market most appropriately. This index contains the capitalization of the largest 500 companies, listed on the New York Stock Exchange (NYSE) and NASDAQ Stock Market weighted by their market value. To make sure we had sufficient data length to analyze all the macroeconomic announcements we collected the closing price and the percentage change of the S&P500 from 02.01.1990-31.12.2015, viewable in Figure 5. The skewness for the change in the S&P500 is slightly negative, as seen in Appendix 1, but approximately symmetric. Together with the high kurtosis, the distribution indicates that large outliers are extremely rare, which makes it a good basis for our research.



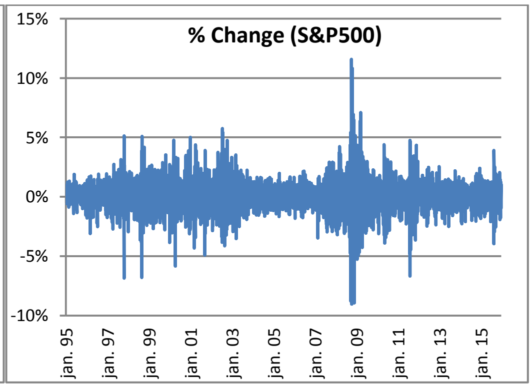


Figure 5: Daily closing prices of the S&P500

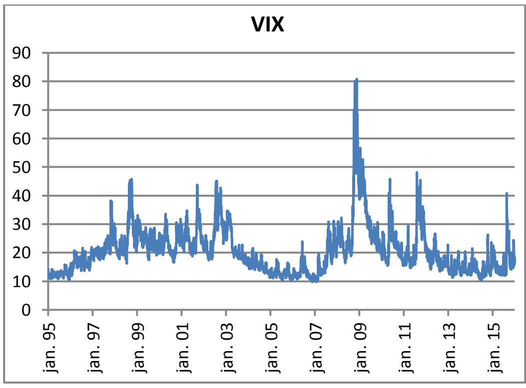
Figure 4: Daily percentage changes of the S&P500

Measuring Uncertainty

In order to capture most of the uncertainty in US markets, we choose to use 2 different measures, namely VIX and Economic Policy Uncertainty Index. We also use the Volume of Trade and the 30-day volatility on the S&P500 as variables in order to further investigate uncertainty.

VIX

The Chicago Board Options Exchange Volatility Index, commonly known as the VIX index, is preferably the best measure to define the level of uncertainty in the US financial market. Since the VIX index uses the 30-day implied volatility on S&P500 options to measure the future stock volatility, we chose this index for the same reasons we selected to use the variance S&P500 to reflect the US stock market. We collected daily and monthly data on the VIX index from 03.01.1995-31.12.2015 from Bloomberg Terminal as seen in Figure 7. As the VIX Index is only dated with the last day of trade in a month, we had to adjust the date to last day of the month to match the VIX with the Economic Policy Uncertainty Index. To compare results in a correct manner, we normalized the figures by dividing the index by its standard deviation. Looking at the graph of the VIX index we see a substantial spike in the dataset when the subprime crisis started to influence the stock market and investors fled the market in panic, this justifies its nickname as "the Fear Index". In comparison to the rest of the proxies, looking at Appendix 2, the VIX index has the lowest kurtosis. Even though the kurtosis of this index is the lowest of all our uncertainty measures, it is still almost twice as large as the "normal" Gaussian distribution, indicating a cluster around the mean. It is also slightly negative skewed, but is within "normal" ranges, so we will still classify the distribution as symmetric.



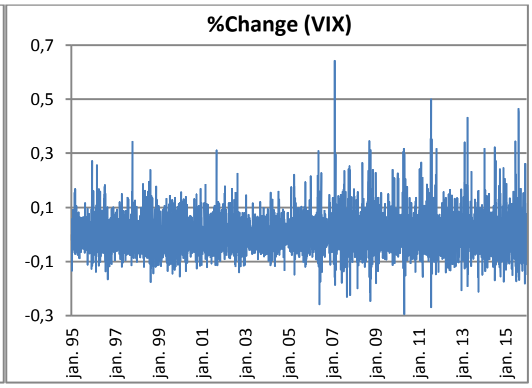
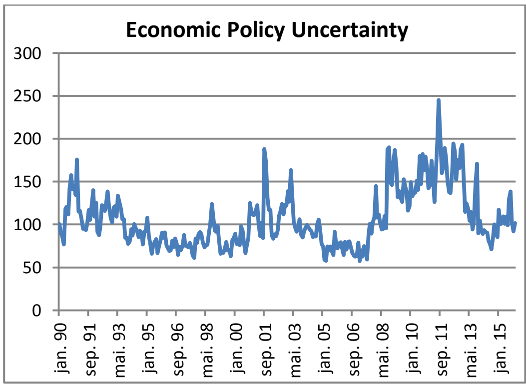


Figure 7: Daily closing prices on the VIX Index

Figure 6: Daily percentage changes on the VIX Index

Economic Policy Uncertainty Index

Another measure of uncertainty is the Economic Policy Uncertainty Index, which captures the uncertainty from three perspectives. The index was first constructed by Baker et al (2013) and contains components from; i) the search results for uncertainty related news for the 10 largest US newspapers, ii) the Congressional Budget Office´s federal tax code provisions and iii) the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. We collected the monthly data directly from their website for the time spanning from 31.01.1990-31.12.2015. We have, as on the VIX index, normalized the measures for comparison reasons. For the EPU index, we find in Appendix 3, that the data is highly right skewed, which indicates large positive tails and a greater change of significantly positive outcomes, viewable in Figure 99. We also see that the kurtosis is greater than 3, which tells us that the series are leptokurtic and that the outcomes are clustering around the mean.



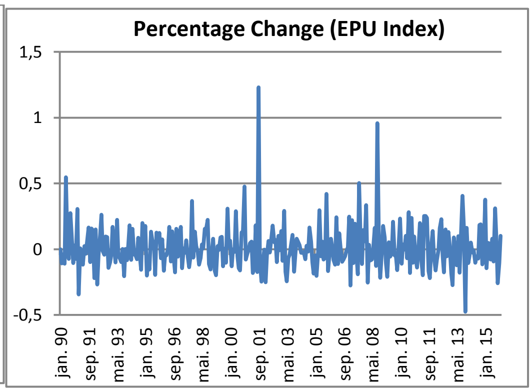


Figure 9: Daily values on the EPU Index

Figure 8: Daily percentage change on the EPU Index

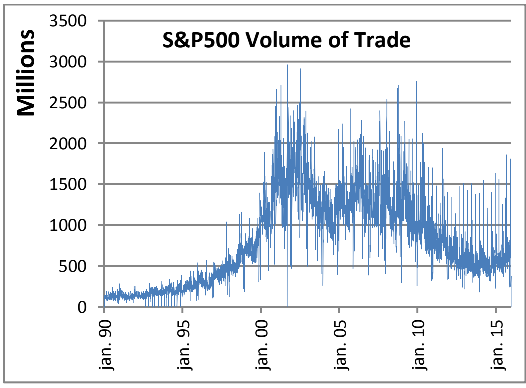
Comparison of VIX and EPU

Following Baker et al (2015), there are several differences between the EPU and the VIX, even though their paper and our study both conclude that they have a correlation of over 0,5. The VIX has increased reaction to news with a strong connection to the financial markets such as the bankruptcy of Lehmann Brother's and the Debt Ceiling Dispute. The EPU has increased reaction to policy concerns with links to stock markets volatility such as the election of presidents or government spending. The VIX have a 30-day look-ahead horizon, while the EPU has no given time horizon. The VIX covers news about uncertainty concerning equity returns, while EPU covers policy uncertainty, not just for equity returns.

The VIX index is the most recognized and frequently used uncertainty measure in a plethora of academic papers regarding general uncertainty, while the EPU index is relatively rather recent. By close inspection of the data, we find that the EPU index is more sensitive, and has larger movement, especially towards higher orders of uncertainty. One possible explanation for this is that media tends to focus on negative news since they have been shown to attract more attention and reaction from the public than positive news.

S&P500 Volume of Trade and 30day Volatility

We extracted the data for the volume of trade in the period 02.01.1990-31.12.2015 from the Bloomberg Terminal. Since there were outliers in the dataset, they are replaced by taking the average of the T-1 and T+1 figure. We see that the volume of trade and 30d volatility peaks in the timespan surrounding times with major financial uncertainty, mainly 00-02 and 08-09, therefore we also wish to use these variables as proxies for economic uncertainty. The 30day volatility has high kurtosis, inferring to a high peak with fat tails. This, in combination with the moderate right skewness, indicates a greater probability of extreme positive outcomes. From the output in Appendix 4 and Appendix 5, the volume of trade is the proxy with the longest positive tail. The interpretation will lead us to witness potential large positive outliers in the dataset, visualized in Figure 10, even though the kurtosis shows a peaked distribution around the mean.



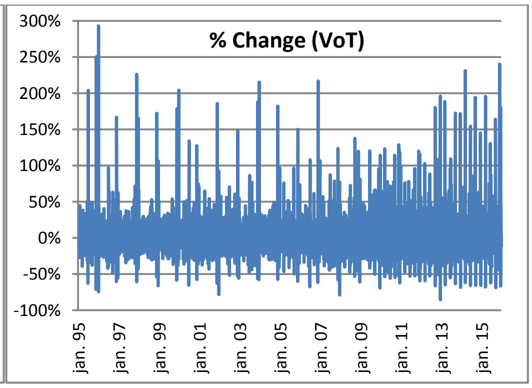
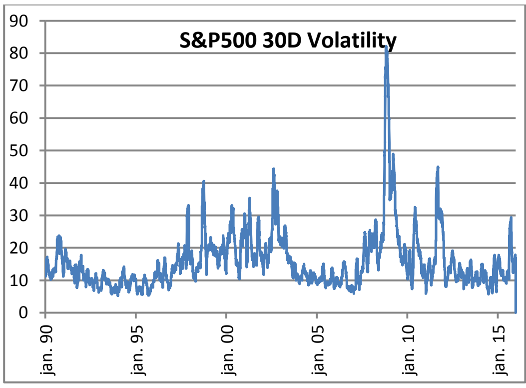


Figure 11: Volume of trade of the S&P500

Figure 10: Percentage change in Volume of Trade of the S&P500



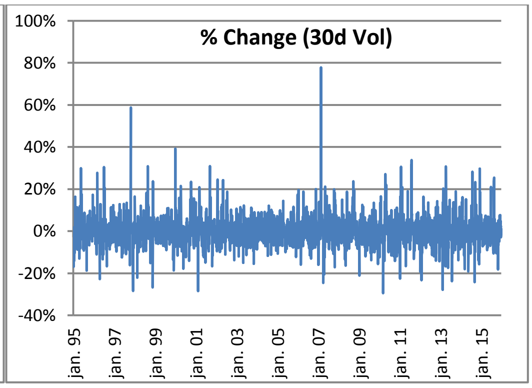


Figure 13: 30day Volatility of the S&P500

Figure 12: Percentage change in the 30day Volatility of the S&P500

Dummy variables

During our research period, there has been two major financial distress periods, namely the “Dot-Com bubble” in the US Technology Sector during March 2000 until October 2002 (Beattie, 2016) and “the Great Recession” which we date September 2008 with the default Lehman Brothers until June 2009 (Beattie, 2016). To extract the effects that economic crisis has upon the “normal” volatility, we created dummy variables.

Macroeconomic Announcement Data

Our supervisor Dagfinn Rime provided us with the macroeconomic news data, where Bloomberg was the primary source. The dataset contains announcements from 41 macroeconomic indicators, seen in table 1, spanning from 1998-2015. The majority of the announcements are released monthly, although there are exceptions. For instance, jobless claims are reported weekly and the nominal account balance is reported quarterly.

To use the macroeconomic announcements data we had to make several adjustments to the datasets. We removed missing observations and unreasonable outliers if there were several subsequent observations and replaced singular insufficient data with averages of the observations before and after. In order to draw conclusions from the analyst dispersion uncertainty measure, we need a sufficient number of participants in each respective macro variable. Due to varying number of participants at the start and the end of the time periods, we adjusted the dataset accordingly. We also did a screening process to select which variables to include from our rich datasets, which will be explained in detail further down.

From the announcement data, there are three main variables, which we rely heavily on to perform our analysis, namely:

Variable	Description
Stdev	*The standard deviation of the analyst's estimations of t+1*
News	*Macroeconomic Announcement subtracted with the Median Analyst Estimate divided by the standard deviation of the forecast*
HighLow	*The difference between the highest and the lowest estimate for t+1*

To classify the level of uncertainty of the announcement data, we divided the datasets into quartiles. We classified the lowest 25% classified as certain, the highest 25% as uncertain and the mid 50% as a medium uncertainty for both our uncertainty measures, “Stdev” and “HighLow”. To condition the impact of macro news on stock prices, we mark the calendar for different uncertainty levels.

Descriptive statistics

Variable Name	Explanation	Category	Number of observations at start	Time period
adpchng	ADP National Employment Report change	Labor	101	2006m8-2014m12
ahemompct	US Average Hourly Earnings MoM	Labor	59	2010m2-2014m12
aheyoypct	US Average Hourly Earnings YoY	Labor	59	2010m2-2014m12
awhtotl	US Average Weekly Hours Total	Labor	59	2010m2-2014m12
costnfrpct	US Unit Labor Costs Nonfarm Bu	Labor	64	1999q1-2014q4
cpiyoy	US CPI Urban Consumers YoY NSA	Inflation	148	2002m9-2014m12
cpichg	US CPI Urban Consumers MoM SA	Inflation	217	1996m12-2014m12
cptichng	US Capacity Utilization % of T	Industrial Production	217	1996m12-2014m12
cpupxchng	US CPI Urban Consumers Less Fo	Inflation	215	1997m1-2014m12
cpurnsa	US CPI Urban Consumers NSA	Inflation	193	1996m11-2014m12
dgnochng	US Durable Goods New Orders In	Industrial Production	207	1997m10-2014m12
gdpdchg	US GDP Implicit Price Deflator	GDP	28	1997q4_2005q1
gdpcqoq	GDP US Chained 2009 Dollars QoQ	GDP	74	1996q3-2014q4
gdpctotpct	GDP US Personal Consumption Change	GDP	49	2002q4-2014q4
imp1chng	US Import Price Index by End U	Trade Balance	194	1998m7-2014q4
imp1yoypct	US Import Price Index by End U	Trade Balance	144	2002m10-2014q4
injcj	US Initial Jobless Claims SA	Labor	916	1996m12-2014m12
injcsp	US Continuing Jobless Claims S	Labor	650	2002m07-2014m12
ipchang	US Industrial Production MoM 2	Industrial Production	220	1996m10-2014m12
jolttotl	US Job Openings By Industry To	Labor	52	2010m9-2014m12
nfppch	US Employees on Nonfarm Payrol	Labor	58	2010m4-2015m1
nfptch	US Employees on Nonfarm Payrol	Labor	217	1997m1-2015m1
ppiyoy	US PPI Finished Goods NSA YoY%	Inflation	135	2002m10-2013m12
ppixyoy	US PPI Finished Goods Less Foo	Inflation	135	2002m10-2013m12
ppichng	US PPI Finished Goods SA MoM%	Inflation	194	1997m12-2014m01
prodnfrpct	US Output Per Hour Nonfarm Bus	Labor	71	1997q1-2014q3
tmnochng	US Manufacturers New Orders To	Industrial Production	220	1996m11-2014m12
uscabal	US Nominal Account Balance In	Trade Balance	69	1997q4-2014q4
ushetotpct	US Avg Hourly Earnings Private	Labor	140	1998m06-2010m01
usmmmnch	US Employees on Nonfarm Payrol	Labor	193	1998m12-2014m12
ustbtot	US Trade Balance of Goods and	Trade Balance	219	1996m10-2014m12
usurtot	U-3 US Unemployment Rate Total	Labor	217	1997m01-2015m01
uswhtot	US Avg Weekly Hours Nonfarm To	Labor	137	1998m09-2010m01

Variable Name	Number of observations after deleting	Average Number of Participants	Median Number of Participants	Stddev Number of Participants	Average Stddev	Stddev of Stddev	Average High-Low	Stddev High-Low
adpchng	101	31,79	35,00	10,52	25,27	10,87	115,69	53,52
ahemompct	59	53,29	53,00	2,80	0,06	0,05	0,26	0,09
aheyoypct	59	11,49	11,00	2,46	0,11	0,05	0,33	0,21
awhtotl	58	0,56	0,56	0,01	0,03	0,05	0,21	0,17
costnfrpct	60	49,50	50,50	9,75	0,42	0,25	2,20	1,31
cpiyoy	133	28,92	35,00	13,52	0,14	0,13	0,54	0,45
cpichg	193	69,23	75,00	14,44	0,10	0,03	0,49	0,21
cptichng	199	58,21	62,00	11,13	0,21	0,11	1,22	0,85
cpupxchng	199	66,75	73,00	15,29	#N/A	#N/A	0,26	0,10
cpurnsa	119	7,32	7,00	2,76	0,16	0,11	0,49	0,35
dgnochng	199	64,74	69,00	14,08	1,10	0,38	6,13	2,36
gdpdchg	28	35,71	39,00	11,52	#N/A	#N/A	0,38	0,90
gdpcqoq	70	64,09	69,50	15,90	0,13	0,05	0,70	0,45
gdpctotpct	49	11,49	11,00	4,84	#N/A	#N/A	0,44	0,55
imp1chng	191	39,34	43,00	12,79	0,38	0,19	1,86	1,03
imp1yoypct	82	9,71	9,00	3,00	0,46	0,29	1,60	1,02
injcj	840	37,50	39,00	9,62	8,11	5,67	38,41	28,50
injcsp	496	9,79	10,00	3,66	30,12	24,25	102,98	94,05
ipchang	197	67,05	72,00	15,34	0,20	0,08	1,02	0,47
jolttotl	33	5,76	4,00	2,98	47,88	24,00	137,98	82,01
nfppch	57	47,65	49,00	5,67	25,14	7,14	123,75	35,06
nfptch	196	72,22	77,00	16,96	34,35	13,60	186,07	76,92
ppiyoy	109	21,24	24,00	9,28	0,32	0,30	1,32	1,38
ppixyoy	109	20,50	23,00	8,57	0,13	0,08	0,50	0,33
ppichng	183	64,94	71,00	13,09	0,21	0,09	1,10	0,49
prodnfrpct	68	53,88	57,00	12,08	0,28	0,14	1,35	0,63
tmnochng	199	55,65	60,00	12,55	0,56	0,33	3,13	1,99
uscabal	66	37,56	40,00	9,54	3,27	1,51	17,29	9,48
ushetotpct	140	49,14	52,00	10,30	#N/A	#N/A	0,26	0,10
usmmmnch	189	18,23	18,00	5,92	9,80	6,32	39,58	25,67
ustbtot	199	62,30	68,00	13,93	1,15	0,48	7,53	10,97
usurtot	199	69,32	73,00	15,31	#N/A	#N/A	0,30	0,18
uswhtot	132	29,99	32,50	7,52	#N/A	#N/A	0,21	0,16

Table 1: Descriptive Statistics

This table describes the different variables we have used in our analysis, including descriptions of what they are measuring, time period and the number of observations pre- and post-cleaning. Some of the above variables lacked explanatory power, which we did not continue to use in our *models. From the 18 variables we continued measuring, we used the whole timespan provided, with corrections for outliers.*

Biases

Specification Bias

An unwanted feature with the data is that it might have specification error. This means that the independent variable is to some degree correlated with the error term, which in our case is our proxy of macroeconomic news. This bias may be caused by a number of causes; i) The functional form may be incorrect, ii) omitted-variable bias, iii) irrelevant variable inclusion and iv) simultaneity-equation bias. If we find evidence of specification bias, we will need to take action according to what kind of cause if found triggering the tests.

Small Sample Bias in Analyst Forecast:

In the analyst forecast data, there are just a handful of analysts that report their forecast. This might introduce a "small sample bias" since a small sample is more likely to deviate from the population or real outcome than a big sample.

The introduction of this bias makes it more likely to detect large outliers and the standard errors of the forecasts may not be good proxies of the population since the standard errors are highly dependent on the sample size. According to the central limit theorem, if the sample size is large enough, the distribution of the data will be normal distributed, hence one can make better assumptions of the population when examining the sample.

Rational Bias

The rational bias has been explained in detail earlier in this paper and is clearly going to be present in our dataset. We expect for instance the contrast effect to be most prominent in the HighLow measure of analysts' dispersion since it captures the spread between the highest and lowest forecast. Nevertheless, due to different reasons for this bias, and diverse incentives from separate firms, this cannot be adjusted for.

Results

Screening

In the first stage of our analysis, we conduct a comprehensive screening of the macroeconomic variables in our dataset. When screening, we considered the number of participants that conducted the forecast survey, the share of missing observations for each macroeconomic variable and the significance level in addition to the R^2 against our selected uncertainty indices. From the original 41 macroeconomic indicators, we ended up with 18 indicators that matched our criteria and that reflected all announcement categories. In the 18 variables, we observe that the coefficients are mostly positive, which indicates that a positive shock to one of the explanatory uncertainty measures will, as expected, lead to an increase of the dependent uncertainty variables. In addition, we find that 77,8% of all the variables are significant at the 1% level and only 12% are not significant on all levels. A high significance level indicates a great impact on the different uncertainty measures, indifferent of the type of economic variable. A high R^2 indicates that the variables have a large explanatory power.

In particular, we see that the VIX and EPU index are in all cases positively related and statistically significant. As Baker et al (2014) discovered, we also found in our research that the VIX and EPU index have an R^2 of around 0,5. If this had not been the case, it would have been a sign of poorly specified regressions. The interpretation from the regression is that an increase in the EPU Index also leads to an increase in VIX, and the Stdev and HighLow follow the same pattern. Since these dispersion measures are based on the same absolute distribution of values, it is expected and observed that these measures have a very high positive correlation.

When analyst dispersion is regressed on the VIX and the EPU we see large differences from one macroeconomic variable to another. “Industrial Production MoM” (IPchng) and “ADP National Employment Report” (ADPchng) are positively related and have a very high explanatory power to both the VIX and the EPU. A high R^2 with the VIX index indicates a close relation with the uncertainty in the stock market.

However, we do not seek to include only variables that have the highest explanatory power with the known uncertainty indices, as they will be mere reflections or substitutes. We are also interested in capturing other dimensions of uncertainty. For example, “Purchasing Power Index” (ppichng) and “US Manufacturers New Orders” (tmnochg) are quality datasets with good features; however, they lack explanatory power against the VIX and EPU. These macroeconomic variables could potentially provide new information about the uncertainty that is not reflected by the VIX and the EPU.

The announcement of “Durable Goods New Orders” (Dgnochg) is the only variable out of our selected variables that have a negative and significant relation with the VIX index. This indicates that if uncertainty in the forecasted announcement of “Dgnochg” increases, the value of the VIX will decrease. In economic terms, it means that if analysts are more uncertain about orders of durable goods, the uncertainty in the stock market will decrease.

Economic variable	Variables in this section	Adpchng	Cpichng	Cptichng	Imp1chng	Injcjc	Injcsp	Ipchng	Ppichng	Tmnochg	Usmmmnch	Cpupxchng
	Included observations	101	193	199	191	840	496	197	183	199	189	200
VIX = a + EPU	Coefficient	**0,504**	**0,444**	**0,439**	**0,433**	**0,523**	**0,667**	**0,443**	**0,419**	**0,437**	**0,457**	**0,439**
	T-stat	5,65***	7,5***	7,4***	7,12***	17,88***	16,25***	7,34***	6,8***	7,33***	7,66***	7,36***
	R^2	*24,0 %*	*22,7 %*	*21,7 %*	*21,0 %*	*28,0 %*	*35,0 %*	*21,7 %*	*20,3 %*	*21,5 %*	*24,0 %*	*21,5 %*
St Dev = a + HILOW	Coefficient	**0,191**	**0,096**	**0,117**	**0,173**	**0,191**	**0,252**	**0,153**	**0,167**	**0,150**	**0,233**	**0,074**
	T-stat	27,3***	13,96***	25,37***	32,17***	99,7***	101,3***	22,82***	28,03***	28,75***	40,59***	7,987***
	R^2	*88,0 %*	*50,5 %*	*76,6 %*	*85,0 %*	*92,0 %*	*95,0 %*	*73,0 %*	*81,0 %*	*80,7 %*	*89,8 %*	*54,2 %*
VIX = a + St Dev	Coefficient	**0,076**	**1,834**	**2,752**	**2,760**	**0,039**	**0,010**	**5,820**	**2,950**	**0,606**	**0,101**	**0,937**
	T-stat	8,81***	7,748***	4,33***	8,04***	6,17***	4,64***	7,16***	3,52***	2,71***	10,2***	0,122
	R^2	*44,0 %*	*23,9 %*	*8,7 %*	*25,5 %*	*4,3 %*	*4,2 %*	*20,8 %*	*6,0 %*	*3,6 %*	*35,7 %*	*0,0 %*
VIX = a + HILOW	Coefficient	**0,014**	**1,480**	**0,233**	**0,446**	**0,007**	**0,003**	**0,869**	**0,572**	**0,073**	**0,026**	**1,950**
	T-stat	7,71***	4,34***	2,66***	6,61***	5,54***	5,05***	5,73***	3,68***	1,94*	10,03***	2,67***
	R^2	*38,0 %*	*8,6 %*	*3,5 %*	*18,8 %*	*3,5 %*	*5,0 %*	*14,4 %*	*7,0 %*	*1,8 %*	*35,0 %*	*3,5 %*
EPU = a + St Dev	Coefficient	**0,037**	**4,730**	**2,596**	**1,360**	**0,050**	**0,008**	**4,360**	**3,599**	**0,509**	**0,043**	**-11,780**
	T-stat	3,48***	1,64***	3,8***	3,32***	8,02***	4,2***	4,79***	4,03***	2,13**	3,35***	-0,97
	R^2	*10,9 %*	*1,4 %*	*6,8 %*	*5,5 %*	*7,0 %*	*3,4 %*	*10,5 %*	*8,0 %*	*2,2 %*	*5,6 %*	*1,7 %*
EPU = a + HILOW	Coefficient	**0,001**	**1,209**	**0,348**	**0,309**	**0,010**	**0,003**	**0,873**	**0,716**	**0,076**	**0,011**	**2,080**
	T-stat	4,46***	3,16***	3,8***	4,06***	8,22***	5,17***	5,44***	4,35***	1,89*	3,66***	2,7***
	R^2	*16,7 %*	*5,0 %*	*6,8 %*	*8,0 %*	*7,5 %*	*5,0 %*	*13,0 %*	*10,0 %*	*1,8 %*	*6,7 %*	*3,5 %*

Economic variable	Variables in this section	Dgnochng	Imp1yoypct	Nfppch	Nfptch	Prodnfrpct	Ustbtot	Costnfrpct	Cpiyoy	Gdpcqoq	Jolttotl	Ppixyoy
	Included observations	200	82	57	196	68	209	60	133	70	33	109
VIX = a + EPU	Coefficient	**0,439**	**0,518**	**0,397**	**0,445**	**0,402**	**0,436**	**0,465**	**0,534**	**0,38**	**0,156**	**0,517**
	T-stat	7,36***	4,26***	6,05***	7,37***	4,25***	7,35***	4,75***	7,93***	4,1***	4,54***	6,6***
	R^2	*21,5 %*	*18,5 %*	*39,9 %*	*22,0 %*	*22,0 %*	*21,0 %*	*28,0 %*	*32,4 %*	*19,8 %*	*40,0 %*	*29,0 %*
St Dev = a + HILOW	Coefficient	**0,134**	**0,272**	**0,165**	**0,156**	**0,116**	**0,008**	**0,128**	**0,267**	**0,074**	**0,274**	**0,189**
	T-stat	21,16***	29,13***	10,55***	26,01***	5,05***	2,56**	6,713***	24,6***	7,21***	16,57***	13,13***
	R^2	*69,3 %*	*91,3 %*	*67,0 %*	*77,7 %*	*28,0 %*	*3,2 %*	*43,7 %*	*82,2 %*	*43,0 %*	*89,9 %*	*62,0 %*
VIX = a + St Dev	Coefficient	**-0,343**	**1,500**	**0,038**	**0,030**	**2,120**	**0,622**	**-0,115**	**0,650**	**0,047**	**-0,002**	**-1,950**
	T-stat	-1,73*	3,14***	2,86***	5,67***	2,48**	4,13***	-0,21	0,84	0,019	-0,75	-1,29
	R^2	*1,5 %*	*11,0 %*	*13,0 %*	*14,0 %*	*8,5 %*	*8,0 %*	*0,1 %*	*0,5 %*	*0,0 %*	*1,8 %*	*1,5 %*
VIX = a + HILOW	Coefficient	**-0,066**	**0,317**	**0,004**	**0,004**	**0,341**	**0,002**	**0,168**	**0,454**	**-0,059**	**-0,001**	**0,072**
	T-stat	-2,085**	2,27**	1,25	4,19***	1,765*	0,24	1,64***	2,04**	-0,22	-1,38	0,2
	R^2	*2,0 %*	*6,0 %*	*3,0 %*	*8,3 %*	*4,5 %*	*0,0 %*	*4,4 %*	*3,0 %*	*0,0 %*	*5,8 %*	*0,0 %*
EPU = a + St Dev	Coefficient	**0,365**	**0,466**	**0,047**	**0,004**	**-1,416**	**1,018**	**-0,430**	**-0,858**	**5,090**	**-0,009**	**-3,860**
	T-stat	1,743***	1,12	2,16**	0,65	-1,39	6,79***	-0,698	-1,05	1,86*	-1,03	-2,5**
	R^2	*1,5 %*	*1,5 %*	*7,8 %*	*0,2 %*	*2,8 %*	*19,0 %*	*0,8 %*	*0,8 %*	*5,0 %*	*3,3 %*	*5,5 %*
EPU = a + HILOW	Coefficient	**0,086**	**0,140**	**0,001**	**0,001**	**0,116**	**0,002**	**0,063**	**-0,046**	**0,449**	**-0,004**	**-0,172**
	T-stat	2,54*	1,17	0,228	0,52	0,51	0,25	0,53	-0,19	1,44	1,88	-0,45
	R^2	*3,0 %*	*1,7 %*	*0,1 %*	*0,1 %*	*0,4 %*	*0,0 %*	*0,5 %*	*0,0 %*	*3,0 %*	*10,2 %*	*0,2 %*

Economic variable	Variables in this section	Ppiyoy	Ahemompct	Aheyoypct	Cpurnsa	Gdpctotpct	Gdpchng	Uscabal	Ushetotpct	usurtot	Uswhtot	Awhtotl
	Included observations	109	59	59	119	49	29	66	140	199	132	59
VIX = a + EPU	Coefficient	**0,518**	**0,395**	**0,396**	**0,530**	**0,485**	**0,653**	**0,402**	**0,957**	**0,440**	**0,968**	**0,396**
	T-stat	6,6***	6,07***	6,07***	7,26***	4,67***	4,65***	4,15***	12,97***	7,36***	13,06***	6,07***
	R^2	*29,0 %*	*39,6 %*	*39,3 %*	*31,0 %*	*32,0 %*	*44,0 %*	*21,0 %*	*55,0 %*	*22,0 %*	*57,0 %*	*39,3 %*
St Dev = a + HILOW	Coefficient	**0,206**	**0,357**	**0,190**	**0,270**			**0,147**				**0,208**
	T-stat	20,6***	6,49***	10,06***	21,35***			18,8***				7,813***
	R^2	*79,9 %*	*42,5 %*	*64,0 %*	*79,6 %*			*85,0 %*				*51,7 %*
VIX = a + St Dev	Coefficient	**0,340**	**2,135**	**-1,660**	**1,540**			**0,055**				**1,835**
	T-stat	0,9	1,08	-0,87	1,47			0,64				0,9
	R^2	*0,8 %*	*2,0 %*	*1,3 %*	*1,8 %*			*0,6 %*				*1,4 %*
VIX = a + HILOW	Coefficient	**0,152**	**1,042**	**0,220**	**0,374**	**0,254**	**-0,204**	**0,012**	**No**	**0,426**	**1,859**	**0,522**
	T-stat	1,76	0,96	0,47	1,18	0,917	1,17	0,88	-0,04	1,01	2,96***	0,88
	R^2	*3,0 %*	*1,6 %*	*0,4 %*	*1,1 %*	*1,8 %*	*5,0 %*	*1,1 %*	*0,0 %*	*0,5 %*	*6,3 %*	*1,4 %*
EPU = a + St Dev	Coefficient	**-0,520**	**4,080**	**0,406**	**0,305**			**0,108**				**3,360**
	T-stat	-1,32	1,31	0,13	0,274			1,124				1,05
	R^2	*1,6 %*	*3,0 %*	*0,0 %*	*0,1 %*			*1,9 %*				*1,9 %*
EPU = a + HILOW	Coefficient	**-0,001**	**0,807**	**0,345**	**0,252**	**0,266**	**-0,199**	**0,008**	**0,810**	**0,433**	**1,750**	**1,464**
	T-stat	-0,096	0,47	0,46	0,75	0,82	-1,12	0,5	1,12	0,97	3,64***	1,59
	R^2	*0,0 %*	*0,4 %*	*0,3 %*	*0,5 %*	*1,4 %*	*4,4 %*	*0,4 %*	*1,0 %*	*0,5 %*	*9,2 %*	*4,3 %*

Table 2: Screening and test results

The independent uncertainty variables are in each regression extracted from the macroeconomic announcements. E.g. St Dev = a + HighLow (Adpchng) means that we regress the HighLow uncertainty measure from Adpchng on the St Dev from Adpchng.

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Bear in mind: The regression VIX = a + EPU is the regression of the two uncertainty indices matched for the dates where the macroeconomic announcements are made

Market Response Conditional on Uncertainty State

Following the methodology previously described from the article by Hu and Li (1998), we were interested to gain knowledge on how the returns on S&P500 were related to the macroeconomic announcements conditioned upon states of uncertainty. From the HighLow, VIX and EPU measure, we witness that on average, low financial uncertainty affects the stock returns less, than in medium or higher uncertain times. According to the coefficients extracted by the uncertainty states from the HighLow and EPU benchmarks, we see that they, in fact on average, make a negative shift in the stock returns. Our research shows that uncertainty states conditioned by the standard deviation are deviating in comparison to the results from three others. The standard deviation shows us that in times of low uncertainty, the returns on the S&P500 are higher than in high uncertainty states. We witness that there is strong evidence for varying coefficients among the different states of economic uncertainty.

In states with high uncertainty, we find that positive news in regards to “US Industrial Production” will be perceived to have a significant negative impact on the returns for the S&P500. The same macroeconomic announcement is also significant in the medium state, even though it have changed sign from positive to negative. Positive news for “Nonfarm Payroll” will in uncertain states have a significant positive influence on the US stock market. When looking at uncertain states represented by the Stdev measure, we see Labor e.g. Jobless Claims has a highly significant positive impact in “certain” times. US Import Price will in times of medium uncertainty according to VIX and EPU have a negative impact on the stock market, in contrast to having a positive impact in times with low uncertainty corresponding to the Stdev.

While announcements conditioned upon uncertainty states derived from the EPU Index is significant in the same pattern as the HighLow and Stdev, we see that uncertainty based upon the EPU index has an increased negative coefficients as the economy gets less uncertain. There is only one variable which is significant on the 10% level in times with low uncertainty from the VIX index. The levels extracted from the VIX index shows lower significance levels in general and fewer announcements that explain the change in the stock returns are present. One interpretation may be that the VIX, also named “the Fear Index” give investors little to no viable information when the market is stable.

An unexpected result is that news regarding the “Consumer Price Index” has little significant impact on stock prices in a stable economy, while no impact at all in medium and high states. This may be caused by the outcome of the CPI news being implied by other macroeconomic variables, as employment, export and import prices, which are already accounted for in their respective news.

Macro Variable:		Change in returns on S&P500 conditional on uncertainty statebased on:					
		Hilow			St dev		
	Unconditional	High	Medium	Low	High	Medium	Low
Adpchng	0,004 ***	0,005	0,003 *	0,006 **	0,005 *	0,004 **	0,001
Adj R^2	*9,00 %*	*5,02 %*	*4,13 %*	*23,13 %*	*8,92 %*	*9,52 %*	*3,12 %*
Usmmmnch	0,001	0,003	-0,002	0,002	0,001	0,000	0,001
Adj R^2	*0,30 %*	*3,49 %*	*1,13 %*	*1,33 %*	*1,79 %*	*0,77 %*	*3,52 %*
Tmnochg	-0,002 **	-0,003	-0,002 *	-0,001	-0,004 *	-0,001	-0,003
Adj R^2	*2,50 %*	*3,17 %*	*1,84 %*	*0,97 %*	*5,49 %*	*0,35 %*	*2,35 %*
Ppichng	0,000	0,000	0,001	-0,009 **	0,000	-0,001	N/A
Adj R^2	*0,50 %*	*2,48 %*	*0,73 %*	*16,29 %*	*2,64 %*	*0,57 %*	*N/A*
Ipchng	-0,001	-0,003 ***	0,002 **	-0,004	-0,003 ***	0,003 **	-0,002
Adj R^2	*0,20 %*	*13,93 %*	*2,44 %*	*2,40 %*	*15,48 %*	*4,87 %*	*1,52 %*
Injcsp	-0,001 **	-0,001	-0,002 **	-0,001	-0,001	-0,002 **	-0,001
Adj R^2	*0,20 %*	*0,34 %*	*1,52 %*	*0,53 %*	*0,57 %*	*1,25 %*	*0,44 %*
Imp1chg	-0,001	-0,002	-0,001	-0,002	-0,001	-0,002	-0,001
Adj R^2	*0,70 %*	*2,11 %*	*7,39 %*	*1,95 %*	*2,11 %*	*1,05 %*	*0,99 %*
Injcjc	-0,001 *	-0,001	0,000	-0,002 *	-0,001	0,000	-0,004 **
Adj R^2	*0,20 %*	*0,53 %*	*0,21 %*	*1,11 %*	*0,76 %*	*0,15 %*	*4,01 %*
Cptichg	0,005	-0,003 **	0,003 ***	0,002	-0,003 **	0,003 **	N/A
Adj R^2	*0,30 %*	*9,53 %*	*5,14 %*	*2,21 %*	*6,71 %*	*2,83 %*	*N/A*
Cpichg	-0,001	-0,001	-0,001	-0,005 **	-0,003	-0,001	-0,001
Adj R^2	*0,27 %*	*3,21 %*	*0,59 %*	*7,55 %*	*0,85 %*	*0,49 %*	*2,28 %*
Cpupxchg	-0,002 *	-0,006 **	-0,001	0,002	N/A	N/A	N/A
Adj R^2	*1,19 %*	*14,22 %*	*0,41 %*	*3,68 %*	*N/A*	*N/A*	*N/A*
Dgnochg	0,001	0,000	0,000	0,002	0,001	-0,001	0,006 **
Adj R^2	*0,28 %*	*1,61 %*	*1,01 %*	*0,40 %*	*0,93 %*	*0,71 %*	*9,36 %*
Imp1yoypct	-0,002	0,006	-0,003 *	-0,012 *	0,006	-0,003 *	0,020 ***
Adj R^2	*0,89 %*	*0,13 %*	*4,32 %*	*15,71 %*	*0,42 %*	*4,40 %*	*36,41 %*
Nfppch	0,004 ***	0,010 **	0,003 *	0,000	0,007 **	0,002	0,001
Adj R^2	*13,11 %*	*37,59 %*	*6,70 %*	*8,96 %*	*33,49 %*	*1,61 %*	*9,03 %*
Nfptch	0,000	-0,001	0,000	0,003	-0,002	0,000	0,004 **
Adj R^2	*0,52 %*	*1,59 %*	*0,88 %*	*2,23 %*	*0,84 %*	*0,94 %*	*6,23 %*
Prodnfrpct	0,002	0,006	-0,001	0,002	0,004	-0,002	0,008
Adj R^2	*1,16 %*	*14,02 %*	*1,56 %*	*2,99 %*	*12,04 %*	*1,01 %*	*21,22 %*
Ustbtot	0,002 *	0,001	0,001	0,004	0,001	0,001	0,008 **
Adj R^2	*0,95 %*	*0,72 %*	*0,13 %*	*2,03 %*	*1,62 %*	*0,32 %*	*12,69 %*
Uswhtot	0,001	0,004	0,000	0,000	N/A	N/A	N/A
Adj R^2	*0,44 %*	*0,76 %*	*1,17 %*	*5,86 %*	*N/A*	*N/A*	*N/A*

Table 3: Unconditional and conditional effect of Macro News on S&P500 based on Highlow and St dev. Regression: $Change\ on\ S\&P500\ matched\ to\ macro\ announcement\ dates = a + \sum Uncertainty\ Level\ (Macro\ Variable)$

E.g. Change in returns on the S&P500 matched for the dates from Adpchng announcements conditional on high uncertainty levels based on the HighLow measure = 0,005

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Macro Variable:	Change in returns on S&P500 conditional on uncertainty statebased on:											
	Vix						EPU					
	High		Medium		Low		High		Medium		Low	
Adpchng	0,006	*	0,005	***	0,000		0,004	**	0,006	***	-0,001	
Adj R^2	*8,23 %*		*18,92 %*		*4,35 %*		*9,83 %*		*22,79 %*		*4,89 %*	
usmmmnch	0,002		0,000		0,002		-0,001		0,003	**	-0,004	**
Adj R^2	*0,51 %*		*1,06 %*		*0,36 %*		*4,58 %*		*4,17 %*		*8,51 %*	
tmnochg	-0,004	**	-0,001		-0,001		-0,003	**	-0,001		0,000	
Adj R^2	*5,90 %*		*0,59 %*		*0,87 %*		*6,61 %*		*0,31 %*		*2,17 %*	
ppichng	-0,001		-0,001		0,000		0,000		-0,002		0,000	
Adj R^2	*1,77 %*		*0,88 %*		*2,52 %*		*1,62 %*		*0,67 %*		*2,69 %*	
ipchng	-0,003	*	0,001		0,001		-0,004	***	0,003	***	-0,001	
Adj R^2	*3,45 %*		*0,81 %*		*0,67 %*		*14,89 %*		*6,34 %*		*2,56 %*	
injcsp	-0,002		-0,001		0,000		-0,003	*	-0,001		0,000	
Adj R^2	*1,69 %*		*0,33 %*		*0,53 %*		*1,96 %*		*0,56 %*		*0,77 %*	
imp1chg	0,000		-0,003	***	0,000		0,000		-0,003	*	-0,002	
Adj R^2	*1,13 %*		*0,31 %*		*0,67 %*		*1,72 %*		*2,78 %*		*1,59 %*	
injcjc	-0,002	*	0,000		0,000		-0,001		-0,001		0,000	
Adj R^2	*0,84 %*		*0,24 %*		*0,08 %*		*0,07 %*		*0,21 %*		*0,47 %*	
Cptichg	-0,002		0,003	**	0,001		-0,003	**	0,003	**	0,002	
Adj R^2	*1,32 %*		*3,43 %*		*1,43 %*		*5,98 %*		*4,71 %*		*0,84 %*	
cpichg	-0,002		-0,001		-0,001		-0,001		0,000		-0,004	**
Adj R^2	*0,48 %*		*0,59 %*		*1,45 %*		*1,29 %*		*1,10 %*		*11,21 %*	
Cpupxchg	-0,001		-0,002		-0,001		0,000		-0,002		-0,006	***
Adj R^2	*1,59 %*		*1,60 %*		*1,00 %*		*1,75 %*		*1,11 %*		*25,77 %*	
dgnochg	0,000		0,000		0,001		0,000		0,001		0,000	
Adj R^2	*1,75 %*		*0,91 %*		*0,46 %*		*1,64 %*		*0,16 %*		*2,27 %*	
imp1yoypct	0,005		-0,004	***	-0,007		0,003		-0,586	***	N/A	
Adj R^2	*0,52 %*		*15,57 %*		*3,38 %*		*0,35 %*		*22,51 %*		*N/A*	
nfppch	0,012	***	0,002		0,002		0,005	***	0,001		N/A	
Adj R^2	*67,55 %*		*2,03 %*		*3,03 %*		*19,33 %*		*2,94 %*		*N/A*	
nfptch	-0,001		0,000		0,002		0,001		0,001		-0,005	**
Adj R^2	*1,49 %*		*0,94 %*		*1,55 %*		*0,95 %*		*0,75 %*		*11,25 %*	
prodnfrpct	0,005		0,000		0,000		0,008	***	-0,002		0,001	
Adj R^2	*5,51 %*		*3,08 %*		*7,06 %*		*30,56 %*		*1,72 %*		*7,54 %*	
ustbtot	0,004	**	0,000		0,000		0,002		0,000		0,002	
Adj R^2	*5,13 %*		*1,05 %*		*2,23 %*		*1,66 %*		*1,06 %*		*0,70 %*	
uswhtot	0,002		0,000		-0,003	*	0,002		0,000		0,001	
Adj R^2	*0,17 %*		*1,78 %*		*10,61 %*		*3,19 %*		*1,32 %*		*2,63 %*	

Table 4: Conditional effects of Macro news based on EPU and VIX

$$Regression: Change\ on\ S\&P500\ matched\ to\ macro\ announcement\ dates = a + \sum Uncertainty\ Level\ (Macro\ Variable)$$

E.g. Change in returns on the S&P500 matched for the dates from Adpchng announcements conditional on high uncertainty levels based on the VIX index = 0,006

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Macro Uncertainty Effects on the 30 Day Volatility and Volume of Trade

Our main findings in respect to the variables of 30-day volatility and the volume of trade in the S&P500 demonstrate that an increase in analyst dispersion clearly leads to a volatility increase in the stock market. In many cases analyst dispersion also leads to an increase in the volume of trade, however, the results are more dispersed. We find evidence that uncertainty has a less significant impact after implementing dummy variables in crisis periods to control for outliers. We discover that the dummy variables are extracting too much of the explanatory power in addition to changing the sign and size in many of the coefficients. We also observe the same trend when running the regression in regards to the volume of trade and volatility with the VIX and EPU as explanatory variables. This suggests that controlling for heavy outliers in periods with financial crisis extracts too much information from the dataset and leaves us with insufficient results.

We know from basic economic theory that the level of the economy varies in different business cycles over a certain timespan. According to Nimark (2013), when financial distress occurs in economies it will lead to trivial events becoming "newsworthy", whereas they would be unimportant in a more normal state of the economy. This phenomenon will, in turn, increase the uncertainty in the economy in periods where the markets are in distress, with the potential of giving us a diluted view of the "true" uncertainty.

Following the methodology previously described by Kozeniauskas et al (2014), we wish to conduct a correction for these periods with turmoil, to see if effects are significant or not. We believe that if we dummy out the data where the uncertainty is at its highest, namely in crisis periods, our results will be biased, and in fact not reflect the whole business cycle as it should. However, we wish to see if the patterns of uncertainty are the same if we control for crisis periods.

We witness from Table 5Table 6 and Table 7, that positive shock in the analyst dispersion affects the volume and volatility on the S&P500 positively for all the significant variables. On the contrary, the same positive shocks will in some instances affect the volume and volatility significant negative after controlling for crisis periods. "Initial Jobless Claims" are one of these variables which change sign after introducing the dummy. One interpretation is that an increase in the dispersion of forecasts of jobless claims will reduce the volume of trade of

S&P500. Surprisingly, due to their importance of details regarding economic activities, US Trade Balance and Production Output per hour have little, to no significant impact on the volume and volatility of the S&P500. This may be a result of the market already anticipating the information revealed by the announcements, hence no substantial movement in the days surrounding will be displayed.

Variable	Without Crisisdummy							
	Volume				Volatility			
	HighLow		St dev		HighLow		St dev	
Adpchng	1,10		10,37	***	0,11	***	0,60	***
Usmmmnch	-0,10		-2,78		0,12	***	0,46	***
Tmnochg	5,72		81,21		0,72	*	5,67	***
Ppichng	14,94		-118,00		6,14	***	31,04	***
Ipchng	-46,73		47,16		9,14	***	60,58	***
Injcsp	-0,57	***	-1,34	*	0,02	***	0,07	***
Imp1chg	37,09		291,00	*	4,63	***	29,05	***
Injcjc	1,73	***	11,77	***	0,05	***	0,29	***
Cptichg	3,16		4,05		2,32	***	27,43	***
Cpichg	163,00		3810,00	***	15,82	***	173,12	***
Cpupxchg	-426,00		10600,00	***	16,03	**	112,78	***
Dgnochg	-33,31	**	-95,39		-0,45		-2,45	
Imp1yoypct	116,00	***	410,00	***	4,32	***	18,60	***
Nfppch	10,07		16,08	***	0,03		0,31	**
Nfptch	0,86	**	7,16	***	0,03	***	0,23	***
Prodnfrpct	80,74		-85,50		2,93		9,61	
Ustbtot	1,75		5,38		0,01		3,60	**
Uswhtot	71,95		-34,88		10,90	*	-0,62	
	in 1.000.000´s							

Table 5: Volume of trade and 30day Volatility of the S&P500 matched by the 18 macroeconomic variables

$$Volume\ of\ Trade = a + HighLow\ //\ Volume\ of\ Trade = a + St\ Dev$$

$$30day\ Volatility = a + HighLow\ //\ 30day\ Volatility = a + St\ Dev$$

E.g. Volume of trade = a +HighLow measure extracted from Adpchng announcements = 1,10

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Variable	With Crisisdummy					
	Volume					
	HighLow	d1	d2	St dev	d1	d2
Adpchng	-0,05	372,00 **	n/a	7,10 *	188,00	n/a
Usmmmnch	1,76	-562,00 ***	106,00	2,79	-489,00 ***	140,00 *
Tmnochg	-27,11 *	375,00 ***	633,00 ***	-167,00 *	383,00 ***	644,00 ***
Ppichng	83,94	160,00	553,00 ***	254,00	202,00	545,00 ***
Ipchng	-77,53	317,00 *	582,00 ***	155,00	181,00	181,00 ***
Injcsp	-0,74 ***	382,00 ***	n/a	-2,00 **	372,00 ***	n/a
Imp1chg	84,19 **	-21,48	589,00 ***	457,00 **	-33,26	568,00 ***
Injcjc	0,96 *	325,00 ***	543,00 ***	6,50 **	316,00 ***	537,00 ***
Cptichg	-7,89	236,00 *	597,00 ***	-229,00	275,00 *	601,00 ***
Cpichg	206,00	269,00	597,00 ***	3170,00 **	110,00	563,00 ***
Cpupxchg	-570,00 *	434,00 ***	590,00 ***	8080,00 ***	303,00 **	476,00 ***
Dgnochg	-36,88 ***	181,00	592,00 ***	165,00 **	178,00	604,00 ***
Imp1yoypct	101,00 ***	445,00 ***	n/a	309,00 **	416,00 ***	n/a
Nfppch	n/a	n/a	n/a	n/a	n/a	n/a
Nfptch	0,11	262,00 *	438,00 ***	2,79	219,00	41000,00 ***
Prodnfrpct	63,66	320,00	636,00 ***	-199,00	388,00 *	637,00 ***
Ustbtot	-1,37	211,00	665,00 ***	30,68	183,00	662,00 ***
Uswhtot	-74,32	70,63	234,00 ***	-39,98	33,55	233,00 **
	in 1.000.000´s					

Table 6: Volume of Trade on the S&P500 matched by the 18 macroeconomic variables with crisis dummies

$Volume\ of\ Trade = a + HighLow + d1 + d2$ // $Volume\ of\ Trade = a + St\ Dev + d1 + d2,$

where d1 is the DotCom bubble and d2 is the Great Recession

E.g. Volume of trade = a +HighLow measure extracted from Adpchng announcements+d1+d2 = -0,05

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Variable	With Crisisdummy					
	Volatility					
	HighLow	d1	d2	St dev	d1	d2
Adpchng	0,03	26,75 ***	n/a	0,15	25,70 ***	n/a
Usmmmnch	0,04	12,54 ***	3,95 *	0,12	13,42 ***	4,37 **
Tmnochg	0,06	23,25 ***	5,99 ***	1,16	22,97 ***	5,75 ***
Ppichng	2,14	24,94 ***	7,19 ***	11,64	25,07 ***	7,27 ***
Ipchng	3,93 **	22,13 ***	6,99 ***	38,17 ***	18,55 ***	7,49 ***
Injcsp	0,00	32,89 ***	n/a	0,01	32,97 ***	n/a
Imp1chg	2,65 ***	20,89 ***	7,62 ***	18,94 ***	18,07 ***	7,20 ***
Injcjc	-0,02 *	32,35 ***	7,23 ***	-0,05	32,10 ***	7,25 ***
Cptichg	0,50	26,61 ***	5,87 ***	9,57	25,20 ***	5,69 ***
Cpichg	5,92 *	24,72 ***	7,39 ***	75,84 ***	21,37 ***	6,51 ***
Cpupxchg	4,58	26,84 ***	6,82 ***	20,83	27,41 ***	6,61 ***
Dgnochg	-0,51 *	25,74 ***	6,71 ***	-3,26 *	25,72 ***	7,00 ***
Imp1yoypct	3,44 ***	26,43 ***	n/a	12,55 ***	25,06 ***	n/a
Nfppch	n/a	n/a	n/a	n/a	n/a	n/a
Nfptch	0,00	29,23 ***	6,47 ***	0,06	28,01 ***	5,73 ***
Prodnfrpct	2,33	9,64	3,85	6,29	10,01	3,86
Ustbtot	-0,04	21,02 ***	6,45 ***	1,03	20,07 ***	6,35 ***
Uswhtot	6,84	28,67 ***	5,47 ***	-0,51	28,71 ***	9,15 ***

Table 7: 30 Day Volatility on the S&P500 matched by the 18 macroeconomic variables with crisis dummies $30day\ Volatility = a + HighLow + d1 + d2$ // $30day\ Volatility = a + St\ Dev + d1 + d2,$

where d1 is the DotCom bubble and d2 is the Great Recession

E.g. 30day Volatility = a +HighLow measure extracted from Adpchng announcements+d1+d2 = 0,03

*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Variable	Without Crisisdummies			
	Volume		Volatility	
Vix	16,91	***	0,71	***
EPU	1,92	**	0,12	***
	in 1.000.000´s			

Table 8: Volume and Volatility of the S&P500 on the VIX and the EPU
$30day\ Volatility = a + VIX$ // $30day\ Volatility = a + EPU$
$Volume\ of\ Trade = a + VIX$ // $Volume\ of\ Trade = a + EPU$
*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Variable	With Crisisdummies											
	Volume		d1		d2		Volatility		d1		d2	
Vix	9,73	**	205,00		546,00	***	0,97	***	9,48	***	1,07	
EPU	1,40	*	358,00	**	600,00	***	0,08	***	6,66	***	28,13	***
	in 1.000.000´s											

Table 9: Volume and Volatility on VIX and EPU w/ crisis dummies
$30day\ Volatility = a + VIX + d1 + d2$ // $30day\ Volatility = a + EPU + d1 + d2$
$Volume\ of\ Trade = a + VIX + d1 + d2$ // $Volume\ of\ Trade = a + EPU + d1 + d2$
where d1 is the DotCom bubble and d2 is the Great Recession
*Significance level: * is at 10%, ** is at 5% and *** is at 1%*

Aggregate uncertainty measure

After employing the method described in the methodology section, we have created an aggregate measure based on cross sectional-news, viewable in Figure 14. We see that the aggregate median forecast, seen in Figure 15, might be used to measure the uncertainty level of the economy. It has a correlation of 0,67 with the S&P500 as analysts make their predictions every month and adjust their forecasts accordingly based on their private and public signals. We also observe that the sign of the aggregate news seems to be random, as 113 out of 200 observations are negative. Explanations for this small negative tendency could include a slight positive skewness as a result of over-optimism amongst forecasters or that more negative news tends to follow the initial negative news.

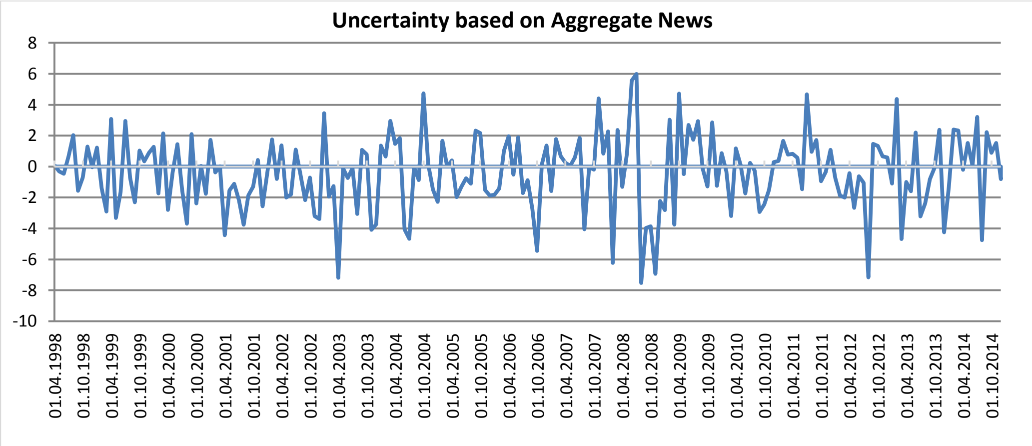


Figure 14: Constructed Aggregate uncertainty measure

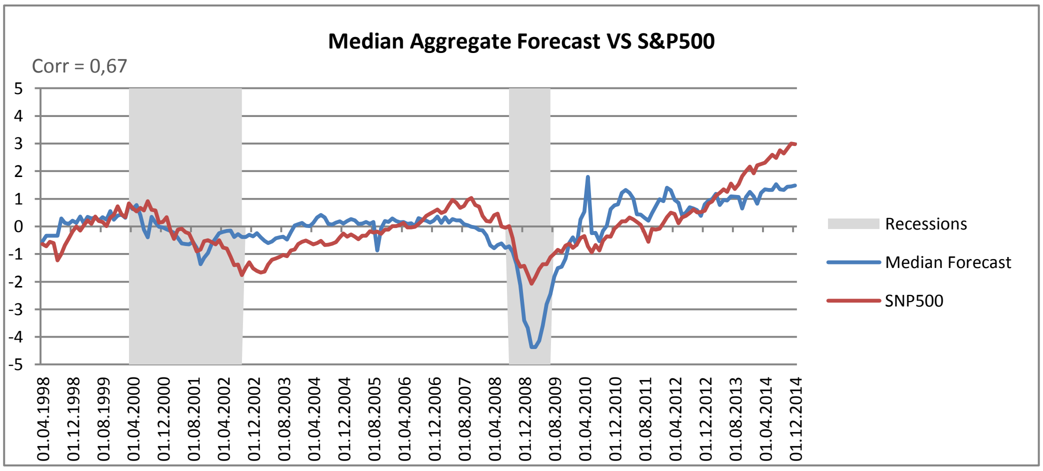


Figure 15: Median Aggregate Forecast compared with the daily returns of the S&P500

Our aggregate uncertainty measure shows visually several common features with our standard uncertainty measures VIX and EPU, seen in Figure 15. They all increase significantly during the above-mentioned recessions and have a higher general level after the subprime crisis than before. When studying the correlation table with both the VIX and EPU, we see that the correlation in Table 10 is substantial regarding both the VIX and EPU. As the VIX is the most common measure of market uncertainty, the graph shows us that our aggregate measure reflects uncertainty in the market relatively well, however as expected, the correlation with EPU is higher.

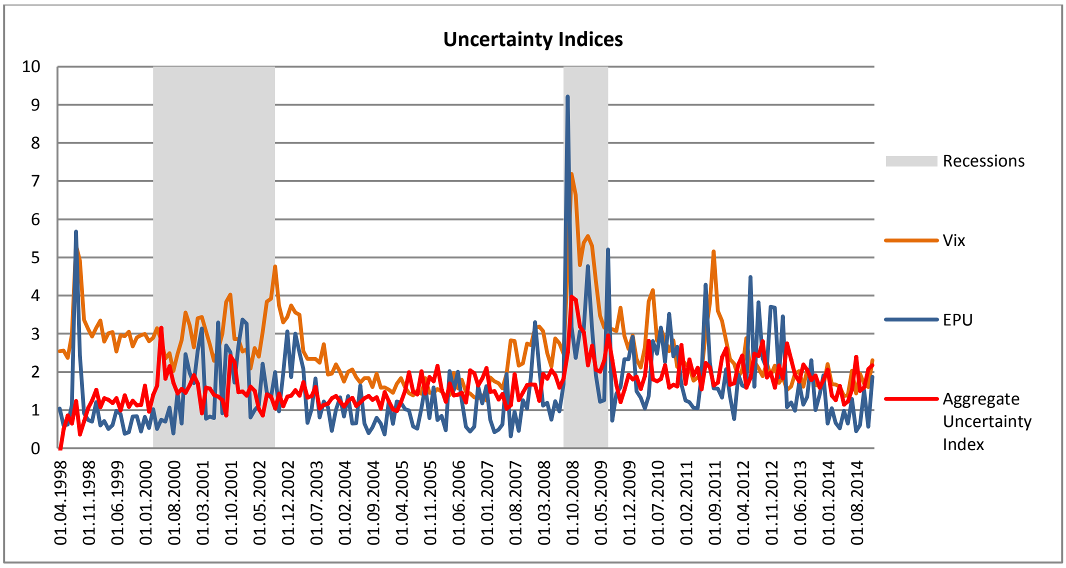


Figure 16: Comparison between our aggregate uncertainty index, the VIX and the EPU

Correlation Matrix

	Aggregate Uncertainty Index	EPU	VIX
Aggregate Uncertainty Index	1		
EPU	48 %	1	
VIX	34 %	50 %	1

Table 10: Correlation matrix between our aggregate uncertainty index, the VIX and the EPU

We suspect that the VIX Index is more specific to risk concerning the stock market, while the EPU are a more general uncertainty measure to cover a broader scope in the economy, and will also cover macro uncertainty to a greater extent. The VIX could be classified as a technical uncertainty which reflects market uncertainty through the market's pricing of stocks and options, while EPU and our aggregate measure have a larger emphasis on market perceptions. As EPU reflects the *media* feature and the aggregate uncertainty reflects the *analyst* element, their correlation could origin from the behavioral aspect of economics.

Conclusion

The research presented in this Thesis finds evidence that the level of macro uncertainty in the economy is clearly dependent on how the financial market interprets the macro news. We used two measures of analyst dispersion and two well-known uncertainty proxies for market uncertainty. Variables in the "Industrial Production" and "Labor" categories are consistent with the Bayesian update method. In these categories, the macro news was significant when uncertainty was high and/or medium and not significant if uncertainty was low. These results are consistent for different levels of uncertainty based on analysis from 4 uncertainty indicators. We found that all variables that were significant were, in fact, sensitive to uncertainty levels.

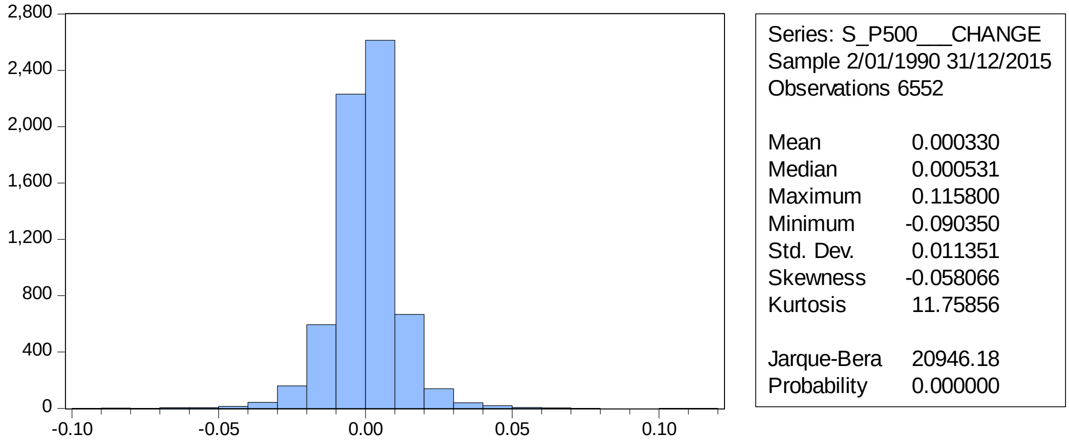
We discovered that an increase in the dispersion of macro analysts lead to an increase in both the volatility on the stock market and volume of trade of the stock market in the US. We controlled for heavy outliers in times of financial crisis, however, this removed too much information from the explanatory variable and hence, we had too little support a reliable conclusion at this point.

We furthermore created an aggregate uncertainty measure, based on a cross-section of macro analyst dispersion. This uncertainty measure clearly has common features with known uncertainty indices and could potentially be used as an uncertainty index.

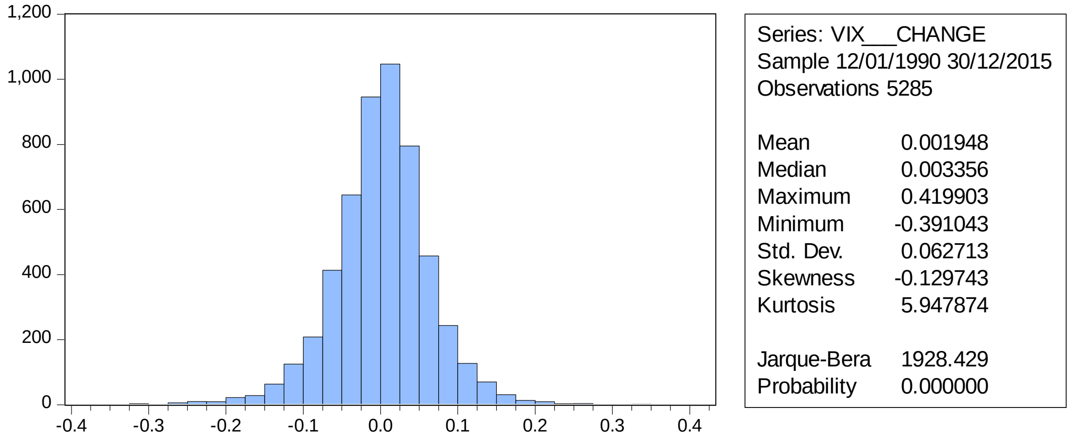
Contribution and future research

We have provided evidence that macro uncertainty affects stock markets in several parameters and we found that our aggregate uncertainty index has a high correlation with VIX and especially EPU. The latter is a highly interesting result and raises a significant amount of questions. We propose some future research questions: Are these relationships consistent over time and different business cycles? On a more detailed level, why does the aggregate uncertainty index have a higher correlation with EPU than VIX? Could we decrease the number of variables and still get the same explanatory power? Are there any other unknown variables that can explain uncertainty? These are only a few questions that are potential future research questions, based on our findings.

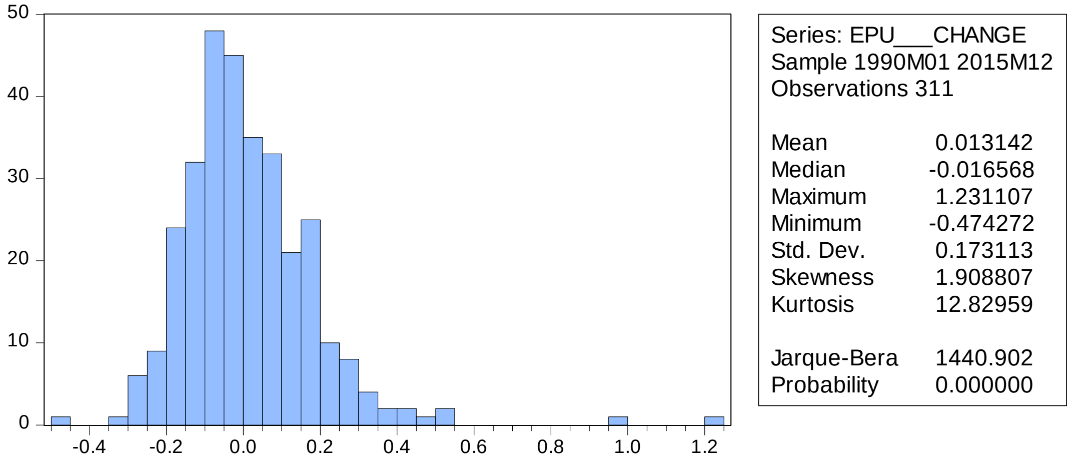
Appendix



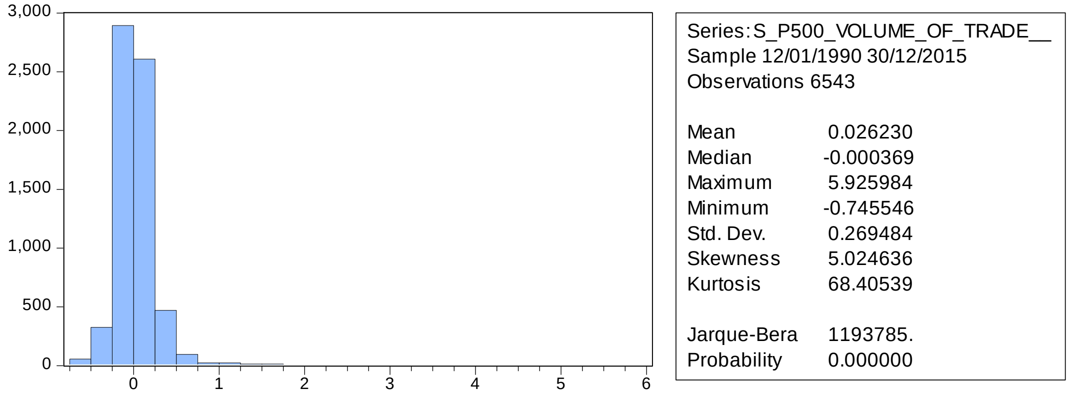
Appendix 1: Descriptive statistics S&P500



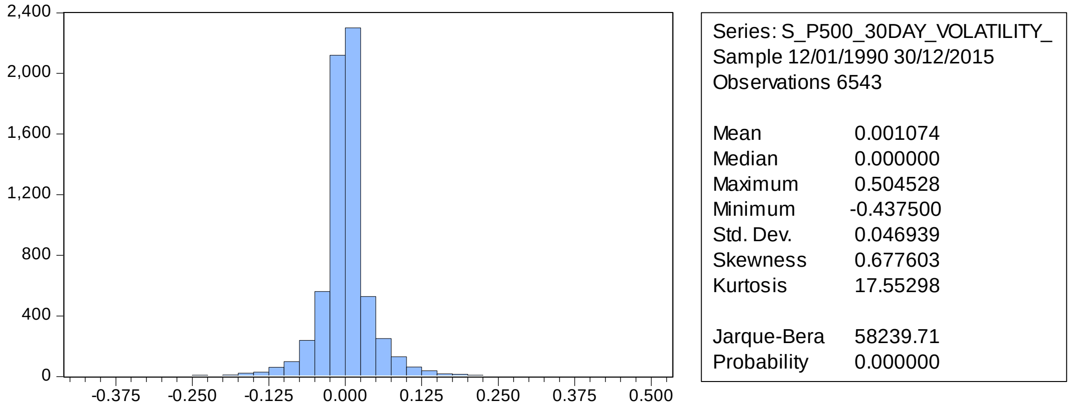
Appendix 2: Descriptive statistics VIX



Appendix 3: Descriptive statistics Economic Policy Uncertainty Index



Appendix 4: Descriptive statistics Volume of Trade on the S&P500



Appendix 5: Descriptive statistics 30Day Volatility on the S&P500

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BI Norwegian Business School –

Preliminary Thesis GRA 19003

How will analysts forecast uncertainty influence the impact of macro news on financial assets, primarily stocks and bonds?

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Abstract

Macroeconomic uncertainty is a hot topic in todays academic literature. We are interested to investigate whether macro uncertainty can affect the implementation of shocks on asset prices. Forecaster disagreement will serve as a proxy for uncertainty.

Contents

Introduction

In recent years, there has been a growing assumption that macroeconomic announcements are influencing the stock and bond market. Some early research on this field from the 1970s has shown that some macro factors have influence upon the prices and returns on different financial assets, but the overall significance is low. From the mid-1990s, there has been an evolution in research, where researchers have found stronger evidence of shock affecting asset prices, primarily when shocks are conditional on state of the economy.

Historically, there have been many measures of uncertainty e.g. stock volatility, implied volatility in options and newspaper articles. One measure we find particularly interesting is the forecaster disagreement on macroeconomic announcements. Analysts are perceived to have the highest possible qualification to predict the future. However, research shows that all analysts have different biases and we see that analyst disagreement varies significantly over time.

The history of research upon this field is crucial in order to fully investigate to which extent analyst forecast uncertainty influences the impact of macroeconomic news on financial assets, primarily stocks and bonds.

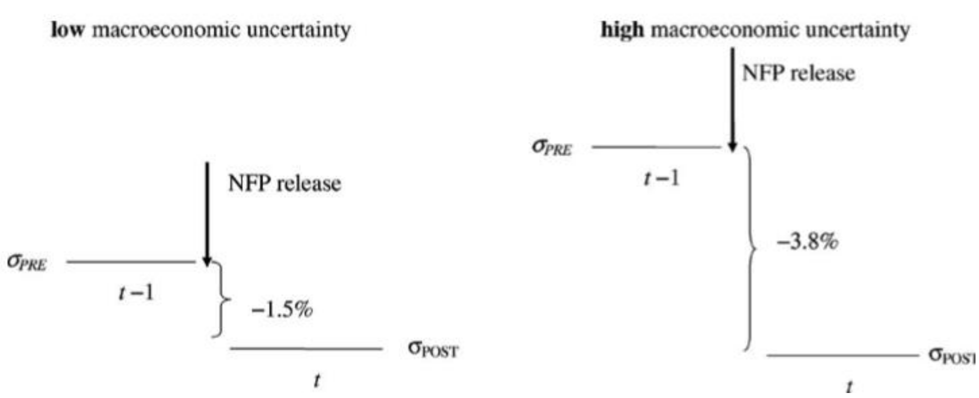

Figure 17: Impact of Macro shocks on volatility (Beber, Brandt and Luisi 2014)

We see that there is a significant impact of shocks on the uncertainty itself, by Beber, Brandt and Luisi (2014). Nevertheless, we are interested in is if this also have an actual effect on asset prices! By using the forecaster disagreement as a proxy for macro uncertainty, we will see if the response of assets to macroeconomic news is different, conditioned upon macroeconomic uncertainty.

There is not a lot of previous work on this particular subject, which is intriguing and challenging when it comes to methodology. However, this paper has adapted to some extent the methodology from Hu and Li (1998) and McQueen and Roley (1993) who condition the impact of macro shocks on the state on the economy. We condition the impact of macro shocks on different forecaster disagreement measures.

Since future predictions and shocks affect financial assets, the importance of uncertainty has an impact on all intermediaries in financial markets. Especially institutional and private investors would be interested to incorporate the result of this thesis in their own strategies. Macroeconomic uncertainty is a general hot topic in academic literature today.

In the following sections of this preliminary, there will be literature review of previous and ongoing research on the impact of macro-news, analyst disagreement and uncertainty. We have also made a review of the data we have and what we plan to use when incorporating the methodology to regress and interpret our findings. We might also encounter some biases, which we have described in a separate section.

Literature Review

Impact of macroeconomic news

It is a common belief that asset prices are sensitive to changes in macroeconomic factors since Fama et al (1969). This is also consistent with the CAPM and Ross (1979) followed with a confirmation of the arbitrage pricing model, which shows that asset returns are determined by exposures to macroeconomic factors, and are not in conflict with the theory of market efficiency.

However, previous research showed little evidence of actual effects of macroeconomic news on stock prices, except monetary news. Pearce and Roley (1985) compiled survey data from 1977-82 and found that consumer price index, unemployment and industrial production had weak links with stock return, but that monetary information were significant. Schwert (1981) found out that the link of stock prices to inflation is weak and slow with data from 1958-78. Cutler et al (1989) applied VAR models to measure news on macroeconomic time series from 1871-1986. The conclusion was that less than one-third of the monthly return variance could be explained by macroeconomic events.

McQueen and Roley (1993) used data from S&P 500 from 1977-88 to show that the both the effect and sign of macroeconomic news on stock returns were in fact dependent on the state of the economy. In particular, they showed that a positive shock in real activity when when the economy was good, led to lower stock returns. Simultaneously, the same positive shock in real activity when the economy was bad, led to higher stock returns.

Along the same lines, Hu and Li (1998) used data from S&P 500, Dow Jones, Russel Indexes from 1980-1996 to see if effect of macroeconomic news on stock prices were dependent on the state of the economy. They found strong evidence for that the response on prices due to macroeconomic shocks were varying through business cycle stages. However, they also stressed the importance of distinguishing variables in association with business stages.

Beber, Brand and Luisi (2014) used 43 distinct U.S. macroeconomic announcements during 1997-2011 with over 8000 announcements 3,800 business days to create a simple technique to extract daily factors from economic news released at different times and frequencies. While doing this, they also showed that forecasters tended to agree on downturns, but could not forecast recoveries with the same accuracy. This again could be an explanation of why forecasters disagree in recessions.

In addition to impact on stock prices, we will also investigate the role new information plays in influencing the price of government bonds. According to Balduzzi, Elton and Green (2001), public news explains much of the volatility of US government bond prices in the minutes after announcements. They see that the volatility in the bond prices increases right after announcement and that the uncertainty is persisting for up to one hour after the new information was published. The researchers also find that several announcement types are affecting the prices significantly and especially the unemployment rate, real activity and consumer price index.

Ludvigson and Ng (2007) suggests that excess returns on bonds are dependent on the same key macroeconomic components that Balduzzi, Elton and Green (2001). They also find that bonds prices respond countercyclical to new information. The countercyclical behaviour in the risk premium of bonds concludes that the returns are forecasted to be high in recessions and low in expansions, hence they find strong support that macroeconomic factors need to be accounted for when forecasting a bonds risk premium and yields.

Uncertainty

Knight (1921) defined early the concept of risk, namely “a known probability distribution over a set of events”. Knight also came up with a definition of uncertainty as “people's’ inability to forecast the likelihood of events happening.”

Given this wide perception of uncertainty, it is no surprise that there is no common, all-accepted measure of risk and uncertainty, but many different proxies with advantages and disadvantages.

The most common measure of uncertainty in finance is the volatility of the stock market. The volatility of the S&P 500 Index is an example of this. This is frequently used due to simplicity and when a data series become more volatile it is harder to forecast (Bloom 2014) and forecasting is plays a major role in the financial sector.

A different proxy for uncertainty is the implied volatility of options, for example, VIX implied volatility. Options have five different variables. Since market prices of options are observable, the implied volatility of the options can be calculated using the other four. Fleming (1998) argues that with a correction for certain biases, it can be a better estimator for predicting conditional volatility of the stock market than historical volatility.

Campbell et al (2001) reports that cross-firm stock-return variation is almost 50 percent higher in recessions compared to booms. One explanation of increase of variance in recessions can be the leverage effect, that negative shocks have higher impact on volatility than the corresponding positive shock. This is due to the increase of debt in bad times, so stock return volatility increases. However, Schwert (1989) showed that only 10% of the volatility increase in recessions is due to the leverage effect, so this cannot be the only explanation.

Scotti (2013) constructs a methodology to implement indexes in order to capture the surprises from the market and uncertainty of the analysts when macroeconomic news is released. These indexes measure the degree of optimism and pessimism about the economy when the “shocks” are released. Positive figures from the surprise index tell us that the expectations have been higher than consensus and the agents had been more pessimistic about the macroeconomic situation. She constructs a surprise and uncertainty index for five different countries to see if there is worldwide consistency. The correlation for the two indexes is found to be negative, so she concludes that bad news increases volatility.

Alexopulos and Cohen (2009) used another measure, namely the “Main Street” measure. It is based on the number of New York Times articles on uncertainty and the economy. Comparing this to a classical measure of uncertainty in finance, the volatility of the stock index, “Main Street” has more ups and downs than the other. Furthermore, “Main Street” has longer downturns and prolonged rebounds than the market index. This supports the idea that the “Main Street” measure is a more comprehensive measure of total volatility than the stock index. However, this measure is also biased with journalist incentives and it is less tradable. Baker, Bloom, and Davis (2012) applied the same methodology across the ten biggest newspapers in the US and found that 51% increase in selected words during recession. This is consistent with Alexopulos and Cohen (2009) study.

Bachmann, Elstner, and Sims (2010) proved that forecaster disagreement is extensively higher in downturns. Periods when analysts and forecast experts from different types of institutions and organizations display more dispersed opinions are likely to reflect higher uncertainty. Therefore, this means that forecaster disagreement can be seen as a proxy for macro uncertainty.

There has also been argued that one can measure the size of forecast errors to measure uncertainty. Both Scotti (2013) and Jurado, Ludvigson and Ng (2013) both did papers concerning this subject and concluded that the magnitude of forecast errors varies against economic cycles, especially the rise of uncertainty in recessions.

Analyst uncertainty

An important part when assessing the impact of analyst uncertainty on macroeconomic shocks is to understand the role macro-analysts play in the market.

Macro-forecasters are employees of different firms that hold skills in interpreting information and utilizing it to project future economic states.

According to Laster, Bennett and Geoum (1999), there are two types of users that utilize economic forecasts, namely intensive and occasional users. The intensive users have a high demand of accurate forecasts because they use them to create value and poor forecasts leads to ineffective usage of recourses and potential losses. The occasional users are not that dependent on accuracy, they rather search for trends.

Following Schuh (2001), the traditional forecaster has had the goal to produce the most accurate and unbiased forecast with uncorrelated forecast errors. This is the result from his assumption that all forecasters use all new information available and use it to get the most correct results. Laster, Bennett and Geoum (1999) concludes that if all forecasters have similar data and seek to have the highest accuracy of future states, their projections will cluster around the consensus.

Roy Batchelor (2007) elaborates that there are three possibilities for deviation between the forecast and true values of assets. The first possibility is that the forecaster lacks the skill to properly utilize all information available at any given time. The second reason might be that the analyst possesses the proper skill to comprehend the signals, but lacks sufficient information to get correct results. The last possibility of deviation is that the forecaster both have the required skill and data, but consequently introducing a rational bias. Since analysts are not directly compensated from the investors, but from the firm, their thoughts about new information are not consistent with the truth. As this rational bias is important, we will further elaborate on it.

According to Laster, Bennett and Geoum (1999), their bonus is defined by their ability to give support to the firm´s investors and to what degree they are able to facilitate growth in client base. The analysts´ reputation is based on the predictability of their forecast and how the investors perceive their recommendations and to what extend they are benefiting from following the forecasters recommendation.

It is not just private investors that is causing the bias, forecasts can also be used as an instrument to rationalize and gaining power in politics and government institutions.

An example of this occurrence is published in a paper by Heinemann (2005), that shows forecasts of economic growth in Germany have been constant optimistic, and is allowing the German government to make unrealistic high spending plans.

Other research by McNees (1978) finds poor support that macroeconomic forecasts, such as GNP, Inflation and Unemployment from professional analysts are completely efficient and unbiased. Ito (1990) finds evidence that FX forecasts are systematically biased in projections that are in favour of the analysts´ firm.

Another possibility of deviations from the true value has been proved by Ehrbeck and Waldeman (1996), which argue that poor forecasters try to mirror respected forecasters. This can also be connected to the "Herding" expression, where forecasters continuously overestimate the accuracy of other forecasters, which leads to clustering of forecasts.

Theory

Analyst disagreement as uncertainty measure.

Following Scherbina (2003), all analysts and investors receive a public signal about next period's expected value of macro announcement that is normally distributed. Each analyst also receives a private signal, which is independent of the public signal (priors). An analyst combines the private and public signals to come up with a forecast that would have the minimum variance. If uncertainty in the prior information occurs, it will lead to higher volatility in the expectations of the macroeconomic variables and be a lesser good predictor of future values. When the firm is experiencing this uncertainty in their priors, it will lead them to depend more on their private signals. This again will lead to more idiosyncratic risk and potential outliers might not be captured since the expectations are more spurious.

Given Bayes theorem:

$$P(H|E) = \frac{P(E|H) \times P(H)}{P(E)}$$

Where a posterior is a result of a prior and the compatibility of observed evidence.

Hence, the analysts' expectation of an asset's price can be written as:

$$E(P) = \gamma V + (1 - \gamma)s$$

Where γ is the analyst confidence in own prediction, V is the private prediction, and s is the value of the unanticipated news. The confidence term γ can again be written as

$$\gamma = \frac{1/\sigma_v^2}{1/\sigma_v^2 + 1/\sigma_s^2}$$

Here, σ_v^2 is the variance of the forecast and σ_s^2 is the variance of the news. The variance of the forecast is the focus of this paper. We see that if this term increase, the confidence term decreases and the value of the second term in the first equation increase, which means that analysts expectation takes greater concern of the news than if confident in own prediction. If forecast confidence is high, the news matter less than if forecast confidence were lower. The implication for this paper is that if analysts' uncertainty is high, the unanticipated news should have more impact than if uncertainty is low.

Implementation of macro news

The classical model of a stock price is that the price is only dependent on the sum of its discounted expected future dividends, given the information set available.

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

Where P_t is the price of the stock at time t, $d_{t+\tau}$ is the dividend at time t+τ, r is the discount factor for the cash flows at time t+τ, and Q_t is the information set at time t

The new information is the difference between Ω_t and Ω_{t-1}. On any given time, the expected part of the news and all previous announcements of all other economic variables are already part of Q_t. Given market efficiency and rational investors and expectations, stock prices should only respond to new information, and respond immediately. Stock prices are known to follow a random walk, and announcements shocks are uncorrelated over time. This makes it possible to combine daily prices with macroeconomic events to capture only the effects of this macro news.

Macroeconomic news will affect stock prices if the new information set changes the expectation of either the discount rate or the future cash flow, or both. Cash-flows responds to both real and nominal forces. Changes in for instance inflation will influence nominal cash flows and nominal interests.

Bonds

Stocks are essentially priced analogously to bonds. Since bonds are prices according to the present value of expected future cash flows, the interest rate that one uses to discount is largely affected by macroeconomic factors. A researcher that was one of the first to explain the macroeconomic factors influencing the interest rate was John B. Taylor (1993). He presented the relation between nominal FED rate (r_N), real FED rate (r_R), inflation (π), target inflation(π^*), target output (y^*) and real output (y) in the following formula:

$$r_N = r_R + \pi + \tfrac{1}{2}(\pi - \pi^*) + \tfrac{1}{2}(y - y^*).$$

Piazzesi, Diebold and Rudebusch (2005) is showing the effect that monetary policy has on the short yield curve slope, and Piazzesi & Ang (2003) discovers that output shocks have a substantial impact on longer yield curves. Not surprisingly, they also find evidence that inflation affects all yield curves, since inflation is seen upon as the bonds “nemesis” and reducing the future expected purchasing power.

Methodology

This methodology will follow in the same direction as Li and Hu (1998), but we will condition the responses on analyst uncertainty instead of economic states.

Initial model for effects on stock indices to macro surprises

To estimate the effect of new macroeconomic information on assets, it seems plausible to use the daily changes of the log of stock indices and government bond prices. We will use data from different countries to see if our conclusions are valid for several countries. First, we test for unbiasedness and efficiency to see if analysts' forecasts are rational expectations for future announcements. If market efficiency is valid, only new information should be important, meaning that the degree of shock itself is of less importance than the degree of the surprise against expectations.

To begin, we use a model for the effect of a macroeconomic surprise on an asset index

$$A_t S = \alpha + X_t^u b + v_t$$

Here, $P_t S$ is the change of the log of the asset price index from day t-1 to day t. X_t^u describes the vector of surprises. A surprise X is defined as

$$X = (x_{act} - E(x))/Stdev(forecast)$$

Where x_{act} is the macro announcement and E(x) is the expected announcement. We define expected announcement as the average/median of analysts' opinions.

Model for effects conditional upon analysts' uncertainty

The model of a conditional response to macroeconomic news given analysts' uncertainty will be specified as follows:

$$A_t S = \alpha + \sum_i D_i X_t^u b_i + v_t$$

To estimate responses that are conditional upon analysts' opinion, we classify the uncertainty in levels using both the standard deviation of the total forecast and a

HighLow measure. The HighLow measure is the difference between the most optimistic forecast and the most pessimistic forecast. The HighLow measure is also a measure of analysts' dispersion like the standard deviation. However, it will be more sensitive to outliers and extremes than the standard deviation.

We will test different kind of macroeconomic news, categorized as inflation, labor, industrial production, trade balance and GDP.

We will also need to select whether we only will use dates with surprises or just use dummy variables on the days that does not contain any surprises.

Comparing the results and significance of different levels of uncertainty will tell us whether analysts' uncertainty matter on stocks response on macroeconomic announcements.

Test for forecast efficiency

Investors watch for announcements, since they might not be incorporated in the expectations from the market and hence, financial asset prices. Isolated, the surprises in a price should solely reflect the news, since the difference between the actual release and the market forecast is formulated: $y_{t+1} = y_t + \varepsilon_t$

Applying the Mincer-Zarnowitz test for forecast efficiency is to test that $\alpha = \beta = 0$ in the following regression $s_t = \alpha + \beta y_t + \varepsilon_t, where\ s_t = y_t - y_{t+1}$ is the forecast error or the macroeconomic surprise.

Data

Description of data

We currently have data on macro announcements and analysts' forecasts, provided by our supervisor, Dagfinn Rime. The dataset includes information on macro news and analysts' forecasts in different categories: GDP, Inflation, Industrial Production, Labor and Trade Balance, with varying degree of observations and participation. This are observed after some preliminary inspections. The data is from Norway, Sweden, US, Great Britain, Germany and Switzerland.

This paper will focus on Norway and US.

The data we need, but that we have yet not acquired, is information on stock returns on market indexes in the respective countries in addition to returns on government bonds in Norway and US. The stock indexes we have in mind are primarily main indexes such as S&P 500 and OSEBX. We will gather this data from DataStream or Bloomberg.

As requested, this is some visual representations of data. Here we have selected GDP in the US.

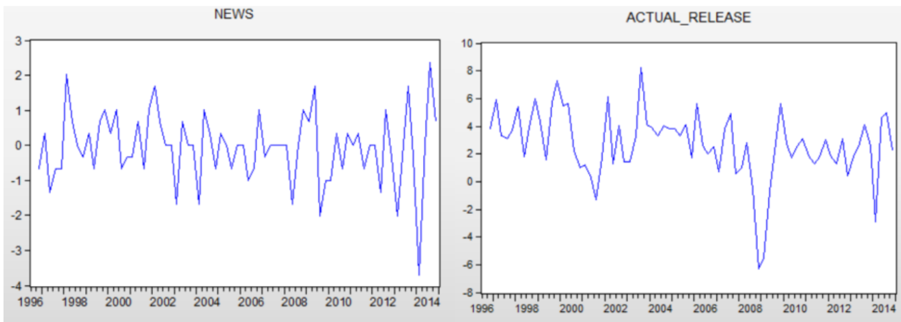

Figure 18: Size of surprise (standardized) and size of the actual announcement.

We see that the size of the surprise does not appear to have obvious correlation with size of the announcement, in accordance with the market efficiency theory.

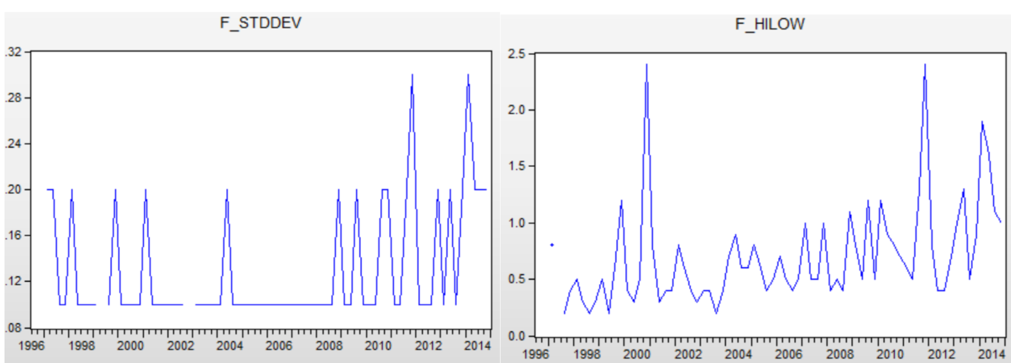

Figure 19: Examples of the 2 uncertainty measures.

Here we see the different measures of analysts' uncertainty, namely the standard deviation of the forecasts and the HighLow measure. It seems that the HighLow measure are have more dispersion, as expected since it is more sensitive to extreme opinions and biases.

Biases

Specification Bias:

An unwanted feature with the data is that it might have specification error. This means that the independent variable is to some degree correlated with the error term, which in our case is our proxy of macroeconomic news. This bias may be caused by a number of causes; i) The functional form may be incorrect, ii) omitted-variable bias, iii) irrelevant variable inclusion, iv) simultaneity-equation bias.

To uncover if this bias is present, we will run the Ramsey RESET test and test whether the forecasts are efficient with Mincer-Zarnowitz test.

If we find evidence of specification bias, we will need to take action according to what kind of cause if found triggering the tests.

Small Sample Bias in Analyst Forecast:

In the analyst forecast data there is just a handful of analysts that report their forecast. This might introduce a “small sample bias”, since a small sample is more likely to deviate from the population or real outcome than a big sample.

The introduction of this bias makes it more likely to get large outliers and the standard errors of the forecasts may not be good proxies of the population, since the standard errors are highly dependent on the sample size. According to the central limit theorem, if one has a big enough size on the sample, the distribution of the data will be normal distributed and hence, one can make better assumptions of the population when examining the sample.

This is a bias we need to be aware of when receiving the results, since we do not have more data available and hence we are not able to adjust for it.

Rational Bias

The rational bias has been explained in detail earlier in this paper, and is clearly going to be present in our dataset. We expect for instance the contrast effect to be most prominent in the HighLow measure of analysts' dispersion. Nevertheless, due to different reasons for this bias, and diverse incentives from separate firms, this cannot be adjusted for.

Thesis progression

Looking forward, the first thing that needs our attention is to extract the necessary data we need in order to compile our regression model. We need to gather stock & bond indexes from the USA and Norway. We will download daily data from either Datastream or Bloomberg on the timespan we have data on macroeconomic news. This will be the basis when we build our regression and start testing when the model is adequate. When we have the test results, we will be able to have a view of how analyst uncertainty will or will not affect the impact of macroeconomic news and if there is a significant difference on the impact on stocks and bonds.

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