Table of Content:

Introduction	1
Primary Research Question	2
Additional Questions to Ask	2
Literature Review	3
"Measuring Economic Policy Uncertainty" by Baker, Bloom and Davis (2016) "Distilling the Macroeconomic Flow" by Beber, Brandt and Luisi (2015) "Measuring Uncertainty" by Jurado, Ludvigson and Ng (2015) "Fluctuations in Uncertainty" by Bloom (2014) "Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro- Surprises" by Scotti (2016) "The Impact of Uncertainty Shocks" by Bloom (2009)	3 3 4 4 4 5
Theory	5
Measuring Uncertainty Macro News and the Impact on Asset Prices	5 6
Methodology	7
Modelling Macro Surprises and the Effect on Stock Indices Responses to News Structural Break Data	7 8 8 8
Bias	10
Specification Bias Small Sample Bias	10 10
Plan for progression	11
References	12

Introduction

The motivation for the paper comes from the increasing uncertainty on the world's political scene. With the changing political landscape and increasing tension between governments, it is interesting to see how this uncertainty transfers to the capital markets. Do periods of increased macro uncertainty lead to more unstable capital markets, and how do investors interpret macroeconomic uncertainty to the capital markets? Those are two questions we would like to get an answer to.

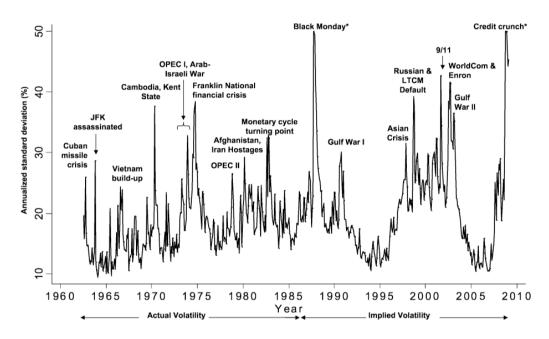


Figure 1: U.S. monthly stock market volatility, VXO index (Bloom 2009)

Volatility in the capital markets is important for all investors, as it is the foundation for all trading. Stocks that are frequently exposed to volatility, are generally regarded as high-risk stocks. Thus, the investor expects a higher return. The prices of options depend on the volatility of the underlying asset. Volatility plays a role in every asset available, and it is important to understand how uncertainty and volatility interacts. Bloom (2014) talks about how bad events trigger uncertainty. That the initial bad news triggers the first movement, and the following uncertainty acts as a second movement to the market. As Bloom points out, it is generally bad news that is being accompanied by uncertainty. The effect of good news is usually more gradual, while bad news acts as shocks to the markets. Being able to understand volatility is important for all investors, and to understand volatility, we must be able to understand how uncertainty is reflected in volatility. In the paper, we use Frank Knights (1921) definition of uncertainty; "people's inability to forecast the likelihood of events happening". As Bloom (2014) points out, the inability to assign probability distributions to unforeseen events.

Primary Research Question

The main focus of this thesis will be to look at how macro uncertainty affect volatility in stock markets. More specifically, we will look at how macro events like terrorist attacks, political changes and annual reports affects the volatility through uncertainty in capital markets. The primary research question that we seek to answer is:

"To what extent does macro uncertainty affect the volatility in capital markets?"

We will mostly be focusing on the capital markets in the USA. The US market is the most capital-intensive market in the world, and hence makes a good proxy for worldwide uncertainty. When discussing the extent of volatility, we will look at how much a specific index departs from its normal in the period after the macro event, as well as the duration it takes for the index to get back to its normal state. Macro events can either be foreseen events, like annual reports or monetary policy meetings, or unforeseen events like terrorist attacks, coup attempts etc.

Additional Questions to Ask

"How volatile are capital markets in the period leading up to a foreseen event?"

Reports of employment rates and inflation are two examples of foreseen macro events that describe the economic stability of a market. It is not uncommon for economists to disagree in their prediction of such reports, and it could be interesting to see if volatility increases in the period leading up to the publication of such reports. Furthermore, we could investigate if a higher standard deviation in analyst forecasts lead to higher volatility in capital markets.

"What are implications of volatile markets for investors?"

Ramey and Ramey (1995) found that countries with higher volatility tend to have lower growth. Later, this negative volatility effect has been confirmed and extended through a number of empirical researchers. We will compare trading volume in periods of high volatility and periods of low volatility, to see if investors take market volatility into consideration, and are risk-averse as we would expect them to be.

Literature Review

The literature review is a selection of journal articles that we find especially relevant for our master thesis. The literature on uncertainty's impact on volatility has grown in the later years and thus the master thesis will include more journal articles than we present here. However, these articles give a good overview of the current state of the research. We choose not to include journal articles older than 10 years, as we want to present the latest research conducted on the topic.

"Measuring Economic Policy Uncertainty" by Baker, Bloom and Davis (2016)

Scott R. Baker, Nicholas Bloom and Steven J. Davis (2016) developed a new index that gathered information from news archives. Searching for keywords related to economic policy uncertainty; uncertainty of *who* will make new policies, uncertainty about *what* new policies are being incorporated, and lastly *when* the policies are being enforced. The index tried to incorporate both direct economic uncertainty and indirect economic uncertainty such as wars.

They found that their index worked as a proxy for change in economic policy uncertainty. The index had large spikes during times of political uncertainty, such as 9/11, the Gulf war and the 2008 financial crisis. From the data, they find that economic policy uncertainty results in higher stock market volatility.

"Distilling the Macroeconomic Flow" by Beber, Brandt and Luisi (2015)

Alessandro Beber, Micheal W. Brandt and Maurizio Luisi (2015) created a technique to extract daily macroeconomic news from data released at different times and frequencies. Their findings indicate that the technique stipulates a more authentic forecast about shifts in future economic factors than previous methods. The method is able to explain a large fraction of the volatility that occurs in financial markets, in other words being able to explain much of the interactions between financial markets and the macroeconomics factors.

"Measuring Uncertainty" by Jurado, Ludvigson and Ng (2015)

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

"Fluctuations in Uncertainty" by Bloom (2014)

In his review article, Bloom (2014) seeks to answer the four following questions:

- What are the stylized facts about uncertainty over time?
- Why does uncertainty vary?
- Do fluctuations in uncertainty matter?
- Did higher uncertainty worsen the Great Recession of 2007-2009?

On the first question, Bloom finds that uncertainty tends to vary over time. Furthermore, he argues that uncertainty also varies across countries, that developing countries have more uncertainty than developed countries. On the second question, he finds that exogenous shocks that typically cause recessions directly increase uncertainty. Also, the uncertainty continues to rise during recessions, as the economic slowdown caused by recessions increase uncertainty on both macro- and micro level. Bloom also finds that uncertainty does matter, as a high measured uncertainty is damaging for short-term growth, and it reduces firms and consumers' willingness to spend, hire and invest. However, he argues that uncertainty might stimulate research and development. On the fourth and final question, Bloom argues that the uncertainty shock that followed the Great Recession accounted for more than 30 % of the drop in GDP during the recession.

"Surprise and Uncertainty Indexes: Real-Time Aggregation of Real-Activity Macro-Surprises" by Scotti (2016)

Scotti (2016) presents a new methodology for measuring macroeconomic surprises. In her paper, she constructs two real time, real activity indexes. The first one is called the surprise index, which measures deviation from consensus expectations after economic data surprises. The second index is called the uncertainty index, and measures uncertainty related to the actual state of the economy. These indexes measure the degree of pessimism or optimism about the economy when news, or shocks, are released. To investigate if there is a world-wide consensus in these indexes, she constructs both indexes for five countries or economic zones, the US, the Euro area, the UK, Canada, Japan, as well as an aggregate of the five. Her data stretches from 2003-2016. In her research, Scotti finds that the surprise and uncertainty indexes tend to be negatively correlated in all five countries and economic zones, which indicates that bad news occurs in times with increased volatility.

"The Impact of Uncertainty Shocks" by Bloom (2009)

Shocks like terrorist attacks, wars and sudden changes in the oil price are often associated with uncertainty. In this paper, Bloom introduces a framework to analyse the impact of shocks that cause uncertainty. Through simulation, he finds that uncertainty shocks lead to a reduction in investment and hiring among firms. Further, due to the reduced economic activity, an overshoot in employment, productivity and output follows. The result is recessions followed by recoveries. When comparing the results from the simulated models with vector autoregression on real data, Bloom found that the results are similar, i.e. uncertainty shocks do have an impact on economic stability, and might cause recessions.

Theory

Measuring Uncertainty

Uncertainty is unobservable, and it is difficult to explain what uncertainty really is. Therefore, empirical studies usually rely on proxies of uncertainty, which are observable. Baker, Bloom & Davis (2016) used the appearance of uncertainty-related keywords in newspapers, while Dick, Schmeling & Schrimpf (2013) built their proxy upon measuring the dispersion of forecasters prediction. By the use of such proxies, we can somehow measure real-time uncertainty. The proxies have been valuable insights into the perception of uncertainty, and the impact of uncertainty on economic variables and volatility. However, most proxies have lately been criticised. Scotti (2016) argues that proxies are market-based forecast errors, and that they do not capture the perceived uncertainty about the state of the economy. Agents base their decisions on perceived uncertainty, not on an objective and unobservable uncertainty. Following the theory from Hu and Li (1998):

Knight (1921) argues that uncertainty frequently is confused with risk, and that the two concepts should be treated individually. Risk, according to Knight, is a situation where we know the potential outcomes in advance. We might also know the odds of these outcomes in advance. Rolling a pair of dice is a typical example of a risk. We know the potential outcomes, and we can easily calculate the odds of every outcome. Hence, the risk is easy to cope with, as we can match our investment with the calculated odds. However, the nature of uncertainty is different from risk. In uncertainty, we do not know the potential outcomes in advance, and there exist no sensible probability distribution of possible outcomes. Uncertainty occurs in complex systems with many individual actors, like for example an economic system.

In an economic environment, uncertainty becomes applicable when considering a problem of choosing among irreversible investments when valuable information becomes available over time. This problem has been studied in a number of contexts, and some researchers have pointed out that there is an option value to avoiding irreversible investments. For example, by not allowing oil drilling in Lofoten, which is an irreversible step, or investment, the Norwegian government retains the option of choosing between drilling and other alternatives in the future. If the Norwegian government allowed for drilling, it eliminates the potentially valuable real option of waiting. Later information might prove that other alternatives were more valuable, and the uncertainty of not knowing what the future brings drives the value of the real option. If the future is certain, and no uncertainty exists, the value of a real option is zero.

Macro News and the Impact on Asset Prices

Volatility is in is essence unobservable and are established ex-post. Meaning that volatility must be measured after the shocks are observable based on historical data. Shocks are independently and identically distributed random variables; therefore, the news needs be implemented after the event is observable. According to the market efficacy hypothesis, semi-strong efficiency, the current stock price incorporates historical data and available public news. When a new information is being presented, the stock price has to adjust to the new information.

$$P_t = E_t \left(\sum_{t=0}^{\infty} \frac{D_{t+n}}{1+r_{t+n}} | \Omega_t \right)$$

Where D is the dividend, r is the discount rate and Ω_t is the information available in the market. As we can see, changes in the price of a stock is depended on signals to the market. When new information is available, the expected future return will change and the price is adjusted in the market. Often referred to the "Peso problem" from Milton Friedman, that states that there is a possibility that asset prices may move due to some unexpected event in the future.

Methodology

In this chapter, we seek to introduce the empirical approach we intend to use in the thesis. As of now, we have several methodologies at hand going forward. The first idea is the same as Li and Hu (1998) used in their paper, where proxies like macroeconomic surprises are used to estimate uncertainty.

Arnold and Vrugt (2008) state that the most common approach when measuring the effect of uncertainty on volatility in stock markets is to use absolute residuals by AR models, and compare them to stock returns and macroeconomic growth rates. Both approaches have been criticised and have their limits. However, they are recognized in the previous literature.

Modelling Macro Surprises and the Effect on Stock Indices

It seems reasonable to estimate the effect of macroeconomic surprises by using daily changes of log stock indices. We will mostly focus on the S&P 500, as this index is a good representation of the state of the US economy. First of all, we will test our data for unbiasedness and efficiency. We will do this to conclude whether or not analysts' forecasts are rational expectations for future announcements. To model the effect of macroeconomic surprises on the S&P 500, we will use the following model where macroeconomic surprises are used as a proxy for uncertainty in the macroeconomy:

$$\Delta \log(P_t)_{S\&P500} = a + X_t^I b + v_t$$

Where $\Delta \log(P_t)_{S\&P500}$ is the daily change of log S&P 500, and X_t^I is a vector of macroeconomic surprises. A surprise is defined as the difference between the actual announcement and the expectation of the announcement, divided by the standard deviation of the analyst forecasts:

$$X = \frac{x_{actual} - E(x)}{\sigma_{forecast}}$$

In our regression analysis, we will also use additional proxies for uncertainty, which will be described further.

Responses to News

We follow the methodology of Hu and Li (1998), where we only focus on days where there exist announcements to the market.

$$\Delta \log(P_t)_{S\&P500} = \alpha + \sum_i^\infty D_i X_t^u \beta_i + \varepsilon_t$$

Where D_i is the dummy variable, that is 1 if there are any announcements that date, and 0 otherwise.

Structural Break

A structural break is an unexpected shift in a time series, which can lead to huge forecasting errors. Structural breaks typically happen due to unforeseen external factors, like for example extreme weather or natural disasters. We know that the S&P 500 index is a victim of structural breaks from time to time, and we will have to identify these to make sure they do not make noise in our data. If a structural break is identified without being related to a macroeconomic surprise, we will have to take actions and consider removing the observation from our dataset. If the break can be related to a surprise or an event, we do not necessarily have to remove it, as we might have an explanation for the sudden break.

Data

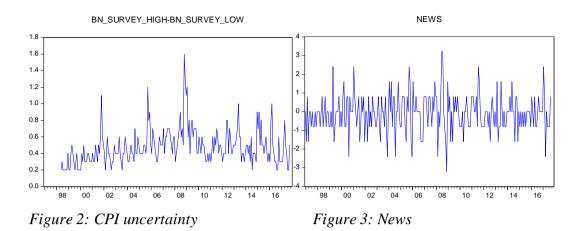
We have several proxies for uncertainty that we will apply in our analysis. Since uncertainty is an obscure topic, previous research has been conflicted in what the best proxy to use when capturing uncertainty. We have three main sources of proxies that we will use as measures of uncertainty. The Volatility index (VIX), the Economic Policy Uncertainty index (EPU) and the Survey of Professional Forecasters (SPF). We will use the S&P500 as the index for testing, the data is available on Bloomberg. The data from the VIX index is available on the Chicago Board of Exchange website, and the EPU index is also available online at policyuncertainty.com.

The VIX is an index that captures the expected 30-day volatility on the S&P500. Using index-options as a proxy for risk in the market. As pointed out previously, option prices depend on the volatility of the underlying assets. Applying this principle to the S&P500, the index calculates the possible changes in the option price today and to the expiry date in 30 days. Thus, retrieving an estimate of the current uncertainty in the market. The benefit with the VIX is that it is forward-looking, and we do not need to calculate the volatility ex-post.

The EPU index was developed by Baker, Bloom & Davis (2016). Utilizing mainly newspaper articles to extract an overview of the current uncertainty in a nation, but also differences in macroeconomic forecasts by professional investors and tax provisions set to expire in the future. Research has shown that the index manages to capture uncertainty, and move counter-cycle to the leading indexes. Again, a benefit of the EPU index, is that it gives an overview of the current situation based on current data without looking ex-post.

Lastly, we plan to utilize the SPF. Professor Dagfinn Rime was so kind to offer a dataset which includes macroeconomic data (CPI, GDP, inflation etc.), announcement dates and the SPF for several countries including the United States. The data on the different macroeconomic parameters have asymmetrical timeframes. Some data goes back to 1996, while other macroeconomic factors date back to 2006. The SPF is a survey among professional investors on what they expect of the different macroeconomic announcements ex-ante. Utilizing the difference between answers among the professionals as a proxy for uncertainty. Higher spread indicates higher uncertainty. Figure 2 displays the spread (high minus low) in professional forecasts of monthly changes in CPI, while Figure 3 displays news, or surprises, calculated by the previous outlined formula:

$$X = \frac{x_{actual} - E(x)}{\sigma_{forecast}}$$



The S&P500 is an American index consisting of the 500 large companies in the United States. Since the index only consists of large companies weighted by size, it is considered a good indicator of the American market.

Bias

Statistical biases are tendencies of erroneous estimations of a parameter.

Specification Bias

The omitted variable bias might be a problem in our data. If X_2 and X_3 are correlated and X_3 are omitted, then the estimator of B_2 will be biased and not consistent. However, if X_2 and X_3 are uncorrelated, then b_2 will be a correct estimate of B_2 even if X_3 is omitted. If we have omitted variable bias in our data, we cannot trust the estimation of our regression model. There are also other types of specification biases. For example, specification bias will be present if we include irrelevant variables as well. We will have to test our data for specification bias, and if we find evidence for bias, we will need to consider actions depending on what is the cause of the bias.

Small Sample Bias

The small sample bias means that we are more likely to find large outliers in small samples, which means that the standard error of a sample does not represent the population. Standard errors are highly dependent on sample size, and they might therefore be misleading in small samples. The central limit theorem states that if a sample is big enough, then the distribution of the sample will be normally distributed. When the sample data is normally distributed, we can make more accurate assumptions about the population when studying the sample. We only have a limited number of forecasters' expectations in our dataset. As a result, the sample data is more likely to deviate from the population. We will have to be aware of this bias going forward, especially when working with surprises as proxy for uncertainty.

Plan for progression

Month	Activity
January	Complete and hand in preliminary
February	Build theoretical framework Pinpoint research question and methodology Provisioning and organization of data
March	Apply empirical methodology and present findings
April	Interpret, discuss and criticize findings
May	Quantitative- and qualitative analysis
June	Continue quantitative- and qualitative analysis Quality assurance and concluding adjustments
June 30th	Hand in

References

Arnorld, I.J.M. and Vrugt, E.B. (2008). Fundamental Uncertainty and Stock Market Volatility. *Applied Financial Economics*, 18(17), 1425-1440.

Baker, S.R., Bloom, N. and Davis, S.J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Beber, A., Brandt, M.W. and Luisi, M. (2015). Distilling the Macroeconomic Flow. *Journal of Financial Economics*, *117*(3), 489-507.

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment. *The Quarterly Journal of Economics*, 98(1), 85-106.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica*, 77(3), 623-685.

Bloom, N. (2014). Fluctuations in Uncertainty. *The Journal of Economic Perspectives*, 28(2), 153-175

Dick, C. D., Shemeling, M., & Schrimpf, A. (2013). Macro-Expectations, Aggregate Uncertainty, and Expected Term Premia. *European Economic review*, *58*, 58-80.

Giordani, P. and Söderlind, P. (2003). Inflation Forecast Uncertainty. *European Economic Review*, 47(6), 1037-1059.

Jurado, K., Ludvigson, S.C. and Ng, S. (2015). Measuring Uncertainty. *American Economic Review*, 105(3), 1177-1216.

Knight, F. (1921). Cost of Production and Price Over Long and Short Periods. *Journal of Political Economy*, 29(4), 304-335.

Hu, Z. and Li, L. (1998). *Responses of the Stock Market to Macroeconomic Announcements Across Economic States*. International Monetary Fund. Ramey, G and Ramey V. (1995). Cross-country evidence on the link between volatility and growth. *The American Economic Review* 85(5), 1138-1151.

Schwert, G.W. (1989). Why Does Stock Market Volatility Change Over Time?. *The Journal of Finance*, *44*(5), 1115-1153.

Scotti, C. (2016). Surprise and uncertainty indexes: Real Time Aggregation of Real-Activity Macro-Surprises. *Journal of Monetary Economics*, 82, 1-19.