NATIONAL TECHNICAL UNIVERSITY OF ATHENS
SCHOOL OF APPLIED MATHEMATICAL AND PHYSICAL SCIENCE

MSc Thesis

Mathematical Modelling in Modern Technologies and Financial Engineering

# The Impact of Scheduled Macroeconomic Announcements on Implied Volatility Index

by

Georgios Kiapekos

Student Number: 09316018

Supervisor: Athanasios Triantafyllou

Athens, March 2021

# Acknowledgements

Firstly, I would like to express my sincere gratitude to my supervisor, Mr Athanasios Triantafyllou, for his support and guidance throughout this research project and his thoughtful comments and recommendations on this thesis. My completion of this project could not have been accomplished without him.

I would like to thank my fellow student, Konstantinos, with whom we shared a lot of beautiful moments during all these years of this postgraduate programme. I am also thankful to my friends who stood by my side when I needed them and especially Ioanna for her efforts to keep me in the right track.

Last but not least, I could not forget to thank my family, my parents Marina and Yannis and my brother Alexandros, for their unconditional love and support in order to fulfil my goal.

# Abstract

Over the past few years, the relationship between options implied volatility indices and macroeconomic indicators, has stimulated the interest of both the academic community and financial market participants, such as investors, analysts and managers. The VIX index has been created by Chicago Board Options Exchange (CBOE) in 1993, is derived from options written on S&P 500 index, reflects the market's expectations for short-term volatility over the next 30 days in the U.S. stock market. It widely known as the 'fear gauge' index, as it can be used by investors to measure market risk or to hedge against investment risk in order to protect their portfolio.

The purpose of this study is to examine the impact of scheduled macroeconomic announcements on the implied volatility index VIX. This thesis aims to focus on major macroeconomic indicators like consumer price index (CPI), producer price index (PPI), gross domestic product growth rate (GDP), employment report (EMP) and Federal Open Market Committee meetings (FOMC), over the sample period of 3$^{rd}$ January 1990 to 31$^{st}$ December 2020. Therefore, the main objective of this study is to investigate whether the macroeconomic news releases affect the VIX index significantly and analyse how the VIX behaves around these scheduled macroeconomic announcements.

The empirical findings of this research originate from the constructed econometric models of the study through OLS regression and GARCH family models. The whole of the related literature is based on the hypothesis resulting from past literature, according to which the VIX increases before the scheduled announcements, drops during the release day and continues to decrease after the announcements. The empirical results reveal that VIX is significantly attributed toward the macroeconomic indicators. VIX is found to be more responsive to CPI, GDP and Employment reports, while VIX seems to be in full compliance with the hypothesis only for GDP and Employment situation reports. Besides, the study shows that investors regard more than one scheduled announcement in the valuation of their financial assets, which means that investors consider the joint effect of CPI, PPI, GDP, EMP, and FOMC in their financial planning.

# Table of Contents

# 1. Introduction

The concept of volatility in determining the price and the return on assets is directly related to finance with the notion of uncertainty and risk. Being aware of the relationship between risk and return as well as the importance of this relationship for proper pricing and consequently valuation of financial assets, it is easily understood why there is a particular interest in the academic community and market participants in the study and analysis of volatility, as well as the effort to predict and model it. In addition to the volume of academic studies related to volatility, market interest on this subject is evident through the tangible example of the construction, dissemination and increasingly widespread use of volatility indicators. In finance, volatility refers to the standard deviation of the continuously compounded returns of a financial asset at a specific time horizon. It is often used to quantify the risk of the instrument during this time period and is usually expressed in annual terms. Volatility is a measure of risk of a financial asset and this is the main reason that its development is monitored daily by participants in the money and capital markets.

There are two fundamentally different approaches for the determination and calculation of volatility. On the one hand, volatility can be determined by calculating the standard deviation of an asset's prices over a given period of time. This method attributes the historical volatility or otherwise known as ex-post volatility. On the other hand, volatility can be measured by the prices of options contracts written upon the asset and this calculation process gives the implied volatility. This method yields the current volatility, or otherwise the ex-ante or forward-looking volatility, which is implied by the market. Implied volatility is a forward-looking measure hence it differs from historical volatility because the latter is calculated from the historical values of the asset. In more detail, implied volatility of an option contract is the volatility implied based on its market price which is produced by an option pricing model. In other words, when a particular option pricing model (Black and Scholes, 1973) is used, then its volatility yields the current market price for this option contract.

Predicting and detecting implied volatility of elements such as stocks, indices and financial derivatives have been from time to time the subject of numerous studies and researches by academics. What makes implied volatility a subject of extensive research is that, by its nature, it cannot be observed and for this reason its estimation becomes a difficult and complicated process. Consequently, modelling volatility is not an easy task and proof of this is the fact that in pricing theory of an option (Black and Scholes, 1973), the only unknown variable that cannot be observed directly from market data is volatility. Variables such as the current price of the underlying asset, the strike price of the option, the maturity, the risk-free rate, are given by the market and thus the determination of implied volatility remains and it is unnoticeable. The impact of information releases related to stock prices is well documented in the existing literature rather than the impact on option prices. One of the major challenges for pricing options is to understand the information contents that determine the implied volatility of asset prices. Hence, the market participants are aware of these factors, in addition to future volatility, at the time of pricing an option or positioning their investment portfolios. The fact that this volatility cannot be observed makes it unknown to market participants but also a tool that captures the market sentiment, by reflecting the expectations, concerns and fears of investors.

In the present thesis, the object of study and research is the implied volatility and more specifically the indices of implied volatility. These indices measure the market's expectancy and anticipation of future volatility based on the prices of options. The most widely known and used volatility index is the VIX of Chicago Board Option Exchange (CBOE) and is the index with which the specific study is engaged. VIX is calculated by the prices of options which are written on S&P 500 stock index (SPX options) and measures the forward-looking volatility of the underlying index. Hence, the VIX constitutes the investor's forecast for short-term (30-days) risk of the stock market. A great quantity of research and a lot of studies have been done to examine the connection between macroeconomic announcements and volatility of equity markets. Nevertheless, a small number of them are related to the effect of the macroeconomic news releases on options implied volatility. The existing literature deals with the reaction of equity prices, exchange rate, interest rate, futures, etc., although less interest has been shown on the option implied volatility index, therefore this study is an attempt in this direction.

The main objective of this thesis, along with the assistance of some major macroeconomic indicators, is to examine and analyse the behaviour of the VIX index around the scheduled announcements of these macroeconomic variables. This research is based on various studies which come from the relevant literature so far. Initially, the analysis uses a data sample of daily closing prices of an implied volatility index over a 30-year time period, from 1990 to 2020, as well as a set of scheduled announcements for five major macroeconomic indicators.

Specifically, it uses the CBOE VIX index that concerns the U.S. financial market and the news releases of macroeconomic variables, which are CPI, PPI, GDP, Employment Report and FOMC meetings. Subsequently, a methodology is adopted and applied which is based on the relevant literature and includes the development and construction of models in order to make the empirical analysis of the data. The estimation output is carried out through the dummy variable technique, where the scheduled announcements are used as announcement dummies taking the value one on actual announcement days otherwise the value is zero. Then, the empirical results produced through OLS regression and GARCH family models in order to draw the necessary conclusions, which should be able to inform whether the scheduled announcements of macro indicators impact the VIX individually or aggregately, how significant or not are these findings in terms of the effect they have on VIX, but also what is the economic interpretation for each significant result observed and affects the index.

### 1.1 Review of related literature

The response of the stock markets and implied volatility index to these announcements draws the attention of the market participants. Investors, policy makers, financial press and academics have shown a particular interest in the impact of macroeconomic news on stock markets. It has been observed that the reports of analysts and financial press, such as monetary policy meetings and changes in macroeconomic indicators, affect the markets. The impact of scheduled announcements on stocks valuation and analysis is a matter of great importance for the market, while it has been proven that the release of macroeconomic news works as a tool by investors to manage and strategize their portfolios. Specifically, Nikkinen and Sahlström (2001, 2004), Chen and Clements (2007), Fuss et al. (2011) report that the relation between VIX index and macroannouncements verified that market participants consider the news releases into their financial organization.

The vast majority of studies have shown that financial markets are governed by greater uncertainty prior to scheduled macroeconomic news, because of the element of surprise in the announcements. The studies moving in this direction are those of Nikkinen and Sahlström (2001, 2004) and Chen and Clements (2007), who are dealing with the impact of macroannouncements on stock returns and implied volatility index and their results indicate that these markets react positively and significantly to the scheduled news. Nikkinen and Sahlström (2001) conducted a study consisting of different macroeconomic announcements on VIX index and their analysis takes into account the macroeconomic indicators of employment rate, PPI) and CPI reports. More specifically, they found that every single announcement has a decreasing effect on uncertainty, while the most significant is the employment. The investigation results in an important finding that the rise in implied volatility on the days prior to an announcement is a sudden increase and not a gradual process of growth. The key in their study is the usage of different macroeconomic indicators apart from FOMC which confirms that implied volatility declines after the release of macroeconomic announcements. In addition, Nikkinen and Sahlström (2004) and Chen and Clements (2007) investigate the FOMC meetings reports and US macroeconomic news on implied volatility index and they conclude that VIX rises prior to the scheduled announcement and it maintains at a normal level on the announcement day.

Following the studies that examine the effects of monetary policy on stock returns and volatility, Bomfim (2003) analyses the stock prices in the US stock market throughout the monetary policy announcements and concludes that scheduled and unscheduled news have not the same impact on the market volatility. Moreover, Gospodinov and Jamali (2012) present a monthly analysis for the impact of FOMC meetings reports on VIX and VXO implied volatility indices and they found that there is a positive significant reaction by the volatility index on federal fund rates surprises. Moreover, they came to the conclusion that macroeconomic indicators such as industrial growth, non-farm payroll employment and inflation tend to have an effect on VIX index. Vähämaa and Äijö (2011) investigate the behaviour of VIX around US monetary policy announcements and discover that implied volatility usually declines after FOMC meetings. They found that implied volatility is falling after FOMC meetings and their results suggest a powerful effect of the announcements and a reducing VIX after positive monetary policy announcements.

In the framework of the existing literature, Ederington and Lee (1993, 1996), Bomfim (2003) and Kearney and Lombra (2004) have shown that asset prices volatility and implied volatility increases significantly before the announcement and returns to normal level on the day of news release. More specifically, Ederington and Lee (1993) argue that scheduled announcements are the main factor for monitoring many of the patterns of volatility in foreign exchange and interest rates markets. Ederington and Lee (1996) are the first to investigate the impact of macroeconomic news on option implied volatility interest rate option markets, concluding that implied volatility tends to increase before scheduled announcements, while they found that there is a sharp drop in their prices immediately after the announcements as the announcement itself helps to resolve the uncertainty. In addition, they made a separation between scheduled and unscheduled news and discovered that implied volatility was even more uncertain during non-scheduled announcements. Donders and Vorst (1996) studied the behaviour of implied volatility of call options around scheduled earnings announcement by firms. They showed that only on the day of the news release, implied volatility of the underlying stocks rises significantly during the period before the event, reaches its maximum level on the report days and drops sharply afterwards. Kearney and Lombra (2004) find a significant positive connection between the CBOE VIX and unexpected changes in employment, but not inflation. Füss et al. (2011) focus only on macroeconomic indicators like Gross Domestic Product, Producer Price Index and Consumer Price Index announcements and find that VIX decreases on the announcement days.

Finally, it is important to mention the recent studies concerning the emerging financial market of India. Shaikh and Padhi (2013) conducted a study on how the scheduled macroeconomic announcements of Indian macroeconomic indicators like RBI monetary policy statements, CPI, WPI, IIP, Employment rate and Gross domestic product impact the implied volatility index of India IVIX. The study reveals that during non-announcement periods the IVIX increases significantly, however once results are announced, uncertainty is resolved and the India VIX returns to normal levels. It confirms that the India VIX declines significantly following scheduled GDP news, but it rises significantly on the announcement of WPI. In the same study framework, Srinivasan (2017) explored the effect of monetary policy announcements and macroeconomic news on the Indian implied volatility index (IVIX), by using OLS regression model and EGARCH model. They examine the behaviour of IVIX with reference to several macroeconomic indicators such as export, import, fiscal deficit, IIP, CPI, WPI, GDP, MCIR, for a sampling period of March 2009 to August 2016. They anticipated that the IVIX will reduce on the same day with the scheduled announcement and the day after the macroeconomic announcement. Nevertheless, the results have proved that the content of the news of macroeconomic indicators on the day and the day after the release has insignificant effect on IVIX, excluding the MCIR.

## 1.2 Thesis contribution to the literature

As mentioned before, the two most fundamental and significant studies that discover the impact of scheduled macroeconomic announcements on the VIX index but also that influence and inspire almost the entire of existing literature are the studies of Ederington and Lee (1996) and Nikkinen and Sahlström (2004). Just like the related literature, so the present study has been influenced by the work of Ederington and Lee (1996) and Nikkinen and Sahlström (2004), which have been carried out in the distant 1996 and 2004 respectively. Even the work of Chen and Clements (2007), which is related to the above studies, took place in 2007 and focuses mainly on the impact of FOMC meetings on the VIX index.

From there on and specifically in the recent years, the studies that have been conducted are based on Ederington and Lee (1996) and Nikkinen and Sahlström (2004) but mainly considering the emerging financial market of India. More precisely, the most important and main studies are of Shaikh and Padhi (2013) and Srinivasan (2017), which deal with the impact of Indian macroeconomic announcements on the Indian implied volatility index IVIX. From the specific studies, this thesis has drawn many elements from the methodology followed but also from the findings of the empirical data analysis.

Therefore, based on all the above, the idea and development of the present study was born out of the need for further research, because it is considered necessary to carry out a study that examines the last fifteen years, hence the research of this study includes data for a longer time horizon (1990 – 2020). In addition, the U.S. stock market is investigated and analysed, which is currently the world’s biggest equity market (over than 50% of the world’s total market capitalization). In short, the gap that exists in the literature and is covered by this study is that there is no corresponding recent study that examines the behaviour of American VIX index around scheduled U.S. macroeconomic announcements and in such a long sample period.

The present study can be characterized as an extension of Nikkinen and Sahlström (2004) with the main differences being the following extensions. In this work is used, as mentioned before, a longer time horizon, another key macroeconomic variable (GDP) is added, a wider range of days is applied around macroeconomic announcements (two days before the scheduled news release until two days after) and finally GARCH family models are used for the estimation output.

Compared to the work of Nikkinen and Sahlström (2004), since this study is a benchmark for the present thesis, the common findings are that the empirical results support the Nikkinen and Sahlström (2004) hypothesis that VIX index increases before the scheduled news release and then decreases and goes normal on the macroeconomic report days. In addition, all macroeconomic variables in both studies appear negative, so this shows that the index falls on the report day, also the results show that in both studies the investors regard the joint effect of all macro indicators. Finally, they have in common that Employment report is the most significant and has the largest impact on VIX. Although in this study, apart from the Employment, the CPI and GDP show a strong significance and a great impact on the VIX the days around the scheduled announcements.

Nevertheless, this study and the work of Nikkinen and Sahlström (2004) show some significant differences. The pattern, according to theory, where the VIX suddenly rises before the macroeconomic news releases but it falls and goes back to its initial level during the report days, is observed in this study for Employment, GDP, PPI, FOMC, while the CPI results are in contradiction to the past literature. On the other hand, Nikkinen and Sahlström (2004) reveal that FOMC meetings, where the results indicate that VIX on the FOMC reports drops before the announcement and that behaviour is against the above pattern. Besides, another main difference is that Nikkinen and Sahlström (2004) disregard the nature of news releases and assume a symmetric and mechanical impact of all macro announcements, while in this study the asymmetric effect on the index is examined through the EGARCH model.

This research contributes to existing literature in two ways. Firstly, the findings of this study will be useful for the investors, who should regard and take into account all the scheduled announcements of major macroeconomic indicators as a whole in their portfolio selection. This, however, becomes possible under the efficient market hypothesis, which explains that if the market is efficient, then it responds to the macroeconomic news releases. The uncertainty related to the information content of macroannouncements directly impact both the stock and options valuation, hence through its effect on hedging and pricing, the short-term expected volatility can be used by market participants to price future options. Secondly, this study reveals that there is a predictable movement in the VIX index around scheduled macro announcements. Therefore, a possibly better forecast in expectations for stock market volatility, can affect a profitable strategy. Since the VIX is an ex-ante measure of future volatility, profits can be made by trading VIX futures or VIX options.

### 1.3 Structure of the study

The present thesis is structured and organized in the following way. First of all, this study presents its purpose, the research steps, the related literature, as well as its contribution to the literature gap and future research. Then, the theoretical background is introduced, where the meaning of implied volatility is explained in order to understand its role in the financial markets, but also the meaning of implied volatility indices and specifically of VIX is explained in order to understand its usefulness and the method it is constructed. Besides, the macroeconomic indicators are presented, the scheduled announcements of which will be used to develop empirical results through econometric analysis. In addition, the sources from which the data were sampled are mentioned, as well as the research methodology that followed and applied. Finally, the research findings are introduced via empirical data analysis on the impact of macroeconomic news releases from two days before the report day until two days after the scheduled announcement and then, in the final section, the conclusions of this study are drawn.

# 2. Theoretical Framework

## 2.1 Implied Volatility

Implied volatility is the market's forecast for a possible change in the price of a financial asset. It is a measure used by investors to estimate future volatility in the price of a security based on certain forecasting factors. Implied volatility can often be considered as a proxy of market risk and it is usually expressed using percentages and standard deviations over a set time horizon. When applied to the stock market, implied volatility generally increases in bearish (declining) markets, when investors believe stock prices will fall in the long run. On the contrary, implied volatility decreases when the market is bullish (increasing), and investors believe that prices will rise over time. Generally, option traders look to buy options when implied volatility is low as premiums are lower, hoping to see the underlying stock move in a favourable direction along with an increase in volatility which will make premiums increase, while traders look to write options when implied volatility is high as option premiums tend to be higher, in hopes of seeing the underlying stock move in a favourable direction to their position along with a decrease in volatility which would make premiums decrease. Implied volatility does not forecast the direction in which the price movements will proceed. For example, high volatility means a large price fluctuation, but the price could move up or down, or fluctuate between the two directions. Low volatility means that the price is unlikely to make wide and unpredictable changes.

The calculation method of implied volatility is related to the pricing of options. More specifically, the current price of the option is equal to the value which is given by the option's pricing formula and solving in terms of volatility, implied volatility is calculated. The estimated volatility value is the market's best estimate regarding the expected volatility value of the underlying asset. The model that is widely used for option pricing and for calculating implied volatility is the Black and Scholes Pricing Model (1973), which assumes that volatility, is constant. The other method as mentioned earlier is that of historical volatility, according to which volatility is calculated from past data and specifically from annualized square of the logarithmic returns of past option prices. As for which method produces more accurate results, Granger and Poon (2003) conducted a study reviewing the results of 93 studies on predictability of volatility and concluded that implied volatility is a better predictor of future volatility compared to other methodologies, mainly because it uses a wider and more relevant range of information.

## 2.2 Implied Volatility Indices

Volatility is a measure of the change in the price of a financial asset, such as a stock. More specifically, it is an indication of whether the price of a share will move up or down. The stochastic behaviour of volatility creates uncertainty and risk, in combination with the financial crises that have occurred in the financial markets in recent decades, such as the Asian crisis of 1997. Based on these parameters, many financial and academic experts considered the risk arising from price volatility as one of the main risk factors in the capital markets. Therefore, there is a need to bring to the fore the so-called volatility indices, the importance of which is constantly being strengthened in the modern financial system.

An implied volatility index is obviously a measure of implied volatility, as it represents this specific volatility of an option contract with a fixed duration until expiration. As indicated by the name, implied volatility is used for the calculation of the index and it is the best estimate of the course that volatility of option market will follow. The implied volatility indices received greater attention from the academic community and practitioners in the financial markets since 1993, when the Chicago Board Options Exchange (CBOE) introduced the VIX index, which was a major breakthrough in this area, as it was the first volatility index to be introduced by an official stock exchange and had daily prices. The index is generally calculated as a weighted average of the implied volatility of call and put options, having as underlying financial assets that are traded on an index, such as S&P 500 or Nasdaq 100. A unique feature of this index is that it was the first to use option contracts written on a stock index (S&P 100) and not on individual stocks. In this way, the index reflected the volatility of the overall market (market risk), as explained by the S&P 100, instead of the equity risk which contains non-systematic or otherwise idiosyncratic risk. The concept of taking into account a stock index is very important because, due to the diversification of the portfolio, the unsystematic risk of each share is eliminated. Systematic risk that remains is the one that matters for the purposes of the distribution of assets. Since then, many studies have been performed. The index is mainly based on the work of Whaley (1993).

### 2.3 Construction of Implied Volatility Indices

The idea of constructing an implied volatility index was first proposed by Brenner and Galai (1989). Implied volatility indices are constructed from buy and sell options contracts (call and put options). They represent the forward-looking volatility of an underlying stock index. In order to achieve a single value for each day, a process of weighting the implied variables of the options used is performed. The idea behind this weighting plan is to build a synthetic at-the-money option that has a fixed expiration date of thirty calendar days (or the equivalent of twenty-two business days).

#### 2.3.1 VIX Index

In 1993 the CBOE introduced the first implied volatility index, named VIX, and was constructed based on the options of the S&P 100 using the models of Black-Scholes (1973) and Merton (1973) (Whaley, 1993). In this option pricing framework, the variables required are the spot price of the underlying asset, the exercise price of the option, the risk-free interest rate, the dividend yield of the underlying security and of course the volatility. Dividends can be easily predicted, as the companies whose shares belong to the S&P 100 must announce the distribution of dividends quite early. The risk-free rate corresponding to the continuous performance of a government bond whose maturity is close to expiration of the option. The exercise price of the option and the time to maturity determined by the terms of the contract, while the current value of the index changes continuously during the trading day. Moreover, considering the market prices of options, as formed by the demand and supply, the only remaining variable is the volatility. By converting the formula and solving in terms of volatility we extract the so-called implied volatility.

The Black-Scholes model has a set of assumptions that do not match the actual conditions. It assumes that volatility is constant throughout the option, but we know that volatility is a function of exercise value and time to expiration. Given this fact, calculating the VIX index requires eight options for each day and these contracts conclude four options for short-term contracts (two call and two put options) and four for the second shortest time contracts. For all these options the implied variables are exported and a weighting procedure is performed in order to achieve a single price.

### 2.3.2 New VIX Index

In 2003 the CBOE revised the methodology for constructing the volatility index into a model-free formula for calculating the implied volatility of the S&P500 index. The model of Black Scholes (1973) and Merton (1973) is no longer used. The new VIX is calculated based on the weighted average price of out-of-money options. The main reason why the CBOE decided to change the index is to create a more accurate and powerful measure of the expected market volatility. This idea of non-parametric estimation of implied volatility (model-free), regardless of the type of option pricing, started with the creation of variance and volatility swaps. These products, as mentioned earlier, are derivatives whose value depends only on volatility. It is based on the study by Britten-Jones and Neuberger (2000) on variance and volatility swaps. The new way of calculating volatility is simpler to calculate but it is a more realistic measure of expected volatility, as it draws information from a much wider range of option prices, thereby enclosing the entire asymmetry of volatility and not just the part that refers to the implied volatility of at-the-money options. Another significant change in the calculation of the implied volatility index VIX is that it uses options that are written on the stock index S&P 500 and not on the S&P 100.

Despite the changes, the basic nature of the index remains the same. The new index continues to use the option prices on an index to measure market expectations regarding the short-term volatility of the stock market as well as the weighted average of options with a maturity of up to thirty days. Also, the value of the index continues to be calculated in real time during the trading day. Whaley (2009) presents the VIX index as a forward-looking measurement of expected volatility and also refers to the VIX as an investor fear gauge and that is the reason the VIX is called the fear index. In addition, Whaley creates an assumption that VIX index tends to follow a mean-reverting process. Specifically, whether the VIX is at a high point, it’s not anticipated to expand over time but return back to its long-run average. Moreover, the VIX removes the measurement errors resulting from the calculation of implied volatility (Blair, Poon and Taylor, 2001). Therefore, the behaviour of VIX becomes particularly interesting, as it reflects the uncertainty of the market.

It is essential to be mentioned that there is an explicit difference between VIX and realized volatility. In particular, for Carr and Wu (2009) the VIX is an index of implied volatility and is considered as a representation of risk neutral expected price of return variance. On the other hand, expected realized volatility is just the historical volatility. The difference between them is called variance risk premium (VRP) and this is used by market participants to offset against the variance risk. They also investigate that investors of US stock indices who are exposed to variance risk are rewarded. Furthermore, Bollerslev et al. (2010) propose that VRP can describe a part of the variation in stock market returns. Therefore, VIX involves the risk premium factor which is added to the expected realized volatility element. More specifically, VIX is equal to the certainty of ex-ante volatility consisting of the uncertainty part that market participants have to be compensated for. The uncertainty factor of VIX is also explained by the way the implied volatility is measured by CBOE. As mentioned by Whaley (2009), in periods of high uncertainty, investors can use put options as financial coverage.

The calculation of the VIX index is performed as follows:

$$\sigma^2 = \frac{2}{T} \Sigma \frac{\Delta Ki}{Ki^2} e^{RT} Q(Ki) - \frac{1}{T}\left[\frac{F}{Ko} - 1\right]^2 \quad (1)$$

Where: VIX÷100 = σ ⇨ VIX = σ × 100

T: time until expiration.

F: forward index level desired from index option prices

$K_0$: first strike price lower than the forward index level F

K$i$: strike price of the ith out-of-the-money option

If K$i$ > $K_0$ it is a call option, if K$i$ < $K_0$ it is a put option and if K$i$ = $K_0$ it is both call and put.

ΔK$i$: it is the interval which is equal to the difference between strikes prices divided by two.

R: risk-free interest rate until expiration

Q (K$i$): midpoint of bid-ask spread for each option with strike price K$i$

Furthermore, during periods of uncertainty where there is a bigger demand for put options, due to the loss aversion of the investors there can be a lower supply of put options. Thus, the midpoint of bid-ask spread is considered to be at a greater level regarding to more certain periods of time. The link between VIX and the bid-ask spread is positive, due to the fact that the first part of the formula (1) cannot be negative. Consequently, VIX will be at a higher degree in times with greater uncertainty. There is a variety of parameters that can impact and affect uncertainty, such as macroeconomic announcements or profits releases from corporations. Bomfim (2003) suggests that macro announcements have a significant impact on asset markets. The releases of macroeconomic news give market participants useful information, fact that can lead to uncertainty decrease (Chen et al. 2010).

### 2.3.3 Other Implied Volatility Indices

The widespread use of the index and its universal acceptance has led other stock exchanges to identify similar indices. The most important indices worldwide, beyond the VIX, are the following: VXO, VXN, VXD, VDAX, VX1 and VX6. The first three, as well as the VIX, are traded on the U.S. options exchange (CBOE). Following the example of the CBOE, the Deutsche Börse, in 1994, also introduced a German implied volatility index called VDAX. This index is the most representative European index, due to the importance and position of the German stock market worldwide. In 1997, the French Marché des Options Négociables de Paris (MONEP) introduced two implied volatility indices called VX1 and VX6. The VXO index is essentially the old VIX and is calculated based on the S&P 100. VXN index is constructed based on the implied volatility of the options on Nasdaq 100, which mainly includes stocks of technology related companies. On the other hand, the VXD index is produced based on options implied volatility with underlying index the Dow Jones 100, which involves 100 large cap stocks.

## 2.4 Usefulness of Implied Volatility Indices

Implied volatility indices have stimulated the interest of both financial market participants and the academic community, especially for their multifaceted utility in recent decades. Specifically, the VIX index is commonly used by investors for three specific reasons. Its first use and purpose is to provide an instant measure of how much the market thinks the S&P 500 will vary over the next 30 days. The second main use and perhaps the most interesting one, is for hedging the risk of investments. Something like that is possible, because as it has been observed that VIX index generally has a negative correlation with the S&P 500. Finally, the index can be used for speculation reasons. Many investors make their living by using profitable investment strategies, by betting on the increase or the decrease of the index. Specifically, for the reasons above, the following financial assets have been generated on the VIX index.

### 2.4.1 Implied Volatility Derivatives

The implied volatility derivatives, which are derivatives and have as their underlying asset implied volatility indices, pricing and hedging of whom are demanding, especially because they were traded in over-the-counter markets.  They can be used for speculation or hedging of a portfolio. The trading of VIX options dates back to February 2006 after the introduction of VIX futures in March 2004.

#### 2.4.1.1 VIX Futures

In 2004, the CBOE introduced the first futures on the VIX index. Futures contracts are agreements between two parties to buy or to sell an asset at a certain time (expiration time) in the future for a certain price (strike price). Future contracts are traded on exchanges. Each future is written on a specific underline asset. The underline of the VIX future is the VIX index. In July 2015, the CBOE Future Exchange introduced VIX weekly futures. In general, weekly futures have the same contract specifications as the monthly expiring contracts. The advantage of weekly expirations to standard monthly futures expirations is the fact that they offer volatility exposures that track the performance of the VIX Index more precisely.

#### 2.4.1.2 VIX Options

In 2006, CBOE introduced for the first-time options written on the VIX index. Options are products that are traded in exchanges and in the over-the-counter market. There are two categories of options. The first one is the call options and the second one is the put options. The VIX options are written on the VIX index. Investors who believe in the increase of the market volatility buy VIX calls. On the other hand, many investors use VIX options as hedging tools and they can choose among many strategies (bullish, bearish) that consist of calls and puts.

#### 2.4.1.3 VIX ETFs

It is well known that many Exchange traded funds trade the VIX index. An ETF is a fund that tracks an index, a commodity, a bundle of bonds, or a basket of assets like an index fund. Mutual funds are different from ETF though. ETF is traded exactly like a stock on a stock exchange. ETFs experience price changes throughout the day as they are bought and sold. ETFs in general have higher daily liquidity and lower fees than mutual funds This is the main reason that especially individual investors use them as an alternative to mutual index funds. The first S&P 500 VIX ETF was launched in 2010 by Source UK Services11.

### 2.4.2 Variance/Volatility Swaps

Volatility and variance swaps are derivative products which resemble futures contracts. Characteristic of these derivatives is that the complex position on them contains no risk of exposure to the underlying security moves. Volatility indices affect the pricing and hedging of volatility swaps, as the index can be translated as the variance/volatility swap rate which affects the market value of the contract. The swap rate is the fluctuation of a portfolio with options, which simulates the behaviour of the underlying index (replicating portfolio). This synthetic portfolio is structured in such a way that its value remains unaffected by stock price movements. Therefore, the fluctuation derived from the market value of the portfolio is also the derivative swap rate. And because the construction of implied volatility indices is done by forming a similar portfolio with options, the value of the index can be used as the swap rate.

### 2.4.3 Identifying Trade Opportunities

Due to the nature of the implied volatility indices, it is argued that there is a strong correlation between the path that follows an implied volatility index and the course of stock returns. This helps to interpret the levels of volatility in terms of uncertainty in the markets and consequently a fall in prices on them. The course of the implied volatility ratios is an indication of the purchase or sale of financial assets for the investor portfolio, provided that there is a high autocorrelation in volatility.

### 2.4.4 Forecasting Future Volatility

The implied volatility indices are used to predict future volatility of stock index (Fleming, 1995 and Giot, 2005b). These indicators are the most effective assessment of short-term volatility and provide useful information to investors due to their characteristics. However, other studies (Jiang and Tian, 2005) have shown that at times the predictive power of indicators is subject to bias.

### 2.4.5 Risk Measurement and Value-at-Risk

Another use of implied volatility indicator is their contribution to the determination of parameters and variables applied to market risk measurement models, such as the Value at Risk methodology (Giot 2005a). Market risk is the risk that comes from the uncertainty of the value of a portfolio of securities resulting from changes in market prices of portfolio assets. An approach to this market risk can be made using the Value at Risk (VaR) method, created in 1994 by JP Morgan Bank. VaR estimates within a given confidence interval and with certain probabilities, the worst return we can get from a portfolio in a certain period of time, due to changes in the market prices of the underlying securities. Implied volatility ratios provide accurate and important information about forecasting the future volatility of underlying indices when used for market risk management purposes.

### 2.5 Macroeconomic Indicators

The measurement of an economy and the prediction of its future course are based on analysing the key parts of macroeconomic data. These pieces of data are known as economic indicators and they quantify different features of an economy. More specifically, macroeconomic indicators provide information on the economic conditions and whether the economy is expanding or shrinking. Most of the indicators are published on a monthly basis and typically provide the contribution to the activity of the previous month and year for comparison purposes. Investors can refine their investment decisions with the support of macro indicators, aiming to optimize their portfolio strategy and financial planning. No indicator alone can give the necessary information that investors are looking for, however the use of a significant number of indicators together can provide indications on the state of the economy. Here are some important and major US economic indicators that investors watch very carefully and will then be used by the present study for research purposes.

#### 2.5.1 CPI

The Consumer Price Index (CPI) is released in a monthly basis by the U.S. Bureau of Labor Statistics (BLS) and measures changes in the price level of the basket of consumer goods and services purchased by American households. More specifically, The CPI is a statistical estimate which is established using the prices of a representative data sample whose values are collected periodically. Sub-indices and secondary indices are calculated for different categories and subcategories of goods and services, which are combined to produce the total index with average weights that reflect their share of the total consumer expenditure covered by the index.

CPI is one of the several price indices calculated by most national statistical offices and the annual percentage change in CPI is used as a key and most widely measure of inflation. The CPI can be used to adjust the fair values of wages, earnings, pensions, price regulations and monetary deflation to show the changes in fair values (i.e., adjustment for the effect of inflation). In most countries, the CPI, along with the population census, is one of the most frequently monitored national economic statistics for indicating periods of inflation or deflation.

### 2.5.2 PPI

The official measure of producer prices in the economy of United States is called the Producer Price Index (PPI). It is a group of indices that calculates the average changes in prices received by domestic producers for their production at all stages of processing. The prices included in the PPI come from the first commercial transaction for many products and several services. The PPI was known as the Wholesale Price Index (WPI) until 1978.

The PPI is one of the earliest continuous statistical systems released by the Bureau of Labor Statistics (BLS) each month, as well as one of the oldest time series compiled by the Federal Government. The Bureau of Labor Statistics (BLS) publishes monthly information that includes the calculation of approximately 10.000 individual products and group products. This data contains almost all industries that produce goods in the United States. Some of the sectors covered include construction, agriculture, manufacturing, and mining.

There is a major difference between PPI and CPI. The PPI differs from the CPI in that it measures costs in terms of the industries that produce the products, while the CPI measures prices from the perspective of consumers. More precisely, the PPI measures price movements from the seller's point of view whereas the CPI measures cost changes from the buyer’s viewpoint. In other words, this index tracks change to the cost of production.

### 2.5.3 GDP

Gross Domestic Product (GDP) is the total national income and production for the economy of a given country. The U.S. GDP equals the total expenditure on all final goods and services that produced within the borders of America at a specified period of time. The GDP of an economy provides the overall value of the goods and services it produces and signifies if an economy is under growth or recession. As a broad measure of total domestic production, it serves as a key economic indicator in order to monitor the progress of economic health of a given country.

It is announced by the U.S. Bureau of Economic Analysis (BEA) each month as a percentage change. The government submits a preliminary first estimate, is updated with a revised second reading as it receives more input and then submits a third and final report. In the U.S., the BEA calculates the GDP using data verified through retail surveys, manufacturers and builders, and by examining trade flows GDP gives an economic snapshot of a country, which is used to estimate the size of an economy and growth rate. The measurement of a GDP for a country takes into account a number of several different factors related to the country's economy, including its consumption and investment.

GDP is likely the most closely monitored and crucial economic indicator for all the financial market participants due to the capture of the overall value of all goods and services produced by an economy. Investors pay close attention to GDP because percentage changes in GDP (rise or fall) can have a significant impact on the stock market. In general, a ‘bad’ economy usually means lower profits for enterprises and hence this can lead to lower stock prices. Investors can consider the positive and negative GDP growth rates when planning a portfolio strategy. However, it is worth mentioning that because GDP is a measure of the economy for the previous quarter, it is better to use it to explain how economic growth and production have affected stocks and investments in the past. Finally, as a simple number figure, a country's GDP is capable of providing a very limited range of information about that country's economy. Despite this, it remains a helpful and useful data point for economists and investors, although in terms of forecasting, GDP is not considered as useful predictor about how the market will move in the future.

### 2.5.4 EMP

The Bureau of Labor Statistics (BLS) publishes the Employment Situation Summary, or otherwise known as the employment or jobs report, at 8:30 a.m. EST on the first Friday of each month. The report is based on two statistical surveys, the Current Population Survey of households and the Current Employment Statistics Survey of employers. It estimates the number of employed and unemployed people in the economy and the number of hours they worked. Many Wall Street companies publish estimates of these employment data and these forecasts are in turn used by business decision-makers.

The release of Employment report can affect corporate trust, and hence future business and hiring decisions. While the report may be volatile and subject to significant revisions long after the event, it remains a broadly monitored indicator of financial well-being. The data are widely expected by the financial market participants and the numbers it provides on employment directly impact the financial markets. The number of new jobs being created provides hints about the economy and corporate profits and indirectly provides information on interest and exchange rates.

### 2.5.5 FOMC

The Federal Open Market Committee (FOMC) is a committee under the Federal Reserve System (Fed) which is entrusted with the U.S. law on the supervision of the nation's open market operations (e.g., buying and selling U.S. securities). This Federal Reserve Committee makes key decisions about interest rates and money supply growth in the United States. The FOMC is the primary instrument of US national monetary policy. The committee determines monetary policy by setting the short-term objective for the Fed's open market operations, which is usually a target level for the federal funds rate (the rate that commercial banks charge each other for overnight loans). The FOMC also directs the Federal Reserve's operations in foreign exchange markets, although any intervention in foreign exchange markets is coordinated with the US Treasury Department, which is responsible for US policy-making regarding the exchange rate of the dollar.

By law, the FOMC must meet at least four times a year in Washington, D.C. Since 1981, eight regularly scheduled meetings have taken place each year at intervals of five to eight weeks (usually six weeks). If circumstances require consultation or examination of an action between these regular meetings, members may be invited to participate in a special meeting or conference call or to vote for a proposed action by proxy. At each scheduled regular meeting, the committee shall decide on the policy to be followed during the interval between meetings. The FOMC meets eight times a year to discuss monetary policy changes, review economic and financial conditions and assess price stability and employment output. The minutes of the scheduled meetings are released three weeks after the date of the policy decision. For traders and investors, FOMC meetings are a time of particular volatility because any change in federal fund rates can affect a range of economic variables such as short-term interest rates, foreign exchange rates, long-term interest rates, employment output and prices of goods and services.

# 3. Data and Methodology

### 3.1 Sources of Data

In this study, research is conducted on how the scheduled macroeconomic announcements impact the behaviour of CBOE VIX (Chicago Board Options Exchange implied volatility index). The econometric approach is focused on the daily closing prices of the VIX index and these values are collected via Yahoo Finance. The sample period starts from 3$^{rd}$ January 1990 and ends on 31$^{st}$ December 2020. The macroeconomic indicators used in the present research are Consumer Price Index (CPI), Producer Price Index (PPI), Gross Domestic Product (GDP), Employment Situation (ES) and Federal Open Market Committee meetings (FOMC). The dates of scheduled news releases of the CPI, PPI and Employment Report are made available on monthly basis and are collected from U.S. Bureau of Labor Statistics website. In addition, the declaration of GDP results is given on monthly basis and the data are extracted from the website of U.S. Bureau of Economic Analysis. The FOMC is a branch of the U.S. Federal Reserve, which makes future monetary policy decisions. FOMC meetings are held on average eight times on annual basis and the dates are notified on the Federal Reserve`s website. All major macroeconomic variables announcement dates that are used in the study are predefined and known in advance. All the macroeconomic news releases are made at 8:30 a.m. Eastern Time (ET).

### 3.2 Descriptive Statistics

Table 1 shows the summary statistics of VIX index closing values and its respective percentage changes for the sample period of 3$^{rd}$ January 1990 to 31$^{st}$ December 2020. These VIX changes are essentially a series of returns, which is created by the method of logarithmic transformation and differencing of the VIX closing prices. The average VIX observed for the study period is found to be 19.47 points, with an average mean return of 0.0035 percent. The highest VIX points observed for the period is 82.69 and the lowest is 9.14, while for the VIX changes series the highest positive return is 77% and the lowest negative is 35% Analysing and focusing on the standard deviation of the log-return, the SD of VIX is 6.6%. The table results also show that log-returns series of VIX is non-normally distributed, but positively skewed and leptokurtic. The Jarque-Berra statistic rejects the null hypothesis that the return series is normal distributed against the alternative hypothesis that the series is non-normal.

Finally, the Augmented Dickey-Fuller Test statistic is employed in order to check whether the time series VIX level and VIX log-returns that are studied are stationary. In Tables A1 and A2 (see Appendix A) can be easily observed that the t-statistic of ADF test is statistically significant at one percent level and that signifies that the null hypothesis about the existence of a unit root is rejected, so both VIX level and VIX log-returns time series are free from unit root and therefore they are considered stationary.

Figures 1 & 2 present the VIX during the sampled period and they show the time series plot of VIX index level and its log-returns respectively and it can be easily observed that the VIX follows a mean-reverting process. In addition, these figures imply that there is no problem of trend and so both of the VIX series are stationary. It is important to mention that there is an inverse relationship between the S&P500 index and the VIX, a high (low) volatility of the VIX generally leads to a fall (rise) of the underlying index. High volatility in the daily closing values of the VIX implies more buying pressure on the S&P500 index options. Paying a higher premium rather than the theoretical price of the option leads to an increase (decrease) in the VIX level. More precisely, when the macroeconomic news is not in favour of the market, creating more uncertainty, investors buy more options to hedge their market position and protect their portfolio. Ultimately, the VIX rises and the underlying index drops significantly. Whaley (1993) examined and documented this phenomenon on a large scale.

**Table 1.** Descriptive Statistics of CBOE Volatility Index (VIX) for period January 1990 to December 2020

| Statistics | VIX Level | VIX Log-Returns |
|---|---|---|
| Mean | 19.47 | 0.000035 |
| Median | 17.46 | -0.0036 |
| Maximum | 82.69 | 0.768 |
| Minimum | 9.14 | -0.350 |
| Std. Dev. | 8.11 | 0.066 |
| Skewness | 2.19 | 0.95 |
| Kurtosis | 11.26 | 9.46 |
| Jarque-Bera | **28502.87** | **14760.19** |
| Probability | 0.0000 | 0.0000 |
| ADF test | **-6.48** | **-37.60** |
| Observations | 7808 | 7808 |

Bold values are statistically significant at 1% significance level.

**Figure 1.** Time Series plot of VIX Level index for period January 1990 to December 2020

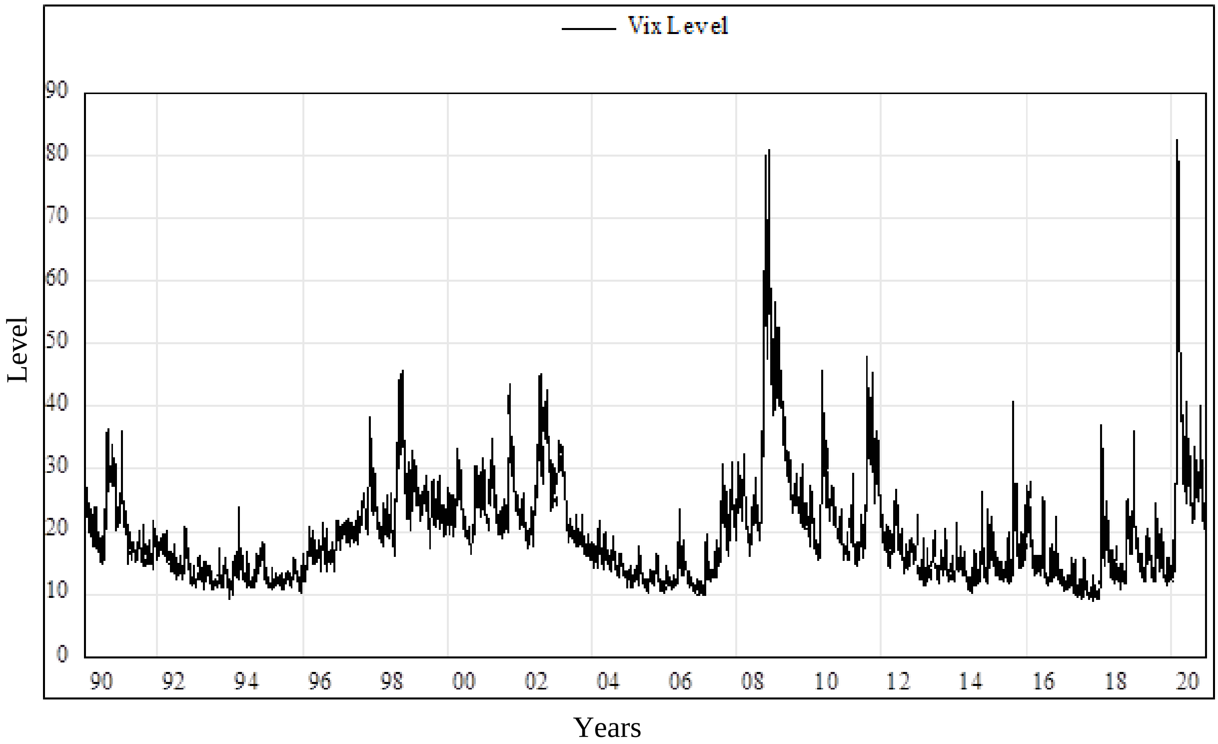
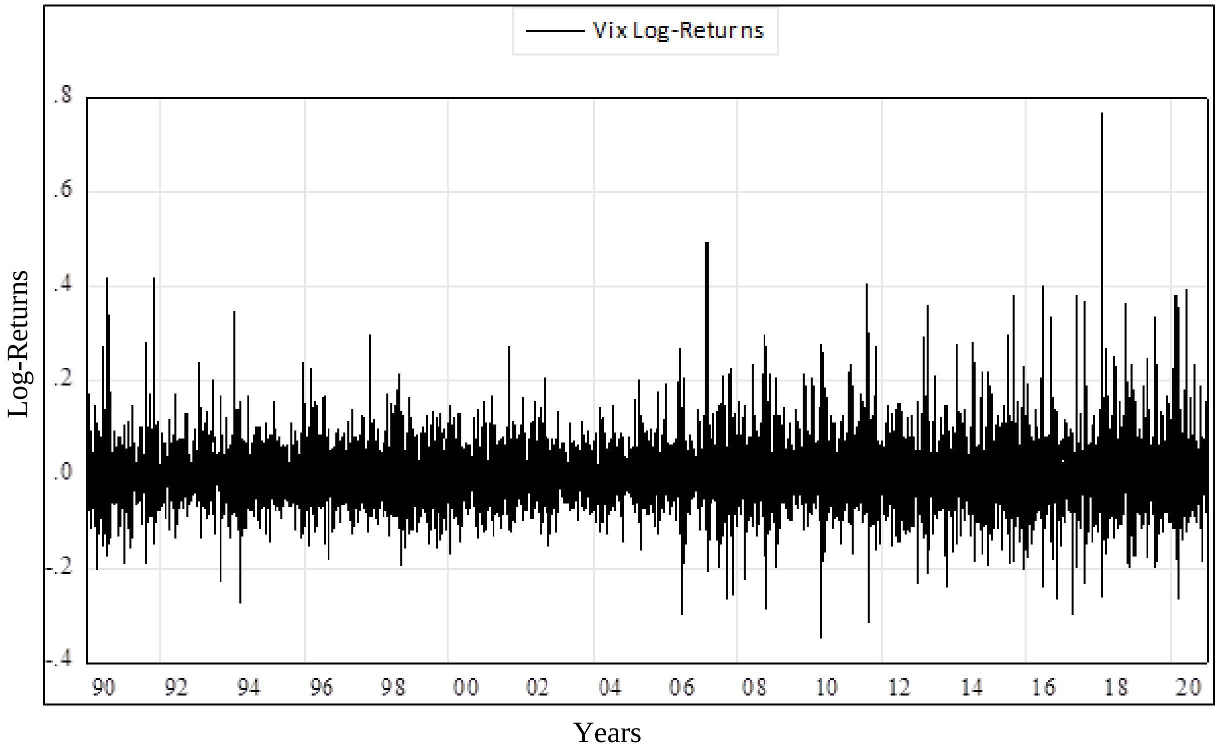



**Figure 2.** Time Series plot of VIX Log-Returns index for period January 1990 to December 2020



### 3.3 Research Methodology

The existing literature on the relation between the macroeconomic announcements and the effect on financial assets draws particular interest for the market participants but also for the academic community, mainly because the financial assets are becoming more and more uncertain around scheduled announcements. Therefore, the purpose of this research is to analyse the impact of news releases before, the day of announcement and after the report days. Previous studies deal primarily with stock prices volatility and interest-rate futures, while on the contrary this study deals with the VIX index. Studying the asset price volatility on the news releases, the return of the underlying assets can be classified as normal and abnormal returns, for example, the CAPM models. On the other hand, when dealing with changes in implied volatility, returns on the VIX, there are no any such pricing models that can give the expected returns on VIX. As a result, this research calculates the log-returns of the VIX time series in a mean reverting framework.

The present study investigates the behaviour of VIX index during the series of scheduled macroeconomic news releases, such as CPI, PPI, GDP, Employment Report and the FOMC meetings. In order to examine and analyse the impact of these macro announcements, the dummy variable technique is employed as inspired and developed by Ederington and Lee (1996), Nikkinen and Sahlström (2004) and Chen and Clements (2007). The research was conducted through the use of econometric software package EViews 11. Following are the regression models constructed using the major macroeconomic indicators as dummy variables.

#### 3.3.1 Model I

This regression model reflects the impact of all macroeconomic announcements on the behaviour of VIX with a holistic approach. All the slope coefficients of this model should be different from zero if this macro indicator contains important information, so that investors include these macroeconomic news releases in their financial planning. Actually, during non-announcement periods investors feel more uncertainty due to lack of information on the forthcoming news, because the content of the news enters the market on the day of actual announcement, therefore the intercept should be different from zero and positive. Model I is presented in the following equation (2).

**Model I**. Regression model for the report days of scheduled macroeconomic announcements.

$$ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = a_0 + \beta^{CPI}D_t^{CPI} + \beta^{PPI}D_t^{PPI} + \beta^{GDP}D_t^{GDP} + \beta^{EMP}D_t^{EMP} + \beta^{FOMC}D_t^{FOMC} + \varepsilon_t^{VIX} \quad (2)$$

where $a_0$ is the intercept term that captures the behaviour of VIX index during non-announcement days, $\beta$ is the slope coefficient that captures the impact of macroeconomic announcements and FOMC meetings on release days, $D_t$ is the dummy variable, assuming the value one on the days of scheduled announcements for the macroeconomic indicators, otherwise it is zero. Ultimately, $\varepsilon_t^{VIX}$ is the residual term that reflects shocks due to release of news. Frequently, investors consider the macro news of more than one announcement together at one point of time in stock valuation. Hence, the joint effects of CPI, PPI, Employment, GDP, FOMC meetings are taken into account as a combined impact on VIX index. A Wald F-statistic is calculated for the group of slopes for the announcement dummies.

### 3.3.2 Models II and III

Subsequently, methodology of this study deals with the development of the second and third model, which modifies Model I, in an attempt to isolate the effect of announcements on VIX behaviour. The following equations capture the behaviour of the VIX before and after the releases of schedules macroeconomic news. More specifically, these regression models are structured in order to study and analyse the impact of uncertainty on the element of surprise that exists around scheduled announcements. The rationale behind this has been analysed by Ederington and Lee (1996), Nikkinen and Sahlström (2004) and Chen and Clements (2007), which shows that before an announcement, due to lack of information in the news the market becomes more volatile. Hence, investors overreact to the upcoming news and the VIX rises. After the news is released and uncertainty is resolved, the VIX returns to its normal level. This takes place regardless of the nature of the news. In detail, Model II and Model III are presented in the following equations (3) and (4) respectively.

**Model II.** Regression model one day before, during the report day and a day after the scheduled macroeconomic announcements.

$$ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = a_0 + \sum_{i=-1}^{1} \beta_i^{CPI}D_{i,t}^{CPI} + \sum_{i=-1}^{1} \beta_i^{PPI}D_{i,t}^{PPI} + \sum_{i=-1}^{1} \beta_i^{GDP}D_{i,t}^{GDP} + \sum_{i=-1}^{1} \beta_i^{EMP}D_{i,t}^{EMP} + \sum_{i=-1}^{1} \beta_i^{FOMC}D_{i,t}^{FOMC} + \varepsilon_t^{VIX} \quad (3)$$

**Model III.** Regression model two days before, during the report day and two days after the scheduled macroeconomic announcements.

$$ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = a_0 + \sum_{i=-2}^{2} \beta_i^{CPI} D_{i,t}^{CPI} + \sum_{i=-2}^{2} \beta_i^{PPI} D_{i,t}^{PPI} + \sum_{i=-2}^{2} \beta_i^{GDP} D_{i,t}^{GDP} + \sum_{i=-2}^{2} \beta_i^{ES} D_{i,t}^{ES} + \sum_{i=-2}^{2} \beta_i^{FOMC} D_{i,t}^{FOMC} + \varepsilon_t^{VIX} \quad (4)$$

Where: $D_{i,t}$ is the dummy variable that captures the information content of surprise elements in the macroeconomic news releases, which assumes the value one or zero as explained above. Moreover, $i$ is the subscript that ranges between the values +1 (one day before the scheduled announcement), 0 (is the report release day) and -1 (one day after the announcement).

The log-returns series of the VIX is detected with the problem of autocorrelation, therefore an AR (1) term and a MA (1) term are added to each model in order to solve this problem. Moreover, the Lagrange Multiplier (LM) test for ARCH effect by Engle (1982) shows the presence of conditional heteroskedasticity in the residuals. Hence to resolve this problem of time-varying volatility, the estimation of all the regression models that mentioned above is performed through the GARCH family models. More precisely, the variance of the error term is specified as a GARCH (1, 1) process is fitted. To control the autocorrelation problem, AR (p) and MA (q) terms have been added. The order of the autoregressive-moving average ARMA (p, q) model is selected, where after multiple combinations of time lags for (p) and (q) terms, the optimal lag selection based on the minimization of Akaike Information Criterion (AIC) is the (1, 1) and thus Models I, II and III are expressed in the ARMA (1, 1): OLS ordinary least squares specification using dummy variables.

From the mean equations for models I, II and III, the resulting residual $\varepsilon_t^{VIX}$, is expressed using ARMA (1, 1): GARCH (1, 1). The GARCH model is a symmetric model according to which positive and negative shocks are considered as the same magnitude. Besides that, Christie (1982) and Schwert (1989) assume that downward changes in the market are frequently followed by higher volatility compared to the same upward changes. The different effects on conditional volatility of positive and negative effects of equal magnitude, hence these asymmetric characteristics of volatility are captured in the exponential EGARCH model developed by Nelson (1991).

The exponential nature of EGARCH implies that the conditional variance is always positive even if the parameter values are negative, so there are no restrictions in parameters for non-negativity. The EGARCH model also takes into account the leverage effect in the exponential form. Therefore, an EGARCH (1, 1) model is performed for models I, II and III.

### 3.4 Hypotheses of the Models

The present study develops some hypotheses which are related to the models I, II, III constructed above, inspired by the work of Nikkinen and Sahlström (2004) and Chen and Clements (2007).

a. The first hypothesis concerns the intercept $a_0$. The literature points out that in periods without macro news announcements the volatility becomes more volatile and the VIX rises, which is justified by the lack of information about the upcoming news. Hence, the intercept is assumed to be non-zero, positive and statistically significant ($a_0 > 0$).

b. The second hypothesis deals with the slope coefficients $\beta_i$. Nikkinen and Sahlström (2004) described that the information content of the macro indicators news are only publicly available on the announcement day, so the market absorbs the useful information and the volatility returns to its normal level. Hence, on the scheduled report release day the VIX declines and all the slope coefficients should be negative and statistically significant ($\beta_i < 0$). They also indicate that before a scheduled announcement the VIX index increases significantly and reaches its maximum level, fall on the news release day and going back to the initial level in a few days. Therefore, before the schedule announcements all the slope coefficients assumed to be positive and statistically significant ($\beta_i > 0$) and after the announcements they should be negative and statistically significant ($\beta_i < 0$).

c. The joint effect of macro indicators announcements on the CPI, PPI, GDP, Employment and FOMC meetings has been calculated because investors take into account more than one announcement at one point of time in their portfolio selection. Hence, on the news release days the Wald F-statistic is assumed to be statistically significant if the impact is significant.

# 4. Empirical Results

This chapter presents the results of the empirical data analysis according to the procedure described in the research methodology chapter. Models I, II and III have been constructed to analyse the behaviour of the VIX index during macroeconomic news releases. The outcome of examining the impact of these scheduled macroeconomic announcements and the FOMC meeting days on the VIX index is reported in the following tables. Primarily, before the empirical results are analysed and the AR (1) and MA (1) are added to the models, the estimate includes the tables where Models I, II and III are estimated by OLS regression and their results are in the tables B1, C1, D1 (see Appendices B, C and D respectively). The estimation shall be conducted by employing ARMA (1, 1): OLS, ARMA (1, 1): GARCH and ARMA (1, 1): EGARCH models, which were previously analysed in the methodology.

### 4.1 Results for Model I

Table 2 provides the estimation results of empirical data analysis of Model I, which is based on the days of actual scheduled macroeconomic news releases. In detail, it shows the regression output of the impact of macroeconomic indicators on VIX index during the day they are published. The macroeconomic indicators that are used in the estimation are expressed through the dummy variable technique and the empirical results derived from the OLS, GARCH and EGARCH models.

#### 4.1.1 OLS Results for Model I

The first column of Table 2 presents the estimation output of Model I applying the OLS regression method using dummy variables. The slope coefficients of all macroeconomic variables, i.e. CPI, PPI, GDP, Employment, FOMC meetings, on the report day appear negative. However, only CPI, GDP and Employment are found to be statistically significant. Besides, in case of PPI and FOMC, the slope is statistically insignificant. Therefore, this indicates that investors are less interested in PPI, FOMC in assessment of their portfolio.

In addition, as investors take into account more than one macroeconomic indicators at one point of time in the stock valuation, Wald F-stat is calculated to discover the joint effect of slopes with negative sign and is found to be statistically significant. This shows that joint effect of CPI, PPI, GDP, EMP, FOMC, are probably one of the main factors that define the behaviour of investors regarding their future financial planning. The results of the Wald F-statistic are presented in Table B2 (see Appendix B). Moreover, it is observed that the intercept term appears positive and statistically significant on the report days. This happens because during non-announcement periods there is an uncertainty in the financial markets and the investors overreact due to the upcoming scheduled news, which leads them to buy more options in order to protect their market position.

### 4.1.2 GARCH Results for Model I

The second column of Table 2 concerns the estimation results of Model I through the use of GARCH (1, 1) model. The need to use the GARCH model arises after the diagnostic tests in residuals of Model I: OLS to check the problems of ARCH effect and autocorrelation. The ARCH-LM test results in Table B3 and Breusch-Godfrey test output in Table B4 (see Appendix B) show that t-stats for these tests are significant, so the presence of ARCH effect and serial correlation are observed in Model I. In this estimation, as with the OLS regression, the slope coefficients are again all negative and statistically significant. Besides that, the intercept is found to be positive, but it is not statistically significant. This implies that during the non-announcement periods there is an uncertainty in the market but it does not seem so important. The GARCH coefficients are found to be positive and statistically significant, suggesting that when a shock occurs, volatility tends to be persistent for long periods of time.

### 4.1.3 EGARCH Results for Model I

The third column reports the EGARCH (1, 1) estimation results of Model I, which describes the leverage effect on asset prices. The output shows that the parameters of the conditional variance equation of the EGARCH model are different from zero, positive and statistically significant. Therefore, a positive and significant leverage effect term signifies a strong asymmetric effect on the VIX index, both from positive shocks (good news) and negative shocks (bad news) regarding the scheduled announcements of macroeconomic indicators. Nevertheless, the positivity of this term indicates asymmetry but not a leverage effect, hence it is not possible to know whether good (bad) news has a greater impact on conditional volatility of the VIX than bad (good) news of equal magnitude. The EGARCH model shows that once again all macro indicators have a significant impact on the VIX, with the index declining significantly on good news related to macroeconomic variables. Moreover, residual diagnostics tests are applied in order to check if ARCH effect and serial correlation exist even after GARCH models are employed. ARCH-LM test statistic as well as the Q-Statistics are found to be insignificant in the estimated GARCH model and confirm the absence of any further ARCH effects and serial correlation. ARCH-LM test results appear in Table B5 and Correlogram-Q-Statistics results are presented in Table B6 (see Appendix B).

**Table 2**. Regression Estimation and Results of Model I

| | ARMA(1,1):OLS | | ARMA(1,1):GARCH(1,1) | | ARMA(1,1):EGARCH(1,1) | |
|---|---|---|---|---|---|---|
| Variables | Estimate | p-value | Estimate | p-value | Estimate | p-value |
| Intercept | **0.0024** | 0.0000 | 0.0005 | 0.1772 | **0.0009** | 0.0222 |
| CPI report day | **-0.0137** | 0.0001 | **-0.0149** | 0.0000 | **-0.0148** | 0.0000 |
| PPI report day | -0.0027 | 0.3702 | **-0.009** | 0.0000 | **-0.0096** | 0.0000 |
| GDP report day | **-0.0096** | 0.0078 | **-0.0078** | 0.0083 | **-0.0076** | 0.0087 |
| EMP report day | **-0.0211** | 0.0000 | **-0.0263** | 0.0000 | **-0.0266** | 0.0000 |
| FOMC report day | -0.0064 | 0.1310 | **-0.0067** | 0.0410 | **-0.0077** | 0.0178 |
| AR(1) | **0.7829** | 0.0000 | **0.8246** | 0.0000 | **0.8213** | 0.0000 |
| MA(1) | **-0.8714** | 0.0000 | **-0.9185** | 0.0000 | **-0.9089** | 0.0000 |
| ARCH(1) | | | **0.1260** | 0.0000 | **0.1526** | 0.0000 |
| GARCH(1) | | | **0.7974** | 0.0000 | **0.9302** | 0.0000 |
| Leverage effect | | | | | **0.1196** | 0.0000 |
| Adj. R-squared | 0.0266 | | 0.0181 | | 0.0214 | |
| F-statistic | **31.566** | | | | | |
| (p-value) | (0.0000) | | | | | |
| Joint effect CPI, PPI, GDP, ES, FOMC (p-value) | **10.732** (0.0000) | | | | | |

The table presents the regression result and the estimation output of Model I: $\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = \alpha_0 + \beta^{CPI} D_t^{CPI} + \beta^{PPI} D_t^{PPI} + \beta^{GDP} D_t^{GDP} + \beta^{EMP} D_t^{EMP} + \beta^{FOMC} D_t^{FOMC} + \varepsilon_t^{VIX}$

Bold values are statistically significant at 5% level of significance.
Parentheses values show the p-values of the F-statistic.

### 4.2 Results for Model II

Table 3 provides the estimation results of empirical data analysis of Model II, which is based on the one day before and one day after the scheduled macroeconomic news releases. It should also be mentioned that the variables that have the (-1), refer to the macroeconomic indicators for one day before the scheduled announcement, while variables with (+1) are related to the indicators for one day after the actual announcement.

**Table 3**. Regression Estimation and Results of Model II

| | ARMA(1,1):OLS | | ARMA(1,1):GARCH(1,1) | | ARMA(1,1):EGARCH(1,1) | |
|---|---|---|---|---|---|---|
| Variables | Estimate | p-value | Estimate | p-value | Estimate | p-value |
| Intercept | -0.0002 | 0.7198 | **-0.0013** | 0.0267 | 0.0001 | 0.7581 |
| CPI(-1) report day | -0.0032 | 0.3640 | **-0.0062** | 0.0262 | **-0.007** | 0.0094 |
| CPI report day | **-0.0152** | 0.0001 | **-0.0143** | 0.0000 | **-0.0135** | 0.0000 |
| CPI(+1) report day | 0.0004 | 0.9180 | 0.0037 | 0.2311 | 0.0042 | 0.1520 |
| PPI(-1) report day | **0.0089** | 0.0088 | 0.0031 | 0.2072 | 0.002 | 0.4076 |
| PPI report day | -0.0014 | 0.6753 | **-0.0084** | 0.0002 | **-0.0095** | 0.0000 |
| PPI(+1) report day | 0.0047 | 0.1257 | **0.0048** | 0.0623 | **0.0041** | 0.0809 |
| GDP(-1) report day | **0.0114** | 0.0016 | **0.0095** | 0.0006 | **0.0087** | 0.0012 |
| GDP report day | **-0.0072** | 0.0467 | **-0.0059** | 0.0459 | **-0.0063** | 0.0288 |
| GDP(+1) report day | -0.0003 | 0.9158 | -0.0031 | 0.2838 | **-0.0047** | 0.1033 |
| EMP(-1) report day | **0.0254** | 0.0000 | **0.0225** | 0.0000 | **0.0222** | 0.0000 |
| EMP report day | **-0.0205** | 0.0000 | **-0.0259** | 0.0000 | **-0.0257** | 0.0000 |
| EMP(+1) report day | 0.0049 | 0.1677 | 0.0023 | 0.3925 | 0.0011 | 0.6755 |
| FOMC(-1) report day | 0.0046 | 0.2750 | 0.0013 | 0.6898 | 0.0002 | 0.9512 |
| FOMC report day | -0.0053 | 0.2117 | **-0.0056** | 0.0829 | **-0.0063** | 0.0504 |
| FOMC(+1) report day | -0.0022 | 0.6031 | -0.0033 | 0.3104 | -0.004 | 0.2132 |
| AR(1) | **0.7876** | 0.0000 | **0.8245** | 0.0000 | **0.9183** | 0.0000 |
| MA(1) | **-0.8761** | 0.0000 | **-0.9174** | 0.0000 | **-0.9753** | 0.0000 |
| ARCH effect | | | **0.1266** | 0.0000 | **0.152** | 0.0000 |
| GARCH effect | | | **0.7987** | 0.0000 | **0.9068** | 0.0000 |
| Leverage effect | | | | | **0.1556** | 0.0000 |
| Adj. R-squared | 0.0341 | | 0.0251 | | 0.0249 | |
| F-statistic | **17.248** | | | | | |
| (p-value) | (0.0000) | | | | | |

The table presents the regression result and the estimation output of Model II:

$$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = \alpha_0 + \sum_{i=-1}^{1} \beta_i^{CPI} D_{i,t}^{CPI} + \sum_{i=-1}^{1} \beta_i^{PPI} D_{i,t}^{PPI} + \sum_{i=-1}^{1} \beta_i^{GDP} D_{i,t}^{GDP} + \sum_{i=-1}^{1} \beta_i^{EMP} D_{i,t}^{EMP} + \sum_{i=-1}^{1} \beta_i^{FOMC} D_{i,t}^{FOMC} + \varepsilon_t^{VIX}$$

Bold values are statistically significant at 5% and 10% level of significance.
Parentheses values show the p-values of the F-statistic.

### 4.2.1 OLS Results for Model II

The OLS regression results report that for the inflation rates, the slope coefficient of CPI found to be statistically significant and negative on the report day, on the other hand though the results for CPI around the release day are not significant and the signs of slopes are in contrast to the literature. PPI appears positive and statistically significant only on the day before the announcement and on report day is negative but not significant, which indicates that these results are consistent with the literature and the hypothesis mentioned in the methodology. In addition, GDP has a positive slope a day before the scheduled announcement and a negative slope on the report day, with both of them being statistically significant. The same is observed respectively with the slope of Employment variable. Therefore, the results for GDP and EMP verify the hypothesis based on the literature which states that before the announcement the VIX rises due to increased uncertainty of the lack of information about the forthcoming news, but after the news is released on the scheduled day, the uncertainty is resolved and the VIX falls and returns to its initial level. Finally, the slope of FOMC is negative before the announcement and positive on the release day but in both cases is not statistically significant, which indicates that changes in the VIX around the report days regarding the monetary policy meetings are not significant and investors seem to underestimate this macroeconomic indicator.

### 4.2.2 GARCH Results for Model II

The second column of Table 3 deals with the GARCH (1, 1) estimation output of Model II. The need to use the GARCH model arises after the diagnostic tests in residuals of Model II: OLS to check the problems of ARCH effect and autocorrelation. The ARCH-LM test results in Table C2 and Breusch-Godfrey test output in Table C3 (see Appendix C) show that t-stats for these tests are significant, so the presence of ARCH effect and serial correlation are observed in Model II. The intercept term found to be negative and significant and a potential explanation for this is that during non-announcement periods, investors undergo a high level of uncertainty about upcoming news, hence the VIX index remains at normal level and continues to decline until the news enters the market. GDP and EMP results, just like in OLS regression, are in compliance with the studies of Nikkinen and Sahlström (2004) and Chen and Clements (2007), which means that before the announcement the slopes of GDP and EMP are positive and statistically significant and on the report day they found to be negative and significant. However, CPI results are in contradiction to the study of Nikkinen and Sahlström (2004), which assumes that before the announcements the VIX increases and returns to normal on release days. More specifically, CPI found to be negative and significant one day before but also on the report day and positive and non-significant one day after. A possible explanation for the negative and significant CPI one day before the release could be that for the longest period of the sample, inflation rate during these periods stays under control, so the VIX continues to decline. PPI slope is negative and significant on report day and is the only macro indicator with a significant and positive slope one day after the announcement, showing that is not consistent with the literature and signifies that investors overreact and VIX rises due to more uncertainty about the future rate of PPI in economy. FOMC results follow the literature but only on report day the slope is negative and significant with the slopes around the release day being insignificant. Finally, for PPI and FOMC, VIX increases before the announcement with no significance, implying that investors do not pay as much attention and show less interest in the announcements of these macro variables.

### 4.2.3 EGARCH Results for Model II

The third column of Table 3 presents the estimation results of model EGARCH (1, 1) for the second Model. The output shows that the parameters of the conditional variance equation of the EGARCH model are different from zero, positive and statistically significant. Moreover, a positive and significant leverage effect term signifies an asymmetric effect on VIX both from positive (good news) and negative shocks (bad news) regarding the scheduled announcements of macroeconomic indicators. Nevertheless, the positivity of this term indicates asymmetry but not leverage effect, hence it is not possible to know whether good (bad) news has a greater impact on conditional volatility of the VIX than bad (good) news of equal magnitude. The EGARCH model shows that once again all macro indicators have a significant impact on the VIX, with the index declining significantly on good news related to macroeconomic variables. Compared to the GARCH model, the exact same slopes of macro indicators are statistically significant and have the same sign, except that for EGARCH the GDP on the day after the scheduled announcement appears negative and significant, which is consistent with the hypothesis inspired by the literature and indicates that positive changes in GDP lead to a significant fall in the VIX index after the announcement. Finally, residual diagnostics tests are applied in order to check if ARCH effect and serial correlation exist even after GARCH models are employed. ARCH-LM test statistic as well as Q-Statistics are found to be insignificant in the estimated GARCH model and confirm the absence of any further ARCH effects and serial correlation. ARCH-LM test results appear in Table C4 and Correlogram-Q-Statistics results are presented in Table C5 (see Appendix C).

### 4.3 Results for Model III

Table 4 provides the estimation output of empirical data analysis of Model III, which is based on two days before and two days after the scheduled macroeconomic news releases. It is worth mentioning that the macroeconomic indicators that have the (-2) refer to the macro variables for two days before the scheduled announcement, while variables with (+2) are related to the indicators for two days after the actual announcement.

#### 4.3.1 OLS Results for Model III

The OLS regression results are presented in the first column of Table 4 and initially the CPI reports show a slope coefficient which appears negative around the scheduled announcement and on the report day, however it is found significant with a negative sign two days before, one day before and on release day. This is probably due to the fact that there is no turmoil in the market concerning the CPI and no further uncertainty is created by investors about the information content of CPI release, hence the VIX decreases two days before and continues to decline after the announcement, because the level of CPI is not so volatile and remains under control. The results for the PPI are exactly the same as the previous model (II), they follow the literature but no significance is observed two days before, after and on the day of announcement. Similarly, the same estimation output with Model II is presented by GDP, with no significance in the time frame of two days before and two days after the announcement, however, there is a significant negative slope of GDP on report day. EMP results indicate, as in the literature, that before the actual announcement the VIX rises and after the release VIX is falling, so it is observed that EMP is positive and significant one day before the announcement, but negative and significant on the report day and two days after. The slope of FOMC appears negative and significant only two days after the report, which signifies a decrease of VIX two days after the news release. Finally, as recorded in the hypothesis based on literature, the intercept term found to be positive and significant, implying that during non-announcement days there is an uncertainty in the financial markets and the investors overreact due to the forthcoming scheduled news releases.

**Table 4**. Regression Estimation and Results of Model III

| | ARMA(1,1):OLS | | ARMA(1,1):GARCH(1,1) | | ARMA(1,1):EGARCH(1,1) | |
|---|---|---|---|---|---|---|
| Variables | Estimate | p-value | Estimate | p-value | Estimate | p-value |
| Intercept | **0.0021** | 0.0603 | 0.0002 | 0.8018 | **0.0022** | 0.0111 |
| CPI(-2) report day | **-0.0102** | 0.0055 | **-0.0075** | 0.0071 | **-0.0076** | 0.0049 |
| CPI report day | **-0.0181** | 0.0000 | **-0.0158** | 0.0000 | **-0.0149** | 0.0000 |
| CPI(+2) report day | -0.0058 | 0.1458 | -0.0043 | 0.1579 | -0.0042 | 0.1450 |
| PPI(-2) report day | 0.0034 | 0.3203 | 0.0011 | 0.6163 | 0.0003 | 0.8825 |
| PPI report day | -0.0009 | 0.7897 | **-0.0076** | 0.0013 | **-0.0091** | 0.0001 |
| PPI(+2) report day | -0.0007 | 0.8018 | -0.0029 | 0.2915 | -0.0036 | 0.1568 |
| GDP(-2) report day | 0.0024 | 0.5005 | 0.0041 | 0.1560 | 0.0038 | 0.1750 |
| GDP report day | **-0.0086** | 0.0184 | **-0.0068** | 0.0214 | **-0.0075** | 0.0108 |
| GDP(+2) report day | -0.0032 | 0.3781 | -0.0000 | 0.9974 | -0.0007 | 0.8042 |
| EMP(-2) report day | -0.0007 | 0.8452 | -0.0002 | 0.9278 | -0.0007 | 0.7875 |
| EMP report day | **-0.0225** | 0.0000 | **-0.0274** | 0.0000 | **-0.0275** | 0.0000 |
| EMP(+2) report day | **-0.0091** | 0.0128 | **-0.0059** | 0.0426 | **-0.0069** | 0.0173 |
| FOMC(-2) report day | -0.0005 | 0.8896 | -0.0022 | 0.4897 | -0.0034 | 0.2799 |
| FOMC report day | -0.0051 | 0.2312 | **-0.0055** | 0.0865 | **-0.0067** | 0.0399 |
| FOMC(+2) report day | **-0.0179** | 0.0000 | **-0.0123** | 0.0003 | **-0.0122** | 0.0003 |
| AR(1) | **0.7889** | 0.0000 | **0.8233** | 0.0000 | **0.9205** | 0.0000 |
| MA(1) | **-0.8774** | 0.0000 | **-0.9164** | 0.0000 | **-0.9765** | 0.0000 |
| ARCH effect | | | **0.127** | 0.0000 | **0.1518** | 0.0000 |
| GARCH effect | | | **0.7984** | 0.0000 | **0.1594** | 0.0000 |
| LEVERAGE effect | | | | | **0.9056** | 0.0000 |
| Adj. R-squared | 0.0371 | | 0.0275 | | 0.0273 | |
| F-statistic | **12.15** | | | | | |
| (p-value) | (0.0000) | | | | | |

The table presents the regression result and the estimation output of Model III:

$$\ln\left(\frac{VIX_t}{VIX_{t-1}}\right) = \alpha_0 + \sum_{i=-2}^{2} \beta_i^{CPI} D_{i,t}^{CPI} + \sum_{i=-2}^{2} \beta_i^{PPI} D_{i,t}^{PPI} + \sum_{i=-2}^{2} \beta_i^{GDP} D_{i,t}^{GDP} + \sum_{i=-2}^{2} \beta_i^{EMP} D_{i,t}^{EMP} + \sum_{i=-2}^{2} \beta_i^{FOMC} D_{i,t}^{FOMC} + \varepsilon_t^{VIX}$$

Bold values are statistically significant at 5% and 10% level of significance.

Parentheses values show the p-values of the F-statistic.

### 4.3.2 GARCH Results for Model III

The GARCH (1, 1) model is introduced in the third Model, is presented in the second column and shows similar estimation results with the OLS regression. The need to use the GARCH model arises after the diagnostic tests in residuals of Model III: OLS to check the problems of ARCH effect and autocorrelation. The ARCH-LM test results in Table D2 and Breusch-Godfrey test output in Table D3 (see Appendix D) show that t-stats for these tests are significant, so the presence of ARCH effect and serial correlation are observed in Model III. The only and main difference between them is that in GARCH model the slope of all macroeconomic indicators is negative and significant, which is in compliance with the literature that VIX is declining due to the resolution of uncertainty on the report days. Therefore, CPI, PPI, GDP, EMP and FOMC are negative and statistically significant on days with scheduled macroeconomic announcements. The Intercept term is in contradiction with OLS and specifically it is negative and insignificant. For the time span of two days before and after the announcement the results are similar with OLS output, i.e. the CPI is significant two days before with a negative sign and EMP and FOMC are negative and significant two days after the report. The GARCH coefficients are all positive and statistically significant, suggesting that when a shock occurs (scheduled announcement), volatility tends to be persistent for long periods of time.

### 4.3.3 EGARCH Results for Model III

The third column of Table 4 presents the estimation results of model EGARCH (1, 1) for the third Model. The output shows that the parameters of the conditional variance equation of the EGARCH model are different from zero, positive and statistically significant. In addition, a positive and significant leverage effect term signifies an asymmetric effect on VIX both from positive (good news) and negative shocks (bad news) regarding the scheduled announcements of macroeconomic indicators. Nevertheless, the positivity of this term indicates asymmetry but not leverage effect, hence it is not possible to know whether good (bad) news has a greater impact on conditional volatility of the VIX than bad (good) news of equal magnitude. The EGARCH model shows that once again all macro indicators have a significant impact on the VIX, with the index declining significantly on good news related to macroeconomic variables. Compared to the GARCH model, the exact same slopes of macro indicators are statistically significant and have the same sign. More specifically, the CPI two days before and EMP, FOMC meetings two days after the announcement found to be statistically significant. The only difference observed is that the intercept term is positive and significant just like in the OLS model and as defined in the literature. Finally, residual diagnostics tests are applied in order to check if ARCH effect and serial correlation exist even after GARCH models are employed. ARCH-LM test statistic as well as the Q-Statistics are found to be insignificant in the estimated GARCH model and confirm the absence of any further ARCH effects and serial correlation. ARCH-LM test results appear in Table D4 and Correlogram-Q-Statistics results are presented in Table D5 (see Appendix D).

### 4.4 Economic Interpretation of Results

The efficient market hypothesis explained that if the market is efficient, it reacts to the main macroeconomic scheduled announcements, hence when new information enters the market it is absorbed by the stock prices and VIX reflects the expectation of market participants for the near future volatility. Accordingly, the analysis reveals that investors should take into account the macro news releases in their stock valuation and portfolio selection. Further the finding that the joint effect of CPI, PPI, GDP, EMP and FOMC found to be highly statistically significant indicates that investors regard the news on more than one macro indicator at a point of time.

The results for GDP and EMP are consistent and completely in line with the hypotheses made for this study. It is observed that the VIX increases significantly one day before GDP and EMP announcements, it declines on the report day for both and continues to fall one day after the news release for GDP and two days after the release for EMP. In the time frame in which the study is conducted the news related to GDP and EMP have basically a positive impact on the economy of the United States and the financial markets experience positive shocks once the content of news is publicly available. Therefore, the empirical results indicate that investors consider Employment and GDP growth rate as the most important source of information in the framework of this study and as a result, VIX is more responsive to the GDP and EMP announcements and so positive changes in these two macro indicators lead to a significant reduction in the VIX index.

The results relating to inflation rates, i.e., CPI and PPI are largely inconsistent and contradictory to the hypotheses based on the literature. The CPI indicator appears negative and statistically significant both one day before and two days before the scheduled announcement and again negative and significant on the report day. This is most likely due to the fact that there is no market turmoil and increased uncertainty regarding the CPI hence investors are not particularly concerned about the forthcoming announcement of CPI. Nevertheless, on the news release day, the CPI has a high significant impact on the VIX due to the information content of CPI news according to which, just like GDP, is in favour of the U.S. economy, so these announcements affect the VIX as positive shocks by decreasing it. On the other hand, PPI results found to be positive and significant one day after the announcement. The PPI is negative on the report day, so VIX decreases when the news are available and one day after PPI is positive and significant, which signifies that VIX increases and this can be attributed to the fact that investors sometimes overreact after an information release leading to a rise in uncertainty. Finally, FOMC meetings show a significant impact on VIX two days after the release, where the FOMC is negative hence the VIX declines and this finding is in support of the existing literature on VIX reduction and return to the original level after the FOMC meetings report days.

# 5. Conclusions

This study investigates the behaviour of the implied volatility index (VIX) during scheduled announcements on major macroeconomic indicators and specifically CPI, PPI, GDP, EMP and FOMC meetings. These indicators have been selected and analysed as announcement dummies and the sample period under which the study is conducted is from 3$^{rd}$ January 1990 to 31$^{st}$ December 2020. The impact of the macroeconomic news releases is calculated in terms of log-returns for the VIX index both for the report day and for the days around the announcement.

The empirical results generally support the hypotheses that are based on past literature, according to which the VIX rises prior to the scheduled macroeconomic announcements and then falls until the index reaches its normal level on report day and after the release day. A potential explanation for this phenomenon is that investors feel more uncertain before the declaration of the results of macroeconomic variables due to the lack of information about upcoming news releases.  However, from the report day and for a few days after, the news on macro indicators are published and the investors are now informed, therefore the uncertainty is resolved and the market returns to normalcy and tranquillity.

The present study shows that there is a relatively predictable movement in the VIX around scheduled macroeconomic announcements. The findings from this study may contribute in two ways. First, it can affect a future profitable trading strategy by forecasting short-term stock market volatility. Since the VIX index is an ex-ante measure of future volatility, profits can be made through the trade of VIX futures or VIX options. Second, it has an impact on hedging and pricing of options, because the expected volatility can be used in options pricing and therefore help in portfolio selection and financial planning. The study shows that there is a relatively predictable movement in the VIX around scheduled macroeconomic announcements.

## References


Black, F., & Scholes, M. (1973). The Pricing of Options and Corporate Liabilities. *The Journal of Political Economy*, *81*(3), 637–654.

Blair, B. J., Poon, S.-H., & Taylor, S. J. (2001). Forecasting S&P 100 volatility: The incremental information content of implied volatilities and high-frequency index returns. *Journal of Econometrics*, *105*(1). 5-26.

Brenner, M., & Galai, D. (1989). New Financial Instruments for Hedging Changes in Volatility. *Financial Analysts Journal*, *45*, 61-65.

Bollerslev, T., Tauchen, G., & Zhou, H. (2009). Expected Stock Returns and Variance Risk Premia. *Review of Financial Studies*, *22*(11), 4463–4492.

Bomfim, A. N. (2000). Pre-Announcement Effects, News, and Volatility: Monetary Policy and the Stock Market. *Finance and Economics Discussion Series*, *2000*(50), 1–33.

Britten-Jones, M., & Neuberger, A. (2000). Option Prices, Implied Price Processes, and Stochastic Volatility. *The Journal of Finance*, *55*(2), 839–866.

Carr, P., & Wu, L. (2009). Variance Risk Premiums. *Review of Financial Studies*, *22*(3), 1311–1341.

Chen, E.-T., & Clements, A. (2007). S&P 500 implied volatility and monetary policy announcements. *Finance Research Letters*, *4*(4), 227–232.

Chen, D., Krieger, K., & Mauck, N. (2010). The Uncertainty Resolution of FOMC Meeting Days. *SSRN Electronic Journal*, 26.

Donders, M. W. M., & Vorst, T. C. F. (1996). The impact of firm specific news on implied volatilities. *Journal of Banking & Finance*, *20*(9), 1447–1461.

Ederington, L. H., & Lee, J. H. (1993). How Markets Process Information: News Releases and Volatility. *The Journal of Finance*, *48*(4), 1161–1191.

Ederington, L. H., & Lee, J. H. (1996). The Creation and Resolution of Market Uncertainty: The Impact of Information Releases on Implied Volatility. *The Journal of Financial and Quantitative Analysis*, *31*(4), 513.

Fleming, J., Ostdiek, B., & Whaley, R. E. (1995). Predicting stock market volatility: A new measure. *Journal of Futures Markets*, *15*(3), 265-302.

Füss, R., Mager, F., Wohlenberg, H., & Zhao, L. (2011). The impact of macroeconomic announcements on implied volatility. *Applied Financial Economics*, *21*(21), 1571–1580.

Giot, P. (2005, a). Implied volatility indices and daily Value-at-Risk models. *Journal of Derivatives*, *12*, 54-64.

Giot, P. (2005, b). Relationships between implied volatility indices and stock index returns. *Journal of Portfolio Management, 31*(3), 92-100.

Gospodinov, N., & Jamali, I. (2012). *The effects of Federal funds rate surprises on S&P 500 volatility and volatility risk premium*. *19*(4), 497–510.

Granger, C., & Poon, S.-H. (2003). Forecasting Volatility in Financial Markets: A Review. *Journal of Economic Literature*, *41*(2), 478–539.

Jiang, G. J., & Tian, Y. S. (2005). The Model-Free Implied Volatility and Its Information Content. *Review of Financial Studies*, *18*(4), 1305–1342.

Kearney, A. A., & Lombra, R. E. (2004). Stock market volatility, the news, and monetary policy. *Journal of Economics and Finance*, *28*(2), 252–259.

Merton, R. C. (1973). Theory of Rational Option Pricing. *The Bell Journal of Economics and Management Science*, *4*(1), 141-183.

Nikkinen, J., & Sahlström, P. (2001). Impact of Scheduled U.S. Macroeconomic News on Stock Market Uncertainty: A Multinational Perspective. *Multinational Finance Journal*, *5*(2), 129–148.

Nikkinen, J., & Sahlström, P. (2004). Impact of the federal open market committee's meetings and scheduled macroeconomic news on stock market uncertainty. *International Review of Financial Analysis*, *13*(1), 1–12.

Shaikh, I., & Padhi, P. (2013). Macroeconomic Announcements and the Implied Volatility Index: Evidence from India VIX. *Margin: The Journal of Applied Economic Research*, 7(4), 417–442.

Srinivasan, P. (2017). Macroeconomic Information and the Implied Volatility: Evidence from India VIX. *Theoretical Economics Letters*, *07*(03), 490–501.

Vähämaa, S., & Äijö, J. (2011). The Fed's Policy Decisions and Implied Volatility. *Journal of Futures Markets*, *31*(10), 995–1010.

Whaley, R. E. (1993). Derivatives on Market Volatility: Hedging Tools Long Overdue. *The Journal of Derivatives*, *1*(1), 71–84.

Whaley, R. E. (2009). Understanding the VIX. *The Journal of Portfolio Management*, *35*(3), 98–105.

# **Appendix A -** Augmented Dickey-Fuller (ADF) tests

**Table A1.** ADF test for VIX Level

Null Hypothesis: VIX LEVEL has a unit root

Exogenous: Constant

Lag Length: 10 (Automatic - based on SIC, maxlag=35)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -6.4807 | 0.0000 |
| Test critical values: | 1% level | -3.4310 | |
| | 5% level | -2.8617 | |
| | 10% level | -2.5669 | |

**Table A2.** ADF test for VIX Log-Returns

Null Hypothesis: VIX LOG-RETURNS has a unit root

Exogenous: Constant

Lag Length: 7 (Automatic - based on SIC, maxlag=35)

| | | t-Statistic | Prob.* |
|---|---|---|---|
| Augmented Dickey-Fuller test statistic | | -37.607 | 0.0000 |
| Test critical values: | 1% level | -3.4310 | |
| | 5% level | -2.8617 | |
| | 10% level | -2.5669 | |

## **Appendix B** - OLS regression, Wald F-stat & Residual Diagnostics for Model I

**Table B1.** OLS regression for Model I

Dependent Variable: VIX
Method: Least Squares
Sample: 3/01/1990 31/12/2020
Included observations: 7808

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.0025 | 0.0008 | 3.0955 | 0.0020 |
| CPI | -0.0129 | 0.0035 | -3.6412 | 0.0003 |
| PPI | -0.0043 | 0.0030 | -1.4314 | 0.1523 |
| GDP | -0.0104 | 0.0035 | -2.9387 | 0.0033 |
| EMP | -0.0223 | 0.0035 | -6.2636 | 0.0000 |
| FOMC | -0.0061 | 0.0042 | -1.4325 | 0.1520 |

| | | | |
|---|---|---|---|
| R-squared | 0.0076 | Mean dependent var | 3.55E-05 |
| Adjusted R-squared | 0.0069 | S.D. dependent var | 0.0664 |
| S.E. of regression | 0.0661 | Akaike info criterion | -2.5918 |
| Sum squared resid | 34.179 | Schwarz criterion | -2.5865 |
| Log likelihood | 10124.69 | Hannan-Quinn criter. | -2.5900 |
| F-statistic | 11.956 | Durbin-Watson stat | 2.1571 |
| Prob(F-statistic) | 0.0000 | | |

**Table B2.** Wald F-Stat for Model I

Wald Test for Equation: MODEL I:OLS
Null Hypothesis: CPI=0, PPI=0, GDP=0, EMP=0, FOMC=0

| Test Statistic | Value | df | Probability |
|---|---|---|---|
| F-statistic | 29.746 | (5, 7794) | 0.0000 |
| Chi-square | 148.73 | 5 | 0.0000 |

**Table B3.** ARCH-LM Test for Model I: OLS

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 251.82 | Prob. F(1,7805) | 0.0000 |
| Obs*R-squared | 244.01 | Prob. Chi-Square(1) | 0.0000 |

**Table B4.** Breusch-Godfrey LM Test for Model I: OLS

Breusch-Godfrey Serial Correlation LM Test:

Null hypothesis: No serial correlation at up to 1 lag

| | | | |
|---|---|---|---|
| F-statistic | 48.507 | Prob. F(1,7801) | 0.0000 |
| Obs*R-squared | 48.251 | Prob. Chi-Square(1) | 0.0000 |

**Table B5.** ARCH-LM Test for Model I: GARCH

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 0.0002 | Prob. F(1,7804) | 0.9881 |
| Obs*R-squared | 0.0002 | Prob. Chi-Square(1) | 0.9881 |

**Table B6.** Q-Statistics for Model I: GARCH

Null hypothesis: No serial correlation at up to 10 lags

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | 0.009 | 0.009 | 0.6483 | |
| \| \| | \| \| | 2 | 0.000 | 0.000 | 0.6484 | |
| \| \| | \| \| | 3 | 0.008 | 0.008 | 1.2003 | 0.273 |
| \| \| | \| \| | 4 | 0.002 | 0.001 | 1.2208 | 0.543 |
| \| \| | \| \| | 5 | 0.008 | 0.008 | 1.7376 | 0.629 |
| \| \| | \| \| | 6 | -0.002 | -0.002 | 1.7705 | 0.778 |
| \| \| | \| \| | 7 | -0.007 | -0.007 | 2.1085 | 0.834 |
| \| \| | \| \| | 8 | 0.003 | 0.002 | 2.1574 | 0.905 |
| \| \| | \| \| | 9 | 0.013 | 0.013 | 3.4853 | 0.837 |
| \| \| | \| \| | 10 | 0.042 | 0.041 | 16.970 | 0.030 |

# **Appendix C -** OLS regression & Residual Diagnostics for Model II

**Table C1.** OLS regression for Model II

Dependent Variable: VIX
Method: Least Squares
Sample (adjusted): 4/01/1990 30/12/2020
Included observations: 7806 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | -0.0001 | 0.0010 | -0.1826 | 0.8551 |
| CPI(-1) | -0.0027 | 0.0035 | -0.7778 | 0.4367 |
| CPI | -0.0136 | 0.0038 | -3.5334 | 0.0004 |
| CPI(1) | 0.0024 | 0.0039 | 0.6125 | 0.5402 |
| PPI(-1) | 0.0066 | 0.0033 | 1.9598 | 0.0500 |
| PPI | -0.0031 | 0.0033 | -0.9546 | 0.3398 |
| PPI(1) | 0.0038 | 0.0030 | 1.2461 | 0.2128 |
| GDP(-1) | 0.0107 | 0.0035 | 2.9908 | 0.0028 |
| GDP | -0.0079 | 0.0035 | -2.2218 | 0.0263 |
| GDP(1) | -0.0012 | 0.0035 | -0.3462 | 0.7292 |
| EMP(-1) | 0.0258 | 0.0035 | 7.1990 | 0.0000 |
| EMP | -0.0202 | 0.0035 | -5.6223 | 0.0000 |
| EMP(1) | 0.0052 | 0.0035 | 1.4538 | 0.1460 |
| FOMC(-1) | 0.0047 | 0.0042 | 1.1137 | 0.2654 |
| FOMC | -0.0049 | 0.0042 | -1.1525 | 0.2491 |
| FOMC(1) | -0.0014 | 0.0042 | -0.3357 | 0.7370 |

| | | | |
|---|---|---|---|
| R-squared | 0.0163 | Mean dependent var | 2.88E-05 |
| Adjusted R-squared | 0.0144 | S.D. dependent var | 0.0664 |
| S.E. of regression | 0.0659 | Akaike info criterion | -2.5979 |
| Sum squared resid | 33.876 | Schwarz criterion | -2.5836 |
| Log likelihood | 10155.80 | Hannan-Quinn criter. | -2.5930 |
| F-statistic | 8.6089 | Durbin-Watson stat | 2.1596 |
| Prob(F-statistic) | 0.0000 | | |

**Table C2.** ARCH-LM Test for Model II: OLS

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 254.27 | Prob. F(1,7803) | 0.0000 |
| Obs*R-squared | 246.31 | Prob. Chi-Square(1) | 0.0000 |

**Table C3.** Breusch-Godfrey LM Test for Model II: OLS

Breusch-Godfrey Serial Correlation LM Test:

Null hypothesis: No serial correlation at up to 1 lag

| | | | |
|---|---|---|---|
| F-statistic | 50.188 | Prob. F(1,7789) | 0.0000 |
| Obs*R-squared | 49.975 | Prob. Chi-Square(1) | 0.0000 |

**Table C4.** ARCH-LM Test for Model II: GARCH

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 0.0003 | Prob. F(1,7802) | 0.9859 |
| Obs*R-squared | 0.0003 | Prob. Chi-Square(1) | 0.9859 |

**Table C5.** Q-Statistics for Model II: GARCH

Null hypothesis: No serial correlation at up to 10 lags

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | 0.008 | 0.008 | 0.4832 | |
| \| \| | \| \| | 2 | 0.001 | 0.001 | 0.4871 | |
| \| \| | \| \| | 3 | 0.011 | 0.011 | 1.4058 | 0.236 |
| \| \| | \| \| | 4 | 0.003 | 0.003 | 1.4681 | 0.480 |
| \| \| | \| \| | 5 | -0.001 | -0.001 | 1.4767 | 0.688 |
| \| \| | \| \| | 6 | 0.003 | 0.003 | 1.5593 | 0.816 |
| \| \| | \| \| | 7 | -0.006 | -0.006 | 1.8592 | 0.868 |
| \| \| | \| \| | 8 | 0.002 | 0.003 | 1.9040 | 0.928 |
| \| \| | \| \| | 9 | 0.013 | 0.013 | 3.2804 | 0.858 |
| \| \| | \| \| | 10 | 0.034 | 0.034 | 12.117 | 0.146 |

# **Appendix D -** OLS regression & Residual Diagnostics for Model III

**Table D1.** OLS regression for Model III

Dependent Variable: VIX
Method: Least Squares
Sample (adjusted): 5/01/1990 29/12/2020
Included observations: 7804 after adjustments

| Variable | Coefficient | Std. Error | t-Statistic | Prob. |
|---|---|---|---|---|
| C | 0.0027 | 0.0013 | 2.0616 | 0.0393 |
| CPI(-2) | -0.0103 | 0.0036 | -2.8566 | 0.0043 |
| CPI(-1) | -0.0052 | 0.0039 | -1.3364 | 0.1814 |
| CPI | -0.0161 | 0.0040 | -3.9890 | 0.0001 |
| CPI(1) | 0.0004 | 0.0040 | 0.1095 | 0.9127 |
| CPI(2) | -0.0037 | 0.0040 | -0.9403 | 0.3471 |
| PPI(-2) | 0.0003 | 0.0034 | 0.1042 | 0.9170 |
| PPI(-1) | 0.0066 | 0.0034 | 1.9276 | 0.0539 |
| PPI | -0.0034 | 0.0034 | -0.9883 | 0.3230 |
| PPI(1) | 0.0039 | 0.0033 | 1.1735 | 0.2406 |
| PPI(2) | -0.0018 | 0.0031 | -0.5869 | 0.5572 |
| GDP(-2) | 0.0015 | 0.0036 | 0.4202 | 0.6744 |
| GDP(-1) | 0.0085 | 0.0036 | 2.3329 | 0.0197 |
| GDP | -0.0097 | 0.0036 | -2.6637 | 0.0077 |
| GDP(1) | -0.0033 | 0.0036 | -0.9037 | 0.3662 |
| GDP(2) | -0.0046 | 0.0036 | -1.2812 | 0.2001 |
| EMP(-2) | -0.0004 | 0.0036 | -0.1304 | 0.8962 |
| EMP(-1) | 0.0242 | 0.0036 | 6.6511 | 0.0000 |
| EMP | -0.0226 | 0.0036 | -6.2014 | 0.0000 |
| EMP(1) | 0.0024 | 0.0036 | 0.6629 | 0.5074 |
| EMP(2) | -0.0097 | 0.0036 | -2.6831 | 0.0073 |
| FOMC(-2) | -0.0013 | 0.0042 | -0.3190 | 0.7497 |
| FOMC(-1) | 0.0040 | 0.0042 | 0.9487 | 0.3428 |
| FOMC | -0.0056 | 0.0042 | -1.3220 | 0.1862 |
| FOMC(1) | -0.0020 | 0.0042 | -0.4830 | 0.6291 |
| FOMC(2) | -0.0181 | 0.0042 | -4.2432 | 0.0000 |

| | | | |
|---|---|---|---|
| R-squared | 0.0206 | Mean dependent var | 2.35E-05 |
| Adjusted R-squared | 0.0175 | S.D. dependent var | 0.0664 |
| S.E. of regression | 0.0658 | Akaike info criterion | -2.5996 |
| Sum squared resid | 33.722 | Schwarz criterion | -2.5764 |
| Log likelihood | 10170.00 | Hannan-Quinn criter. | -2.5917 |
| F-statistic | 6.5737 | Durbin-Watson stat | 2.1607 |
| Prob(F-statistic) | 0.0000 | | |

**Table D2.** ARCH-LM Test for Model III: OLS

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 254.55 | Prob. F(1,7801) | 0.0000 |
| Obs*R-squared | 246.57 | Prob. Chi-Square(1) | 0.0000 |

**Table D3.** Breusch-Godfrey LM Test for Model III: OLS

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 1 lag

| | | | |
|---|---|---|---|
| F-statistic | 50.762 | Prob. F(1,7777) | 0.0000 |
| Obs*R-squared | 50.608 | Prob. Chi-Square(1) | 0.0000 |

**Table D4.** ARCH-LM Test for Model III: GARCH

Heteroskedasticity Test: ARCH-LM

Null hypothesis: No presence of ARCH effects

| | | | |
|---|---|---|---|
| F-statistic | 0.0533 | Prob. F(1,7801) | 0.8173 |
| Obs*R-squared | 0.0533 | Prob. Chi-Square(1) | 0.8173 |

**Table D5.** Q-Statistics for Model III: GARCH

Null hypothesis: No serial correlation at up to 10 lags

| Autocorrelation | Partial Correlation | | AC | PAC | Q-Stat | Prob* |
|---|---|---|---|---|---|---|
| \| \| | \| \| | 1 | 0.008 | 0.008 | 0.4444 | |
| \| \| | \| \| | 2 | 0.002 | 0.002 | 0.4869 | |
| \| \| | \| \| | 3 | 0.010 | 0.010 | 1.2639 | 0.261 |
| \| \| | \| \| | 4 | 0.003 | 0.003 | 1.3397 | 0.512 |
| \| \| | \| \| | 5 | -0.001 | -0.001 | 1.3453 | 0.718 |
| \| \| | \| \| | 6 | 0.003 | 0.003 | 1.4297 | 0.839 |
| \| \| | \| \| | 7 | -0.006 | -0.006 | 1.7292 | 0.885 |
| \| \| | \| \| | 8 | 0.003 | 0.003 | 1.7917 | 0.938 |
| \| \| | \| \| | 9 | 0.013 | 0.013 | 3.0571 | 0.880 |
| \| \| | \| \| | 10 | 0.035 | 0.035 | 12.558 | 0.128 |