ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis Economics and Business Economics

The impact of macroeconomic news announcements on S&P500 implied volatility during the COVID-19 pandemic

Abstract

This paper examines the impact of macroeconomic news announcements, mainly focussing on the Federal Open Market Committee (FOMC) meetings, on the S&P500 implied volatility (VIX) during the COVID-19 pandemic. By regressing the most important macroeconomic news announcements, the CPI, employment, and PPI report, together with FOMC meeting days whilst also controlling for the economic business cycles, the effects are estimated. In addition, GARCH and AR specifications are added to the models. The results indicate that there is no additional volatility reducing effect of macroeconomic news announcements during the pandemic. Furthermore, in contrast with what previous literature suggests, no evidence is found of the regular behaviour of the VIX around FOMC meetings, the CPI and PPI report release, or during economic business cycles as well. However, evidence was found for the volatility reducing effect of the employment report release. Finally, the implications of the findings from this paper are discussed and future research recommendations are given.

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1. Introduction

COVID-19 impacted the worldwide economy greatly in 2020 (Ozili & Arun, 2020). Spillovers from the crisis have resulted in large losses on the global financial market, and especially on the stock market. The S&P500 index dropped 28% from 3,373 to 2,409 between February 20 and March 19 2020[1]. This was mainly due to investors looking for safety during the pandemic. However, with the amount of administered vaccines rising globally, the world is slowly recovering from the pandemic (*Coronavirus (COVID-19) Vaccinations*, n.d.).

Now that the world is entering a recovery phase, the effects of the pandemic can slowly be examined. The pandemic has affected the stability of the global financial market over the past year. As a result, the Federal Reserve (FED) has been trying to provide stability to the market. For example, they announced a zero percent interest policy, as well a quantitative easing program in March 2020 promising to buy back 700 billion USD worth of government debt bond and mortgage-backed securities[2]. By doing so they aimed to provide certainty in uncertain times. However, substantial increases of volatility were still found in global markets due to the outbreak according to research by Zhang et al. (2020).

The FED regularly conducts Federal Open Market Committee (FOMC) meetings, and shortly after statements are released with their policy announcements. These reports have major macroeconomic impact. For example, large excess returns are observed before the scheduled FOMC meetings and this phenomenon is called the pre-FOMC announcement drift (Lucca & Moench, 2015). Savor and Wilson (2013) examined the link between macroeconomic risks and security returns. They found that during the days prior to macroeconomic news announcement, as such FOMC decisions as an example, the uncertainty that the market experiences on how the news will affect asset prices results in an increase in risk. As a result, the average stock returns are higher during these macroeconomic news announcement days. Other literature by Cieslak et al. (2014), Savor and Wilson (2014), and Mueller et al. (2017) also showed the macroeconomic impact of FOMC meetings and announcements. The extensive evidence in the literature on the macroeconomic effect of the FOMC meetings made it reasonable to continue examining its exact implications.

The period preceding, during, and after the FOMC meetings and the report releases results in a lot of uncertainty in the market[3]. Nikkinen and Sahlström (2004) have conducted research on the topic and concluded that the uncertainty the market experiences around the

[1] From Ozili and Arun (2020)
[2] From Zhang et al. (2020)
[3] When referring to the *market*, the *financial market* is meant onwards

FOMC meeting days indeed resulted in an increase of the implied volatility[4] of the S&P100 index (VIX)[5]. Immediately after the meetings have taken place, they observed a decrease of the VIX. This indicates that the additional uncertainty that is observed in the market in anticipation of the meetings is resolved. Throughout the literature a relationship between the monetary policy discussed during the FOMC meetings and that of stock price movements was identified (see, e.g., Bomfim, 2003; Ehrmann & Fratzscher, 2004; Hausman & Wongswan, 2011). Therefore, it can be expected that the market anticipates the impact of the FOMC meetings and acts on this, thus affecting the implied volatility.

Besides focussing on the FOMC meetings, this paper will also take into account the impact of other macroeconomic indicators that investors follow. Research by Nikkinen and Sahlström (2004) has shown a significant effect of the consumer price index (CPI) report, the employment report and the producer price index (PPI) report on the implied volatility. These reports were also identified by Ederington and Lee (1993) as the most important macroeconomic news indicators.

The aim of this paper is to continue on previously conducted research on the impact of FOMC meetings on stock market volatility and examine if the COVID-19 pandemic has had any influence on the market's reaction. The effect of the FOMC meetings on stock market volatility continues on the work from Nikkinen and Sahlström (2004), Vähämaa and Äijö (2011), Rosa (2013) and Zhang et al. (2020) on the topic. By combining the impact of the pandemic on such a widely debated subject in academic literature, this paper aims to contribute to the research and give new insights on market behaviour during a crisis. The main research question will be

"Has uncertainty in the financial market during the COVID-19 pandemic increased the influence of FOMC meetings on the implied volatility for the S&P500 index?".

Besides this research topic being important academically, this paper aims to help determine how monetary policy can best be conducted during times of crisis. Perhaps the outcome of this paper can therefore benefit society by providing insights on how stability can best be ensured in uncertain times.

This paper will be structured into six parts. First, research on the impact of FOMC meetings on the implied volatility during a crisis will be explained in Chapter 2. In addition, Chapter 2 will elaborate on the effects that this study aims to examine. In Chapter 3 the data

[4] Implied volatility represents the markets expectation for the volatility of an option during its lifetime
[5] The VIX used to be based on the S&P100 index but in 2003 this was changed to the S&P500

will be described. The methodology used for the research in this paper will be explained in Chapter 4. Next, Chapter 5 will present the results of the analysis as well as a robustness check. Finally, Chapter 6 will conclude on the findings from this paper, discuss possible limitations, and elaborate on the implications of this study.

2. Behaviour of implied volatility during a crisis

2.1. The impact of FOMC meetings

Prior to macroeconomic news announcements, the volatility of financial asset prices increases due to the uncertainty regarding the information scheduled to be released in the announcements. The FOMC meetings are an example of a macroeconomic news announcement that affects volatility on the financial market. Empirical research on this effect has been done by, for instance, Bomfim (2003), Nikkinen and Sahlström (2004), Chen and Clements (2007), and Vähämaa and Äijö (2011). According to Bomfim, when the FED started to mainly communicate their monetary policy through FOMC meetings from 1993 onwards, the meetings have had a significant impact on volatility in the market. Nikkinen and Sahlström investigated the behaviour of the implied volatility index of the S&P500, the VIX[6], as well. They found a significant decrease of the VIX on FOMC meetings days. Further evidence supporting this was found by Chen and Clements, and Vähämaa and Äijö.

As stated by Nikkinen and Sahlström (2004), the theoretical behaviour of the implied volatility around scheduled news releases is caused by the fact that the information scheduled to be released affects the value of the financial assets. And therefore, it also affects the valuation of these assets. On the day of the scheduled announcement, the volatility will be higher at first just prior to the scheduled news release. Then, after the news release, due to the price adjustment process, the new information will be incorporated into the price reducing the volatility again. The implied volatility can be derived from the Black and Scholes (1973) framework[7] on option pricing. According to their model, all determinants for option pricing can be observed except for volatility. However, by observing the options' characteristics on the market, including its market price, the options' volatility implied by the market can be calculated. This implied volatility can be seen as the market's expectation of future volatility for an option on the market. Combining the expected pattern of the volatility around scheduled news releases, as well as the markets anticipation of this pattern derived through Black-Scholes

[6] From now on, when referring to the VIX, the implied volatility index of the S&P500 is meant.
[7] From now on, when referring to the Black-Scholes framework, the option pricing model by Black and Scholes (1973) is meant.

framework as the implied volatility, the theoretical behaviour of the implied volatility around scheduled news releases over time can be derived.

The announcements following FOMC meetings are an example of macroeconomic news that affects the value of financial assets. This is mainly due to the policy discussed during these meetings. Therefore, the previously presented theoretical analysis by Nikkinen and Sahlström (2004) depicts a possible pattern for the VIX around the FOMC meetings as well.

Furthermore, the COVID-19 pandemic has led to an overall increase in volatility worldwide. Whenever volatility in the market is high, the effect of the FOMC meetings on the VIX is larger than when volatility is low (Krieger et al., 2012). Meaning, a stronger decrease of the VIX is expected on FOMC meeting days during the COVID-19. The main hypothesis for this paper that follows is whether during the COVID-19 crisis the financial market showed significantly higher volatility around the scheduled FOMC meetings, and therefore sharper drops on announcement days, than what would be expected before the crisis. A larger than expected change of the observed implied volatility pre-covid leads to the belief that when the market already deals with great uncertainty, its reaction to uncertain events like the FOMC meetings intensifies.

2.2. The impact of other macroeconomic indicators

In addition to the FOMC meetings, several other macroeconomic news announcements have shown a significant impact on the financial market. As determined by Ederington and Lee (1993), the CPI report, the employment report, and the PPI report are macroeconomic information releases that have the greatest impact on interest rates on the financial market. Continuing on the research by Ederington and Lee, Nikkinen and Sahlström (2004) investigated the releases of these reports as well. They also found a significant impact of the report releases on the VIX. Because the CPI, employment, and PPI reports are also macroeconomic news indicators that affect the value of financial assets, the theoretical pattern that the VIX is expected to follow is similar for these indicators as it is for the FOMC meetings which can be found in Section 2.1.

Investigating the effect of these other macroeconomic indicator is essential for correctly examining the effect of the FOMC meetings. As stated by Bomfim (2003) based on findings by Chen et al. (1999), when using daily data, a possible confounding effect can arise due to the release of multiple types of economic data on the same day. Therefore, it is important to take the release of important macroeconomic news into account besides the FOMC meetings.

Later research by Füss et al. (2011) and Grieb et al. (2016), also found evidence of the significant effect of the CPI, employment, and PPI report on the VIX and they identified aforementioned reports as the most important macroeconomic announcements. The second hypothesis that this paper will therefore test, is whether the COVID-19 pandemic has affected the reaction of the market on other macroeconomic news as well. By doing so, it can be determined if the COVID-19 pandemic only impacts the FOMC meetings or has a broader influence. Meaning, that the pandemic similarly affects the financial market's reaction to other macroeconomic news. If the latter is not the case, this would indicate that the informational content is received differently by the market.

2.3. The impact of a recession

Throughout academic literature, several factors including the business cycle state have been mentioned for having a possible effect on volatility. As an example, this was suggested in recent work by Huang (2018) in a paper examining the reaction of the US bond and equity market to macroeconomic news during and around the financial crisis. The results of the paper indicated that business cycles are one of the determinants that can impact the volatility reaction. Meaning, that during times of recession the uncertainty in the market increases due to the risk associated with the exact value of financial assets. Therefore, this affects the volatility reaction and needs to be taken into account.

In addition, findings by Farka (2009) and Chuliá et al. (2010) also showed that the increase in volatility is stronger during a recession in anticipation of monetary policy changes. As a result, the pre-announcement volatility is more elevated during times of economic contraction compared to economic expansion due to higher market uncertainty. The potential cyclical variation of the response of implied volatility due to FOMC meetings is examined by Vähämaa and Äijö (2011). Their findings indicated that the market reaction to monetary policy as discussed in FOMC meetings, is more pronounced during a recession, when expansive policy is conducted. Therefore, another possible outcome of this paper could be that the larger change in implied volatility is due to the economic climate and not because of the pandemic. The cyclicity of the economy will be added to the model to investigate this effect, which will be done through a variable for whether the economy is in a recession, or not. By doing so, it can be examined whether the expansive monetary policy, as conducted during a recession, is the cause of a strong market reaction. And therefore, it can be determined whether the market expectations of the outcome from FOMC meetings influences the magnitude of their reaction.

3. Data

3.1. FOMC-meeting data

The information on when FOMC meetings are to take place is public and published by the FED. Each year, the FOMC holds eight regularly scheduled meetings and in some cases others when needed (The Federal Reserve, 2021). For this paper the sample will consist of all the FOMC meetings, both scheduled as well as unscheduled, between April 2016 and May 2021. This sample is obtained directly from the FED and contains 41 scheduled meeting days as well as two unscheduled meetings, adding up to a total of 43 FOMC meetings. Due to COVID-19 the two unscheduled meetings occurred in 2020 on 3rd March and 15th March. Even though these meetings were unscheduled and therefore not anticipated by the market, they will be kept in the sample as a robustness test. The robustness test will be conducted because, as suggested by Vähämaa & Äijö (2011), unscheduled meetings have a weaker impact on the VIX compared to scheduled meetings. However, the meeting that occurred on the 15th of March took place on a Sunday. Because the market is closed on Sundays and therefore this date is not included in the business calendar, the unscheduled meeting on the 15th of March was removed from the final sample.

In addition, several FOMC meetings are spread out over two days. The statements made in the meetings are released shortly after the meetings by the FOMC. Therefore, the time at which the statements are released, which is usually briefly after the final meeting day, will be used as an indication on when the meeting took place. This is because after the statement has been released, the market can respond to the outcome of the meeting and the volatility should drop again as hypothesized.

3.2. Macroeconomic report releases

To test the second hypothesis, the three most important macroeconomic news announcements will be added to the sample as well. These will consist of the monthly CPI report, employment report, and PPI report releases. Previous empirical research has identified the CPI, employment, and PPI report as the most important macroeconomic news releases (e.g. Ederington & Lee, 1993, Ederington & Lee, 1996, Füss et al., 2011, Nikkinen & Sahlström, 2004).

Table 3.1

Macroeconomic news announcements

This table represents the number of macroeconomic news announcements between April 2016 and May 2021.

Macroeconomic News	**Scheduled FOMC**	**Unscheduled FOMC**	**CPI report**	**Employment report**	**PPI report**
Number of releases	41	2	61	61	61

Notes: For the unscheduled FOMC meetings one of the observations was removed from the final sample due to this meeting not occurring on a business day.

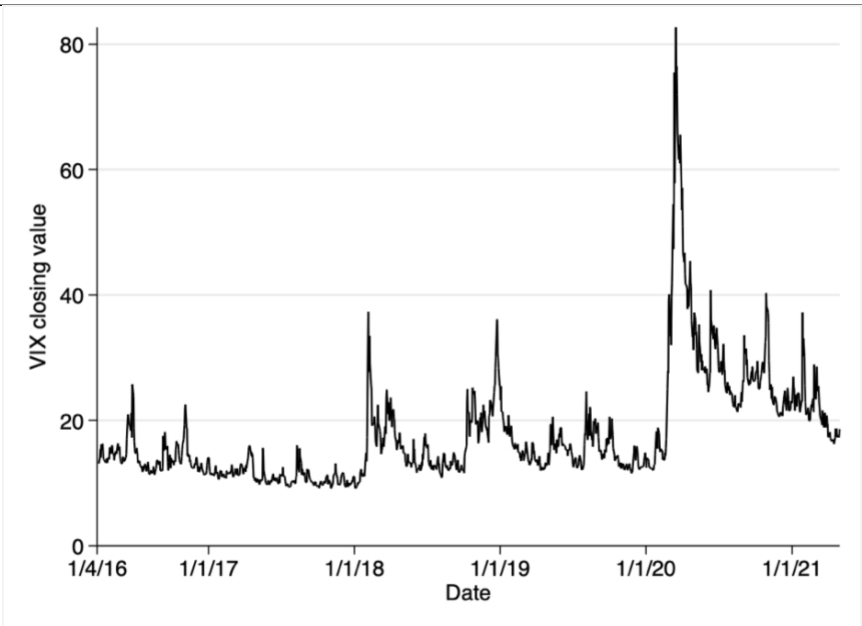
The employment report is released monthly on the third Friday after the reference week is concluded (U.S. Bureau of Labor Statistics, 2021). The CPI report and PPI report follow a schedule that is published by the Bureau of Labor Statistics. The exact publishing dates for the CPI, employment, and PPI report will therefore be obtained from the bureau as well. In total, the sample will contain 183 report release dates between April 2016 and May 2021. Each of the different reports will have 61 individual dates within the sample.

Table 3.1 shows the number of observations for the releases of the scheduled FOMC meetings announcements, unscheduled FOMC meetings announcements, CPI report, employment report, and PPI report.

Figure 3.1

VIX closing values

This figure shows the closing values for the VIX from 1st of April 2016 until the 1st of May 2021. On the Y-axis, the VIX closing values are depicted. The X-axis shows the date range. The data was obtained from Eikon.



3.3. VIX

The VIX is the implied volatility of an index option on the S&P500. It is a powerful proxy for the market's assessment of expected volatility, according to Nikkinen and Sahlström (2004). Macroeconomic uncertainty is strongly linked to the volatility of the US stock market (Arnold & Vrugt, 2008). Therefore, for this paper the VIX will be used as a proxy for uncertainty in the market. The data for the VIX closing values was obtained from Bloomberg.

According to Day and Lewis (1988) measuring implied volatility is often noisy, for example due to transaction costs on the market as well as the inability to observe the option price and the price of the underlying security simultaneously. However, the VIX mitigates most of these problems and is seen as the best measure for implied volatility. Because the VIX does not remove all biases, the changes in volatility will be used for this paper (Butler & Schachter, 1996). The change in implied volatility at day t is calculated by dividing VIX_t by VIX_{t-1} and then taking the natural logarithm. Table 3.2 provides the summary statistics of the VIX. A plot of the closing values of the VIX during the sample period is shown in Figure 3.1.

Table 3.2

Descriptive statistics of VIX

This table shows the descriptive statistics for the VIX from 1st of April 2016 until the 1st of May 2021. Column (2) shows the summary statistics of the level of the VIX based on the closing values. The change in Column (3) depict the summary statistics of the logarithmic percentage change of the VIX.

Statistics	**Level**	**Change[a]**
Mean	17.75	0.02%
Median	14.80	-0.43%
Minimum	9.14	-29.98%
Maximum	82.69	76.82%
S.D.	8.76	8.22
Skewness	2.79	1.61
Excess kurtosis	14.72	12.70
Number of observations	1,326	1,326[b]

[a] Change: ln $(VIX_t - VIX_{t-1})$

[b] When usually calculating change, one observation is lost. However, to ensure that the sample period remains the same, the VIX closing value on the 31st of March 2016 was used to calculate the change on the 1st of April 2016. This observation for the 31st of March 2016 was then dropped.

3.4. The COVID-19 pandemic

On the 25th of February 2020 the Centers for Disease Control and Prevention (CDC) first told the American public to prepare for the outbreak of COVID-19.[8] Therefore, this date will be used as an indication date when the pandemic first started to affect the American financial market. Table 3.3 shows a statistically significant difference of the mean of the closing value of the VIX. However, the logarithmic change in closing value for the VIX does not show any statistical significance pre- and during COVID. In Figure 3.1, a spike can also be observed from the 25th onwards. Closer inspection of the VIX closing value data confirms an increase on the 25th, therefore indicating that the closing value of the VIX was affected by the pandemic.

Table 3.3

Descriptive statistics of the VIX pre- and during COVID

This table represents the descriptive statistics of the mean of the VIX closing values pre-COVID and during COVID, as well as their difference. Column (2) and (3) show the mean pre-COVID and during COVID respectively. In Column (4), the difference between the mean pre- and during COVID is calculated. Row (2) shows the level of the VIX, based on the closing values. Row (3) shows the daily change of the level of the VIX in percentage. The standard errors in Column (4) are in parentheses. The statistical significance stars of the tests in Column (4) are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.

Mean	**Pre-COVID**	**COVID**	**Difference**
Level	14.3922	28.8222	-14.4300***
			(0.4080)
Change[a]	0.0575%	-0.0959%	0.1533%
			(0.5345)
Number of observations	1,017	309	1,326

[a] Change: ln (VIX_t-VIX_{t-1})

4. Methodology

The main research question of this paper, which is whether the COVID-19 pandemic has affected the reaction of the market on FOMC meetings, will be tested by examining if the implied volatility drops more on the announcement dates of the FOMC meetings during the pandemic compared to the period before the announcement. As shown by the research presented in Section 2.1, in the period preceding macroeconomic news announcements like the FOMC meetings, the VIX is hypothesized to gradually increases only to sharply drop back to

[8] From an article written for Reuters by Taylor (2020).

its normal level on the actual announcement date. Due to COVID-19, this drop is expected to be more pronounced during the pandemic compared to before.

To test the hypothesis, a similar regression model as used by Nikkinen and Sahlström (2004) will be estimated. The model that will test the first hypothesis will be

$$\ln(VIX_t/VIX_{t-1}) = \alpha + \beta D_{0,t}^{S\_FOMC} + \gamma D_{0,t}^{S\_FOMC} * D_{0,t}^{COVID} + \epsilon_i \ . \quad (1)$$

Where VIX_t is the implied volatility of the S&P500, derived from the closing values of the VIX, at day *t*. $D_{0,t}^{S\_FOMC}$ is a dummy variable for the days on which the scheduled FOMC meeting announcements are released. $D_{0,t}^{COVID}$ is a dummy variable for when the COVID-19 pandemic started. Finally, $D_{0,t}^{S\_FOMC} * D_{0,t}^{COVID}$ is an interaction term between the two dummy variables.

The theory presented in Section 2.1 leads to the following formal hypothesis.

Hypothesis 1. *Null:* The impact of FOMC meetings on the implied volatility has not changed during COVID (meaning $\gamma=0$). *Alternative:* The uncertainty in the market during COVID has resulted in a stronger decrease of implied volatility (meaning $\gamma<0$) on FOMC meeting announcement days.

In addition, in accordance with the theory, the coefficient $\alpha>0$ because the implied volatility is expected to increase on days with no macroeconomic news announcements. Also, because the implied volatility is expected to decrease on scheduled FOMC days regardless of the pandemic, it is hypothesized that $\beta<0$.

As discussed in Section 2.2, other macroeconomic news announcements, besides the FOMC meetings, have a possible significant effect on the level of the VIX on their release dates. To prevent a confounding effect, these news releases are added to the model as well. The general behaviour of the VIX is hypothesized to be the same for the CPI, employment, and PPI report release in comparison to the FOMC meeting announcements. However, the CPI, employment, and PPI report release may impact the VIX differently during the pandemic compared to the FOMC meetings. Therefore, for the second hypothesis, Model 1 will be extended to examine whether this is the case. The model that will test the second hypothesis will be

$$\ln(VIX_t/VIX_{t-1}) = \alpha + \beta D_{0,t}^{S\_FOMC} + \gamma D_{0,t}^{S\_FOMC} * D_{0,t}^{COVID} + \delta D_{0,t}^{CPI} + \theta D_{0,t}^{CPI} * D_{0,t}^{COVID} + \mu D_{0,t}^{Employ} + \pi D_{0,t}^{Employ} * D_{0,t}^{COVID} + \rho D_{0,t}^{PPI} + \tau D_{0,t}^{PPI} * D_{0,t}^{COVID} + \varepsilon_i \ . \quad (2)$$

Where VIX_t is the implied volatility of the S&P500, derived from the closing values of the VIX, at day *t*. $D_{0,t}^{S\_FOMC}$ is a dummy variable for the days on which the scheduled FOMC meeting announcements are released. $D_{0,t}^{CPI}$ is a dummy variable for the CPI report release. $D_{0,t}^{Employ}$ is a dummy variable for the employment report release. $D_{0,t}^{PPI}$ is a dummy variable for the PPI report release. $D_{0,t}^{COVID}$ is a dummy variable for when the COVID-19 pandemic started. $D_{0,t}^{MACROECONOMIC\_NEWS} * D_{0,t}^{COVID}$ is an interaction term between a macroeconomic news announcement variable (e.g. FOMC meetings announcements, CPI report, PPI report, and employment report release) and the dummy variable for COVID.

The theory presented in Section 2.2 leads to the following formalized hypothesis for Model 2.

Hypothesis 2. *Null:* The impact of macroeconomic news announcements, for example CPI, PPI, and employment report, on the implied volatility has not changed during COVID (meaning $\theta=0$, $\pi=0$, and $\tau=0$). *Alternative:* The uncertainty in the market during COVID has resulted in a stronger decrease of implied volatility on days when other macroeconomic news announcements (meaning $\theta<0$, $\pi<0$, and $\tau<0$).

In addition, in accordance with the theory and Model 1, the coefficient $\alpha>0$ because the implied volatility is expected to increase on days with no macroeconomic news announcements. Also, because the implied volatility is expected to decrease on macroeconomic news announcement days regardless of the pandemic, it is hypothesized that $\delta<0$, $\mu<0$, and $\rho<0$. The FOMC meeting dummy variable as well as the interaction term with the COVID dummy, are left in the model. Therefore, it is also possible to revisit the findings of Hypothesis 1 and test whether the coefficients for the FOMC meetings are robust when adding other macroeconomic news announcements.

Finally, as explained in Section 2.3, it is possible that a stronger market reaction is caused by the state of the economy. For example, when expansive monetary policy is conducted during a recession, this may cause a strong market reaction. Most of the monetary policy by the FED is communicated through the FOMC meeting announcements. By adding a dummy variable to Model 1 for the state of the economy, it can be examined whether larger changes in the closing value for the VIX occur during a recession. To test the third and final hypothesis, Model 1 will be extended. The model that will test the third hypothesis will be

$$\ln(VIX_t/VIX_{t-1}) = \alpha + \beta D_{0,t}^{S\_FOMC} + \gamma D_{0,t}^{S\_FOMC} * D_{0,t}^{COVID} + \delta D_{0,t}^{RECESSION} + \varepsilon_i \,. \tag{3}$$

Where VIX_t is the implied volatility of the S&P500, derived from the closing values of the VIX, at day t. $D_{0,t}^{S\_FOMC}$ is a dummy variable for the days on which the scheduled FOMC meeting announcements are released. $D_{0,t}^{COVID}$ is a dummy variable for when the COVID-19 pandemic started. $D_{0,t}^{RECESSION}$ is a dummy variable indicating whether the economy is in a recession ($D_{0,t}^{RECESSION} = 1$) or not ($D_{0,t}^{RECESSION} = 0$). $D_{0,t}^{S\_FOMC} * D_{0,t}^{COVID}$ is an interaction term between the two dummy variables.

The theory presented in Section 2.3 leads to the following formalized hypothesis for Model 3.

Hypothesis 3. *Null:* The state of the economy does not have a statistically significant impact on the change in implied volatility (meaning $\delta=0$). *Alternative:* When the economy is in a recession, the uncertainty in the market results in larger daily changes in implied volatility (meaning $\delta<0$ or $\delta>0$).

In addition, in accordance with the theory and Model 1, the coefficient $\alpha>0$ because the implied volatility is expected to increase on days with no macroeconomic news announcements. Also, because the implied volatility is expected to decrease on scheduled FOMC days, it is hypothesized that $\beta<0$. The interaction term from Hypothesis 1, which is expected to be $\gamma<0$, will be left in the model as well to test whether the coefficient is robust when controlling for the cyclicity of the economy.

Statistical tests and empirical research indicate that several specifications need to be added to all three models. To test for serial correlation Godfrey's test is used, which is the preferred option to the Durban Watson test. Following the findings from Nikkinen and Sahlström (2004), who also conducted Godfrey's test, there is statistically significant first order autocorrelation present. By adding an AR(1) effect to the model, the first order autocorrelation is accounted for. Second, when using the Lagrange Multiplier (LM) test, evidence for heteroskedasticity in the error terms is found. Therefore, a GARCH(1,1) specification is added to the models. The coefficients from the GARCH(1,1) specifications show statistical significance in the models. In addition, when repeating the LM tests it can be concluded that the GARCH(1,1) specification for the models is adequate. Finally, to the tests pointing out that the error terms are heteroskedastic and show significant autocorrelation, HAC-standard errors are used for all the models (Brooks, 2019).

Because previous literature uses a student distribution (e.g., Nikkinen & Sahlström, 2004, Vähämaa & Äijö, 2011), this is also applied to this model. The regular GARCH model assumes a normal distribution, which is not necessarily the case with financial data. Therefore, the t-distribution will be used for this paper. However, by using a t-distribution certain assumptions are made which can result in possible biases (Brooks, 2019). Nonetheless, these biases are noted and will be taken into consideration when interpreting the results.

5. Results

5.1. FOMC meetings and the VIX change

The results from Model 1 are reported in Table 5.1. Firstly, in contrast to Hypothesis 1, on a 1% significance level[9] the constant term α is smaller than zero. This implies that the VIX decreases on days without macroeconomic report releases. The estimation results therefore already showed a different outcome in comparison to previous literature. Secondly, both the coefficients for the scheduled FOMC meeting announcement release, as well as the interaction term of the release dummy with the pandemic, are not statistically significant on a 10% level. As a result, the null hypothesis[10] cannot be rejected. Meaning that there is no statistically significant evidence that indicates that the FOMC meetings have had any additional uncertainty reducing effect on the market during the pandemic.

A number of implications for economic theory follow from the outcome of this regression. Firstly, it was expected that whenever volatility in the market is high, the effect of the FOMC meetings on the VIX would be larger than when market volatility is low (Krieger et al., 2012), and in addition, Zhang et al. (2020) also found evidence of an increase in worldwide implied volatility during the pandemic. However, even though this would mean that the markets reactions should be stronger during the pandemic, this effect was not observed in the regression. Meaning, that this paper was unable to find evidence that heightened market uncertainty results in a sharper VIX decrease on FOMC meetings days.

Secondly, the Black-Scholes framework, through which the implied volatility can be calculated, leads to the expectation of a certain pattern in the behaviour of the VIX (Section 2.1). Upcoming news that affects the underlying value of an asset should result in an increase of implied volatility prior to their announcements. Therefore, the FOMC meetings should have a significant VIX decreasing impact because their informational contents affect S&P500 asset value. However, the impact was not observed in this regression, meaning that the findings are not in line with the expectations following the Black-Scholes framework. Because the overall uncertainty reducing effect of the FOMC meetings cannot be confirmed, two possible explanations can be given. Either the limitations of this paper have affected the outcome, or otherwise the underlying asset values is less affected by the FOMC meetings than expected. Nonetheless, the results should be interpreted with caution and further research is necessary.

[9] From now on, when referring to an X% level, a X% significance level is meant.
[10] From now on, when referring to H0, the null hypothesis is meant.

Table 5.1

Regression results Model 1 and 2

This table shows the regression results for Model 1 and 2. The regressions use the first difference of the natural logarithm of the VIX as a dependent variable. Column (1) shows the variables used in the models, as described in Chapter 3 and 4. Column (2) and (3) show the regression results for the Models 1 and 2 respectively. The announcement days dummy variables take on a value of 1 on the day of the announcement or are zero otherwise. The dummy variables for the pandemic takes on a value of 1 from the start of the pandemic. The HAC standard errors in Column (2) and (3) are in parentheses. The AIC and BIC are reported in Row (20) and (21) respectively. The Wald test statistics are reported in Row (22). A t-distribution is used to estimate the coefficients. The statistical significance stars are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.

Coefficient	**Model 1**	**Model 2**
Intercept	-0.0045***	-0.0028*
	(0.0015)	(0.0015)
Scheduled FOMC meetings	0.0016	- 0.0008
	(0.0103)	(0.0104)
S_FOMC*COVID	-0.0201	-0.0206
	(0.0155)	(0.0160)
CPI report		-0.0077
		(0.0077)
CPI*COVID		0.0026
		(0.0202)
Employment report		-0.0378***
		(0.0110)
Employment*COVID		0.0014
		(0.0172)
PPI report		-0.0012
		(0.0134)
PPI*COVID		0.0134
		(0.0211)
ARMA		
AR(1)	-0.0660**	-0.0685**
	(0.0267)	(0.0274)
ARCH		
Constant	0.0010***	0.0010***
	(0.0003)	(0.0003)

ARCH(1)	0.1911***	0.2015***
	(0.0525)	(0.0548)
GARCH(1)	0.6900***	0.6804***
	(0.0574)	(0.0586)
Observations	1,326	1,326
AIC	-3,319	-3,330
BIC	-3,278	-3,258
Wald test	9.2300**	28.8500***

5.2. Macroeconomic news and the VIX change

To test Hypothesis 2, whether other important macroeconomic announcements had any uncertainty reducing effect during the pandemic, Model 2 was formed. The results from estimating this model can be found in Table 5.1. Firstly, in contrast to prior literature and consistent with Model 1, the constant term α is smaller than zero on a 10% level. Meaning that the VIX decreases on days without macroeconomic report releases.

Secondly, the coefficients for the CPI and PPI report release, as well as their interaction terms with the pandemic, are not statistically significant on at least a 10% level. Meaning that the H0 cannot be rejected implying that there is not enough statistical evidence that the CPI and PPI report releases have any additional uncertainty reducing effect during the pandemic. Furthermore, the results indicated that the overall uncertainty reducing effect of these releases as found in prior literature are not statistically significant in this sample.

Finally, the coefficient from the employment report showed statistical significance on a 1% level. This is in accordance with prior literature and implies that there is statistical evidence that the VIX decreases on the days that the employment reports are released. However, for Hypothesis 2 the main goal was to examine whether the release of other macroeconomic reports during COVID had any additional uncertainty reducing effect. Because the interaction term between the employment report release and the pandemic does not show statistical significance on at least a 10% level, it can be concluded that for the employment report this is not the case. Meaning that the H0 cannot be rejected for this macroeconomic report release as well, because there is insufficient statistical evidence that the coefficient is not zero.

As mentioned, the results from this regression are not fully in line with economic theory. Accordingly, this has several implications. Firstly, the additional volatility reducing effect for the release of the CPI, employment, and PPI reports during COVID was not observed.

Even though these are some of the most important macroeconomic indicators, these findings imply that their content do not have a greater market impact during the pandemic. Therefore, regardless of the increase in implied volatility during the pandemic[11], macroeconomic news has had no additional uncertainty reducing effect. According to these findings, it can be concluded that the timing at which important macroeconomic indicators are released is not an important factor during a crisis.

Secondly, even though the CPI and PPI reports are both important macroeconomic indicators, an overall VIX decreasing effect is found only with the release of the employment report release. This strongly contradicts earlier findings, where a significant effect was observed with the release of the CPI and PPI reports. One possible explanation could be that the CPI and PPI report have lost their macroeconomic importance. However, this seems highly unlikely because fairly recent work still appears to find evidence for the importance of these indicators (e.g., Füss et al., 2011, Grieb et al., 2016). In addition, the reason that the employment report has a highly significant impact on the VIX could be due to it being released together with other important macroeconomic indicators (Chan & Gray, 2018). As a result, the effect is the result of the entire Employment Situation Report rather than the employment report in isolation (U.S. Bureau of Labor Statistics, 2021).

The third and final remark is whether there is a confounding effect between FOMC meetings and the CPI, employment, and PPI report releases. As suggested by the theory in Section 2.2, when using daily data, the effect of multiple releases on a single day can be captured (Bomfim, 2003). Nonetheless, in this study daily data was still used to estimate the results. However, by adding macroeconomic indicators announcements with the FOMC meetings, this should help to prevent the aforementioned bias and isolate the effect of the FOMC meetings. Because the regression results in Table 5.1 show no increase in significance for the FOMC coefficient, this could imply that the confounding effect between different indicators announcements is not as strong as expected. For future economic research, this could mean that a confounding effect should be taken into account when news releases occur on the same day, as is the case with the employment report release. Nonetheless, a confounding effect does not seem to be important when estimating the effect of releases occurring on different days.

[11] See Table 3.3.

5.3. Recession, FOMC meetings and the VIX change

Model 3 was formed to test Hypothesis 3. The results from this estimation are shown in Table 5.2. Firstly, the constant coefficient α is smaller than zero on a 10% level. This outcome is similar to Model 2 and also consistent with the findings from Model 1. However, previous literature indicated that α was expected to be larger than zero due to the VIX increasing on days without macroeconomic report releases.

Secondly, the recession coefficient in Model 3 was added to the regression to investigate whether the state of the economy impacts the magnitude of the market reaction. As can be seen in Table 5.2, the coefficient for the recession is not statistically significant on at least a 10% level. Implying that there is no relationship between the change in implied volatility and the state of the economy, which is in contrast to what was suggested in prior literature. Therefore, the H0 cannot be rejected meaning that there is not enough significant statistical evidence in this sample to conclude that the state of the economy affects the change in implied volatility.

In addition, the recession coefficient was also added to examine whether the outcome of Model 1 was robust when the state of the economy was included. As shown in Table 5.2, this is not the case due to two reasons. The first reason, as explained in Section 5.1, is that there is no statistically significant evidence with regard to a change in market reaction on the FOMC meetings during COVID. The second reason, when controlling for the state of the economy, the statistical significance of the market reaction to FOMC meetings during COVID is not affected. To conclude, no connection is found in this paper between the state of the economy and an increased daily change in implied volatility.

The findings from the third and final model would have one main implication for economic literature. That is, if the state of the economy does not affect implied volatility, this would imply that the cyclical variation does not have to be added to models for a correct estimation of the effect of the FOMC meetings. However, because there is sufficient proof in economic theory that the state of the economy does affect the reaction in the market, this seems highly unlikely (see e.g., Chuliá et al., 2010; Farka, 2009; Vähämaa & Äijö, 2011).

Table 5.2

Regression results Model 1 and 3
This table shows the regression results for Model 1 and 3. The regressions use the first difference of the natural logarithm of the VIX as a dependent variable. Column (1) shows the variables used in the models, as described in Chapter 3 and 4. Column (2) and (3) show the regression results for

the Models 1 and 3 respectively. The announcement days dummy variables take on a value of 1 on the day of the announcement or are zero otherwise. The dummy variables for the pandemic takes on a value of 1 from the start of the pandemic. The HAC standard errors in Column (2) and (3) are in parentheses. The AIC and BIC are reported in Row (15) and (16) respectively. The Wald test statistics are reported in Row (17). A t-distribution is used to estimate the coefficients. The statistical significance stars are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.

Coefficient	**Model 1**	**Model 3**
Intercept	-0.0045***	-0.0037*
	(0.0015)	(0.0015)
Scheduled FOMC meetings	0.0016	0.0007
	(0.0103)	(0.0104)
S_FOMC*COVID	-0.0201	-0.0164
	(0.0155)	(0.0160)
Recession		-0.0034
		(0.0035)
ARMA		
AR(1)	-0.0660**	-0.0664**
	(0.0267)	(0.0268)
ARCH		
Constant	0.0010***	0.0010***
	(0.0003)	(0.0002)
ARCH(1)	0.1911***	0.1899***
	(0.0525)	(0.0524)
GARCH(1)	0.6900***	0.6912***
	(0.0574)	(0.0574)
Observations	1,326	1,326
AIC	-3,319	-3,318
BIC	-3,278	-3,271
Wald test	9.2300**	10.3900***

5.4. General remarks on the results

A few general remarks can be made on the results from the regression models estimated in this paper. Firstly, usually the R-squared (or Adjusted R-squared) is used to examine how well the model fits the data. However, due to heteroskedastic and autocorrelated errors, (G)ARCH and AR coefficients were added to the models. As a result, different methods have to be used to investigate the fit of the models (Brooks, 2019).

Secondly, as an alternative method to compare the fit of the models, the information criteria (IC) were used. This was suggested by Brooks (2019) as one of the options to investigate the best model, where the model with the lowest IC is the preferred model. When selecting based on AIC (Akaike information criterion), Model 2 is the most adequate model. When selecting on the BIC (Bayesian information criterion), Model 1 is the most adequate model for the data. However, because the AIC and BIC cannot be compared, the outcome is inconclusive as to whether Model 1 or 2 is the best fit for the data.

The third remark is on the use of a Wald test. A Wald test statistic is used as a replacement for the F-test to indicate whether variables can be removed from the model, without affecting its fit and therefore implying that at least one of the coefficients in the model is equal to zero. Because several of the regression coefficients estimated for Models 1, 2, and 3 are not significant on a 10% level, as can be seen in Table 5.1 and 5.2, the conclusion based on the Wald tests is as follows. For Model 1, the Wald test statistic implies that on a 5% level, one of the coefficients from the model can be removed without affecting the fit of the model. While for Models 2 and 3, the same conclusion can be drawn but on a 1% level.

5.5. Robustness Test

To test whether the results from this paper are robust, three robustness checks were conducted. They are the sensitivity of the outcomes to outliers will be tested, an event day estimation as recommended by Vähämaa and Äijö (2011), and a sub-sample regression to test the sensitivity of the results in different time periods.

5.5.1. Sensitivity Analysis: Outliers

Throughout this analysis, two papers have been used as the general guideline. The first paper by Nikkinen and Sahlström (2004), and the second by Vähämaa and Äijö (2011). The descriptive statistics of the VIX from the aforementioned papers were noticeably different when compared to the descriptive statistics of the sample used in this paper, in particular the sample ranges. Therefore, the sensitivity of this analysis to outliers will be examined. However, instead of trimming the data by removing the outliers, a process called winsorization will be used to test the robustness of this paper. By doing so, instead of losing valuable observations, the value of the outliers in the bottom and in the top 5^{th} percentile will be set to the minimum value of the 5^{th} and the maximum value of the 95^{th} percentile respectively. This process will affect the closing values of the VIX, after which the three models will be re-estimated with the new logarithmic differences (Blaine, 2018).

The results from the winsorization can be found in Appendix 8.1 and the process has led to the following findings. First of all, the winsorization was done to the VIX closing values.

In Table 8.1 contains the new descriptive statistics for the winsorized closing values and the newly calculated changes. When comparing this table to Table 3.2, it is clear that the outliers in the closing values have decreased significantly. However, when looking at the change in VIX closing values, the difference between the outliers in Table 8.1 and 3.2 is not that significant. This is probably caused by the fact that large changes in VIX closing values also occurred between the 5th and 95th percentiles of the VIX closing value data. Therefore, the impact of removing the outliers of the VIX closing values by winsorization did not result in an obvious change in VIX closing value.

Secondly, when examining the re-estimated regression results with the new change in VIX, it is clear that the winsorization has not had a significant impact on the outcomes. The results from the re-estimation can be found in Table 8.2. By removing the outliers, the statistical significance of almost all the (previously) significant coefficients has dropped or remained unchanged. All the regular model coefficients remain insignificant. In addition, the AR and ARCH effects dropped in significance.

To conclude, by removing the outliers, the robustness of the findings from this paper was tested by changing the most extreme closing values. The result indicated that the initial model was sufficiently robust for extreme closing values. The main reason for this was probably due to the fact that instead of actual values, the logarithmic change in closing values was used. Therefore, the actual dependent variable in the regression was not that strongly affected by the winsorization. The conclusion that the outcome of this paper is fairly robust to outliers can therefore be drawn.

5.5.2. Event day regression

Vähämaa and Äijö (2011) use an event-day regression approach to test whether their findings are consistent. An event-day regression uses only event days as observations in the regression instead of the full dataset (Basistha & Kurov, 2008). In this paper, four different macroeconomic announcements were modelled. Namely the FOMC meetings announcements, CPI report, employment report, and PPI report. Model 1 used only scheduled FOMC meetings announcements. Therefore, the 41 observations for FOMC meetings will remain in the model and be used to re-estimate. Model 2 contained the CPI, employment, and PPI report releases in addition to the scheduled FOMC meetings announcements, resulting in a total of 215 observations. Finally, in Model 3 the first model was extended with a dummy variable for whether the economy was in a recession or not. Even though the state of the economy is not necessarily an event-day, the number of recession days will be used in the event-day regression, resulting in a total number of 471 observations.

In Appendix 8.2 the results of the event-day regressions of the models are reported. The outcomes showed that the re-estimated event day regressions did not change the findings of this paper. The coefficients of the regressions are reported in Table 8.3. One surprising result is that for Model 3, the coefficient for the interaction term between scheduled FOMC meetings and the pandemic showed statistical significance on a 10% level. This was not the case in the previously conducted regressions in Section 5.3. This implies that when running an event-day regression and controlling for the state of the economy, there is a statistically significant uncertainty reducing effect of the FOMC meetings during the pandemic. Nonetheless, this result should be interpreted with caution because there may be other reasons as to why this coefficient is suddenly significant. In conclusion, the findings from this paper are robust when performing a regression solely on event day data.

5.5.3. Sub-sample regression: pre-COVID estimation

As a final robustness test, a sub-sample regression will be performed on the data from the sample period pre-COVID. Table 3.3 shows that there is a statistically significant difference between the mean of the VIX closing values pre-COVID and during COVID. Therefore, this is an indication of a different behaviour of the VIX before the pandemic.

The result of this paper has not generated any outcome that is similar to what previous literature would suggest. A possible cause could be due to the different behaviour the VIX during the pandemic which in turn affected the statistical significance of the results. To test whether this is the case, the results will be re-estimated but now by only using the sample period pre-COVID. Those results can then be compared to the findings from previous economic literature to check if the subsample does generate the expected outcomes.

A couple of consequences have to be taken into consideration when performing this sub-sample regression. Firstly, the main consequence is that the interaction terms from the Models 1, 2, and 3, as well as the recession term from Model 3, cannot be estimated. Even though these interaction terms are the main interest of this paper, the purpose of this sub-sample regression is not to show the robustness of the findings, but more to show the robustness of the data. In addition, because the recession dummy variable has a value of zero in the sub-sample[12], this coefficient has to be dropped from the regression as well, therefore, eliminating Model 3 altogether. Secondly, the date that was identified as the start of the pandemic is the 25th of February 2020. Because the sub-sample regression will not use all the data from this date

[12] Meaning, the economy was not in a recession in the period preceding COVID.

onwards, this removes a large part of the original sample. As a result, the remaining sub-sample may not be large enough to correctly estimate the results.

Appendix 8.3 shows the results from the pre-COVID sub-sample regression. Table 8.4 contains the new descriptive statistics for the sub-sample followed by the report of the new regression models. Table 8.5 shows the sub-sample regression results from Models 4 and 5.

The aim of this robustness check was to test whether the sub-sample would generate similar results to what was previously estimated in this paper, or if it is more in line with other empirical findings. From the results in Table 8.5 several conclusions can be drawn. Firstly, the coefficients that both the sub-sample Models 4 and 5 as well as the full sample Models 1 and 2 respectively contain, appear to be robust even when the samples were changed. Meaning, that apart from the employment report release, still no statistical significance was found on the volatility reducing effect for the CPI report, PPI report, and FOMC meetings announcements. These results are consistent with the previous findings from this paper.

Secondly, by changing the sub-sample period, similar outcomes to what previous economic literature would suggest were not found (see e.g., Nikkinen & Sahlström, 2004, Vähämaa & Äijö, 2011). The sub-sample regression did not find any evidence of an increase in implied volatility during the days without macroeconomic news announcements. In addition, with the exception of the employment report release, the expected volatility reducing effect from the macroeconomic news announcements in Model 5 was also not been found. Implying that the findings from previous literature cannot be confirmed by this dataset.

Consequently, this robustness check has shown that the findings from this paper do not change when the sample period is changed.

6. Conclusion

Important macroeconomic news is closely followed by the financial market. Because their contents can include valuable information about assets, the news releases can decrease uncertainty in the market when their implications become public knowledge. The VIX, which is the implied volatility index of the S&P 500, can be seen as a measure for market uncertainty. The aim of this study was to examine whether the influence of FOMC meetings on VIX has increased during the COVID-19 pandemic. In specific, it investigated if the FOMC meetings announcements had additional uncertainty reducing effect during the pandemic.

When investigating the literature on the subject, several other macroeconomic indicators and factors were added to the model with reference to previous literature suggesting their significance in affecting uncertainty. These factors are the CPI, employment, and PPI report releases, as well as the state of the economy. By combining the aforementioned factors together with the FOMC meeting announcement releases, the impact of the pandemic on the market reaction to these variables was tested. In accordance with prior literature, a regression model was estimated similar to Nikkinen and Sahlström (2004), and Vähämaa and Äijö (2011). However, the outcome of this paper resulted in different findings compared to previous studies. These will now be discussed.

The first hypothesis tested if the uncertainty in the market during COVID resulted in a stronger decrease of implied volatility on FOMC meeting announcement days. The results from this study did not find any evidence supporting this hypothesis. In contrast to prior literature, the FOMC meetings did not show statistically significant evidence on the reduction of the VIX.

The second hypothesis tested if the uncertainty in the market during COVID resulted in a stronger decrease of implied volatility on days, than what was expected pre-COVID, when other macroeconomic news announcements were done. Again, no statistical evidence was found on any additional VIX reducing effect for the investigated macroeconomic news announcements during the pandemic. In addition, despite previous empirical evidence, for the FOMC meetings, the CPI, and the PPI report releases, no statistical significance was found for any volatility reducing effect at all. However, the employment report release did show a statistically significant volatility reducing effect.

The third and final hypothesis tested if when the economy is in a recession, the uncertainty in the market would result in larger daily changes in implied volatility. Similarly, in spite of empirical work showing a statistically significant effect of the state of the economy on the VIX, the findings of this paper do not draw the same conclusion. Nevertheless, this may be the result of a bias due to a possible confounding effect between the state of the economy and the pandemic.

A number of limitations have to be taken into account when interpreting the results and outcome of this paper. First of all, the dataset used in this paper generates different results compared to the empirical findings from, for example, Nikkinen and Sahlström (2004), and Vähämaa and Äijö (2011). A possible explanation could be that the implied volatility has behaved differently over the sample period used in paper as compared with the sample period used in previously mentioned work. The descriptive statistics of the aforementioned papers show noticeably different means, range, and standard deviation when comparing to the descriptive statistics of the sample used in this paper. In addition, another possible explanation as to why the results differ from Nikkinen and Sahlström, and Vähämaa and Äijö is that in 2003, the Chicago Board Option Exchange (CBOE) changed the method through which the

VIX was calculated due to fundamental changes in index option market structure (Whaley, 2009). As a result, because sample used by Nikkinen and Sahlström predates 2003 this could generate different outcomes. Even though Vähämaa and Äijö used a sample that did include the level of the VIX after the changes were implemented by the CBOE, they did not take this change into account and can therefore bias their results as well. The difference in descriptive statistics, as well as the new method used for computing the VIX can affect the outcome and thereby the lack of statistical significance for the results in this paper.

Another limitation that can cause the results from this paper to differ from previous empirical findings can be due to technical differences. The techniques used to estimate the models by, for example, Nikkinen and Sahlström (2004), and Vähämaa and Äijö (2011), can be different from the ones used in this paper. For example, if the daily change in VIX closing values were computed differently in those papers, this could lead to different regression outcomes. Also, the aforementioned papers do not clarify what exact estimation technique were used to run the models. All in all, technical differences can influence the findings from this paper.

The third limitation, as mentioned, is whether the results from Model 3 can be correctly interpreted. Because the start of the COVID pandemic coincides with the start of the recession, the separate effect of the two variables cannot be correctly estimated. It is therefore uncertain if the change in implied volatility is due to either of these effects, or if it is caused by a confounding effect. To correctly examine the effect of the two variables, future research must increase the sample period to include at least two periods of recession. By doing so, the effect of a recession can be determined and isolated, and allow for a better estimation of the impact of the pandemic on implied volatility.

The fourth limitation is related to the surprise element as described by Vähämaa and Äijö (2011). They documented that the outcome of FOMC meetings determines how strong the market reacts. Meaning that whether the market is positively or negatively surprised by the contents of the meetings influences their reaction. This effect was not examined in this study and may be important to investigate for future research.

The final limitation is a possible confounding effect between the CPI and PPI report release. Because the CPI report is released just briefly after the PPI report release and their informational content is strongly dependent on one another, it can possibly affect the outcome (Nikkinen & Sahlström, 2004). Therefore, for future research it is important to take this into account and perhaps examine if the two effects can be combined as a single report release.

Another option would be to use intraday data instead of daily data for a more precise estimation of the effects of these report releases.

The main objective of this paper was to show how policy making, as conducted in FOMC meetings, could best be done during times of crisis. The general idea was that the FED could increase certainty during uncertain times. However, as this paper generated inconclusive results, recommendations are therefore not possible. Solely based on literature review, uncertainty reducing effect was expected but this was not supported by this paper due to the lack of statistical significance. Future research could revisit the models, adapt them where necessary and use different estimation techniques to further investigate the relationship.

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8. Appendix

8.1. Sensitivity Analysis: Outliers

Table 8.1

Descriptive statistics of winsorized VIX closing values		
This table shows the descriptive statistics for the winsorized VIX closing values from 1st of April 2016 until the 1st of May 2021. Winsorizing was done to the bottom and top 5% of the sample. Column (2) shows the summary statistics of the level of the VIX based on the closing values. The change in Column (3) depict the summary statistics of the logarithmic percentage change of the VIX.		
Statistics	**Level**	**Change**[a]
Mean	17.18	0.02%
Median	14.80	0.00%
Minimum	10.03	-29.98%
Maximum	33.42	65.78%
S.D.	6.51	7.51
Skewness	1.09	1.45
Excess kurtosis	3.23	11.50
Number of observations	1,362	1,362[b]

[a] Change: ln (VIX_t-VIX_{t-1})

[b] When usually calculating change, one observation is lost. However, to ensure that the sample period remains the same, the VIX closing value on the 31st of March 2016 was used to calculate the change on the 1st of April 2016. This observation for the 31st of March 2016 was then dropped.

Table 8.2

Regression results Model 1, 2, and 3			
This table shows the regression results for Model 1, 2, and 3. The regressions use the first difference of the natural logarithm of the VIX as a dependent variable. Column (1) shows the variables used in the models, as described in Chapter 3 and 4. Column (2), (3), and (4) show the regression results for the Models 1, 2, and 3 respectively. The announcement days dummy variables take on a value of 1 on the day of the announcement or are zero otherwise. The dummy variable for the pandemic takes on a value of 1 from the start of the pandemic. The dummy variable for the recession takes on a value of 1 from the start of the recession. The HAC standard errors in Column (2), (3), and (4) are in parentheses. The AIC and BIC are reported in Row (21) and (22) respectively. The Wald test statistics are reported in Row (23). A t-distribution is used to estimate the coefficients. The statistical significance stars are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.			
Coefficient	**Model 1**	**Model 2**	**Model 3**
Intercept	-0.0028*	-0.0019	-0.0031*

	(0.0016)	(0.0012)	(0.0018)
Scheduled FOMC	0.0007	0.0000	0.0011
meetings	(0.0084)	(0.0087)	(0.0085)
S_FOMC*COVID	-0.0288	-0.0283	-0.0299
	(0.0209)	(0.0197)	(0.0218)
CPI report		-0.0032	
		(0.0068)	
CPI*COVID		0.0023	
		(0.0115)	
Employment report		-0.0296**	
		(0.0116)	
Employment*COVID		0.0101	
		(0.0158)	
PPI report		-0.0035	
		(0.0065)	
PPI*COVID		0.0126	
		(0.0122)	
Recession			0.0009
			(0.0022)
ARMA			
AR(1)	-0.0536*	-0.0589**	-0.0539**
	(0.0273)	(0.0279)	(0.0274)
ARCH			
Constant	0.0006	0.0007	0.0006
	(0.0006)	(0.0004)	(0.0008)
ARCH(1)	0.5139	0.4490*	0.5238
	(0.4705)	(0.2566)	(0.5594)
GARCH(1)	0.6689***	0.6699***	0.6688***
	(0.0640)	(0.0537)	(0.0693)
Observations	1,326	1,326	1,326
AIC	-3,590	-3,595	-3,588
BIC	-3,548	-3,522	-3,541
Wald test	6.5400*	17.0100**	6.3900

8.2. Event day regression

Table 8.3

Event-day regression results for Model 1, 2, and 3

This table shows the event-day regression results for Model 1, 2, and 3. The regressions use the first difference of the natural logarithm of the VIX as a dependent variable. Column (1) shows the variables used in the models, as described in Chapter 3 and 4. Column (2), (3), and (4) show the regression results for the Models 1, 2, and 3 respectively. The announcement days dummy variables take on a value of 1 on the day of the announcement or are zero otherwise. The dummy variable for the pandemic takes on a value of 1 from the start of the pandemic. The dummy variable for the recession takes on a value of 1 from the start of the recession. The HAC standard errors in Column (2), (3), and (4) are in parentheses. The AIC and BIC are reported in Row (21) and (22) respectively. The Wald test statistics are reported in Row (23). A t-distribution is used to estimate the coefficients. The statistical significance stars are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.

Coefficient	**Model 1**	**Model 2**	**Model 3**
Intercept	-0.0095***	-0.0067**	-0.0167***
	(0.0027)	(0.0031)	(0.0052)
Scheduled FOMC	0.0076	0.0054	0.0151
meetings	(0.0093)	(0.0092)	(0.0103)
S_FOMC*COVID	-0.0200	-0.0210	-0.0300*
	(0.0152)	(0.0151)	(0.0162)
CPI report		-0.0067	
		(0.0082)	
CPI*COVID		0.0069	
		(0.0209)	
Employment report		-0.0310**	
		(0.0123)	
Employment*COVID		0.0004	
		(0.0183)	
PPI report		0.0031	
		(0.0084)	
PPI*COVID		0.0143	
		(0.0229)	
Recession			0.0096
			(0.0060)
ARMA			

AR(1)	-0.1160**	-0.1172**	-0.1179**
	(0.0521)	(0.0521)	(0.0524)
ARCH			
Constant	0.0011*	0.0010	0.0010*
	(0.0006)	(0.0007)	(0.0006)
ARCH(1)	0.1920*	0.1878*	0.2043*
	(0.1030)	(0.1011)	(0.1067)
GARCH(1)	0.6869***	0.7030***	0.6871***
	(0.1081)	(0.1218)	(0.1055)
Observations	471	471	471
AIC	-1,157	-1,160	-1,158
BIC	-1,124	-1,102	-1,121
Wald test	7.8200*	21.2500**	10.4500**

8.3. Sub-sample regression: pre-COVID estimation

Table 8.4

Descriptive statistics of pre-COVID sub-sample VIX closing values

This table shows the descriptive statistics for pre-COVID sub-sample VIX closing values from 1st of April 2016 until the 25th of February 2020. Column (2) shows the summary statistics of the level of the VIX based on the closing values. The change in Column (3) depict the summary statistics of the logarithmic percentage change of the VIX closing values.

Statistics	**Level**	**Change[a]**
Mean	14.39	0.06%
Median	13.41	-0.25%
Minimum	9.14	-29.98%
Maximum	37.32	76.82%
S.D.	3.87	8.08
Skewness	1.70	1.60
Excess kurtosis	7.60	13.99
Number of observations	1,017	1,017[b]

[a] Change: ln (VIX_t-VIX_{t-1})

[b] When usually calculating change, one observation is lost. However, to ensure that the sample period remains the same, the VIX closing value on the 31st of March 2016 was used to calculate the change on the 1st of April 2016. This observation for the 31st of March 2016 was then dropped.

The following model, which is derived from Model 1, is the first regression model for the sub-sample regression

$$\ln(VIX_t/VIX_{t-1}) = \alpha + \beta D_{0,t}^{S\_FOMC} + \epsilon_i \ . \tag{4}$$

The next model, which is derived from Model 2, is the second regression model for the sub-sample regression.

$$\ln(VIX_t/VIX_{t-1}) = \alpha + \beta D_{0,t}^{S\_FOMC} + \delta D_{0,t}^{CPI} + \mu D_{0,t}^{Employ} + \rho D_{0,t}^{PPI} + \varepsilon_i \ . \tag{5}$$

For both the models, the meaning of the regression coefficients as well as their expected behaviour can be found in Chapter 3 and 4.

Table 8.5

Regression results Model 4 and 5

This table shows the regression results for Model 4 and 5. The regressions use the first difference of the natural logarithm of the VIX as a dependent variable. Column (1) shows the variables used in the models, as described in Chapter 3 and 4. Column (2) and (3) show the regression results for the Models 4 and 5 respectively. The announcement days dummy variables take on a value of 1 on the day of the announcement or are zero otherwise. The HAC standard errors in Column (2) and (3) are in parentheses. The AIC and BIC are reported in Row (15) and (16) respectively. The Wald test statistics are reported in Row (17). A t-distribution is used to estimate the coefficients. The statistical significance stars are based on p-values and denote * p<0.10 ** p<0.05 *** p<0.01.

Coefficient	**Model 4**	**Model 5**
Intercept	-0.0038**	-0.0018
	(0.0017)	(0.0018)
Scheduled FOMC meetings	0.0011	0.0002
	(0.0104)	(0.0106)
CPI report		-0.0083
		(0.0078)
Employment report		-0.0388***
		(0.0111)
PPI report		-0.0020
		(0.0077)
ARMA		
AR(1)	-0.0424	-0.0468
	(0.0304)	(0.0316)
ARCH		
Constant	0.0011***	0.0011***
	(0.0003)	(0.0003)
ARCH(1)	0.1944***	0.2133***
	(0.0613)	(0.0646)

GARCH(1)	0.6704***	0.6550***
	(0.0678)	(0.0658)
Observations	1,017	1,017
AIC	- 2,556	- 2,568
BIC	- 2,522	- 2,518
Wald test	2.0100	14.6100**