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# Analysis of Trump's tweets relationships with VIX and S&P 500

Filipe Neto David

Work project carried out under the supervision of:

Prof. Emanuele Rizzo

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Abstract

Trump’s tweets effects in financial markets are frequently discussed, this thesis objective is to analyze these relationship. The data consisted on Trump tweets regarding a S&P500 company and VIX and S&P500 daily data. For the robustness check it was included tweets with specific words and a vector of economic exogenous variables. The models applied were the VAR and the VARX. The S&P500 tweets do not present significant coefficients or granger cause to S&P500 or VIX. The robustness check shows that total tweets helps to predict the S&P500. The results indicate that the S&P500 tweets do not affect the financial markets.

Keywords (Social Media, Finance, Asset Valuation, Politics)

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## I. Introduction

“Don’t be afraid of Covid.” Trump Twitter account on October 5th of 2020. Arguably, one of the worst pandemic of the contemporary history, COVID-19 had already caused two hundred thousand deaths and affected seven millions Americans when Trump posted this Tweet. Without a doubt, the 45th President of the United States of America, Donald Trump, changed how politicians communicate throughout the online Social Media. When Twitter banned the Donald Trump’s social media account already had 88,7 million followers (Küfner 2021). Nevertheless, the use of these social media channels could have provoked undesired effects to stock market, and it has caused a higher confusion and concern to the investors (Tobey 2019).

Donald Trump's relationship with Twitter started in 2009, with a simple announcement of an interview in an American talk show, but as time goes by, it gained importance in how he transmitted information to his followers. Actually, since July 2015, when Trump announced his candidacy to the white house, until July 2016 when he wins the primary elections of the Republican Party, Trump tweeted 3876 tweets in this time course, giving a mean per month of 276 tweets (Richardson 2021). When Trump already was in the White House, to be more exact, on November 13th of 2017, his tweets became official government statements, even though Twitter is a private platform and Trump blocked people on Twitter (Schneier 2017).

During his term of office, Trump tweeted 16584 tweets and retweeted 9655, performing 26239 during 48 months, resulting in a mean of 546 tweets per month. Of course, this would include some tweets more controversial regarding some topics such as tariffs, trade war, COVID-19 and companies in specific that could affect the stock market.

After his appointment for US President, because of the expectation of massive tax cuts and financial deregulation the S&P500 increased 5% in the first month, and it didn’t stop there, in the next four years S&P500 index increased 69,6% of its value, reaching several all-time records. This value corresponded to 13,7% annual return, a value significantly superior to the long term average annual return of the S&P500 (9,64%).

It is important to understand the market reactions to the Trump's tweets, since generally the social media growth can start to affect the financial market and how the businesses operate. For example, the General Motors (GM) case in March 27th 2020, when Trump wanted GM to produce ventilators for COVID-19 treatment. The in time US president tweeted how GM wasn't being committed to the established delivering date of 40000 ventilators and the importance of these. Hours after these statements in social media, GM announced that would build this medical equipment by deploying 1000 workers in a factory (Shepardson 2020). Even though Trump criticized the company, the S&P500 index and the General Motors stock values increased.

As seen, the Trump appealed in a very often way to tweets during its term at office, one may find that tweets affected the stock market or the market's volatility. The goal of this paper is to determine the conditions of the relationships between Trump's tweets, S&P500 and VIX. To understand these, we selected the Trump's tweets regarding the S&P500 companies, thus collecting 729 tweets. With this in mind, this work offers a time series analysis to understand how these three variables influence each other over the Trump's presidency time period. After performing the estimations with the first sample of tweets, we prove that Trump's tweets do not affect the market. Nevertheless, after applying some transformations to the model, the tweets start to help to predict the S&P500.

The thesis has the following structure: in section 2 is presented the Literature Review; in section 3 is presented the Data; in section 4 is presented the Methodology; in section 5 is presented the

Estimations Results; in section 6 is presented the Robustness Check; in section 7 is presented the Conclusion, and finally, in the section 8 is presented the Limitations and Further Research.

## II. Literature Review

In this section, we will present previous studies related to the field of research and with the thesis theme. With this said, the first works explore the Twitter relationship with the stock market. It is important to understand how, simply, the social media Twitter can affect the stock markets. Moving on, we will show in the second sub-section effects on the stock caused by sentiments inputted on tweets. Finally, in the last two sub-sections, reports the Trump's tweets effects on equity market. The third sub-section presents several types of work related to the Trump's tweets regarding companies, sentiments, daily flow, and other topics. The last papers presented reported the specific case of the Trump's tweets and the trade war with China. Since the last two sub-sections contain the work more similar to the one developed, we will compare the results of the thesis with these.

### a. Twitter and the Stock market

With the evaluation of the social media and its exponential growth, different authors have realized studies to understand how tweets are now being considered by the investors as an indicator for predicting the financial markets. (Ganesh 2021) studied the relationship between the S&P500 companies' tweets and their respective profits, they concluded that a shock of tweets from the company would increase the stock price. (Azar 2016) studied the tweets regarding the Federal Open Market Committee meetings and showed that these tweets could predict future returns, even after controlling for risk and asset pricing factors. Additionally, the authors concluded that a tweet-based asset allocation strategy outperforms several benchmarks.

b. Twitter sentiments and the stock market

Some authors included feelings to specify how these could influence the financial market in different ways. (Hassanein 2021) discovered that tweets with positive (negative) sentiments regarding the 100 world largest firms are likely to affect positively (negatively) the market's cumulative abnormal return and its buy-and-hold return. While (Zhang 2011) found that tweets with emotional feelings, such as fear and hope, had a significant positive correlation with VIX but a negative one with DJIA, NASDAQ and S&P500. Besides, both concluded that the effects would disappear in a short time of period.

(Behrendt 2018) had different conclusions regarding the short-time period analysis. They focused on an intraday perspective regarding the dynamics of individual-level stock volatility measured by Twitter sentiment and activity. They discovered that Twitter sentiment does not improve the forecast performance, and it is not useful for intraday volatility assessment.

c. President Trump's Tweets and how affected the Stock market

During his time in the office, several authors analysed Donald Trump's tweets mainly because these affected companies, which he tweeted about, and the financial markets itself.

As to specific companies, (Ajjoub 2020) distinguished his analyses between tweets regarding media companies or non-media companies, for the first ones they concluded that Trump's tweets with a positive content would have a positive impact on stock price, while for non-media firms the tweets with a negative content provoked negative effect on the stock prices, in the following day the stock price would reverse the decrease. (Ge 2017) took in account every tweet from Trump that included the name of a publicly traded company. The authors concluded that the tweets previous the beginning of Trump's presidency moved equity prices and increased traded volume and volatility with a higher effect. Although the impact disappears over the next trading days.

(Borna 2017) stated that Trump's tweets with positive content provoked positive abnormal returns on its date and practically all the tweets effect happen between the opening stock price to close price. The authors also concluded that trading volume response was consistent with the semi-strong form efficient market hypothesis, and also that traders who performed based on the tweets derived the impact and their effects were transitory.

Regarding the stock indexes, (Colonescu 2018) studied the daily effect of the daily flow of Donald Trump's tweets on the Dow Jones Industrial Average index. The author used text mining techniques and discovered a correlation between some moving average window lengths of tweets content and the DJIA index. (Yuan 2020) stated that the President tweets contained symptomatic information for short-term market trends. In addition, the authors found that Trump's tweets relative to trade and political events in comparison with different categories are the ones most probable to be linked with short-term market movement, and the authors also stated the relevance of the effects would not perish as time passes.

By the other hand (Juma'h 2018) showed, on average, no significant effect of Trump's tweets on stock indexes and on most of the targeted companies share prices, when selecting Trump's tweets with finance, economy, public policy, political considerations and companies targeted.

d. President Trump's Tweets and the Trade War with China

Several authors also analysed the Trump's tweets regarding the US-China trade war. (Burggraf 2019) namely analysed the tweets containing "China", "tariffs", "trade" and "trade war", which negatively predicted S&P500 and positively predicted VIX. (Gjerstad 2021) implied that US stock market responds to the tweets related to this topic by decreasing the price, increasing trading volume and uncertainty. In the Chinese stock market, the president's tweets also provoked the prices to decline. (Guo 2021) examined the Chinese manufacturing stock market. The authors discovered positive sentiments tweets related to the trade war significantly raise abnormal returns for this industry.

The Social Media and Financial Markets analysis will only get deeper because of the growing of the first one and how it affects the second. There still is some gaps in the literature review, namely studies with only the Trump's tweets regarding the S&P500 companies. And considering the presented literature, the following paper will contribute to the literature by including the relationship between these Donald Trump's tweets and the Volatility Index, while also still studying the relationship with S&P500.

## III. Data

### a. Data Period

The empirical data cover the period from September 1, 2016 to December 31, 2020 and comprise 1091 daily observations in the business calendar. The data period covers two months prior to Donald Trump's victory in the US presidential election to twenty days prior to the end of his term as US president. The reasons the last 20 days of his term did not enter the data period was because Trump's Twitter account was suspended on January 8, 2021 and, second, no tweet was eligible for the data sample in January 2021.

### b. Endogenous Variables

Considering the existing literature and most existing studies, we use the daily, non-seasonally adjusted closing values of the Standard and Poor's 500 Index (S&P500) to represent the movements of the entire U.S. stock market. The S&P500 represents 505 companies and 80%

of the capitalization of the US equity market. The S&P500 data is available on the S&P Global Website.

The Volatility Index (VIX) is a measure of the expected volatility of the U.S. equity market and considers the mid-quote prices of S&P500 call and put options. The VIX concept is often used to study financial and monetary relationships. Since the VIX is based on the option prices of the S&P 500 index, it also represents economic uncertainty (Evgenidis 2017). We retrieved the VIX data from the Wharton Research Data Services.

The sample for the number of tweets per day comprised 729 tweets or retweets sent from Donald Trump's Twitter official account before his nomination for the presidency and during his administration, except January 2021. The statements on the social media platforms that were eligible for the data sample had to include at least one name of a company included in the S&P500 index. The Trump's tweets are available on https://www.thetrumparchive.com/.

The number of tweets per day variable comprises Trump's daily tweets on the business calendar system. The application of this method followed the article of (Burggraf 2019) in which tweets on weekends are treated as Friday tweets, i.e., Saturday and Sunday tweets are (t-1) tweets for subsequent Monday returns, and the same procedure occurs regarding holidays, i.e., Thanksgiving tweets are treated as Wednesday tweets (t-1) for subsequent Friday returns. The companies Trump tweeted about can be seen in the Appendix 1.

### c. Robustness Check Data

For robustness checks, the original VAR undergoes some transformations, nevertheless, the data sample period remains the same. The transformations will create two models. In the first model will not happen modifications structurally, will still be a VAR because the changes will only occur on the variable number of tweets per day. The second model will be a VARX because, besides the variable transformation, it will include a vector of economic exogenous variables.

The variable for the number of tweets per day in the robustness check will include tweets with the name of a S&P500 company and the sample will also include tweets with the following words:

- Coal
- Covid
- Deregulation
- Economic Growth
- Employment
- Export
- Gas
- Imports
- Industry
- Inflation
- Investment
- Migration
- Regulation
- Steel
- Tariffs
- Trade War
- Unemployment

The reason we chose these words relied on the presented literature, namely the following works of (Juma'h 2018); (Burggraf 2019); and (Ajjoub 2020). The number of tweets with the new list is 794, increasing the sample from 729 tweets to 1523 tweets. The new tweets are also available in the same source as the initial ones.

The vector of the exogenous variables, in our robustness check VARX, contains the following monthly variables: the Industrial Production Index (IPX) as a measure of economic activity; the Consumer Price Index (CPI) as a measure of prices, since it is commonly used by financial analysts to understand prices trends and usually is seen as an indicator of the inflationary process in the economy (Aleema e Lahianic 2014). Additionally, it is commonly used IPX and CPI in this model specification to examine the transmission of different types of shock to the economy (Evgendis e Athansios 2017).

The Treasury bill rate represents the short-term monetary market rate and the rate which US government pays for loans of a one year duration. The IPX, the CPI and the Treasury bill rate data are available on the Federal Reserve website (https://fred.stlouisfed.org).

Finally, M3 is a measure of money supply and includes currency in circulation, overnight deposits, deposits with an agreed maturity of up to two years, deposits redeemable at notice of up to three months, repurchase agreements, money market fund shares/units and debt securities with maturities of up to two years (European Central Bank s.d.). The M3 data is available on the International Monetary Fund website (https://data.imf.org).

d. Matrix of Correlations and Descriptive Statistics

Table 1: Matrix of Correlations

| Variables | -1 | -2 | -3 |
|---|---|---|---|
| (1) S&P500 | 1.000 | | |
| (2) VIX | 0.263 | 1.000 | |
| (3) Number of tweets | 0.247 | 0.163 | 1.000 |

Table 1 shows the matrix of correlations between the endogenous variables. Correlation is a statistic that measures how one variable moves in relation to another and vice versa. Since the correlations are all positive, this means that each variable moves in the same direction as the other, i.e., the correlation between the S&P500 and the VIX is 0.263, meaning that if the S&P500 increases, the VIX will also increase. It is also important to state that all the correlations values correspond to weak relationships.

The mean of VIX is 17.805 and has a standard deviation of 9.328; VIX is positively skewed and contains a large kurtosis, meaning that the distribution is longer and the tails fatter than the normal distribution. The number of tweets per day variable presented similar results regarding the skewness and kurtosis, the mean is 0.668 and the standard deviation is 1.289. Finally, the S&P500 presents a symmetric distribution because of small skewness value and the kurtosis is like the normal distribution; the mean is 2782.091 and the standard deviation is 368.824. We show the descriptive statistics of all variables used in this thesis in the Appendix 2.

## IV. Methodology

Time series analysis assumes that the variables are stationary. To satisfy this condition, the Augmented Dickey-Fuller test is used to analyse the presence of unit roots in the variables under study. After performing the test and the necessary transformations of the variables, the model estimation begins.

To study the relationship between the number of tweets per day, the VIX and the S&P500, we perform a Vector Autoregressive (VAR) Model. This consist on a multivariate regression of each endogenous variable on the lags of itself and on the lags of all other endogenous variables. In this sense, it allows multiple endogenous variables and allows the study of dynamic effects without strict restrictions.

$$y_t = \mathrm{A}_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \varepsilon_t \quad \text{Equation 1}$$

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t \quad \text{Equation 2}$$

Where $y_t$ denotes a $(n * 1)$ vector of n time series variables, $\mathrm{A}_0$ is a $(n * 1)$ vector containing constant terms, $\Phi_i$ are a $(n * n)$ coefficient matrices, and $\varepsilon_t$ is an $(n * 1)$ unobservable zero mean white noise vector process, with a constant variance for each regression.

The post-estimation analysis comprises Granger Causality, Impulse Response Function (IRF), and Robustness Checks.

The Granger Causality test can determine whether one variable and its lags can predict the current value of the other variable. The null hypothesis is that the estimated coefficients for the lagged values of one variable are jointly zero, while the other variable is the dependent variable of the regression. If the test does not reject the null hypothesis, then a variable has no Granger cause for the variable in question.

The Impulse Response Function is the response of a variable to a shock from the same or from a different variable. In this work, each variable in each model hits every variable and we perform an analysis to observe the reactions on the other variables in a specific time horizon.

Robustness checking is a common exercise in empirical studies that provides the behaviour of the variables when changes occur in the regression specification, in this case by adding exogenous variables and by changing the sample of tweets by adding a new list of tweets. We present in the robustness checking two models, the first with the only with the new sample of tweets and the second with the vector of exogenous variables.

The second model suffers transformations at the structural level. Consequently, the model is not more a VAR because we added a vector of exogenous variables, and is now referred to as VARX.

$$y_t = A_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \Theta x_t + +\varepsilon_t$$

Equation 3

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \Theta x_t + \varepsilon_t \text{ Equation 4}$$

Where all the symbols maintain the significant and Θ is a vector containing the coefficients of the exogenous variables, the exogenous variable will not contain lags. Also, $x_t$ denotes a $(m * 1)$ vector of m exogenous economic variables. We will also analyse the Impulse Response Functions and Granger Causality of the robustness check models.

## V. Estimations Results

### a. Pre-estimation

The Augmented Dickey-Fuller (ADF) test confirms the stationarity of the VIX and the number of tweets, with a result of 0.0024 and 0.0000 respectively, and rejects the null hypothesis of non-stationarity at a 1% significance level. For the S&P500, the result was a p-value of 0.7954, so the null hypothesis is not rejected and there was a non-stationarity situation and a unit root during the analysis period. The Table 2 displays all the p-values and critical values (CV).

Table 2 Dickey-Fuller test for unit root

| Variables | Test Statistic | 1% CV | 5% CV | 10% CV | P-value |
|---|---|---|---|---|---|
| Z(t) S&P500 | -0.877 | -3.43 | -2.86 | -2.57 | 0.7954 |
| Z(t) VIX | -3.849 | -3.43 | -2.86 | -2.57 | 0.0024 |
| Z(t) Number of Tweets | -26.939 | -3.43 | -2.86 | -2.57 | 0.0000 |

As mentioned earlier, all endogenous variables in VAR must be stationary. Accordingly, we applied first differences to the S&P500 to make the variable stationary. The first difference comprises differentiating the current period's value from the previous one.

We performed again the ADF test, now on the transformed S&P500, rejecting the null hypothesis of non-stationarity, presenting a result of 0.0000. The Table 3 shows all test values.

Table 3 Dickey-Fuller test for unit root

| Variable | Test Statistic | 1% CV | 5% CV | 10% CV | P-value |
|---|---|---|---|---|---|
| Z(t) dS&P500 | -41,596 | -3,43 | -2,86 | -2,57 | 0.0000 |

The model VAR comprises a system of equations with a constant, the three endogenous variables specified earlier, the number of tweets per day, the VIX and the first differences of the S&P500, and finally their respective lags.

Table 4 Lag Selection Criteria

| lag | df | FPE | AIC | HQIC | SIC |
|---|---|---|---|---|---|
| 0 | 20.542 | 20.556 | | | |
| 1 | 9 | 2921.010 | 16.493 | 16.514 | 16.5485* |
| 2 | 9 | 2804.220 | 16.453 | 16.489 | 16.549 |
| 3 | 9 | 2733.550 | 16.427 | 16.479 | 16.565 |
| 4 | 9 | 2674.93* | 16.4053* | 16.4731* | 16.584 |

To select the optimal lag length, we performed various model selection tests. The Akaike Information Criterion (AIC), the Hannan-Quinn Information Criterion (HQIC) and Schwarz Information Criterion (SIC) state that the best lag is the one that has the smallest criterion value. The AIC and the HQIC selected the fourth lag as the best, while the SIC choose the first lag as the best. Since two criteria selected four lags, the VAR model will include four lags in each variable. We could test it with more lags, but we base this choice on the reason for: the high cost of estimating additional parameters each additional parameter significantly reduces the power of the estimation substantially (Baum 2011).

b. VAR

Based on the Appendix 3, the equation, where the dependent variable is the VIX, shows the estimated coefficients of the number of tweets, the S&P500, the lags of the three endogenous variables and a constant. We can see that the VIX lags significantly affect the current value, namely the one period before and the four period before at 1% level, the two periods before at 5% level. The other statistically significant at 1% level estimator corresponds to the first lag of the S&P500. The number of tweets variable does not have a statistically significant coefficient to estimate the current value of VIX. Moreover, the constant was statistically significant at the 5% level.

In the equation where the S&P500 is the dependent variable, the first, the third, and the fourth lags of the variable in question have statistically significant coefficients of at least 5% level on the estimate of the dependent variable. The number of tweets per day in this equation also did not have a statistically significant coefficient on the estimate of the S&P500 variable.

The VIX lags of order 2 and 4 were statistically significant at 1% level. The values are -2.925 and 3,475 respectively, so considering the mean of the S&P500 (1,454; Appendix 2), the 50% percentile of the S&P500 (2,1; Appendix 2), and the mean of the VIX (17.805; Appendix 2), we can understand the significance of the VIX for the S&P500. The constant was not statistically significant in this case.

Finally, the equation where the dependent variable is the tweets variable, shows an important result: the lag 3, the lag 4 of the VIX and the lag 3 of the S&P500 are statistically significant at the 1% level. The first and second lags of the number of tweets are also statistically significant coefficient. The constant was not statistically significant in this case.

c. Granger Causality

Table 5 Granger Causality Wald Tests

| Equation | Excluded | chi2 | df | Prob>Chi2 |
|---|---|---|---|---|
| VIX | dS&P500 | 17.371 | 4 | 0.002 |
| VIX | Number of tweets | 1.938 | 4 | 0.747 |
| VIX | ALL | 19.798 | 8 | 0.011 |
| dS&P500 | VIX | 26.823 | 4 | 0.000 |
| dS&P500 | Number of tweets | 3.796 | 4 | 0.434 |
| dS&P500 | ALL | 29.957 | 8 | 0.000 |
| Number of tweets | VIX | 32.810 | 4 | 0.000 |
| Number of tweets | dS&P500 | 27.738 | 4 | 0.000 |
| Number of tweets | ALL | 52.651 | 8 | 0.000 |

We conducted the Wald test to investigate Granger Causality, the table 5 shows the values of the test. The test revealed that the coefficients of the four lags of S&P500 that appear in the equation for VIX are not jointly zero. This rejected the null hypothesis of the test and, consequently, proved the existence of Granger causality. The same is not true for the number of tweets, as the test did not reject the null hypothesis of the Wald test that the coefficients of this variable are jointly zero.

For the equation where the S&P500 is the dependent variable, the Wald test found that the VIX Granger causes the S&P500 because it rejected the null hypothesis, it is also important to state the mutual Granger-causality between S&P500 and VIX. Nevertheless, Wald test found that the number of tweets did not show Granger causality regarding S&P500 or VIX.

In the last equation, both the VIX and the S&P500 reject the null hypothesis, meaning that these variables have Granger causality with the number of tweets.

d. Impulse Response Functions

Appendix 4 shows the impulse response functions over 8 business days for the specification VAR. Since the purpose of this paper is to analyse the relationship between the number of tweets with the VIX and the S&P500, we showed all possibilities of impulse response functions. The top line and the bottom line represent the 95% confidence interval of the impulse response function, while the line in the middle is the actual impulse response function.

A shock to the VIX on the S&P500 causes the second to rise in the first period and then causes a sharp decline until the fourth period after the shock, after which the effects slowly decay until the eighth and final period in the analysis. A shock of the VIX on the number of tweets leads to a rise in the first period, then falls to zero and then rises in the third period, followed by a fall until the impact slowly subsides in the eighth period.

A shock from the S&P500 to the VIX causes the second to rise slightly in the first period and remains at that level, with small fluctuations until the last period of the analysis. The effect of the S&P500 causes the number of tweets variable to decrease in the first period, to be neutral in the second period, and to increase significantly in the next period, but to decrease in the fourth period and the effect slowly decays until the eighth period.

A shock from the number of tweets leads to a constant increase in the VIX until the third period, and then this growth becomes milder until the eighth period. The number of tweets in the S&P500 behaves strongly cyclically, decreasing in the first period, increasing in the second, and then repeating the behaviour of the last two periods in subsequent periods until the effect slowly disappears.

## VI. Robustness Check

### a. Robustness Models

We created two different models for the robustness check in order to analyse and compare them with our model. The first model of robustness check includes tweets containing words with economic meaning, so the sample of tweets is significantly larger. In the second model, besides the new tweet sample, we include a vector of exogenous variables, namely the CPI, the IPX, the Treasury bill rate, and the M3, to complete the model in a more economic sense.

After performing all the necessary steps to estimate the first alternative model (Appendix 5), the biggest differences between our model and the robustness check model were the lag 1 of the S&P500 in the equation of tweets, which became statistically significant at the 5% level, and lag 4 of tweets itself also became significant at the 1% level. Finally, in the VIX equation, the third lag of the number of tweets became statistically significant at the 10% level. In the

S&P500 equation, lag 4 of the tweets becomes statistically significant at the 10% level in this model. We can observe these values in Appendix 6.

In the second model, the tweets equation and the VIX equation presented the same differences from our model as in the first robustness check model. We see the only difference in terms of statistically significant coefficients between the two robustness check models in the S&P500 equation in the fourth lag of tweets, which is not significant in the second model (Appendixes 7 and 8).

b. Granger causality and IRF

The only difference regarding the Granger Causality in these two models in comparison with the original model, is that now the number of tweets per day variable granger causes S&P500.

The IRFs of the robustness checks models are very similar. The major differences between the original model IRFs and these are: how the tweets variable responds to a shock from S&P500 or VIX, and S&P500 or VIX respond to a shock from tweets variable.

The VIX and the S&P500 in the robustness checks affected the number of tweets in a more smooth way. VIX specifically in the second period after the shock, which then did not decrease in the third period. And the S&P500 affects the tweets variable in a less negatively way in the first period and in the third in less positively.

The tweets variable affected the VIX in a less powerful way. But in the behaviour, it presented differences regarding the original model. In the third period the tweets shock made VIX decrease, and the recovers in the fourth period to after this starting to losing the impact. In the robustness check, tweets effects on the S&P500 are also less powerful, the S&P500 has a smooth increase until the third period and then has a great downfall followed by a stabilization over the next periods.

The post-estimation analysis of these models can be shown in Appendix 9 and Appendix 10.

## VII. Conclusion

In this paper, we showed it the relationship between the S&P500, the VIX and the Trump's tweets. The purpose of choosing this idea is the relevance of analysing the financial markets and how this reacted with Trump's tweets, an innovation in how US presidents transmit information to the population or better followers. Even though that some authors analysed the tweets containing publicly traded companies and its effect on S&P500 (Ajjoub 2020) and (Borna 2017), the tweets containing the S&P500 companies did not enter into account, and even though the method of a time series allows for a dynamic interpretation of the variables, while most of the studies did not execute. Since, only (Burggraf 2019) used time series analysis and VAR.

With this said, in this thesis the Donald Trump's tweets containing the S&P500 companies' names do not present significant coefficients regarding the stock market and the VIX in a daily analysis like (Ajjoub 2020) and (Ge 2017) stated but in line with the results presented by (Juma'h 2018). Also, tweets do not help to predict VIX or S&P500 like (Burggraf 2019) appointed, but the other way around, the VIX and the S&P500 help to predict the Trump's tweets. The VIX and the S&P500 have a mutual relationship regarding statistically significant coefficients and Granger Causality. The IRFs presented different effects regarding a shock of VIX on S&P500 and a shock of S&P500 on VIX. A VIX shock increased in the first period, decreases substantially the value of the S&P500 in the second and third period, while the shock of the S&P500 causes the VIX to have a strong rise and maintain the level in the posterior periods.

Furthermore, in the robustness check, with the new tweet sample, the models provided more statistically significant coefficients and the tweets now help to predict the S&P500. All the IRFs regarding the tweets variable altered. The tweets now affect the VIX and the S&P500, and these affect the tweets in a smoother way.

The findings of the thesis allows to concluded that even though existing a lot of confusion regarding Trump and its tweets regarding some companies, the tweets did not affect significantly the S&P500 or VIX daily movements.

## VIII. Limitations and Furter Research

The limitations while developing the thesis comprised themes mainly regarding the Trump's tweets. First, it would be impossible a perfect database because we would need a trustworthy artificial intelligence system to help to analyse the selected tweets. This method happens in the paper of (Juma'h 2018) and also was not available man power and different opinions to analyse the tweets like the (Ajjoub 2020). Second, to have a perfect data base with Trump's tweet, we would need it an enormous list of words or phrases with all possible content. Which could affect the value and volatility of the market and then being analysed by an artificial intelligence system.

The current finding of this thesis about the relationship between the Trump's tweets and the S&P 500 index and the Volatility Index provide several opportunities for further research. Namely, inputting in the model traders and tweets sentiments could allow interesting results. This procedure with an artificial intelligence system could differentiate the ambiguous language used by Trump in different sentiments feelings, consequently increasing the analysis efficiency.

A more complex econometric model could also be used, for example, a threshold vector autoregressive, which analyses the behaviour of the VIX and the S&P500 considering different regimes of the tweets. Finally, could also input the number of retweets and favourites in the model more specially to analyse the popularity of tweet itself and its magnitude on the equity market.

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# X. Appendix

Appendix 1

| | | |
|---|---|---|
| · Aetna | · Facebook | · Pfizer |
| · Alphabet | · Ford | · Pulte |
| · Amazon | · Fox | · Qualcoom |
| · Andeavor | · General Dynamic | · Raytheon |
| · Anthem | · General Electric | · Royal Caribbean |
| · Apple | · General Motors | · S&P |
| · Aptiv | · Gilead Sciences | · Sempra Energy |
| · AT&T | · Harley-Davidson | · Southwest Airlines |
| · Boeing | · Honeywell | · Starbucks |
| · Broadcom | · Humana | · Target |
| · Carnival Corporation | · Intel | · Tesla |
| · Caterpillar | · JPMorgan Chase | · Time warner |
| · Cbs | · Loockheed Martin | · Twitter |
| · Cisco | · Merck | · Ups |
| · Comcast | · Moderna | · Visa |
| · Corning | · Nasdaq | · Walmart |
| · Delta | · Nielsen | · Walgreens |
| · Dish | · Nike | · Walt Disney |
| · Dominion | · Nordstrom | · Wells Fargo |
| · Dupont | · Norwegian | |

Appendix 2

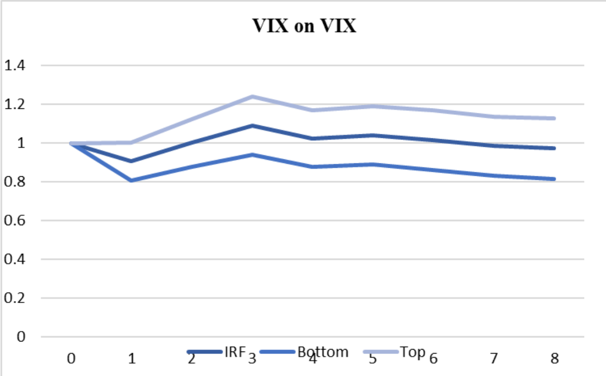
| Variables | Obs | Mean | Std. Dev. | Min | Max | p1 | p99 | Skew. | Kurt. |
|---|---|---|---|---|---|---|---|---|---|
| VIX | 1091 | 17.805 | 9.328 | 9.14 | 82.69 | 9.43 | 61 | 2.741 | 13.718 |
| S&P500 | 1091 | 2782.091 | 368.824 | 2085.18 | 3756.07 | 2131.52 | 3694.92 | .366 | 2.697 |
| Number of Tweets | 1091 | .668 | 1.289 | 0 | 11 | 0 | 6 | 3.162 | 16.432 |
| dS&P500 | 1090 | 1.454 | 34.759 | -324.89 | 230.38 | -113.19 | 90.21 | -1.221 | 20.325 |
| T-bill rate | 1091 | 1.256 | .8 | .09 | 2.4 | .09 | 2.4 | -.1 | 1.592 |
| CPI | 1091 | 1.79 | .265 | .987 | 2.142 | .987 | 2.142 | -1.063 | 4.179 |
| IPX | 1091 | 99.998 | 4.014 | 84.202 | 104.166 | 84.202 | 104.166 | -2.115 | 8.23 |
| M3 | 1091 | 14.922 | 1.733 | 13.033 | 19.131 | 13.033 | 19.131 | 1.28 | 3.368 |
| Total Tweets | 1091 | 1.396 | 2.171 | 0 | 24 | 0 | 11 | 3.492 | 23.546 |
| New Tweets | 1091 | .728 | 1.583 | 0 | 19 | 0 | 8 | 5.043 | 40.825 |
| dTbill | 1090 | 0 | .039 | -1.08 | .22 | -.03 | .09 | -19.979 | 551.213 |
| dCPI | 1090 | 0 | .027 | -.629 | .205 | -.026 | .08 | -10.061 | 271.774 |
| dIPX | 1090 | 0 | .479 | -13.246 | 5.319 | -.377 | .739 | -18.112 | 558.611 |
| dM3 | 1090 | .006 | .048 | 0 | 1.029 | 0 | .119 | 16.113 | 304.719 |

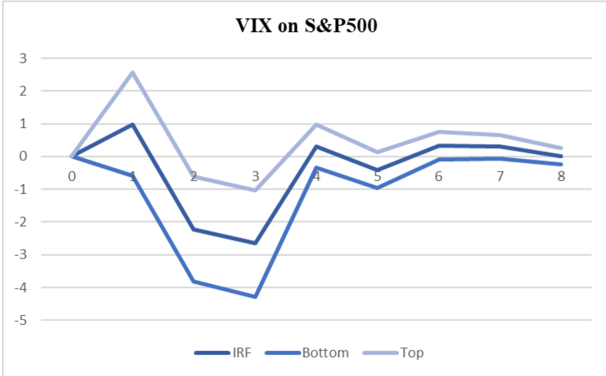
Appendix 3

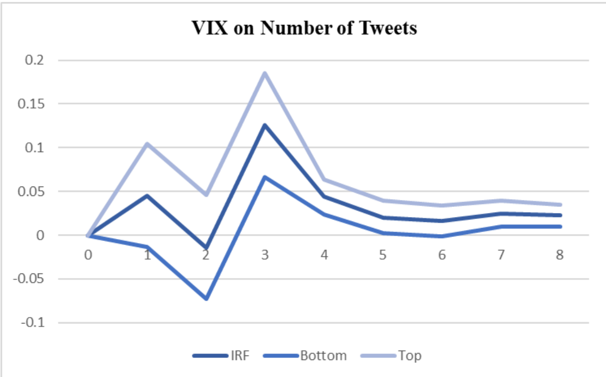
| | Coef. | Std.Err. | z | P>z | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| Number of tweets | | | | | | |
| VIX | | | | | | |
| L1. | 0.045 | 0.030 | 1.510 | 0.131 | -0.013 | 0.104 |
| L2. | -0.062 | 0.041 | -1.490 | 0.137 | -0.143 | 0.020 |
| L3. | 0.135 | 0.041 | 3.300 | 0.001 | 0.055 | 0.215 |
| L4. | -0.100 | 0.029 | -3.410 | 0.001 | -0.158 | -0.043 |
| dS&P500 | | | | | | |
| L1. | -0.001 | 0.002 | -0.300 | 0.765 | -0.004 | 0.003 |
| L2. | -0.001 | 0.002 | -0.430 | 0.669 | -0.004 | 0.003 |
| L3. | 0.009 | 0.002 | 5.210 | 0.000 | 0.006 | 0.013 |
| L4. | -0.000 | 0.001 | -0.380 | 0.703 | -0.003 | 0.002 |
| Number of tweets | | | | | | |
| L1. | 0.167 | 0.030 | 5.540 | 0.000 | 0.108 | 0.226 |
| L2. | 0.064 | 0.030 | 2.100 | 0.036 | 0.004 | 0.123 |
| L3. | 0.032 | 0.031 | 1.060 | 0.291 | -0.028 | 0.092 |
| L4. | 0.030 | 0.030 | 1.000 | 0.317 | -0.029 | 0.089 |
| _cons | 0.132 | 0.084 | 1.570 | 0.117 | -0.033 | 0.297 |

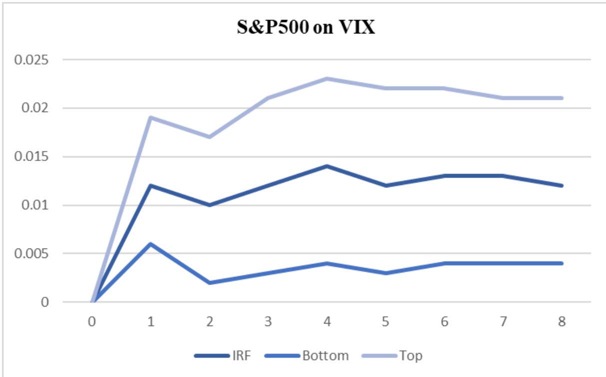
| | | | | | | |
|---|---|---|---|---|---|---|
| VIX | | | | | | |
| VIX | | | | | | |
| L1. | 0.906 | 0.050 | 18.080 | 0.000 | 0.808 | 1.004 |
| L2. | 0.165 | 0.069 | 2.390 | 0.017 | 0.030 | 0.301 |
| L3. | 0.059 | 0.068 | 0.860 | 0.389 | -0.075 | 0.193 |
| L4. | -0.153 | 0.049 | -3.130 | 0.002 | -0.250 | -0.057 |
| dS&P500 | | | | | | |
| L1. | 0.012 | 0.003 | 4.020 | 0.000 | 0.006 | 0.019 |
| L2. | 0.000 | 0.003 | 0.140 | 0.886 | -0.006 | 0.007 |
| L3. | -0.000 | 0.003 | -0.090 | 0.925 | -0.006 | 0.006 |
| L4. | 0.002 | 0.002 | 1.160 | 0.245 | -0.002 | 0.006 |
| Number of tweets | | | | | | |
| L1. | 0.053 | 0.050 | 1.050 | 0.292 | -0.046 | 0.152 |
| L2. | 0.031 | 0.051 | 0.610 | 0.540 | -0.068 | 0.130 |
| L3. | -0.001 | 0.051 | -0.020 | 0.980 | -0.101 | 0.099 |
| L4. | 0.013 | 0.050 | 0.260 | 0.795 | -0.085 | 0.111 |
| _cons | 0.338 | 0.140 | 2.410 | 0.016 | 0.063 | 0.612 |
| dS&P500 | | | | | | |
| VIX | | | | | | |
| L1. | 0.986 | 0.805 | 1.220 | 0.221 | -0.591 | 2.563 |
| L2. | -2.925 | 1.111 | -2.630 | 0.008 | -5.104 | -0.747 |
| L3. | -1.474 | 1.098 | -1.340 | 0.179 | -3.627 | 0.678 |
| L4. | 3.475 | 0.788 | 4.410 | 0.000 | 1.931 | 5.020 |
| dS&P500 | | | | | | |
| L1. | -0.157 | 0.050 | -3.150 | 0.002 | -0.254 | -0.059 |
| L2. | 0.064 | 0.050 | 1.280 | 0.199 | -0.034 | 0.162 |
| L3. | -0.099 | 0.049 | -2.030 | 0.042 | -0.195 | -0.004 |
| L4. | -0.065 | 0.031 | -2.110 | 0.035 | -0.126 | -0.005 |
| Number of tweets | | | | | | |
| L1. | -0.681 | 0.809 | -0.840 | 0.400 | -2.267 | 0.904 |
| L2. | 1.331 | 0.814 | 1.640 | 0.102 | -0.264 | 2.927 |
| L3. | -0.858 | 0.818 | -1.050 | 0.294 | -2.461 | 0.745 |
| L4. | 0.179 | 0.807 | 0.220 | 0.824 | -1.402 | 1.761 |
| _cons | 0.793 | 2.252 | 0.350 | 0.725 | -3.621 | 5.206 |

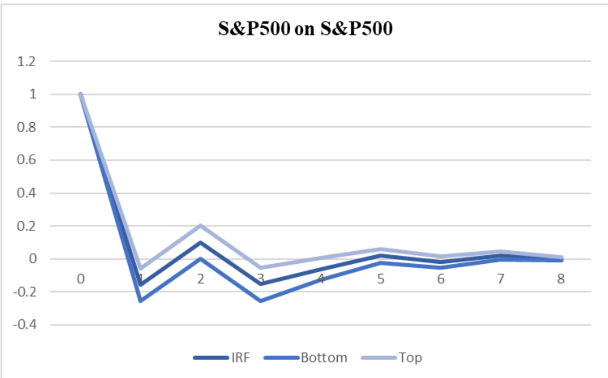
## Appendix 4

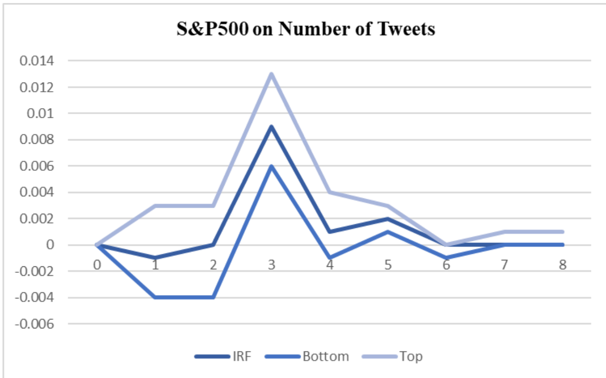

VIX on VIX
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0 1 2 3 4 5 6 7 8
IRF Bottom Top

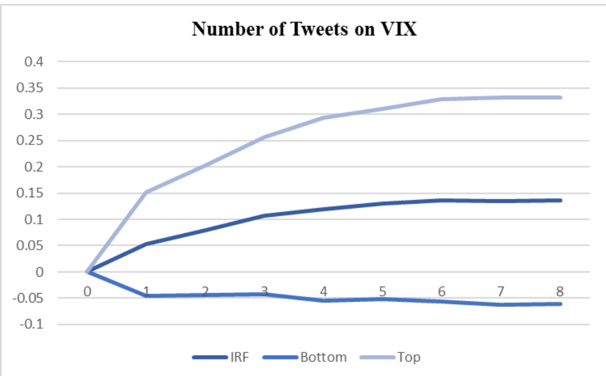

VIX on S&P500
3
2
1
0
-1
-2
-3
-4
-5
0 1 2 3 4 5 6 7 8
IRF Bottom Top

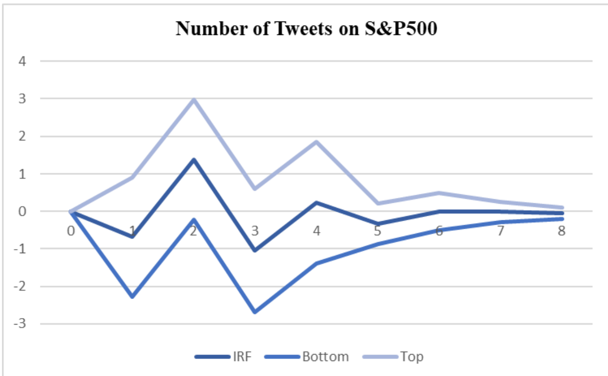

VIX on Number of Tweets
0.2
0.15
0.1
0.05
0
-0.05
-0.1
0 1 2 3 4 5 6 7 8
IRF Bottom Top

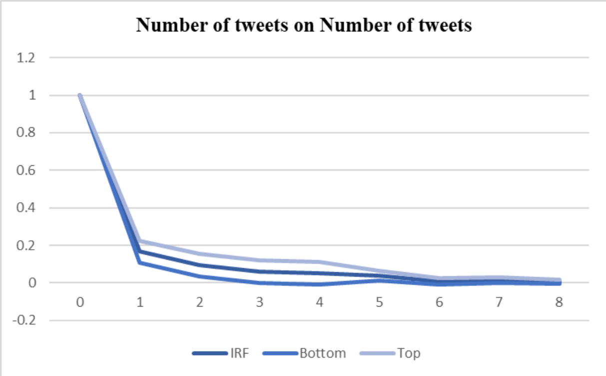

S&P500 on VIX
0.025
0.02
0.015
0.01
0.005
0
0 1 2 3 4 5 6 7 8
IRF Bottom Top


S&P500 on S&P500
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0 1 2 3 4 5 6 7 8
IRF Bottom Top


S&P500 on Number of Tweets
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
0 1 2 3 4 5 6 7 8
IRF Bottom Top


Number of Tweets on VIX
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
0 1 2 3 4 5 6 7 8
IRF Bottom Top


Number of Tweets on S&P500
4
3
2
1
0
-1
-2
-3
0 1 2 3 4 5 6 7 8
IRF Bottom Top




Appendix 5

ADF test

| Variables | Test Statistic | 1% CV | 5% CV | 10% CrV | p-value |
|---|---|---|---|---|---|
| Z(t) Total Tweets | -23,184 | -3,43 | -2,86 | -2,57 | 0 |
| Z(t) New Tweets | -25,324 | -3,43 | -2,86 | -2,57 | 0 |

Lag Selection Criteria

| lag | df | FPE | AIC | HQIC | SIC |
|---|---|---|---|---|---|
| 0 | 21.506 | 21.520 | | | |
| 1 | 9 | 7336.670 | 17.414 | 17.435 | 17.469 |
| 2 | 9 | 6981.680 | 17.365 | 17.401 | 17.4612* |
| 3 | 9 | 6832.450 | 17.343 | 17.395 | 17.481 |
| 4 | 9 | 6531.91* | 17.2981* | 17.3659* | 17.477 |

Appendix 6

| | Coef. | Std.Err. | z | P>z | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| Total tweets | | | | | | |
| Total tweets | | | | | | |
| L1. | 0.293 | 0.030 | 9.750 | 0.000 | 0.234 | 0.352 |
| L2. | -0.062 | 0.031 | -2.000 | 0.046 | -0.124 | -0.001 |
| L3. | 0.028 | 0.031 | 0.900 | 0.369 | -0.033 | 0.089 |
| L4. | 0.106 | 0.030 | 3.560 | 0.000 | 0.048 | 0.165 |
| VIX | | | | | | |
| L1. | -0.059 | 0.047 | -1.240 | 0.213 | -0.152 | 0.034 |
| L2. | 0.027 | 0.065 | 0.420 | 0.677 | -0.101 | 0.155 |
| L3. | 0.264 | 0.064 | 4.100 | 0.000 | 0.138 | 0.390 |
| L4. | -0.186 | 0.046 | -4.000 | 0.000 | -0.277 | -0.095 |
| dS&P500 | | | | | | |
| L1. | -0.008 | 0.003 | -2.590 | 0.010 | -0.013 | -0.002 |
| L2. | 0.003 | 0.003 | 0.900 | 0.371 | -0.003 | 0.008 |
| L3. | 0.009 | 0.003 | 3.200 | 0.001 | 0.004 | 0.015 |
| L4. | -0.002 | 0.002 | -1.140 | 0.255 | -0.006 | 0.002 |
| _cons | 0.055 | 0.131 | 0.420 | 0.672 | -0.202 | 0.313 |
| VIX | | | | | | |
| Total tweets | | | | | | |
| L1. | 0.019 | 0.032 | 0.580 | 0.559 | -0.044 | 0.081 |
| L2. | 0.025 | 0.033 | 0.770 | 0.444 | -0.039 | 0.090 |
| L3. | -0.062 | 0.033 | -1.890 | 0.059 | -0.127 | 0.002 |
| L4. | 0.032 | 0.032 | 1.030 | 0.305 | -0.030 | 0.094 |
| VIX | | | | | | |
| L1. | 0.911 | 0.050 | 18.170 | 0.000 | 0.813 | 1.010 |
| L2. | 0.161 | 0.069 | 2.330 | 0.020 | 0.026 | 0.297 |
| L3. | 0.067 | 0.068 | 0.980 | 0.326 | -0.067 | 0.201 |
| L4. | -0.162 | 0.049 | -3.290 | 0.001 | -0.258 | -0.065 |
| dS&P500 | | | | | | |
| L1. | 0.013 | 0.003 | 4.150 | 0.000 | 0.007 | 0.019 |
| L2. | 0.001 | 0.003 | 0.180 | 0.854 | -0.006 | 0.007 |
| L3. | 0.000 | 0.003 | 0.020 | 0.984 | -0.006 | 0.006 |
| L4. | 0.002 | 0.002 | 1.010 | 0.314 | -0.002 | 0.006 |
| _cons | 0.359 | 0.139 | 2.580 | 0.010 | 0.087 | 0.631 |
| dS&P500 | | | | | | |
| Total Tweets | | | | | | |
| L1. | 0.127 | 0.510 | 0.250 | 0.804 | -0.874 | 1.127 |
| L2. | 0.487 | 0.530 | 0.920 | 0.358 | -0.552 | 1.525 |
| L3. | 0.627 | 0.528 | 1.190 | 0.235 | -0.409 | 1.663 |

| | | | | | | |
|---|---|---|---|---|---|---|
| L4. | -1.421 | 0.507 | -2.800 | 0.005 | -2.415 | -0.427 |
| VIX | | | | | | |
| L1. | 0.706 | 0.804 | 0.880 | 0.380 | -0.870 | 2.283 |
| L2. | -2.633 | 1.109 | -2.370 | 0.018 | -4.808 | -0.459 |
| L3. | -1.375 | 1.094 | -1.260 | 0.209 | -3.519 | 0.769 |
| L4. | 3.375 | 0.788 | 4.280 | 0.000 | 1.831 | 4.920 |
| dS&P500 | | | | | | |
| L1. | -0.173 | 0.050 | -3.490 | 0.000 | -0.270 | -0.076 |
| L2. | 0.074 | 0.050 | 1.470 | 0.141 | -0.024 | 0.172 |
| L3. | -0.091 | 0.049 | -1.860 | 0.064 | -0.187 | 0.005 |
| L4. | -0.065 | 0.031 | -2.090 | 0.037 | -0.126 | -0.004 |
| _cons | 0.809 | 2.227 | 0.360 | 0.716 | -3.556 | 5.174 |

Appendix 7

| Variables | Test Statistic | 1% CV | 5% CV | 10% CV | P-value |
|---|---|---|---|---|---|
| Z(t) T-bill rate | -0,596 | -3,43 | -2,86 | -2,57 | 0,8719 |
| Z(t) CPI | -1,831 | -3,43 | -2,86 | -2,57 | 0,365 |
| Z(t) IPX | -1,963 | -3,43 | -2,86 | -2,57 | 0,3028 |
| Z(t) M3 | 2,519 | -3,43 | -2,86 | -2,57 | 0,9988 |

| Variables | Test Statistic | 1% CV | 5% CV | 10% CV | p-value |
|---|---|---|---|---|---|
| Z(t) dT-bill rate | -32,97 | -3,43 | -2,86 | -2,57 | 0.0000 |
| Z(t) dCPI | -32,976 | -3,43 | -2,86 | -2,57 | 0.0000 |
| Z(t) dIPX | -32,97 | -3,43 | -2,86 | -2,57 | 0.0000 |
| Z(t) dM3 | -33,43 | -3,43 | -2,86 | -2,57 | 0.0000 |

| lag | df | FPE | AIC | HQIC | SIC |
|---|---|---|---|---|---|
| 0 | 21.481 | 21.550 | | | |
| 1 | 9 | 7306.250 | 17.410 | 17.452 | 17.520 |
| 2 | 9 | 6895.640 | 17.352 | 17.410 | 17.5039* |
| 3 | 9 | 6708.260 | 17.325 | 17.398 | 17.518 |
| 4 | 9 | 6426.88* | 17.2819* | 17.3706* | 17.516 |

Appendix 8

| | Coef. | Std.Err. | z | P>z | [95%Conf. | Interval] |
|---|---|---|---|---|---|---|
| Total Tweets | | | | | | |
| Total Tweets | | | | | | |
| L1. | 0.290 | 0.030 | 9.630 | 0.000 | 0.231 | 0.349 |
| L2. | -0.061 | 0.031 | -1.960 | 0.050 | -0.122 | 0.000 |
| L3. | 0.028 | 0.031 | 0.900 | 0.366 | -0.033 | 0.089 |
| L4. | 0.103 | 0.030 | 3.420 | 0.001 | 0.044 | 0.163 |
| VIX | | | | | | |
| L1. | -0.067 | 0.048 | -1.410 | 0.159 | -0.160 | 0.026 |
| L2. | 0.018 | 0.065 | 0.270 | 0.788 | -0.110 | 0.146 |
| L3. | 0.282 | 0.065 | 4.370 | 0.000 | 0.156 | 0.409 |
| L4. | -0.186 | 0.046 | -4.020 | 0.000 | -0.277 | -0.095 |
| dS&P500 | | | | | | |
| L1. | -0.008 | 0.003 | -2.670 | 0.008 | -0.014 | -0.002 |
| L2. | 0.002 | 0.003 | 0.780 | 0.435 | -0.003 | 0.008 |
| L3. | 0.010 | 0.003 | 3.340 | 0.001 | 0.004 | 0.015 |
| L4. | -0.002 | 0.002 | -0.870 | 0.385 | -0.005 | 0.002 |
| dTbill | -4.706 | 2.276 | -2.070 | 0.039 | -9.167 | -0.244 |
| dCPI | -0.245 | 2.811 | -0.090 | 0.931 | -5.755 | 5.265 |
| dIPX | 0.216 | 0.148 | 1.460 | 0.146 | -0.075 | 0.507 |
| dM3 | -0.231 | 1.551 | -0.150 | 0.881 | -3.271 | 2.809 |
| _cons | 0.065 | 0.131 | 0.490 | 0.622 | -0.193 | 0.322 |
| VIX | | | | | | |
| Total Tweets | | | | | | |
| L1. | 0.020 | 0.032 | 0.610 | 0.539 | -0.043 | 0.082 |
| L2. | 0.026 | 0.033 | 0.800 | 0.422 | -0.038 | 0.091 |
| L3. | -0.064 | 0.033 | -1.960 | 0.050 | -0.129 | -0.000 |
| L4. | 0.033 | 0.032 | 1.030 | 0.305 | -0.030 | 0.096 |
| VIX | | | | | | |
| L1. | 0.924 | 0.050 | 18.380 | 0.000 | 0.825 | 1.022 |
| L2. | 0.172 | 0.069 | 2.480 | 0.013 | 0.036 | 0.307 |
| L3. | 0.044 | 0.068 | 0.640 | 0.519 | -0.090 | 0.178 |
| L4. | -0.163 | 0.049 | -3.320 | 0.001 | -0.259 | -0.067 |
| dS&P500 | | | | | | |
| L1. | 0.013 | 0.003 | 4.310 | 0.000 | 0.007 | 0.019 |
| L2. | 0.001 | 0.003 | 0.310 | 0.758 | -0.005 | 0.007 |
| L3. | -0.000 | 0.003 | -0.080 | 0.939 | -0.006 | 0.006 |
| L4. | 0.001 | 0.002 | 0.480 | 0.629 | -0.003 | 0.005 |
| dTbill | 3.885 | 2.406 | 1.620 | 0.106 | -0.830 | 8.600 |
| dCPI | 3.221 | 2.971 | 1.080 | 0.278 | -2.602 | 9.044 |

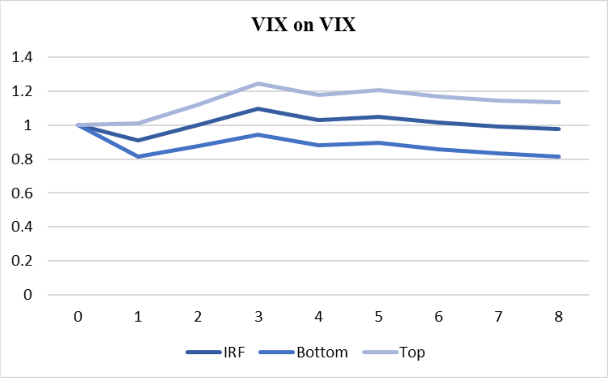
| | | | | | | |
|---|---|---|---|---|---|---|
| dIPX | -0.213 | 0.157 | -1.360 | 0.175 | -0.520 | 0.095 |
| dM3 | 2.327 | 1.639 | 1.420 | 0.156 | -0.885 | 5.539 |
| _cons | 0.373 | 0.139 | 2.680 | 0.007 | 0.101 | 0.645 |
| dS&P500 | | | | | | |
| Total Tweets | | | | | | |
| L1. | 0.048 | 0.506 | 0.100 | 0.924 | -0.943 | 1.040 |
| L2. | 0.485 | 0.523 | 0.930 | 0.354 | -0.541 | 1.511 |
| L3. | 0.723 | 0.523 | 1.380 | 0.167 | -0.302 | 1.749 |
| L4. | -1.549 | 0.509 | -3.040 | 0.002 | -2.546 | -0.551 |
| VIX | | | | | | |
| L1. | 0.302 | 0.800 | 0.380 | 0.705 | -1.265 | 1.870 |
| L2. | -2.814 | 1.098 | -2.560 | 0.010 | -4.967 | -0.661 |
| L3. | -0.802 | 1.085 | -0.740 | 0.460 | -2.930 | 1.325 |
| L4. | 3.433 | 0.778 | 4.410 | 0.000 | 1.907 | 4.958 |
| dS&P500 | | | | | | |
| L1. | -0.192 | 0.049 | -3.890 | 0.000 | -0.288 | -0.095 |
| L2. | 0.062 | 0.049 | 1.250 | 0.210 | -0.035 | 0.159 |
| L3. | -0.085 | 0.048 | -1.750 | 0.080 | -0.180 | 0.010 |
| L4. | -0.040 | 0.031 | -1.300 | 0.195 | -0.101 | 0.021 |
| dTbill | -99.675 | 38.274 | -2.600 | 0.009 | -174.690 | -24.660 |
| dCPI | -64.235 | 47.270 | -1.360 | 0.174 | -156.883 | 28.412 |
| dIPX | 8.381 | 2.495 | 3.360 | 0.001 | 3.490 | 13.272 |
| dM3 | -40.217 | 26.076 | -1.540 | 0.123 | -91.325 | 10.892 |
| _cons | 0.391 | 2.210 | 0.180 | 0.860 | -3.940 | 4.722 |

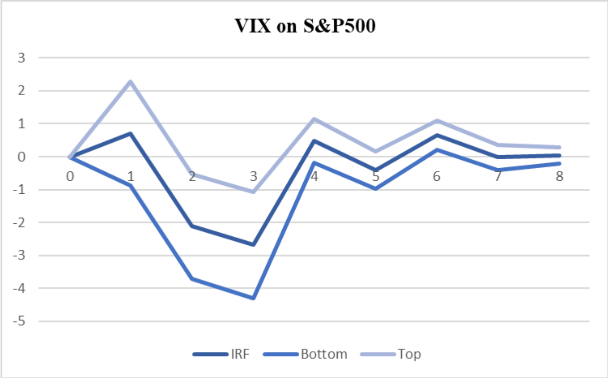
Appendix 9

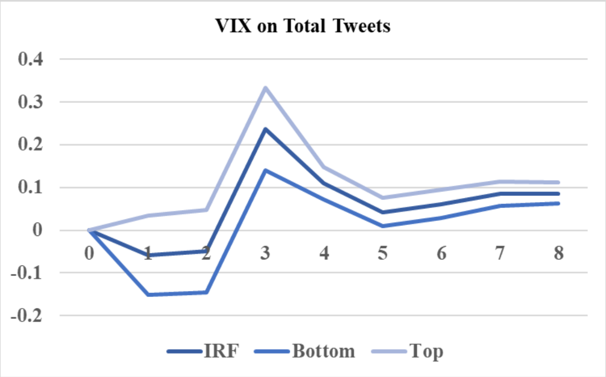
VAR with new tweets sample – Granger Causality

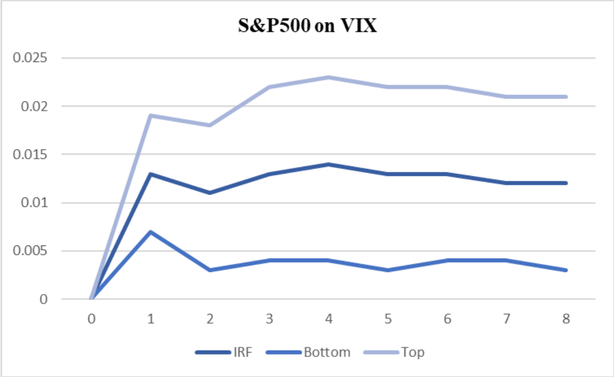
| **Equation** | **Excluded** | **chi2** | **df** | **Prob>Chi2** |
|---|---|---|---|---|
| Total Tweets | VIX | 63.493 | 4 | 0.000 |
| Total Tweets | dS&P500 | 17.751 | 4 | 0.001 |
| Total Tweets | ALL | 88.867 | 8 | 0.000 |
| VIX | Total Tweets | 4.636 | 4 | 0.327 |
| VIX | dS&P500 | 18.159 | 4 | 0.001 |
| VIX | ALL | 22.539 | 8 | 0.004 |
| dS&P500 | Total Tweets | 9.945 | 4 | 0.041 |
| dS&P500 | VIX | 24.905 | 4 | 0.000 |
| dS&P500 | ALL | 36.255 | 8 | 0.000 |

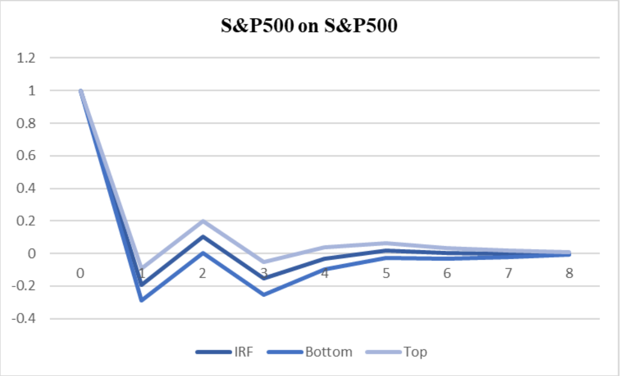
## Var with new tweets sample – Impulse Response Functions

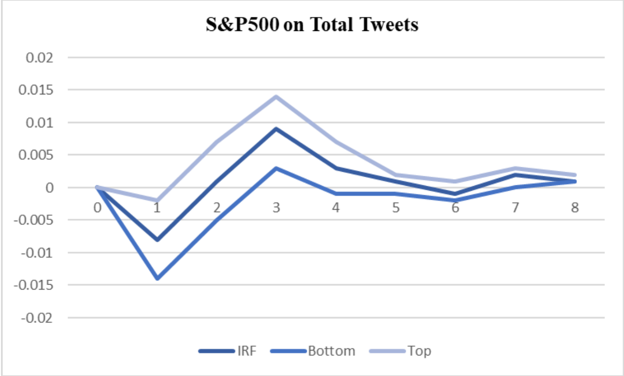


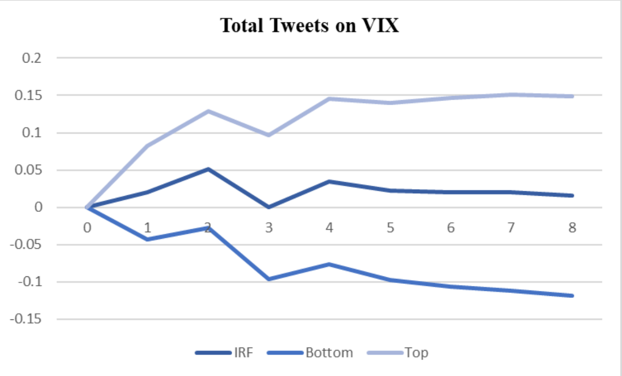



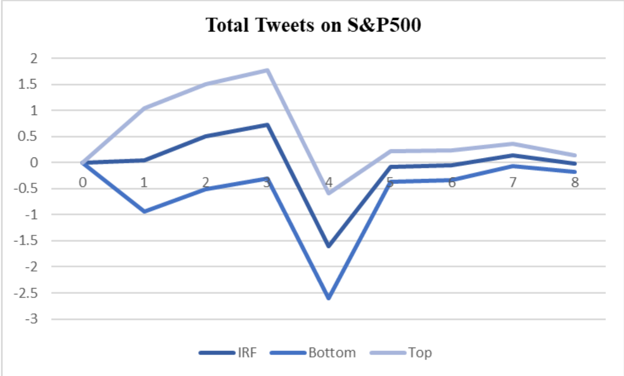



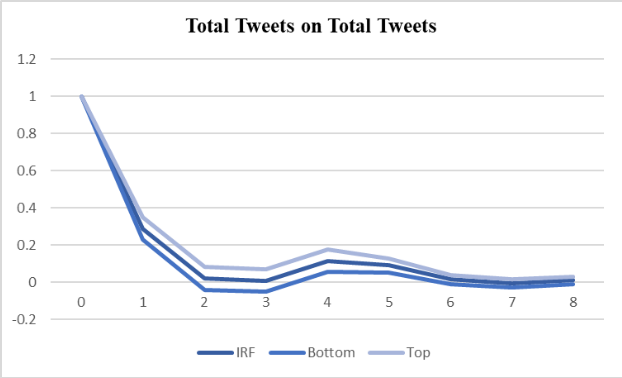



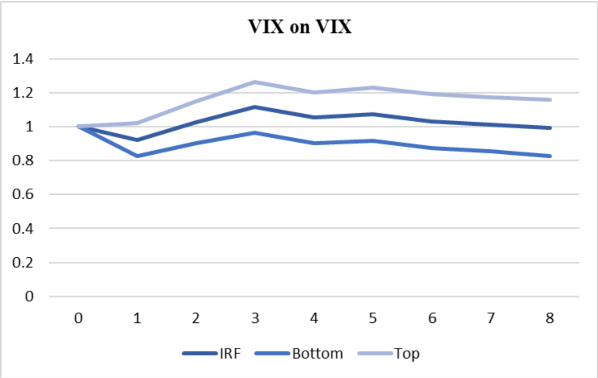


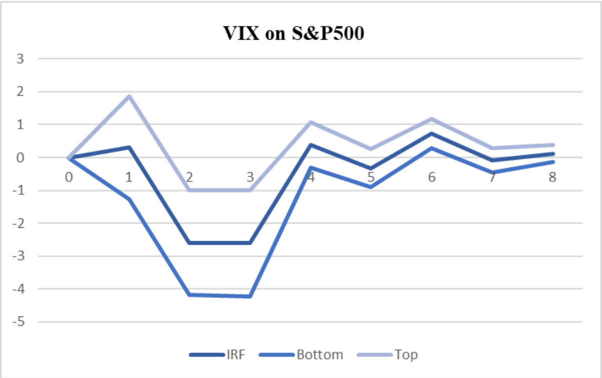

Appendix 10

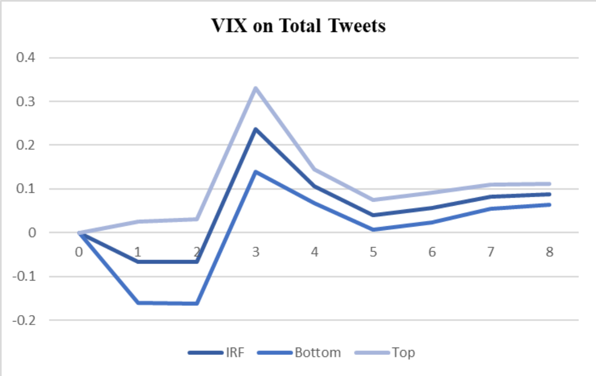
VARX - Granger Causality

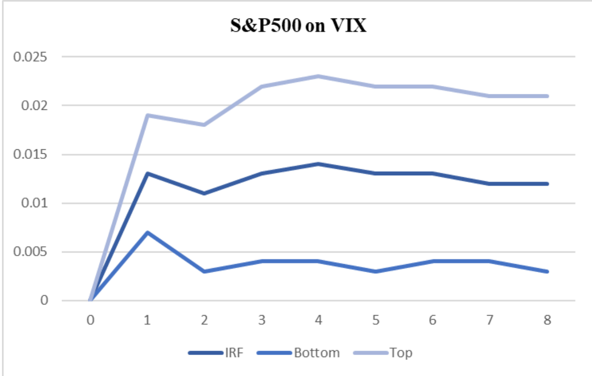
| Equation | Excluded | chi2 | df | Prob>Chi2 |
|---|---|---|---|---|
| Total Tweets | VIX | 64.749 | 4 | 0.000 |
| Total Tweets | dS&P500 | 18.479 | 4 | 0.001 |
| Total Tweets | ALL | 90.260 | 8 | 0.000 |
| VIX | Total Tweets | 4.942 | 4 | 0.293 |
| VIX | dS&P500 | 18.880 | 4 | 0.001 |
| VIX | ALL | 23.061 | 8 | 0.003 |
| dS&P500 | Total Tweets | 11.484 | 4 | 0.022 |
| dS&P500 | VIX | 30.087 | 4 | 0.000 |
| dS&P500 | ALL | 42.388 | 8 | 0.000 |

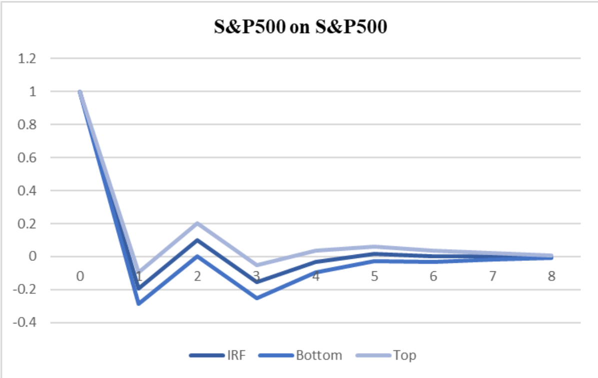
VARX - Impulse Response Functions

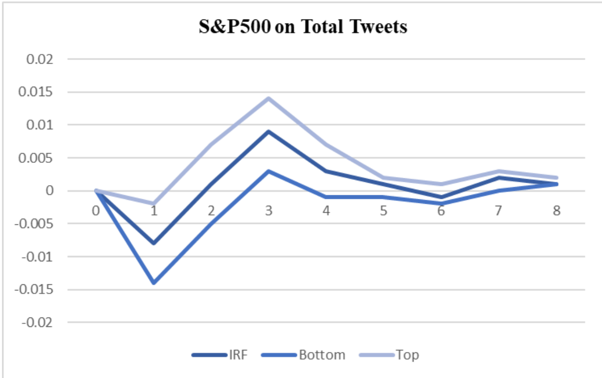


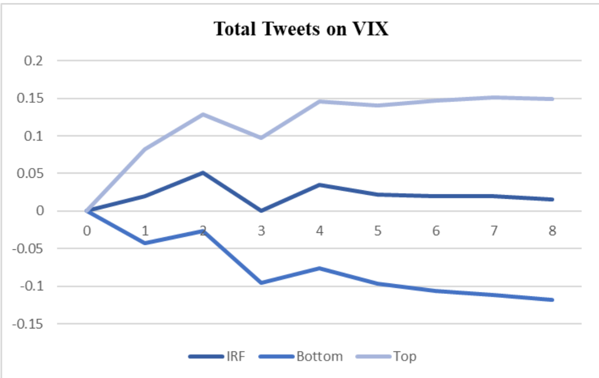



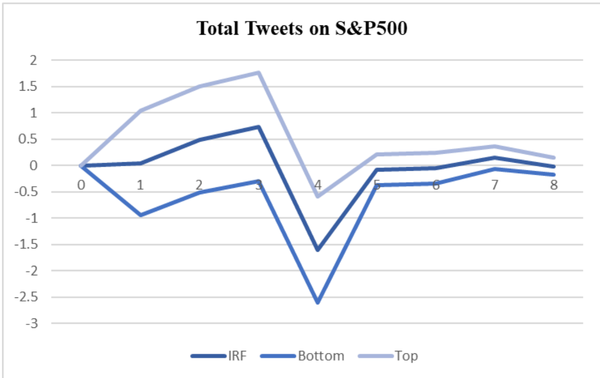

VIX on Total Tweets
0.4
0.3
0.2
0.1
0
-0.1
-0.2
0 1 2 3 4 5 6 7 8
IRF Bottom Top

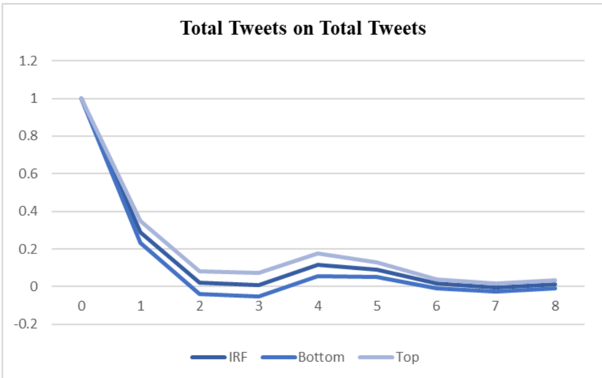

S&P500 on VIX
0.025
0.02
0.015
0.01
0.005
0
0 1 2 3 4 5 6 7 8
IRF Bottom Top


S&P500 on S&P500
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
0 1 2 3 4 5 6 7 8
IRF Bottom Top


S&P500 on Total Tweets
0.02
0.015
0.01
0.005
0
-0.005
-0.01
-0.015
-0.02
0 1 2 3 4 5 6 7 8
IRF Bottom Top


Total Tweets on VIX
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
0 1 2 3 4 5 6 7 8
IRF Bottom Top


Total Tweets on S&P500
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
-3
0 1 2 3 4 5 6 7 8
IRF Bottom Top


Total Tweets on Total Tweets
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0 1 2 3 4 5 6 7 8
IRF Bottom Top