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Charles University

Faculty of Social Sciences
Institute of Economic Studies

MASTER’S THESIS

Effect of Election Preferences on Stock Market Price

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Declaration of Authorship

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Prague, December 28, 2018

Signature

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Abstract

There exist a lot of empirical researches, that examine what factors effect the stock market volatility. The concept of investor sentiment is quite popular and is frequently discussed. However, there does not exist any research which would study the relation between the change in election preferences during the presidential campaigns and stock market volatility. The present thesis explores the effect of political sentiment on United States and French models. Here, we construct the model, which examines the effect of change in election preferences on the volatility. The results suggest, that change in election preferences does not affect the stock market volatility during the presidential campaign. Thus, its inclusion to the model does not increase the prediction power.

JEL Classification	G17, C22, G14
Keywords	sentiment, volatility, GARCH, lexicon

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Abstrakt

Existuje poměrně velké množství empirickch prací zaměřench na zkoumání faktorů ovlivňujících volatilitu akciovch trhů. Koncept tržního sentimentu neboli nálady na trzích je populárním a často diskutovanm tématem. Doposud však neexistuje žádná empirická studie, jež by se zabvala vlivem volebních preferencí na tržní volatilitu. Tato práce zkoumá vliv politického sentimentu v průběhu posledních prezidentskch voleb v USA a Francii na volatilitu akciovch trhů pomocí modelů časovch řad. Vsledky analzy svědčí o tom, že změny volebních preferencí nemají prokazateln vliv na volatilitu akciovch trhů v průběhu volebních kampaní.

Klasifikace JEL	G17, C22, G14
Klíčová slova	sentiment, volatilita, GARCH, lexicon

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Acronyms

EMH Efficient Market Hypothesis

ADF Augmented Dickey–Fuller test

KPSS Kwiatkowski–Phillips–Schmidt–Shin test

ACF Autocorrelation function

PACF Partial Autocorrelation function

US United States

CAC40 Cotation Assistee en Continu

AR Autoregressive

MA Moving Average

ARCH Autoregressive Conditional Heteroscedasticity

ARMA Autoregressive Moving Average

GARCH Generalised Autoregressive Conditional Heteroscedasticity

AIC Akaike Information Criteria

BIC Bayesian Information Criteria

FED Federal Reserve System

OLS Ordinary Least Squares

RNC Republican National Convention

Master's Thesis Proposal

Author	Bc. Ganna Efros
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Proposed topic	Effect of Election Preferences on Stock Market Price

Motivation It is a common knowledge that politics and economics are deeply intertwined. In the modern world where information is freely available every political act affects financial markets to a varying degree. Investors are aiming to determine any information that might change the stock price and adjust their strategies accordingly. In a similar manner, they are concerned about the elections since there is an uncertainty about how the elected candidate would steer the economy.

Historical data provides us with information that presidential terms are correlated with stock markets returns. For example, in past 100 years in USA, Democrats were better for stocks than Republicans, as more wars have started during the Republican presence in the White House. Real market returns were 5 percent higher, while real interest rate 4 percent lower under Democrats (Santa-Clara, Valkanov, 2003). This knowledge has an influence on the decision-making of investors and can be seen as an example of behavioral finance.

In the research we are going to focus on two election races: US and French President Elections in 2016 and 2017 respectively. There are plenty of researches, which would describe political cycles and sensibility of market stock prices with respect to investor sentiments exists (Adjei, Adjei, 2017). Some works investigate correlation of stock prices and a particular political party in power trying to predict a general mood of market participants. Other studies examine volatility of stocks during the elections week (Bialkowski, Gottschalk & Wisniewsky, 2008). Unfortunately, the relation between election preferences during the election race and stock prices volatility has not been answered by any academic work yet. This study aims to answer this by empirically testing the relation between presidential election preferences and stock prices volatility.

Various researches prove that investors' behaviour on stock market during the race period changes due to some level of uncertainty about future of the economy. Handful of studies supports the hypothesis that market reacts more to bad news rather than to good news (Veronesi, 2015). Rising support of less radical candidate is assumed as good news, while rising support for a radical candidate is considered as bad news. Because of a higher level of uncertainty as investors are not entirely sure how the elected candidate would manage the economy. In this paper we are going to test whether stock prices react differently to change in election preferences for different candidates.

Hypotheses

> Hypothesis #1: Including candidates' ratings into stock prices volatility modeling do not have positive effect on the predictions and do not provide us with more accurate outcomes of the model.
>
> Hypothesis #2: Higher support for a radical candidate does not imply stock price volatility.
>
> Hypothesis #3: During election race period market does not tend to be rising.

Methodology First step of our Volatility analysis will be performed by gathering time series data for the chosen indices, closing prices for selected indices (S&P500 and CAC40) from Yahoo Finance database.

Next, surveys for the candidates' support would be gathered and indexed according to their change in preferences. In order to perform this, we will use Naive Bayes algorithm – probabilistic classifier based on applying Bayes theorem. Python programming language will be used to build the classification.

The volatility of the stock prices will be evaluated using GARCH family of models, specifically the GARCH and EGARCH model to estimate the volatility of stock prices. These models can estimate the variance of a series at a particular point in time and thus they are the best estimators as volatility is simply described as "the conditional variance of the underlying asset return". Further we will use TGARCH modeling to find the support for our hypothesis that rising support for radical candidate has more effect on the stock prices volatility rather than the opposite (Brooks, 2014).

Expected Contribution The models will be tested on the latest datasets for the selected indices. We will construct two models for two elections races, what will give us the opportunity of comparison and improvement. The model will deliver predictions for the stock price volatility with the aim to provide more accurate results.

Outline

1. Introduction
2. Literature review
3. Methodology
4. Data Description
5. Empirical Results
6. Conclusion

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Author Supervisor

Chapter 1

Introduction

The functioning of financial markets has changed dramatically in last 50 years. Technology and globalization of the world have played a great deal in this purpose. Internet has brought the rapid speed of online connection with which the information is spreading extremely fast every second. The digitalization of the before printed books, articles, reports, etc. allows market agents to react to the changes in financial markets world within minutes or even seconds. In addition, with the globalization process the financial markets now have to take into account the changes on the foreign financial markets, even in the distant ones. In 70s the behaviour of the market was explained by Efficient Market Theory presented by Fama (1970). According to to this theory stocks are always traded at the fair price, meaning they fully reflect all the available information. This makes it impossible for arbitrage opportunity. Thus, it is unlikely to get the profit by purchasing the undervalued stock or selling overvalued one. Hence, the only opportunity to obtain higher return is to invest into more riskier activities. According to the theory mentioned above, if the new information appears it is immediately incorporated in the shares prices. However, this theory has been massively doubted due to its assumptions of rational agents behaviour. In the years following the theory presentation, there was a lot of theoretical and empirical papers proving the presence of issues in the EMT. The main argument of the opponents is that agents do not always behave rationally. There are plenty of evidence in support of this statement, for example the presence of the Monday effect. This phenomena is defined by significant difference in stock returns between Monday and Friday. The Monday returns are often significantly lower that the Friday ones. The similar effect is associated with January effect, which describes the increase in the stock prices in January in comparison to

December. One more example of similar effect is anchoring, which explains the use of some irrelevant information as a physiological benchmark. For example, using the purchase price of a security when estimating the price of a financial instrument. Since all of this effect happens due to behaviour of the market agents, this phenomena is described by existence of the behaviour finance. The behaviour finance concept is quite modern field in finance. This concept is trying to fill the holes in the traditional theory accounting for the irrational agents' behaviour. It suggests that emotions, opinions and other psychological elements effect the market agents decision making process. Another effect described by behaviour finance is news sentiments. It describes how do market agents react to some specific news about company or market overall taking into account their emotions, etc. There are plenty of studies providing the proof of significance of this phenomena. When the new piece of information enters the market, the market state changes. Thus, the news sentiment has a visible effect on the market dynamics. Therefore, it is important to analyze how does the new information affects the market, and include the result to the forecast models. For example, when company is revealing its annual report with decrease in revenues, one can analyze the past similar news. After performing the investigation of the similar events, the forecast for the stock volatility can be enhanced. This should improve the decision making and increase the profit of the agents.

In this thesis in turn, we aim to study the effect and significance of the political bias on stock market volatility. Even though in the current developed financial markets there is a certain level of independence from the politics, in comparison to the past times. There is still present the government control and necessary acceptance of reforms performed by the state. Thus, the behaviour of agents might be affected by the political sentiment. There are plenty of the papers researching the effect of reforms, economical cycles and political cycles on financial markets and economy overall. Besides, good deal of studies focuses on the presence of one or another power at the head of particular state and its effect on the economy and financial markets. Some of the works study the effect of political orientation of in charge party or president. Unfortunately, the relation between election preferences during the election race and stock prices volatility has not been answered by any academic work yet.

The purpose of this thesis is to empirically examine whether political sentiment, in our case the change of election preferences during the presidential campaign, have any effect on the financial market volatility. In other words, if the knowledge of revealed public preferences will help to model and predict the financial market volatility. Handful of studies supports the hypothesis, that market reacts more to bad news rather than to good ones. Rising support of less radical candidate is assumed as good news, while rising support of a radical candidate is considered as bad news. Because of the level of uncertainty which is associated with level of support for radical candidate, market is expected to be more volatile when the radical's support is higher. Thus, we aim to identify and study any asymmetric effect on stock market volatility. Another objective of this thesis is an exploration of different text analyzing techniques, which would allow us to objectively define the orientation of the presidential candidate. Usually the approach used for studying the sentiment effect on stock market volatility is the one introduced by Bollerslev (1986). In our research we aim to study the effect of election preferences on stock market volatility using the above mentioned GARCH method.

The thesis is structured as follows: Chapter 2 gives the overview of the academic theoretical framework in sentiments modelling. Additionally it presents the overview for existing modern text sentiment analysis techniques. Chapter 3 presents the text analysis suitable for our research and also performs the analyses, which help us to objectively define the final hypothesis. Chapter 4 covers the methodology for conditional heteroscedasticity volatility models as well as explains the augmented model implemented in our work. Chapter 5 describes and discusses the data used in this thesis. Chapter 6 interprets empirical results for the volatility model also constructs the augmented version of the model and presents its results. In addition, in Chapter 6 we perform the robustness checks in order to prove the stability and quality of our model and provide the discussion for the results. Chapter 7 provides the summary for the findings and suggests the possibilities for future improvements.

Chapter 2

Literature review

In this section we are going to present the theory and empirical findings for the functioning of the financial markets. Further, we discuss news and political sentiments and how does it affect the market. In the last part of the section the empirical framework for the text sentiment analyses is provided.

2.1 Efficient Market Hypothesis and Behavioral Finance

In the modern world financial sector is huge and subject to everyday changes, thus it might be highly volatile. Millions of stocks are available for trading and investors all around the world are trying to capture the perfect moment to buy or sell the assets. Each investor creates his own investing strategy based on his belief of the market predictability and truthfulness of the forecasts. Another important issue is how well according to the beliefs of the investor the information is reflected in the stock prices and whether there is something else what matters for the price of stock and thus its volatility.

In 1970 Fama (1970) proposed the Efficient Market Theory (EMT). In the published article he proposed 3 types of market efficiency: strong form, semi-strong and weak efficiency. The difference between those three lies in the amount of information reflected in the stock price. In the weak form of market efficiency the information set is derived only from the historical prices and it is impossible to profit from it. Semi-strong form says that all the public information is already reflected in the stock prices. And the strong form stands in need for all the information, including private, to be incorporated in the prices of the stocks. The EMT was developed on the theory by Samuelson *et al.* (1965), that stock prices take the random walk and thus are unforecasteble (if the market is informationally efficient).

One of the main assumptions of EMT is traditional behavior of the investors. However, recently the concept of behavioral finance is becoming more popular and contradicts the concept of EMT. According to the traditional financial theory rational traders would rapidly correct any mispricing created by irrational traders on the market, since it creates a profitable opportunity. Rationality here means that when investors receive the new information, they change their beliefs correctly according to the Baye's law. Such that they always objectively analyze and process the information, thus make a correct decision. Per contra behavioral studies such as one by Barberis & Thaler (2003), describes the situation when investors become biased in their actions, because of the emotions that affect their beliefs. Keynes (1936) in his work was the first one to point out to the importance of psychology for agents' behavior. He claimed that there is alteration of the underlying stocks from its fundamentals due to irrational optimism or pessimism of the agents. De Long *et al.* (1990) present a model, where irrational ("noise") investors affect the prices due to their beliefs and in the end earn higher expected returns. The mispricing is created because of the behaviour of rational traders who are betting against the irrational ones. This results in the divergence of stock prices from their real values, even if the fundamental risk is not present. The "noise" traders take the risk that they have developed themselves, thus receive higher returns. Here the concept of the investment sentiment should be introduced. Investment sentiment is a tendency of the investors to trade on emotions rather than on facts. There is a research on global sentiment and market returns in a work by Baker *et al.* (2012). In this presented findings we see, that global sentiment is statistically and economically significant contrarian predictor of market returns. According to the paper when sentiment is high, future returns are low and difficult to arbitrage as well as it is complicated to correctly value the stocks.

2.2 Investment Sentiments and Political Uncertainty

This paper is the first study to examine the effect of election preferences on the stock prices volatility during the US President election in 2016 and French President election in 2017. However, there are few studies on changes of investment sentiments and relationship between political cycles and investment sentiments. However, other studies take into account at least the presidential term time frame as a period of examination. While in our study we focus on the presidential race and stock prices volatility during the race.

The concept of the Investment Sentiment has been discussed above, here we would like to introduce the Political Sentiment – it is the investment sentiment, which is connected with personal beliefs, emotions and fears of the investor regarding the political risks. In the paper by Pástor & Veronesi (2013), authors check the political uncertainty effect on the stock prices based on the general equilibrium model. They find that stocks are more volatile and correlated when the political uncertainty is high. In the extended work by Pastor & Veronesi (2014), the focus is on the political events, such as national elections and global summits. The findings of this paper are in line with the original one. During the time around, big political events the uncertainty is higher, thus there is a call for premium. The prices of options, financial instruments that are used as a protection against uncertainty, are rising. Paper by Pasquariello & Zafeiridou (2014) examines how political uncertainty in terms of predictions of the result of US President elections affects the market quality. Authors state that there is a decrease in trading volume before the elections, since investors are not sure about the quality of information, which they receive. Also the decline in volume is increasing with the level of uncertainty of election outcomes. Durnev (2010) in his paper focuses on investment-to-price sensitivity - in the election years the investment sensitivity to stock prices falls by 40%. This paper as well as the paper by Pasquariello and Zafeiridou proves, that investors believe in the presence of information asymmetry on the market.

Wong & McAleer (2009) map the presidential election cycle. As stated in the paper, stocks follow the four-year presidential cycle, where the stock prices fell in first year of presidency followed by the rise in stock prices during the second year and reach its peak in third or fourth year. Another study by Mukherjee & Leblang (2007) presents the evidences that traders in the United States and UK expect higher post-electoral interest rates during the tenure of both Democratic party in the US and Labor party in the UK party and lower interest rates during the incumbency of the Republicans in the US and Conservatives in the UK. The findings also state that if the Democratic President is at the power and there are expectations of higher interest rates, the mean and volatility of the stock prices decrease and vice versa.

There are plenty of factors that influence stock prices and stock prices volatility. According to a research paper by Santa-Clara & Valkanov (2003), the excess return on stock is higher by 9% for the value-weighted and 16% for the equal-weighted portfolio during Democratic presidency. They investigated why such a difference occurs. Santa-Clara & Valkanov (2003) state that this disparity develops from higher real stock returns and lower interest rates. This difference is statistically significant and robust in sub-samples. However there is no difference of the risk of the stock market under different presidencies and the divergence is not explained by business cycles. Here, the idea of political cycles puzzle is presented. Authors prove that the information about returns is not explained by business cycle, however it is captured by the presidential cycle variables.

Another paper by Frederick Adjei & Adjei (2017) supports this idea, but focuses more on the political cycles puzzle. According to Adjei and Adjei, political cycles influence stock market in two ways: directly and indirectly. Direct impact comes from changes in fiscal, regulatory or monetary policies, which may vary according to the ruling party. These policies would lead to a change in stock prices, through change in dividend amount, income of company, etc. However, indirect influence happens through the change in investor sentiment, which in turn impacts stock prices. Investor sentiment is an attitude of the investor towards some particular stock, security or market. Adjei and Adjei examined in their work the relationship of Democratic or Republican presence in the White House and investor sentiment. The authors proved that during Republican presidential terms investor sentiments are higher, and that realized and excess returns are lower. Another important point in their study is that usually after the change of power investment sentiments are higher.

In our paper we assume that rising support for the radical candidate is seen as ”bad news” and rising support for the second candidate is seen as ”good news”. In the paper by Veronesi (1999), we find support for the behavioral finance hypothesis, that investors in order to hedge against change in their own ”uncertainty”, make stock prices overreact to bad news in good times and under react to good news in bad times. By acting like this, investors assume that they would capture the potentially harming volatility of the stock price. The fundamental assumption in the Veronesi’s paper is that economic fundamentals (drift of dividend process) pursue a process with unobserved regime shifts, which has been described by a two-state, continuous-time hidden Markov chain model. Here the two states are seen as bad state – environment with high uncertainty, and good state – when uncertainty is low. In his article Veronesi shows, that during the high uncertainty time, investors’ expectations of their future cash flows are more sensitive. This high sensitivity in turn increases the stock price against which investors are intending to hedge. When it is a good time and bad news arrive, in order to cover the risk of higher uncertainty investor increases the discount over expected future cash flow. As a result when bad news appear in the good time the price drop of the stock is higher than the reduction in the expected future cash flows. In the paper by **?** describes that bad news affects volatility of the stock prices more in good time than in bad times. However, good news neither increases nor decreases the stock prices volatility. Paper by Chen & Ghysels (2010) supports Veronesi’s findings, but also takes into account the volume of news. Moderately good news reduces volatility usually the next day, while unusual very high bad or good news increase volatility with bad news having a more relentless impact.

2.3 Text Sentiment Analysis

The Sentiment Analysis has become quite a popular area in Natural Language Processing in past few years. The text analyzing techniques have been used to proceed different kinds of texts to examine the sentiments of society, individuals or specific documents. One of the first interesting papers was written by Abbasi & Chen (2007), where he derived an approach which would measure the presence of hate, violence, and the resulting propaganda on different extremists group forums. Paper by Pang *et al.* (2008) presents the survey of different techniques and approaches used to define the opinions orientation. In 2006, Esuli & Sebastiani (2006) published a paper, which describes a research of documents orientation. The idea is to determine whether a document expresses a positive or negative motive. The paper by Birmingham & Kingstone (2009) presented the idea of spotting the radicalism online by analyzing various social media sites such as YouTube. Another paper about radicalism by Davulcu *et al.* (2010) discuses the presence of radicalism in online news.

A huge wave of papers came with the rising popularity of Twitter. A lot of researchers saw it as a perfect opportunity to examine public sentiments. One of the first papers was written by Dodds *et al.* (2011). He studied the expressions made online in order to spot the temporal patterns of happiness in society. Another interesting paper in which Twitter data was used is by O'Connor *et al.* (2010). They investigated correlation between official polls and public opinion used in Twitter posts. The correlation was proven to be high and they have captured a large-scale trend. Another paper by Soler *et al.* (2012) shows the relevance of prediction of elections results using the data from Twitter.

All of the papers mentioned above use linguistic approach, meaning there is a list of predefined dictionaries with sentiments. Each sentiment is, in turn, assigned a specific numeric value. Moreover, this approach usually uses words frequency count from the document or data set and a dictionary. There are lots of dictionaries which can be used in the text analyzing. Some of them are general (WordStat, Bing Liu,) others are specific for some field (Loughran and McDonald – financial sentiment dictionary).

Chapter 3

Text Sentiment Analysis

In this section we are going to objectively define, who is a more radical candidate among two running the presidential campaign. In order to do so, we perform the text sentiment analysis. There are two approaches, which work with the text sentiments. One is a lexicon-based sentiment approach, which performs the calculation of the text orientation using the polarity of the words. And the second one is machine learning approach, which builds the classifiers from chosen part of texts or sentences. Due to the specification of our data set and the goal of this analyses, we choose to use the lexicon-based approach. As was stated in introduction we perform the analysis to define the final form of our hypothesis.

Here we perform the analyses and identification of radical candidate only for US model. We assume, that open radical far-right position of Marie Le Pen is good enough evidence to call her the radical candidate in French model. She supports economical nationalism and protectionism as an alternative to free trade also she is opposed to privatization of public services and social securities. She opposes the globalization and European Union as it is, she has proposed France to leave Eurozone and was actively calling the referendum for this purpose. In addition, her and the party she represents (National Front) are fighting for the ”de–islamisation” of French society. As well as cancellation of even a legal immigration. Thus, the French sentiment analyses is irrelevant. And we focus only on the one for Donald Trump and Hilary Clinton.

3.1 Lexicon-based sentiment specification

Lexicon-based approach calculates the overall text orientation from semantic orientation of the words. Semantic orientation, in turn, measures subjectivity and opinion in the text. It usually apprehends the polarity of the text: positive or negative, towards the subjective case. We start with determining the semantic orientation of a word, but our aim is to classify the orientation of the text.

The dictionaries which are used during the lexicon-based approach are already created or can be created manually. In the first part of our analyses we use two lexicon dictionaries ”bing” and ”nrc”. The ”bing” lexicon was proposed by Hu & Liu (2004), it assorts words in a binary way to either positive or negative category. While ”nrc” lexicon proposed by Mohammad & Turney (2013) categorizes the words into positive, negative, anger, anticipation, joy, trust, surprise, disgust, sadness or fear categories. Both of these dictionaries are binary ones, assigning words to one or another category by ”yes/no” method.

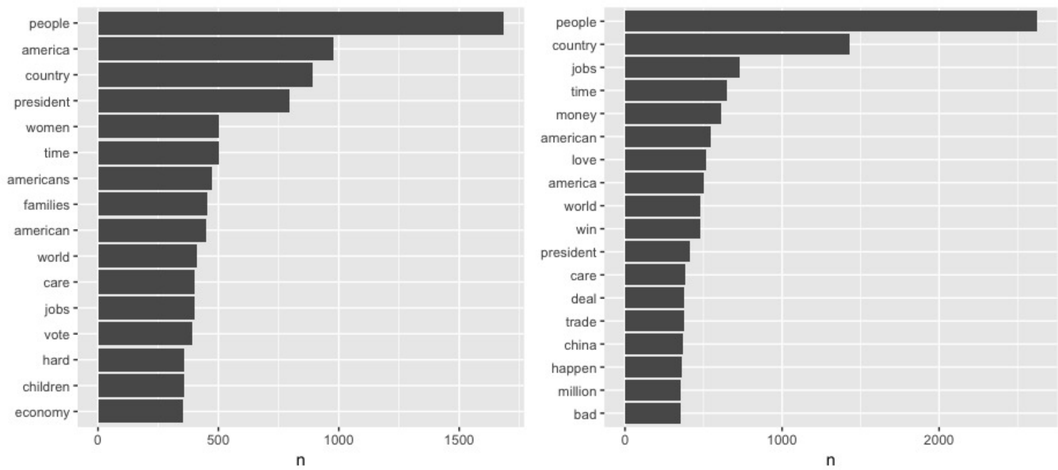
3.2 Data and Text Analyses

In the first part of the text analysis we examine the collection of Donald Trump and Hilary Clinton speeches during their presidential campaigns. Here we use different methods to derive and map their rhetoric. The Donald Trump's data set contains 87 public speeches during his presidential race and for Hilary Clinton it is 126 speeches.

Firstly, we tidy the data and unnest the tokens in order to rearrange our data for text sentiment analysis. Also, we get rid of stop words and then plot the frequency charts.

As we can see from Figure(3.1), some of the words are quite frequent for both candidates, these are to words such as people, country, american, etc. However, some words are specific for each. For example, Hilary Clinton oftenly uses words: women, families and children, which reveals her family-oriented position. While Donald Trump frequently uses words like jobs, time, money, trade and China. From this we can state, that in his speeches he is more business and economic oriented.

Figure 3.1: Clinton and Trump word frequency



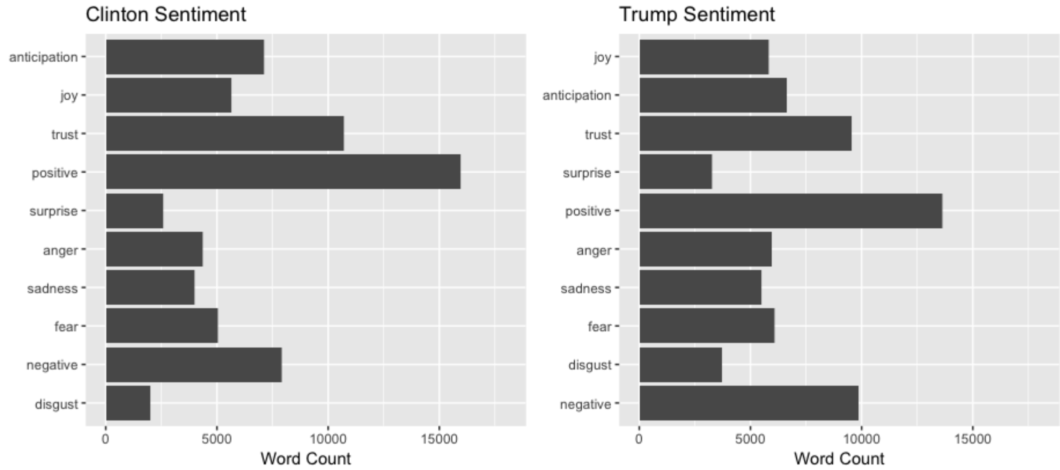
Source: Author's computations.

Secondly, we create a spread using the "bing" dictionary. The spread equals the difference between the sum of positive sentiments and the sum of negative sentiments. In other words, if the spread has a positive value, positive sentiment prevails in the candidate's rhetoric and vice versa. The formula of the spread is as following:

$$Spread = \sum_{i=1}^{I} Positive\ Sentiment - \sum_{i=1}^{I} Negative\ Sentiment \qquad (3.1)$$

The spread for Clinton equals to 547, while for Trump the result is 393. Thus, we can state that Clinton speeches have more positive character, than Trump's. Below in the Figure (3.2) the sentiments for Clinton and Trump can be found.

Figure 3.2: Clinton and Trump Sentiments



Source: Author's computations.

On the figure above Figure(3.2), we can compare the level of each sentiment for both candidates. Sentiments of trust, anticipation and overall positive sentiment are higher in Clinton speeches. While sentiments like anger, sadness, disgust, fear and overall negative sentiment is greater in Trump speeches. Concluding only from this graph, we can talk about more radical rhetoric in Trump's speeches. Nevertheless, we do not make our final decision of who is a radical candidate at this point and move to the radical index section.

3.3 Radical Index

In order to definitively state who is the radical candidate we create the radical index. Since the radical sentiment does not exists in any of the known dictionaries, as the first step we create new dictionary for the radical sentiment. We include there the radical sentiment for the words found in other similar articles such as the one by Davulcu *et al.* (2010) for example. Also we include some other radical words oftenly used by far-right parties in Western world.

Further, we create the index which checks the data set of Trump and Clinton speeches for presence of those words. The higher result of the index check, would mean the higher level of radicalism presence in the candidates' rhetoric.

Once we run it on the obtained data sets we get the following results:

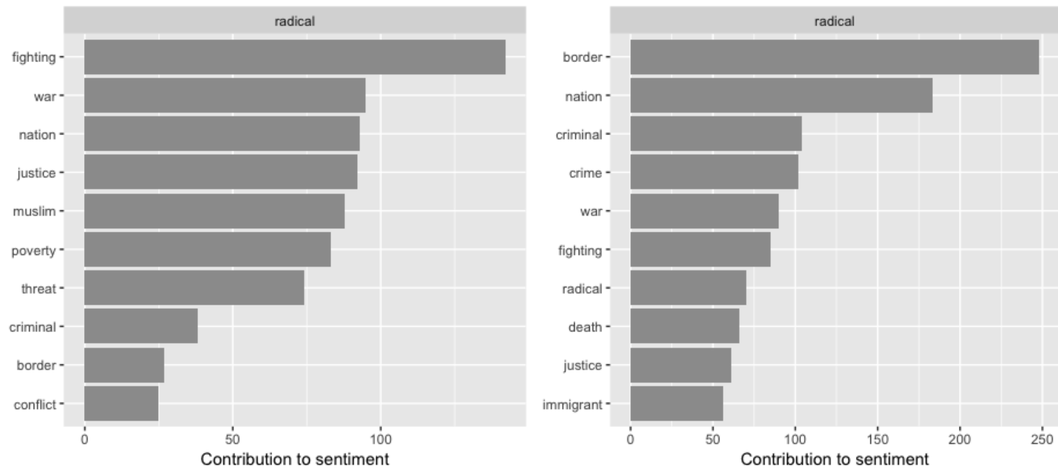
Table 3.1: Radical Index Score

	Radical Index
Clinton	969
Trump	1 359

Source: Author's computations.

As we can see from the Table (3.1) Trump's score is much higher than Clinton's. Thus, we can objectively conclude that the radical candidate for our model is Donald Trump.

Figure 3.3: Clinton and Trump Radical Sentiment



Source: Author's computations.

Figure (3.3) provides us with overview of the words contribution to radical sentiments for Clinton and Trump score. As we can see in Trump's radical words prevails the issue of the national border and immigration. While at Clinton's rather the overall terror threat. Also if we check for pair words in Trump speeches, criminal and illegal are in top 10 of all pairs. While in Clinton's top 10 does not present any radical word.

This section of text analysis has indeed objectively proved the radical rhetoric present in Donald Trump speeches. Thus, we would apply our hypothesis about radical candidate to him.

Chapter 4

Methodology

There is a wide range of non-linear models. However, if we want to apply some of them for modeling of the financial data only few would be useful. The most popular non-linear financial models are ARCH or GARCH models, which are used for modeling and forecasting volatility and switching models, which allow the behavior of a series to follow different process at different point in time. They are preferable to other models, for example to ordinary least squares model. In OLS the variance should be evenly distributed throughout the data. Another reason to use GARCH family of models is that financial data often does not satisfy the homoscedasticity assumption, while GARCH counts with conditional heteroscedasticity by fixing the least squares deficiencies by modeling variance. Thus, allowing us to to work with the heteroscedastic data.

4.1 Conditional Heteroscedastic Models

4.1.1 ARMA

Autoregressive volatility models (ARMA) are quite simple models for time series analysis. These models were introduced by Box *et al.* (1978). The models were developed because simple Autoregressive and Moving Average models were not sufficient, mainly in situations with dynamic structure of the data. Fundamentally, ARMA Models of orders p and q combine autocorrelation methods AR(p) and moving averages MA(q) into one model of the time series. Later it was revealed, that the use of these models in volatility modeling is quite relevant.

AR(p) model uses the future value of a variable as a linear combination of

p past observations and random error as well with a constant term. Mathematically it is represented in the following way:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{4.1}$$

where y_t is the actual value at time t, $\varphi_i (i = 1, 2, \ldots, p)$ are model parameters, c is a constant and ε_t is an error term at time t. The p is an integer and is known as the order of the model.

MA(q) is represented as averages of different subsets of the whole data set over a given time periods, it is using past errors as the explanatory variables:

$$y_t = \mu + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4.2}$$

where μ is the mean of the series, $\theta_j (j = 1, 2, \ldots, q)$ are the model parameters, q is the order of the model and ε_t is an error at time t. Here the error terms are assumed to be a white noise process. i.e. a sequence of independent and identically distributed (i.i.d) random variables with zero mean and a constant variance σ^2. Random shocks are assumed to follow the normal distribution.

Once we combine two models described above, the ARMA model can be represented mathematically as following:

$$y_t = c + \sum_{i=1}^{p} \varphi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \tag{4.3}$$

where p and q are models orders, which refer to p autoregressive and q moving average terms, c is a constant and ε_t is an error term at time t.

The equation (4.3) shows us that AR and MA is just the special case of ARMA model. We can rewrite the standard definition of ARMA model using the back shift operator:

$$(1 - \phi_1 B - \ldots - \phi_p B^p) r_t = \phi_0 + (1 - \theta - \ldots - \theta_q B^q) \tag{4.4}$$

where the polynomial $(1 - \phi_1 B - \ldots - \phi_p B^p) r_t$ represents the AR term and polynomial $\phi_0 + (1 - \theta - \ldots - \theta_q B^q)$ MA terms. And these polynomials have no common factors. Meaning that the model can not be reduced to simpler one, otherwise it would complicates the further analysis of the model.

ARMA methodology can be used only for the stationary time series. MA process is always stationary, and does not depend on the values of MA parameters. For the AR process to be stationary the following conditions have to be satisfied:

- Mean is constant in t: $E(y_t) = \mu \; for \; t = 1, 2, \ldots$
- Variance is constant in t: $Var(y_t) = \sigma^2 \; for \; t = 1, 2, \ldots$
- Covariance is constant in t: $Cov(y_t, y_(t + k)) = \chi k \; for \; t = 1, 2, \ldots$ $and \; k \neq 0$

The conditions of stationarity of MA and AR hold for ARMA process. An ARMA process is stationary if all the roots of the characteristic equation φ_i lie outside the unit circle:

$$\left| \sum_{i=1}^{p} \varphi_i \right| < 0 \tag{4.5}$$

However, in real life, the trends and periodicities often end up in non-stationarity of the timeseries data. In order to apply the econometric models on this data sets we need to remove the non-stationarity. For this purpose we can generalize ARMA(p, q) model to get ARIMA (Autoregressive Integrated Moving Average) model by letting AR process to have a unit-root. In order to transform ARMA(p, q) to ARIMA $(p, 1, q)$ model we have to apply differentiating (logarithmic). In ARIMA$(p, 1, q)$ the number 1 means that differentiating has been applied once. Usually the first differentiating is enough, however when the time-series have multiple unit-roots second and further differentiating might be applied as well. Although it would lead to the loss of information.

4.1.2 ARCH

The Autoregressive Conditional Heteroscedasticity model approach was proposed by Engle (1982) to deal with heteroscedasticity in the data. Least squares model assumes – homoscedasticity of the data, meaning value of all error terms being same at any given point when squared. However, when variances of the error terms are not equal we say the model suffers from heteroscedasticity. In order to work with this problem ARCH and GARCH models treat heteroscedasticity as a variance to be modeled. As a result the prediction for the variance for each error term is computed. This turned out to be useful in financial time series.

As we know, according to Gauss-Markov assumptions, the conditional mean $E(r_t) = 0$ and following is true:

$$\sigma_t^2 = var(r_t|r_{t-1}, r_{t-2}, \cdots) = E[r_t^2|r_{t-1}, r_{t-2}, \cdots] \tag{4.6}$$

Equation above states that conditional variance of a zero mean normally distributed random variable it is equal to conditional expected value of the square it. This is also known as Gauss Markov assumption of homoscedasticity. However, this assumption might be violated while working with financial time-series data. Thus the Autoregressive Contional Heteroscedasticity (ARCH) models are used.

The main goal of ARCH models is to describe the conditional variance h_t. We start describing the ARCH derivation with defining the equation for return r_t:

$$r_t = \mu + \gamma_t \tag{4.7}$$

meaning return in the present equals to the mean value of r plus the standard deviation of r (square root of the variance) times the error term for the present period. The term γ_t also referred to as a shock of return series at time t. And mathematically presented as:

$$\gamma_t = \sqrt{h_t \epsilon_t} \tag{4.8}$$

The presented by Engle ARCH(1) model is:

$$h_t = \alpha_0 + \alpha_1 \gamma_{t-1}^2 \tag{4.9}$$

where $\gamma_t = \sqrt{h_t \epsilon_t}$, $\alpha_1 > 0$ and $\alpha_0 > 0$ are estimation parameters. Using the normality condition Engle extends model to generalizded form:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \gamma_{t-i}^2 \tag{4.10}$$

where $\alpha_i > 0$ and $\alpha_0 > 0$ conditions must hold, to ensure the non-negativity of conditional variance.

If we examine the ARCH equation, we see that effect of shocks have a direct impact on conditional variance. Thus big shock is tend to be followed by another big shock. Since ARCH is the first autoregressive model allowing for conditional heteroscedasticity it has a lot of drawbacks. For example, it does not distinguish positive and negative shocks, since the conditional variance is dependent on the squares of γ_t. Also the model does not cover the source of variations, since it describes the conditional variance mathematically only. Thus, ARCH model was generalized to address these and some other problems of ARCH.

4.1.3 GARCH

The Generalized ARCH model (GARCH) was developed independently by Bollerslev (1986) and Taylor (1994) and proved to be sufficient for the volatility modeling. The GARCH model allows conditional variance to be dependent upon previous own lags. In order to specify the model correctly large number of squared lagged residuals must be included. GARCH models assumes conditional variance as a weighted average of: the long-run variance, the forecast made in previous period and new information, that becomes available after the previous forecast was made.

Mathematically the general form of GARCH can be written as:

$$r_t = \sigma_t \varepsilon_t \tag{4.11}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{4.12}$$

where α_0 is long-term variance, α_i is the period t actual variance or in other words the new information that was not available before and β_j is the variance predicted for the term t. Hence, the main idea of GARCH equation is , that σ_t^2 is a conditional variance of r_t and the information is available only untill the time $t-1$. σ_t^2 has an autoregressive structure and is positively correlated to its own recent past and to recent estimations of squared returns r^2. The equation (4.12) shows that if $p = 0$ the GARCH model reduces to ARCH. And if $p = q = 0$ than ϵ_t is simply "white noise". The model suggests, that the best prediction for the future variance is a weighted average of the long-term average variance, the forecast made for current period and new information in current period available from the recent squared residual. The equation of

GARCH captures the idea of: volatility being persistent. Meaning that the large values will be followed by large numbers, while small numbers are likely to be followed by small numbers.

GARCH (p, q) is stationary, if the sum of all α_i and all β_j is strictly smaller than 1. Moreover, GARCH is built on the ARCH model, by letting the lagged conditional variances of GARCH to come into equation. ARCH can be as the specific case of GARCH, i.e. GARCH$(1, 0)$. Also we call α_i – ARCH parameter and β_i – GARCH parameter.

4.2 Assumptions

In this section we are going to discuss the basic properties needed to be satisfied, in order to start with GARCH modelling.

4.2.1 Zero Mean

If we consider the first order of autoregressive conditional heteroscedasticity (ARCH) process described above. Where r_t is a return, the conditional mean of r_t is:

$$E(r_t|r_{t-1}, r_{t-2}, \ldots) = E(\sigma_t e_t|r_{t-1}, r_{t-2}, \ldots) = \sigma * 0 = 0 \tag{4.13}$$

Then by the law of iterated expectation, the unconditional mean is:

$$E(r_t) = E[E(r_t|r_{t-1}, r_{t-2}, \ldots)] = E[0] = 0 \tag{4.14}$$

So the ARCH process has zero mean.

4.2.2 Lack of serial correlation

In the same way as above, we can show that r_t is not correlated to r_{t+1} for $h > 0$:

$$E(r_t r_{t+1}) = E(r_t \sigma_{t+h} \varepsilon_{t+h}) = E[E(r_t \sigma_{t+h} \varepsilon_{t+h}|\tau_{t+h-1})] = 0 \tag{4.15}$$

Therefore the covariance between r_{t+1} and r_t is:

$$cov(r_t r_{t+1}) = E(r_t r_{t+1}) - E(r_t)E(r_{t+1}) = 0 \tag{4.16}$$

4.2.3 Uniqueness and Stationarity

Another important and sufficient assumption for ARCH and GARCH model is to have unique and stationary solution. Thus, ARCH and GARCH have unique and stationary solution if:

$$\sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1 \tag{4.17}$$

4.2.4 Unconditional variance

If we want to compute $E(r_t^2)$ firstly we should rewrite r_t^2 in the following way:

$$Z_k = r_t^2 - \sigma_t^2 = \sigma_t^2(\varepsilon_t^2 - 1) \tag{4.18}$$

As a next step we show that Z_k is a martingale difference and therefore has zero mean. We do so, to show that for many purposes Z_k can be treated as "white noise" sequence. Further, we continue with the alternative representation:

$$r_t^2 = \sigma_t^2 + Z_k \tag{4.19}$$

$$r_t^2 = \omega + \sum_{i=1}^{p} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + Z_k \tag{4.20}$$

$$r_t^2 = \omega + \sum_{i=1}^{q} \alpha_i r_{t-i}^2 + \sum_{j=1}^{q} \beta_j r_{t-j}^2 - \sum_{j=1}^{q} \beta_j Z_{k-j} + Z_k \tag{4.21}$$

denote $R = max(p, q), \alpha_i = 0$ for $i > p$ and $\beta_j = 0$ for $j > q$, then the equation above can be rewritten as:

$$r_t^2 = \omega + \sum_{i=1}^{R} (\alpha_i + \beta_j) r_{t-i}^2 - \sum_{j=1}^{q} \beta_j Z_{k-j} + Z_k \tag{4.22}$$

In other words r_t^2 is an ARMA process with martingale difference innovations. Now we use the stationarity condition from the assumption above, which implies that $E(r_t^2) = E(r_{t+h}^2)$ and obtain the equation for the unconditional variance:

$$E(r_t^2) = \omega + \sum_{i=1}^{R}(\alpha_i + \beta_j)E(r_{t-i}^2) - \sum_{j=1}^{q}\beta_j E(Z_{k-j}) + E(Z_k) \tag{4.23}$$

$$E(r_t^2) = \omega + E(r_t^2)\sum_{i=1}^{R}\alpha_i + \beta_i \tag{4.24}$$

and rewriting it to:

$$E(r_t^2) = \frac{\omega}{1 - \sum_{i=1}^{R}\alpha_i + \beta_i} \tag{4.25}$$

4.3 Model Specification with Election Preferences Variable

In the previous sections we have described and showed the derivation of plain GARCH modeling. In the standard case explained above only time series data is employed.

In this section we are going to define the augmented model, which adds additional information, in a form of numeric exogenous vectors. The specified model can potentially improve the regular GARCH model abilities. Here we add election preferences as two exogenous variable to the variance equation of GARCH model. We assume, that the information about preferences change is affecting market agents behavior, thus affects the volatility of the market. Furthermore, we study positive and negative change of preferences separately, matching the articles about behavior finance.

The GARCH variance adjusted for exogenous variables model will take the following form:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}\alpha_i u_{t-1}^2 + \sum_{j=1} p\beta_j\sigma_{t-1}^2 + \theta_1 PC_t + \theta_2 NC_t \tag{4.26}$$

Where $\theta_1 PC_t + \theta_2 NC_t = \theta C_t$ is change in preferences. PC_t is a vector of positive values $C_t > 0$, while NC_t vector of negative changes in preferences with values $C_t < 0$. However, we must state that NC_t is entering equation in absolute values$|\ NC_t = C_t < 0\ |$, in this way we ensure the positivity, which is important for GARCH modeling.

Specifically, after dividing our change vector into positive and negative ones, we are able to analyze and study the effects separately, instead of looking at the total change effect. When the positive change occurs, the values is assigned to positive vector, while negative vector reflects 0 for this specific date. In this way we ensure that neutral (0) effect on specific date, does not have any significant effect on the volatility. Thus, we can neglect it.

In order to specify the augmented model correctly, we use the change in preference from time t. Because the polls announce the data during the day, we assume that there is enough time for market agents to adjust to the changes before the market closes. In case of change in preferences during the weekend or public holidays, we move the changes to the closest trading day.

Further, this augmented GARCH model is applied on two markets (United States market and French market) and uses the collected preference changes, separated to two vectors as described above.

Chapter 5

Data

In our research we are constructing two independent models, with two different data sets. First model focuses on the United States Presidential campaign in the time period from July 1^{st} 2015 until November 8^{th} 2016. Second model is constructed based on the data between January 3rd and May 8th 2017 for the French Presidential campaign.

5.1 United States Data

For our research we construct time-series model, which contains two variables: S&P500 Index and the vector for indexed election preferences for United States presidential election race. Data for both of the variables is collected on the daily basis for the period from July 1^{st} 2015 until November 8^{th} 2016 – the election date.

5.1.1 Preferences Data

In this section we present and describe the election preferences data used in the US model.

The variable ”election preferences” is defined as the chance of winning the presidential race by one of the two candidates – Hilary Clinton or Donald Trump. The probability of winning corresponds to the public support for the candidate. The data collected represents the average of 11 polls updated daily. Public preferences have been changing throughout the presidential campaign. Below we can find the summary of the public support variable.

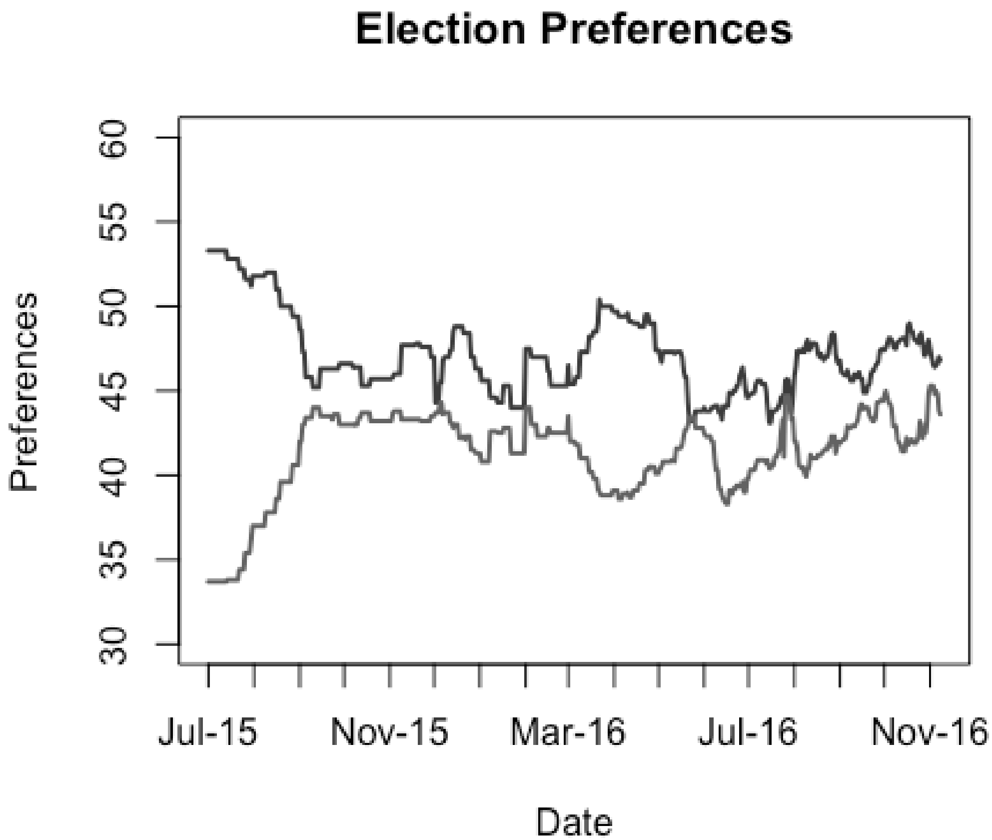
Table 5.1: Summary Statistics for Election Preferences

	Clinton	Trump
Min	43.10	33.70
Median	47	42
Mean	47.17	41.33
Max	53.30	45.30

Source: Author's computations.

The summary statistics is presented in the Table (5.1) above. We can see the maximum, minimum, mean and medium values for the both candidates support. It can be concluded, that Clinton had an advantage over Trump on average, since both mean and median are higher in her case.

Figure 5.1: Election Preferences United States

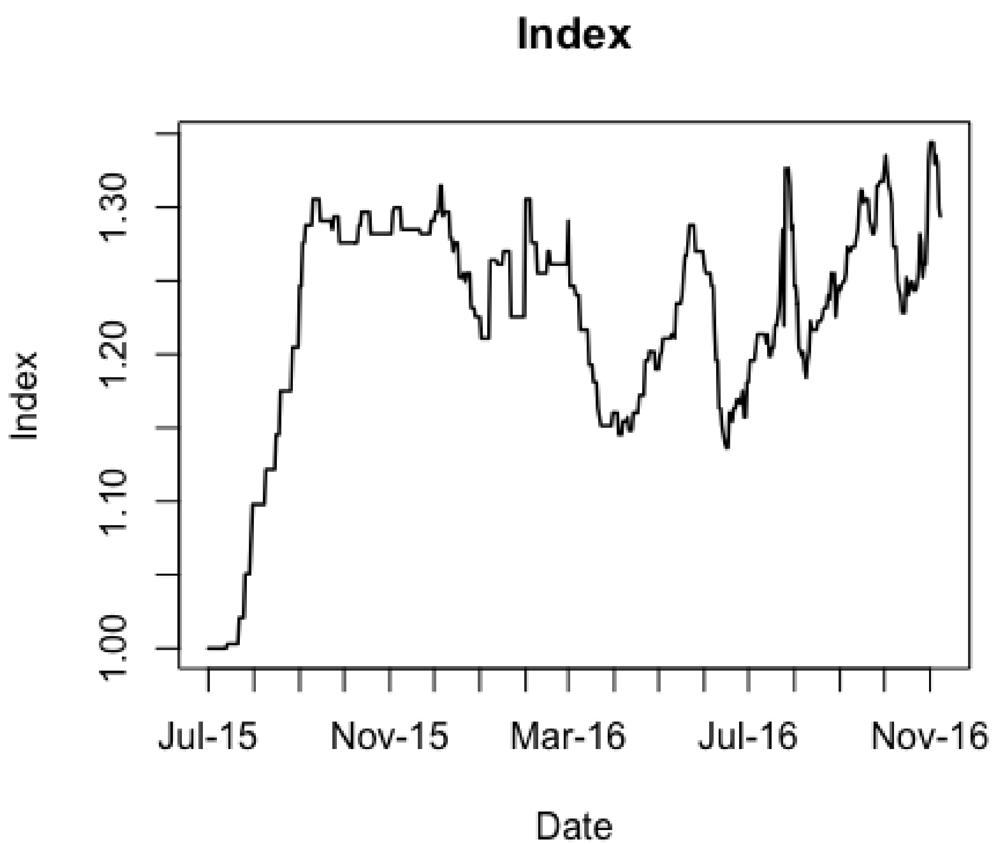


Source: Author's computations.

As we see from the Figure (5.2) above, preferences for the candidates have been quite volatile. Black line – is representing support for Hilary Clinton, while grey – for Donald Trump. As could be seen from the graph, chance of winning for Clinton has been higher all the time with the exception of one day - July 30th 2016. It has been followed by fast rise of Trump's support after the Republican National Convention (RNC) during July 18-21 2016. At RNC Trump won the Presidential nomination. However, this fast rise was followed by rapid decrease in Trump's support and returning of Clinton's domination.

We can tell that the support preferences were quite cyclical, according to the graph we can distinguish few cycles. Each of the cycles contains: period of slow support increase for Trump; the peak; and after, fast decline. Revealing of the scandal tape caused the last drop in the Trump's support in middle October. The tape was published by The Washington Post and enclosed compromising evidence about Donald Trump.

Figure 5.2: Index of Trump's Support



Source: Author's computations.

In the next step we perform indexation of the preferences. July 1st 2015 is taken as base day with index 1 for Trump's support, and all the following days are calculated respectively to that day.

In the Table (5.2), below, the summary statistics for Index of Trump's support is presented. According to this statistic we can clearly see that the average trend over time is positive, meaning the overall positive increase in Trump's support during given period of time. The skewness, which interprets asymmetry of the probability distribution around its mean, has a negative value around -1.34. This means that distribution is highly skewed. As well we can state that the distribution is negatively skewed, which means that the left tail is longer. The kurtosis, which measures the tallness and sharpness of the central peak, is under the threshold for normal distribution. Thus, the data follows the normal distribution.

Table 5.2: Summary Statistic for Index of Trump's Support

Obs	mean	sd	median	min	max	skewness	kurtosis	se
497	1.23	0.08	1.25	1	1.34	-1.34	1.64	0

Source: Author's computations.

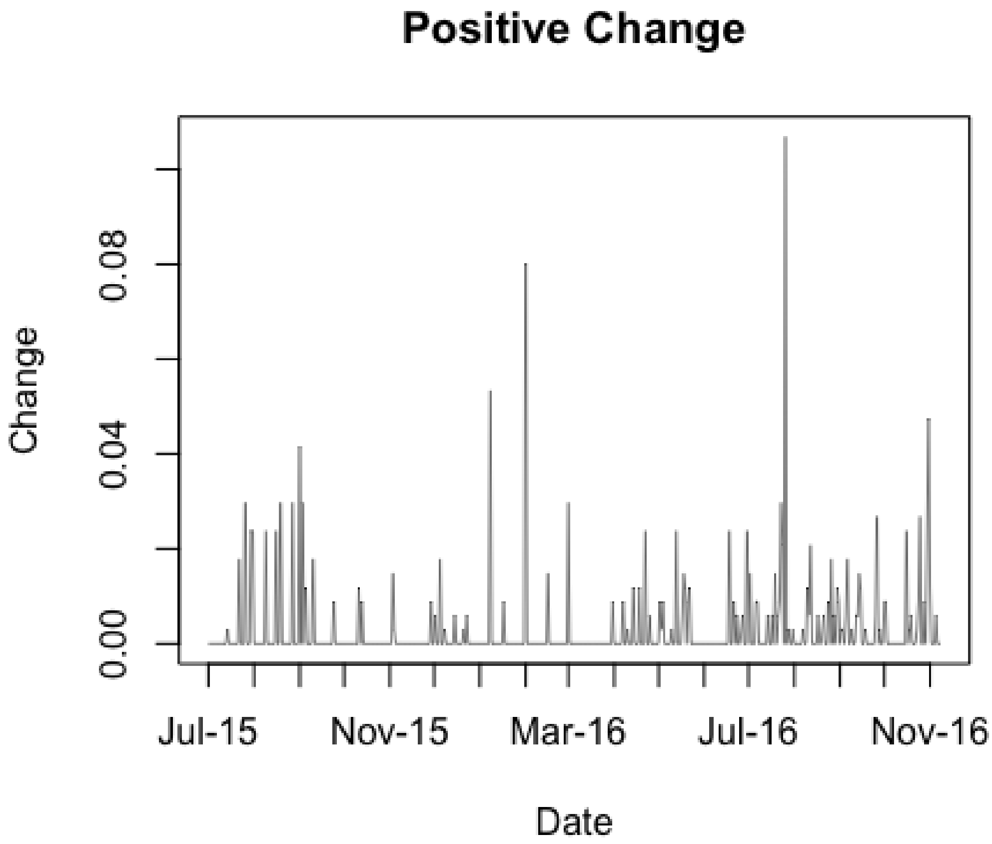
Further we divide the Index of Trump's support into the two vectors: one of Positive (when the support is increasing) Change and one of Negative (when support declines) Change. Each of the vectors represents a difference in terms t and $t-1$, when the difference is positive the values is reflected on the positive vector and 0 appears on the negative one and vice versa. This is made, so we can estimate and distinguish the results separately for positive and negative changes.

It is also important to state, that the values in both vectors are positive. For negative numbers we take the absolute value. This assumption is important to work with the GARCH family of models.

The Figure (5.3), provides us with the overview of positive changes in Trump's preferences. And the Figure (5.4), plots the negative changes in

Trump's support.

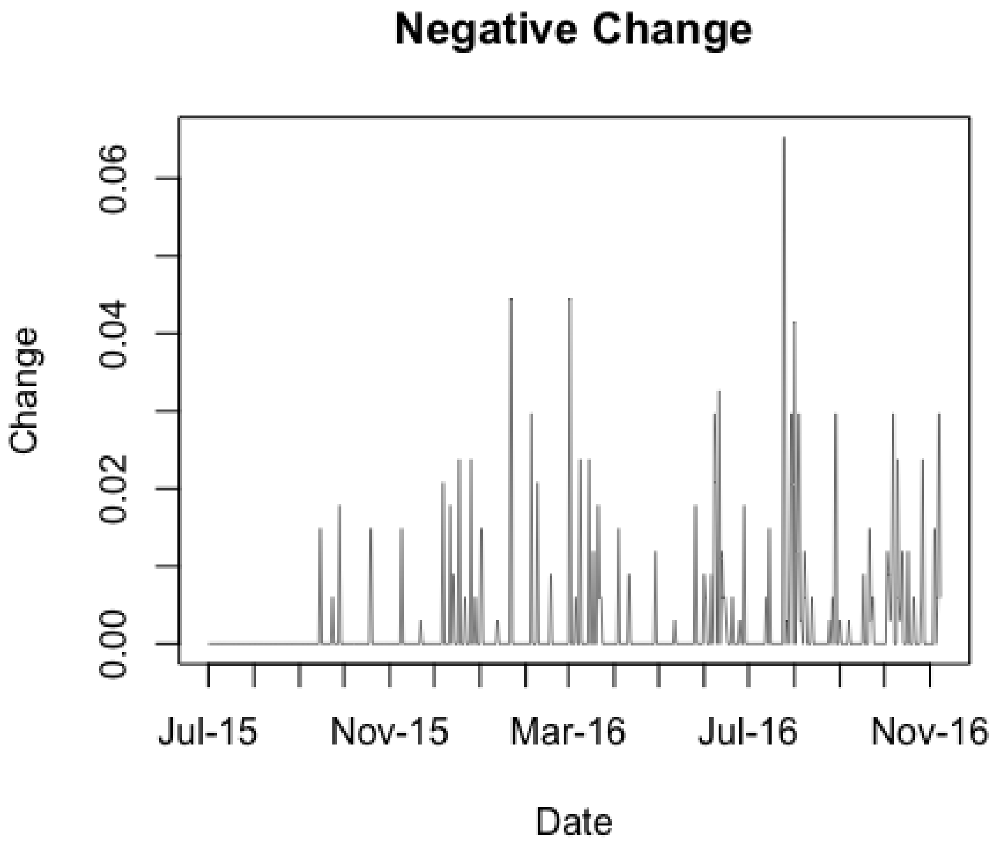
Figure 5.3: Positive Change in Trump's Support



Source: Author's computations.

For each graph we can see few peaks. Interestingly, these peaks usually happen almost at the same time. As was described above the rise of Trump's support to the peak is always followed by the drop, effect of which we see on the graph. As well we notice higher magnitude for negative peaks rather than for positive.

Figure 5.4: Negative Change in Trump's Support



Source: Author's computations.

In order to be able to include the vectors to the model we need to make the statistical tests, the same ones as applied to any other time series data. We check the obtained vectors for stationarity of the data, using Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin(KPSS) tests. The results of the tests are presented in Apendix A.

The p-value for ADF test for both vectors is below the critical value, which means we can reject the null hypothesis of non-stationarity. And KPSS test indicates p-value greater than critical value for both vectors, so the data is stationary.

5.1.2 Financial Time-Series Data

Another variable that we use in the construction of United States is the S&P 500 Index, which we take as proxy for the average behaviour of the market. This index, often referred to as S&P Index, has more than 60 years of history. It represents the market capitalization of biggest 500 corporations listed on New York Stock Exchange and Nasdaq Stock Market. It is calculated as the sum of adjusted market capitalization of 500 stock divided by a factor, often referred to as the Divisor. The value of S&P500 Index is updated every 15 seconds. This Index is the best proxy for the market and economy overall, since it intends to composite and represent the overall economy. It has shown the best reflection of changes in US economy in terms of size and character over time. Stocks have been included and dropped over time from the list of S&P 500 Index. Thus, it has outperformed other major asset classes like commodities or bonds.

The data is collected from Yahoo finance for the time period from July 1^{st} 2015 untill the pre-election date November 8^{th} 2016.

Table 5.3: Summary Statistics for S&P Index

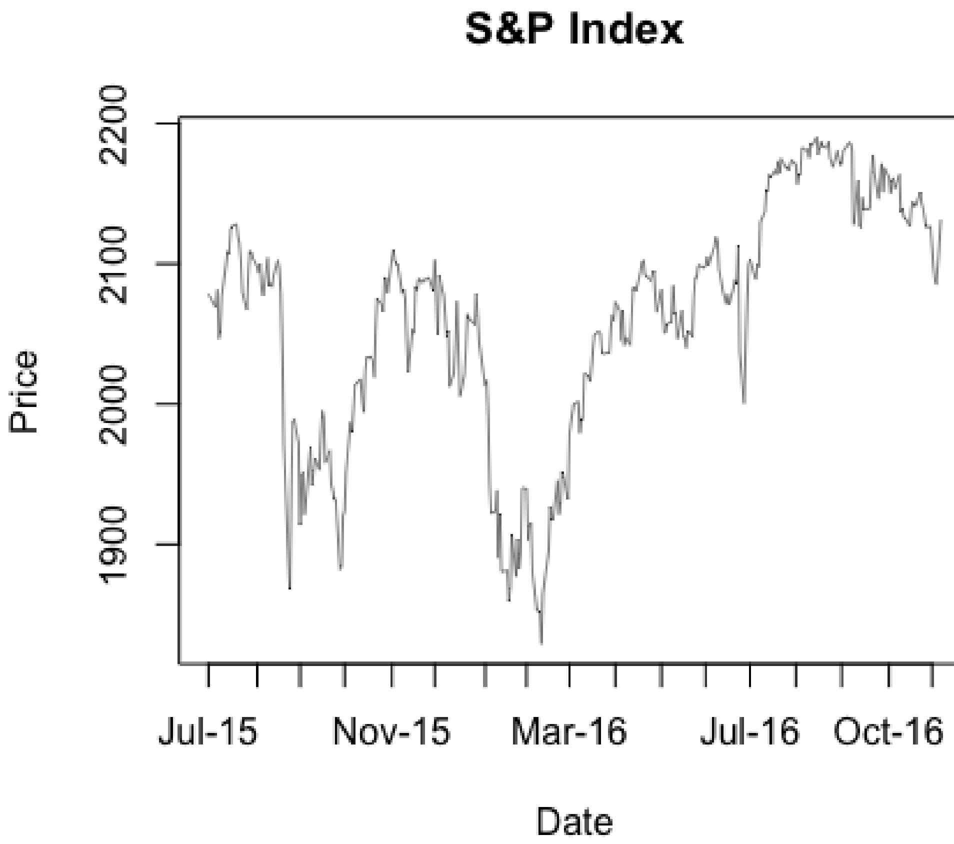
	Close
Min	1 829
Median	2 078
Mean	2 061
Max	2 190

Source: Author's computations.

Summary Statistics for the S&P Index is presented in the Table (5.3) above. As we can conclude from the maximum and minimum values, index has been fluctuating over the time. The minimum value is $1 829, which is 16,5% smaller then the maximum value – $2 190.

From the graph below (Figure (5.5)) we can conclude, that S&P Index has been volatile over the given period of time. However, it is hard to spot any visible correlation between S&P Index Volatility graph and Election Preferences graph.

Figure 5.5: S&P Index Volatily



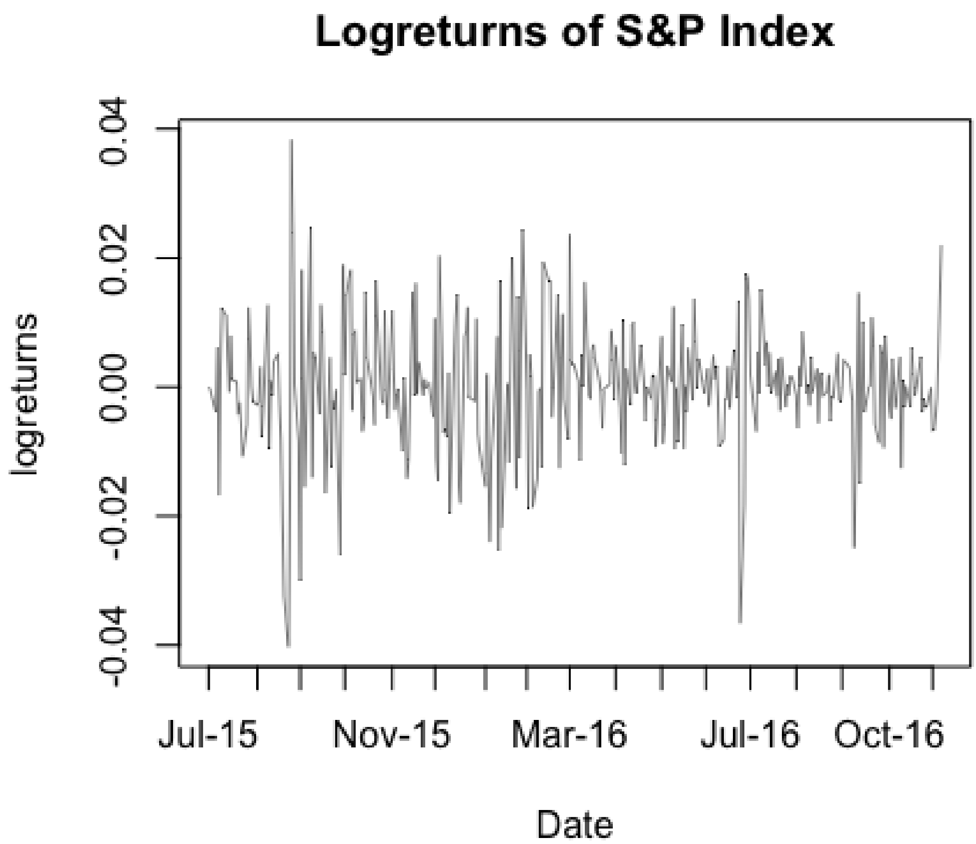
Source: Author's computations.

We begin the analysis of our time-series data set with the stationarity test, since it is necessary assumption for ARMA and GARCH modeling. Financial market indices often follow a non-stationary process. By looking at Figure 5 we can intuitively say that this index is non-stationary, meaning that the mean and variance are not constant over the time. In order to prove it we proceed with formal tests. Here as with vectors of changes we use two tests for this purpose: ADF and KPSS test. For the data set of the stock index ADF test results with p-value of 0.39, which implies that we do not reject the null hypothesis of non-stationarity – existence of the unit–root. KPSS test tells us to reject the null hypotesis of stationarity since the p-value is smaller than the critical value. (Apendix A).

In order to work with the data, we need to stationarize it. We do so by taking the first log difference, as a result we obtain the log returns of S&P

Index. On the Figure (5.6) we can observe stationarized data, it can be seen, that the mean is around zero. In order to prove that data is stationaruzed now, we perform once again KPSS and ADF tests. The p-value in ADF test is smaller than the critical value, thus we reject hypotesis of existence of the unit-root. At the same time in KPSS test we do not reject the null hypothesis of the stationarity. Hence, we can state, that the log returns data is stationarized.

Figure 5.6: Logreturns of S&P Index



Source: Author's computations.

In the Table (5.4), below, we can see the summary statistics for S&P Index logreturns. According to this statistic we can clearly see that the average return over the analyzed time is positive. The skewness, which interprets asymmetry of the probability distribution around its mean. Here we can see that the absolute value is less than 1, thus our distribution is moderately skewed. Also, we can state that the distribution is skewed left, which means that the left tail is longer. If we take a look at kurtosis, which measure the tallness and sharpness of the central peak, we notice that the threshold of three is satisfied, thus there is kurtosis of normal distribution.

Table 5.4: Summary Statistic for S&P Index logreturns

Obs	mean	sd	median	min	max	skewness	kurtosis	se
343	0.007	0.01	-0.0092	-0.04	0.04	-0.32	2.05	0

Source: Author's computations.

5.2 French Data

Another model we construct is a model based on French data. Here we again use two variables: vector of election preferences for the French Presidential campaign and CAC 40 (Cotation Assistee en Continu) index. Both of the datasets are collected for the period from January 3^{rd} 2017 to May 7^{th} 2017.

5.2.1 Election Preferences

Data for election preferences was assembled from the average of 5 French polls which is updated on weekday base. We use the data which takes into account only two candidates and them competing in presidential race.

In this model variable ”election preferences” is defined as the probability of winning the Presidential race for two candidates – Marine Le Pen and Emmanuel Macron. The same as for the United States model, public support here is a proxy for the winning chance for the candidate. We use the data for candidates support for both election rounds time, since from the beginning our data is assuming their procedure to second round.

Table 5.5: Summary Statistics for Election Preferences

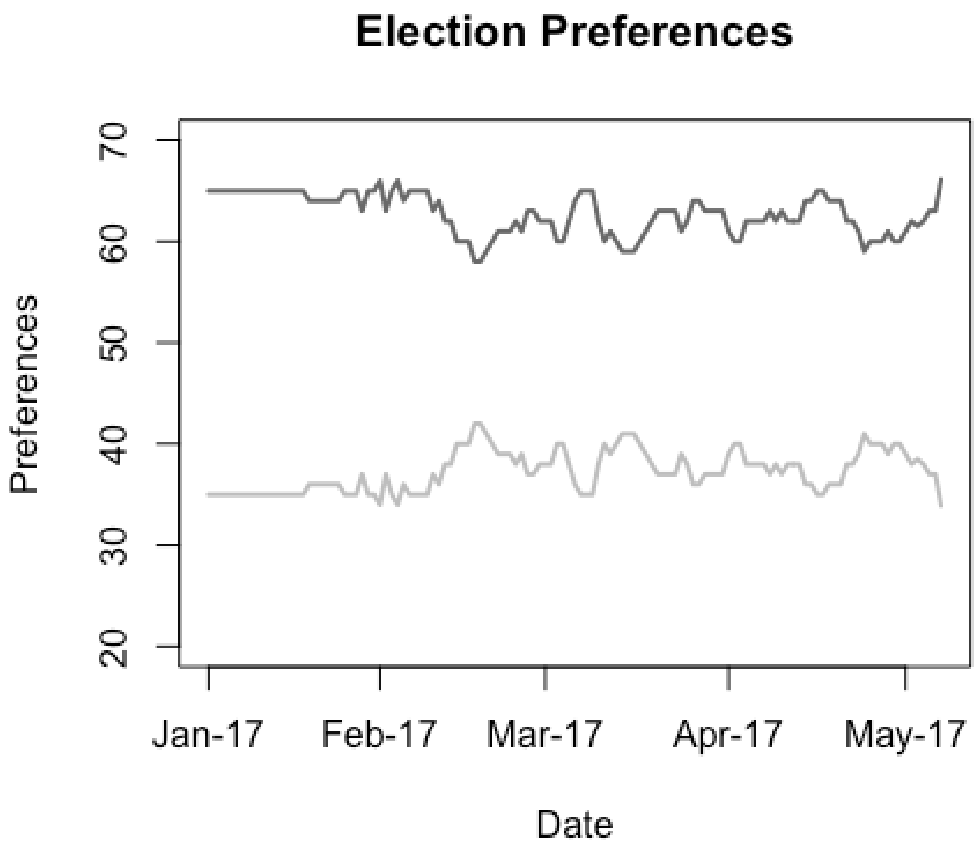
	Macron	Le Pen
Min	58	33.00
Median	63	37
Mean	62.72	37.28
Max	66.10	42

Source: Author's computations.

From the Table (5.5) above, which represents the summary statistics for the French election preferences we can see that on average Marine Le Pen had smaller support then Emannuel Macron. However, the maximum winning probability for her was 42%, while for Emannuel Macron the number was 66,1%.

On the graph (Figure (5.7)) below, the change in election preferences over time can be seen. Support for both of the candidates has been volatile. But here, despite of United States data we cannot emphasize any cycles. We see only fluctuating line, with not clear trend for any of candidate. As can be clearly seen from the graph in the beginning of the race Emannuel Macron, represented in black color, had a visible advantage with increasing support at the end of the race.

Figure 5.7: Election Preferences France

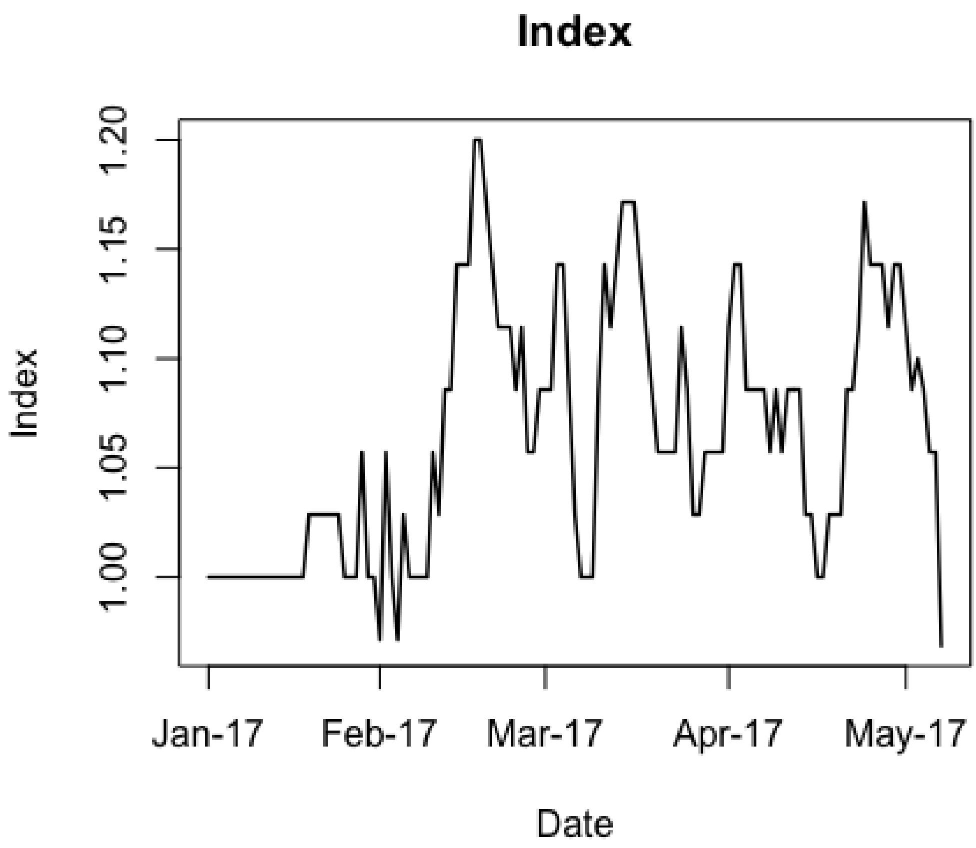


Source: Author's computations.

Similarly, as in our approach in US model we perform indexing for the radical candidate, being Le Pen here. On the first day of our time–series data the index of 1 is assigned to Marie Le Pen support value and following days are calculated respectively.

The figure below presents the graphical representation of the preferences index. As we can see there is a change over time, however it is hard to see any pattern in the index.

Figure 5.8: Index of Le Pen Support



Source: Author's computations.

In the Table (5.6) below, the descriptive statistic is presented. We can see that the mean is greater than 0, so the tendency over time was positive. The skewness is describing the asymmetry in the data set. Our distribution is moderately skewed since the value of it is 0.33. Moreover, it is positively skewed, meaning right tail to be longer. Kurtosis is below the threshold; thus data follows normal distribution.

Table 5.6: Summary Statistics for Index of Le Pen support

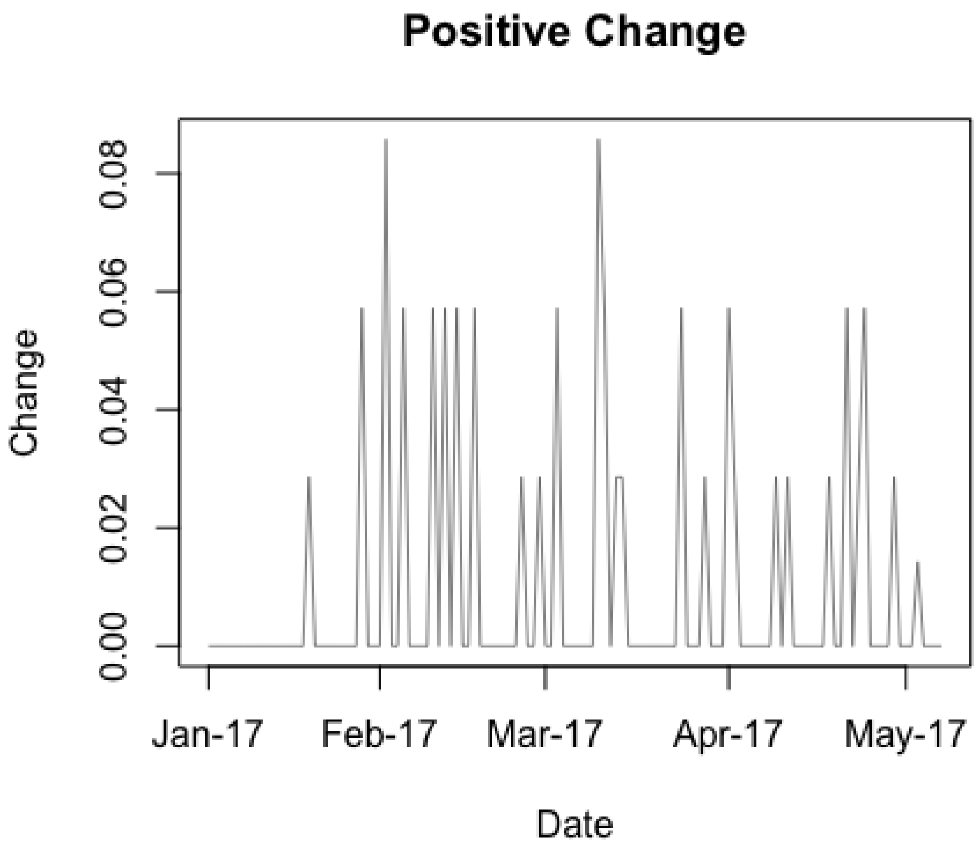
Obs	mean	sd	median	min	max	skewness	kurtosis	se
125	1.07	0.06	1.06	0.97	1.2	0.33	-0.97	0.01

Source: Author's computations.

Alike in United States model we derive positive and negative vectors for election preferences from the support index. Both of them derived in positive values, as to satisfy an important assumption for GARCH model. The graphs for both are presented below. We can notice more visible peaks than in US model.

We have to analyze whether our data is stationary to be able to include it to the model. Thus, we perform ADF and KPSS tests, statistics of which proves the stationarity of the data.

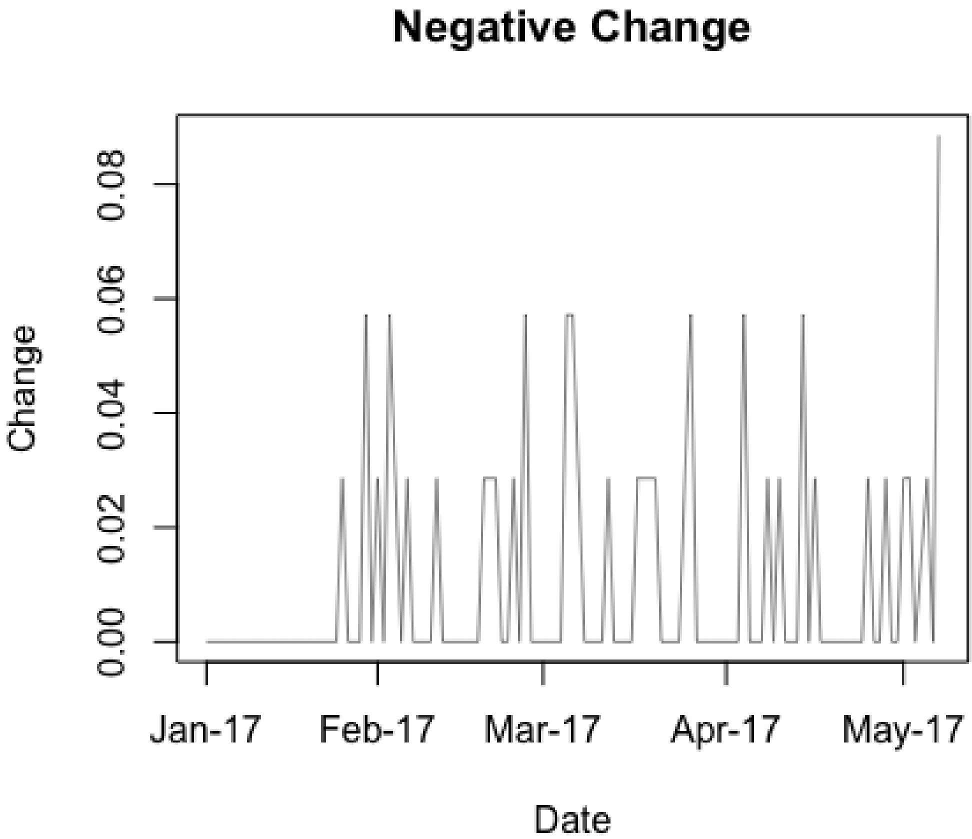
Figure 5.9: Positive Change in Election Preferences Index



Source: Author's computations.

The Figure above (5.9) is graphical representation of positive change in election preferences for Marie Le Pen. While the Figure (5.10) below, for negative ones.

Figure 5.10: Nehative Change in Election Preferences Index



Source: Author's computations.

5.2.2 Financial Time-Series Data

The second variable for the French model is CAC 40 (Cotation Assistee en Continu) index – which can be seen as French approximation of S&P 500 Index. This index represents capitalized–weighted measure of the 40 most significant values among the 100 highest market caps on the Euronext Paris. It is one of the most important national indices of the pan–European stock exchange group Euronext. This index is used as a benchmark index for agents investing to the French stock market. Similarly to S&P500 Index the companies, which stocks are included in the index, have been changing over time. Thus, we assume that CAC 40 is the best proxy for the French financial market.

Table (5.7) below summarizes the data for CAC 40 Index. We see that the values for maximum and minimum differ by 13%. Which gives us the feeling that this index is quite volatile.

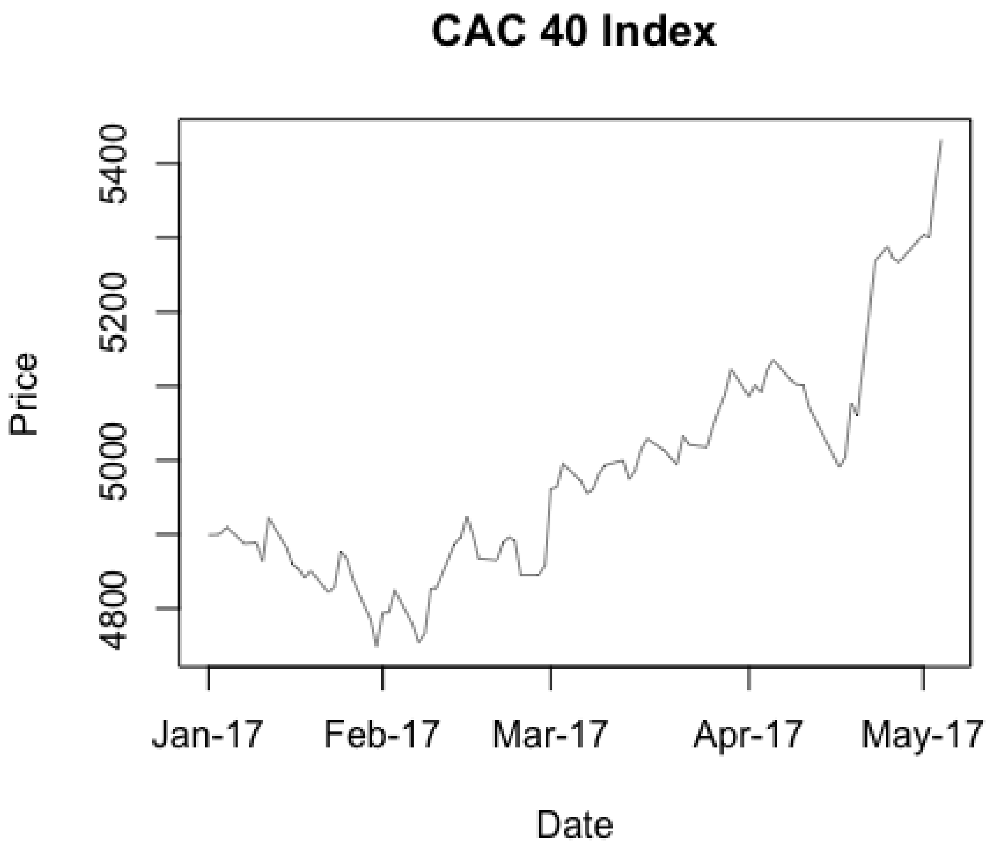
Table 5.7: Summary Statistics Cotation Assistee en Continu

	Close
Min	4 749
Median	4 961
Mean	4 978
Max	5 432

Source: Author's computations.

Overtime graphical representation of the index is provided in Figure (5.11) below. We can easily spot the positive trend in the Index value. However, no similarities to the election preferences volatility are visible.

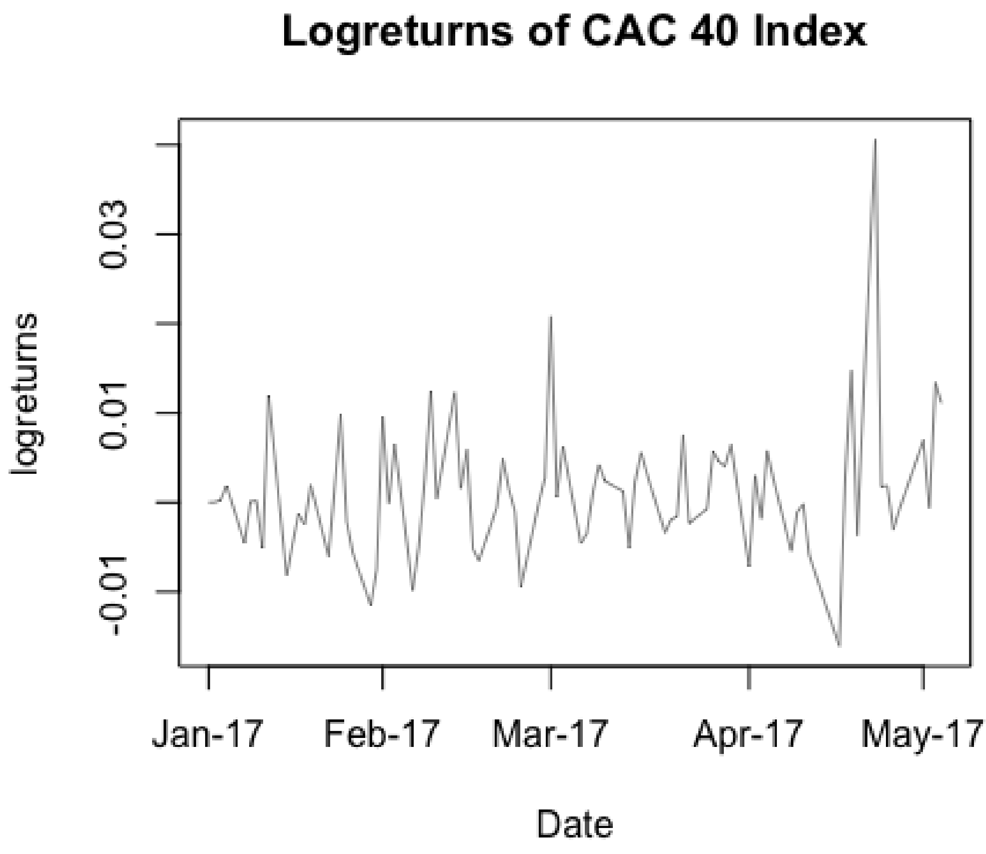
Figure 5.11: Cotation Assistee en Continu



Source: Author's computations.

From the graph (Figure (5.11)) above we can assume the non-stationarity of the data, this observation is supported by ADF and KPSS tests. The tests' statistics provide us with results which show the non-stationarity patern in data. P-value for the ADF test is 0.945, greater than the critical value, so we do not reject the null hyphothesis of non-stationarity. Accordingly, we have to transform the data by taking the first log differences, thus obtaining the log returns for CAC40. The graph of transformed data is presented in Figure (5.12) below, the volatility of CAC40 log returns is clearly non-constant. However, we can notice that log returns are stationary and have nearly zero-mean.

Figure 5.12: Log returns for CAC40



Source: Author's computations.

After transformation of data we confirm the stationarity of log returns with formal analyzing implementing ADF and KPSS tests once again. The results of tests ensure us of stationarity of transformed data. Thus, we can proceed to model fitting.

The next Table (5.8) presents the summary statistics for the index log returns. The mean is indeed nearly 0, and the average return over time is positive. Kurtoises which is the measure of sharpness and tallness of the central peak is above 3 – a threshold of normal distribution. The data is highly skewed, moreover CAC40 returns are skewed right.

Table 5.8: Summary Statistics of CAC40 log returns

Obs	mean	sd	median	min	max	skewness	kurtosis	se
86	0.0012	0.01	0.00019	-0.02	0.04	1.77	7.43	0

Source: Author's computations.

Chapter 6

Empirical Results

In this section the empirical results of the estimations are presented. First, the model is computed without the exogenous preferences variable. Then we add the variable to the variance equitation and construct the augmented model. Also, we work the two vectors for preferences, one with positive changes and second one containing negative changes for Trump's support. This is done for estimating and distinguishing the results separately for positive and negative changes. Firstly, we describe in detail the procedure of fitting the mean and the variance equation for the United States model without the Election Preferences. Next, the two vectors for the Election Preferences are added to the model and results are observed. For the French model the modeling approach is similar, thus we will only present estimation results and its interpretation. In the end of this chapter we perform the robustness checks and provide the discussion of the results. All the computations are computed in statistical software R Studio.

6.1 United States model

6.1.1 Model fitting without Election Preferences

Autocorrelation

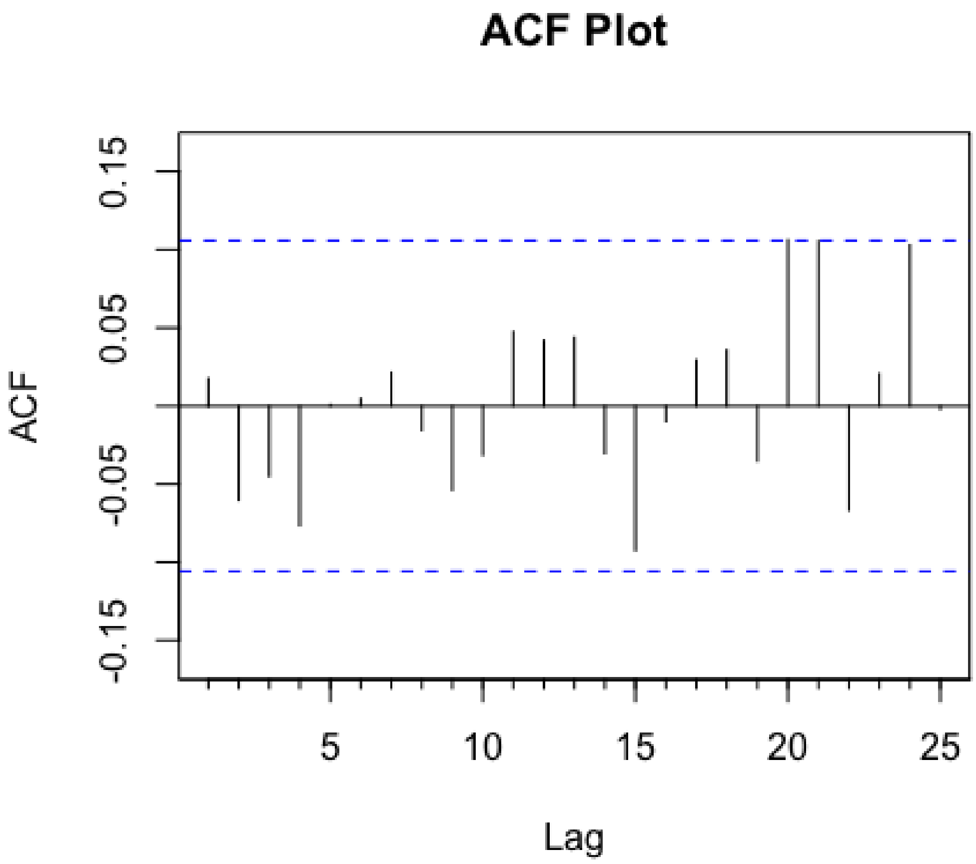
When working with time–series one should always check for the presence of autocorrelation. To proceed in modeling with our already stationarized data we apply Box Jenkins method for ARMA modelling to find the best fit of a time-series model to post values of a time series. However, firstly we have to apply a Box–Ljung test to check if any of a group of autocorrelations of a time series are different from zero. In our data set we apply the Box–Ljung test on log returns of the S&P Index. Box–Ljung results for log returns with p–value of 0.67, thus we do not reject our null hypothesis of data being distributed independently.

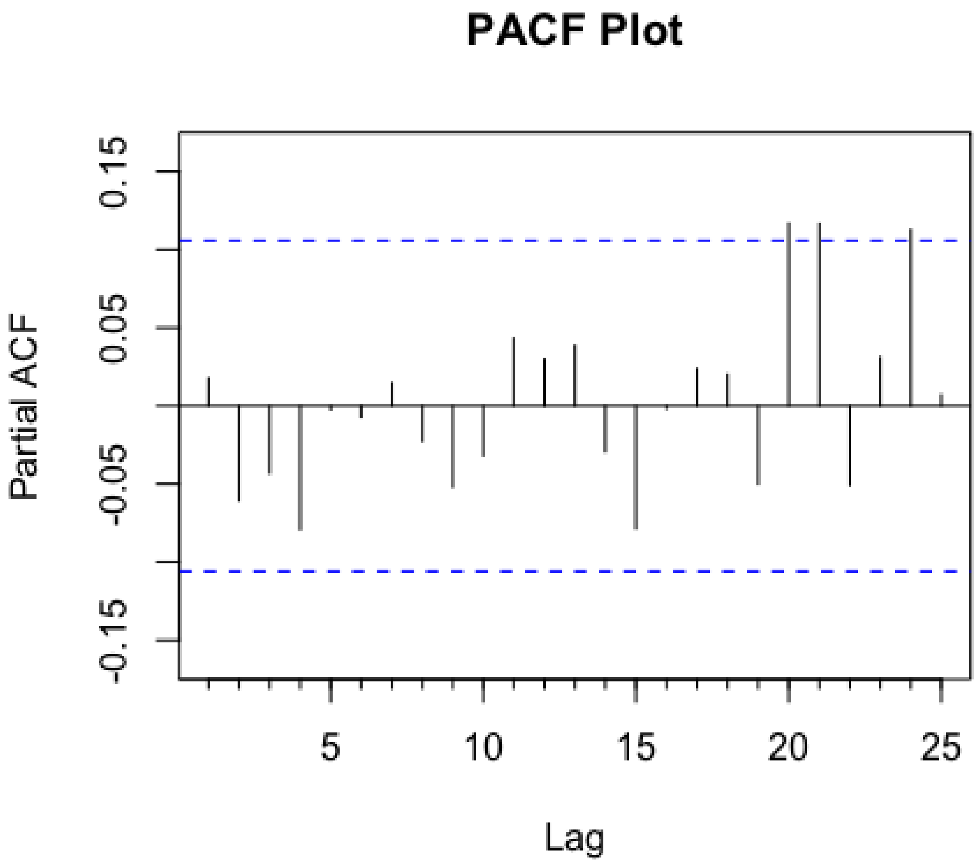
Mean equation determination

As a next step the ACF and PACF plots are composed. These plots let us to draw information about dependencies and identify the terms AR and MA for ARIMA modeling. ACF plot shows correlation between a time series and its lags. PACF plot shows the partial correlation between a time series and its lags that is not explained by correlations at all lower-order-lags. If ACF and PACF of logreturns plots show strong dependencies in the data; we have to model linear dependencies with the help of ARIMA model. ARIMA is an extension of ARMA, which allows to fit non-stationary process but since we have already transformed our data into stationary series, we going to use ARIMA with differentiating term d equal to 1, meaning the first differencing. ARMA model consists of 2 parts: an autoregressive (AR) part and a moving average (MA) part. AR part regresses variable on its own lagged values while MA part models the error term as a linear combination of error terms occurring at various times in the past.

According to the theory, when fitting the ARMA model one should focus on finding the smallest parameters which would be able to to explain the series. The more complex ARMA models are hard to explain as well as more parameters means higher noise in the model, hence greater standard deviation. As visible from the Figure (6.1) below, the plots do not reflect any significant lags. Hence, the original return series simulate a random walk model ARIMA(0,0,0). The Ljung-Box test that we have performed before, suggests that the chosen model is correct. Since the data has been already stationarized and log difference was taken the integration term equals to 0. So, the mean equation for the GARCH model will contain only the constant term and white noise.

Figure 6.1: ACF and PACF Plots for log returns of S&P Index





Source: Author's computations.

Fitting GARCH model without Election Preferences

After we have determined the mean equatin of the model we have to identify the correct equation for the variance model. LM–ARCH test has to be performed in order to check for the heteroskedasticity in the chosen model. This is an assumption for the ARIMA model. The LM–ARCH test shows really small p-values for first few lags, those values are below the critical value, thus we reject the null hypothesis of homoskedasticity.

In order to account for conditional heteroscedasticity in the data, which was confirmed by the ARCH–LM test we are using GARCH (generalized autoregressive conditional heteroskedasticity) modelling. If there was no conditional heteroscedasticity in the data, we would have strict white noise and GARCH model would not bring any additional information.

To find the best suiting model, we will fit the ARCH/GARCH model until there is no dependencies left in residuals. The regular procedure for selecting GARCH model is compairing the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Both AIC and BIC are penalized-likelihood critereas. AIC is an estimate of a constant plus the relative distance between the unknown true likelihood function of the data and the fitted likelihood function of the model, so that a lower AIC means a model is considered to be closer to the truth. BIC is an estimate of a function of the posterior probability of a model being true, under a certain Bayesian setup, so that a lower BIC means that a model is considered to be more likely to be the true model. Both criteria are based on various assumptions and asymptotic approximations. AIC and BIC are both approximately correct according to a different goal and a different set of asymptotic assumptions. The only way they should disagree is when AIC chooses a larger model than BIC.

We have compared differenct modelc for AIC and BIC and the one with the smallest values was choosen – GARCH(1,1). In addition, this is the most common model used for the financial time-series in other academic papers.

The results for the plain model fitting GARCH(1,1) without election preferences are presented in the table below:

Table 6.1: Plain GARCH model of S&P Index

Variance equation		
	Estimate.	Std. Error
μ	0.000366	0.000402
ω	0.000011***	0.000001
α_1	0.250254***	0.043835
β_1	0.649517***	0.044462
LL	1136.328	
AIC	-6.6025	
BIC	-6.6028	

Note: *$p < 0.1$; ** $p < 0.05$; ***$p < 0.01$
Source: Author's computations

Table (6.1) above shows the estimation results for GARCH(1,1). Coefficient α_1 is an effect of ARCH and coefficient β_1 represents GARCH term. Both of the coefficents are positive and statistically significant at 1% significance level. ARCH term is a response of volatility to previous period shocks in return series. Thus, 1% increase in shocks effect the conditional variance increase by 0.25%. GARCH term is the first lag of conditional variance, accordingly 1% increase in one period lagged conditional variance effects the conditional variance to increase by 0.64%. Interestingly, the volatility persistence has much higher effect on volatility, than the effect of previous shocks. If we sum up the two coefficients, we get a persistence level equals to 0.89 – this level is considered high. Persistence in volatility suggests strong presents of ARCH and GARCH effects. The sum of ARCH and GARCH terms is less than 1, so our model satisfies stationarity condition. Thus, we can say that past shocks and variances have longer effect on the future conditional variance.

Furthermore, we perform ARCH–LM test once again in order to check for the presence of significant dependencies. The p-value is greater than critical value and the null hyphotesis of no dependencies is not rejected.

6.1.2 Model fitting with Election Preferences

In this section we discuss the results of augmented GARCH model with election preferences. We have described the algorithm of obtaining election preferences and separating it to two vectors in the chapters above. Further, we study the effect of election preferences on index volatility and whether this addition improves our model.

Table 6.2: Augmented GARCH model of S&P Index

Variance equation		
	Estimate.	Std. Error
μ	0.000366	0.000402
ω	0.000011***	0.000001
α_1	0.250254***	0.043835
β_1	0.649517***	0.044462
vPC	0.00000	0.000444
vNC	0.00000	0.000402
LL	1136.328	
AIC	-6.5237	
BIC	-6.6028	

Note: $*p < 0.1$; $**\ p < 0.05$; $***p < 0.01$
Source: Author's computations

Table (6.2) presents the estimation results for the augmented GARCH model with Election Preferences. PC and NC are the vectors of positive and negative change in election preferences, respectively added to GARCH(1,1) variance equation. As in the plain GARCH model both ARCH and GARCH terms are positive and significant at 1% level. We can notice that the coefficients have slightly changed: the GARCH term shows a small increase in value, while ARCH term decreases. The sum of both is lower than 1, thus model is stationary. Also, the augmented GARCH model has similar behaviour as the plain one: the effect of previous shocks is smaller than the effect of volatility persistence.

The main findings of the augmented GARCH model shows that both of our exogenous variables are small and does not significantly affect the conditional variance of S&P Index. There might be various explanation for such results, we are going to discuss them in the next chapter. However, now we can not reject our hypothesis that higher support for a radical candidate does not imply stock price volatility.

Besides, if we take a look at LL for new augmented model, the value is the same as in plain GARCH model, the similar result is for the BIC. However, the value of AIC has changed: it is lower for the plain model. Meaning that we do not reject the hypothesis that, including candidates' ratings into stock prices volatility modeling do not have positive effect on the predictions and do not provide us with more accurate outcomes of the model.

6.2 French Model

In this section we perform the analyses with the data obtained for the French model. The procedure is following the same logic as in the previous section, when United States model was analysed.

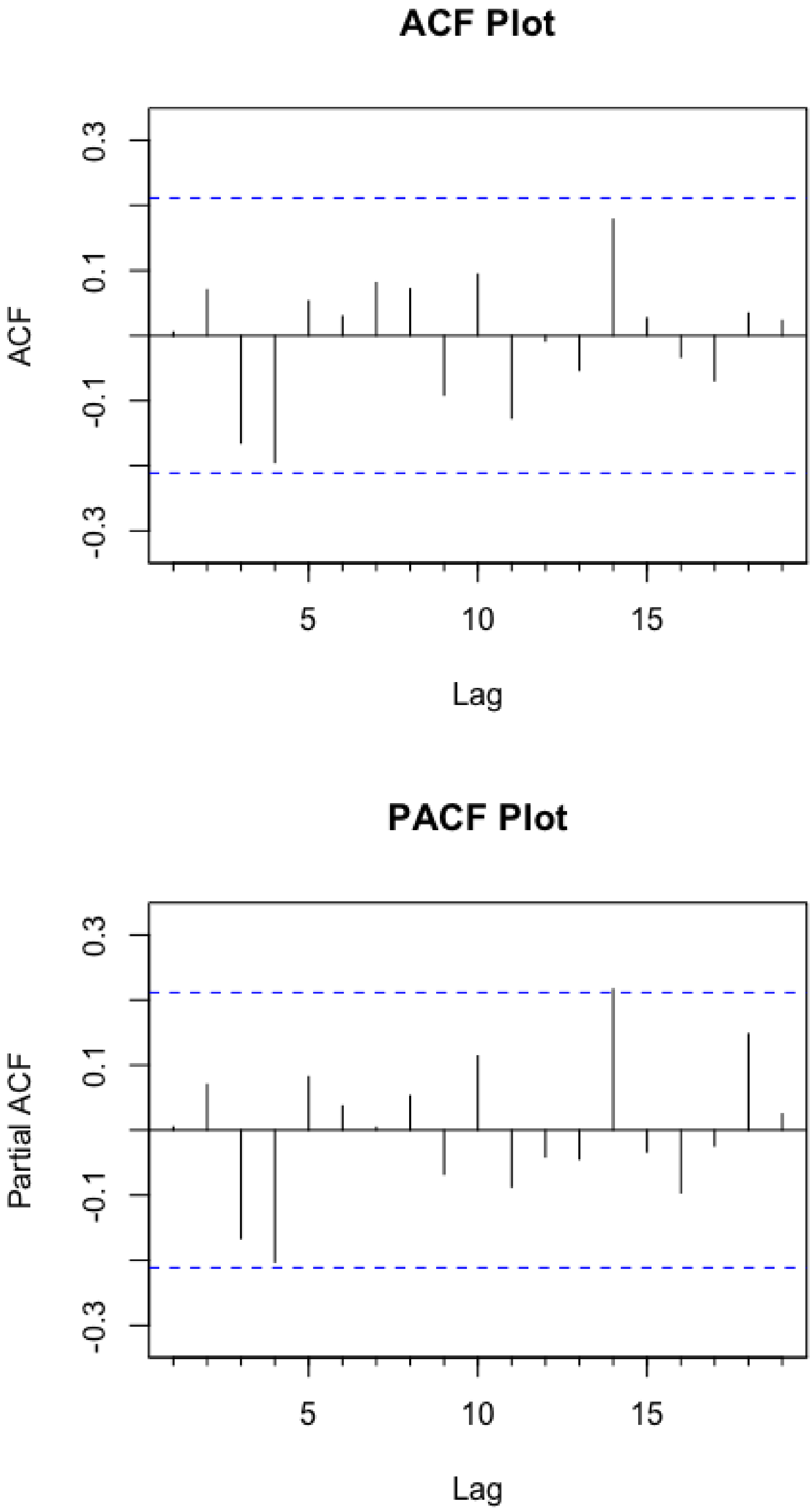
6.2.1 Model fitting without Election Preferences

First of all, before we start fitting the model, we check all the variables for the presence of autocorrelation. The Ljung–Box test does not reject null hyphothesis for any of them. Thus, there is no autocorrelation in our data.

Further, we check ACF and PACF plots (Figure (6.2)) to get information about the dependencies and to find out AR and MA terms. Similarly to the previous model, no dependencies can be spotted, thus we assume that ARMA(0,0) would be the best model. We check this assumption by comparing the Akaike criteria among models with different AR and MA terms.

The results prove our assumption to be true, once again our mean equation will contain only the constant term. ARCH-LM test suggests that our uncorrelated data is still serially dependent due to a dynamic conditional variance process – there is a conditional heteroscedasticity. In order to account for revealed heteroscedasticity we are using GARCH modelling. The results of the best fitting plain GARCH(1,1) model are presented in the Table (6.3).

Figure 6.2: ACF and PACF Plots for log returns of CAC40 Index



Source: Author's computations.

The results of the French model are slightly different than the ones of US model. The α_1 – ARCH term, which is a term of news about volatility from the previous period measured as a lag of the squared residual from the mean equation, is statistically significant at 5%. While the β_1 – GARCH term, which associates with last period's forecast variance, is significant at 1% level. The sum of both coefficients equals to 0.944, this satisfies the stationarity model assumption. As well this indicates, that shocks to volatility have a persistent effect on the conditional variance. In comparison to US model both estimates of the coefficients have increased, but the relationship between them stayed the same. Thus, we can state again that past shocks and variances have longer effect on the future conditional variance. The values for BIC, AIC and LL are provided in the end of the table.

Table 6.3: Plain GARCH model for CAC40 Index

Variance equation		
	Estimate.	Std. Error
μ	0.001185*	0.000690
ω	0.000007***	0.000002
α_1	0.263563**	0.106194
β_1	0.681064***	0.100099
LL	300.699	
AIC	-6.8999	
BIC	-6.7858	

Note: $*p < 0.1$; $**\ p < 0.05$; $***p < 0.01$
Source: Author's computations

6.2.2 Fitting GARCH model with Election Preferences

In the following section we discuss the results of Augmented GARCH estimations on CAC40 with exogenous variables. We have included the vectors of additional information to the variance equation and now can review the results. The Table (6.4) with outcome for Augmented GARCH(1,1) is provided below.

Table 6.4: Augmented GARCH estimation on CAC40

Variance equation		
	Estimate.	Std. Error
μ	0.001066*	0.000802
ω	0.00000	0.00000
α_1	0.000001	0.048145
β_1	0.999998***	0.000656
vPC	0.000027	0.000170
vNC	0.00000	0.000010
LL	300.0797	
AIC	-6.8391	
BIC	-6.6678	

Note: *$p < 0.1$; ** $p < 0.05$; ***$p < 0.01$
Source: Author's computations

The results of the model fitting are summarized in Table (6.4). Here we can spot some interesting changes. Firstly, the ARCH term has lost its significance. And GARCH term is significant at 1%. However, the sum of both never exceeds 1, so the model is stationary. Secondly, the added exogenous variables which represent the vectors of change in radical candidate support, analogously to the US model are not significant. Thus, we can once again state that we do not reject our hephothesis that higher support for a radical candidate does not imply stock price volatility. However, in augmented French model in contrast to US augmented model one of the exogenous variables, which means the increase in support for Le Pen, gets the sign of the coefficient.

Discussing the explanatory power of the augmented model in comparison with plain GARCH, we can address to LL and AIC values. As we see the AIC has increased and LL decreased in the last model, this means that inclusion of variables to the model does not improve its accountability. Therefore, we do not reject our hypothesis, that inclusion of candidates' ratings into stock prices volatility modeling do not have positive effect on the predictions and do not provide us with more accurate outcomes of the model.

6.3 Robustness Check

In this section we perform the robustness checks on the models described above. We do so, to check the stability and quality of the results.

We examine if the result of the model change, when the assumptions change. In United States model we use S&P500 Index, which represents only 500 companies with biggest capitalization. Even though we take it as proxy for the US financial market, and it is often associated with market, it is not the whole one. That is why we perform the same analysis on two other indexes Russel 1000 Index and Russel 3000 Index. Russel 1000 Index is a subset of Russel 3000 Index and consists of 1000 largest companies in the US equity market. Respectively Russel 3000 is a capitalization-weighted index of 3000 biggest companies and it accounts for 98% of total stock market capitalization.

In the French model we used the CAC 40 stock market index. However, it represents only 40 largest companies on the market. In the robustness check we are going to use CAC All-Tradable, which is the index on French stock market. This index was introduced instead of SBF 250 and contains 120 companies. 40 companies comes from CAC 40 Index, another 20 from CAC Next 20 and 60 stock which are listed on Premier Marche and Second Marche on Euronext Paris.

For the exogenous variables - positive and negative change in election preferences, we use the same data as was used in the model above.

6.3.1 United States model

We start with robustness check for US model by analyzing the data. Time series data for Russel 1000 Index – RUI and Russel 3000 Index – RUA is extracted for the same period of time as the preferences data. Similarly to the model construction, we check all the necessary assumptions on new data set. The stationarity test: Augmented Dickey-Fuller test and KPSS test reveal that our data is non-stationary. Thus, we take the first log differencing and check for stationarity once again. The Ljung-box test provide us with the knowledge, that the autocorrelation is not presented in our data. Hence, we can start with model fitting. Firstly we define our mean equation, which turns out to be ARIMA(0,0) for both indecies, similarly to the main model. Then, we construct the GARCH model, since ARCH-LM test discloses the presence of heteroskedasticity in our model. The best fitting model plain GARCH model for both indecies is presented in the Table (6.6) below:

Table 6.5: Plain GARCH model for Russel 1000 and Russel 3000 Indecies

Variance equation		
Variables	RUI	RUA
μ	0.000339	0.000307
	(0.000413)	(0.000426)
ω	0.000011***	0.000011***
	(0.000001)	(0.000001)
α_1	0.230312***	0.216991***
	(0.039657)	(0.036972)
β_1	0.668259***	0.678835***
	(0.042475)	(0.041718)
LL	1137.137	1131.026
AIC	-6.5880	-6.5525
BIC	-6.5433	-6.5078

Note: $*p < 0.1$; $** \ p < 0.05$; $***p < 0.01$;Standard errors in parentheses
Source: Author's computations

The results are similar to the one in our model. New variables' models are stationary and follow similar logic, that past shocks and variances have longer effect on the future conditional variance and are persistent. Further, we add exogenous variables to the variance equation and construct the Augmented GARCH model. The Augmented GARCH(1,1) model is represented in Table (6.6):

The results of robustness check follows the same pattern as the one obtained

Table 6.6: Augmented GARCH model for Russel 1000 and Russel 3000 Indecies

Variance equation		
Variables	RUI	RUA
μ	0.000339	0.000306
	(0.000417)	(0.000429)
ω	0.000011***	0.000011***
	(0.000000)	(0.000000)
α_1	0.230316***	0.216778***
	(0.064589)	(0.061962)
β_1	0.668271***	0.679056***
	(0.049020)	(0.047832)
vPC	0.000000	0.000000
	(0.000329)	(0.000346)
vNC	0.000000	0.000000
	(0.000384)	(0.000395)
LL	1137.137	1131.026
AIC	-6.5764	-6.5408
BIC	-6.5094	-6.4739

Note: $*p < 0.1$; $** \ p < 0.05$; $***p < 0.01$;Standard errors in parentheses
Source: Author's computations

in our model. ARCH and GARCH terms keep their significance for both indicies Russel 1000 and Russel 3000 at 1% level. The sum of those terms is less than 1, thus, the model is stationary. The value of estimates is almost the same as the plain GARCH model and very similar to results of S&P 500 Index. Nevertheless, the value for ARCH term is slightly smaller, while value of GARCH term is comparatively bigger. This means that effect of magnitude of shocks is smaller for RUI and ROA, than for S&P500. At the same time, the effect of volatility today have slightly bigger impact of volatility ahead, than in plain model. Also, total volatility persistence is smaller, meaning that a mean reversion process is quicker. However, the exogenous variables included in the model are not significant at any level. In fact, inclusion of these variables to the model worsens the model results: increases the AIC criteria and decreases the Log–likelihood ratio. Hence, the robustness check for United States model allows us to make the conclusion that our model is stable and the results are correct.

6.3.2 French model

For the robustness check in French model, we are going to change the assumption of stock market proxy. Instead of running our model on CAC 40 Index we are going to use CAC All-tradable. We collect the new data for the same time period as CAC 40. And perform the necessary tests to satisfy the assumptions. The data turns out to be non-stationary, thus we take first log diferencieng. Performing ADF and KPSS tests again on log returns data, we obtain the statistic which proves the stationarity of data. As a next step we plot ACF and PACF plots on differenced CAC All-tradable. The plots do not reflect any significant lags. Thus, we construct the ARIMA(0,0,0) model and apply Ljung-box test to confirm no autocorrelation. ARCH-LM test suggest further dependencies in data, thus we need to fit the ARCH and GARCH until there are no dependencies. After comparing various model we decide that GARCH(1,1) is the most appropriate one to use.

Table 6.7: Plain GARCH model for CAC All-Tradable Index

Variance equation		
	Estimate.	Std. Error
μ	-0.000924	0.000745
ω	0.000000	0.000009
α_1	0.000040	0.006421
β_1	0.993393***	0.008277
LL	304.9667	
AIC	-6.992	
BIC	-6.8851	

Note: $*p < 0.1$; $**\ p < 0.05$; $***p < 0.01$;Standard errors in parentheses
Source: Author's computations

The robustness check for plain GARCH model differs from the one in our research. Table (6.7) presents the results. The ARCH term α_1 is not significant in any level, meaning that the magnitude of the shock does not have any influence on the CAC All-Tradable volatility. The GARCH term β_1, in turn, is significant at 1% level and the coefficient value is much higher – 0.99. Meaning, that 1% increase in one period period lagged conditional variance results in increase of conditional variance by 0.99%. The sum of two terms is less than 1, thus model satisfies the stationarity condition. As the next step we add the vectors of exogenous variables to the model and present the Augmented GARCH(1,1) model below:

Table 6.8: Augmented GARCH model for CAC All-Tradable Index

Variance equation		
	Estimate.	Std. Error
μ	-0.001052	0.000761
ω	0.000000	0.000001
α_1	0.000000	0.063797
β_1	0.999999 ***	0.014738
VPC	0.000024	0.000086
vNC	0.000000	0.000241
LL	304.1513	
AIC	-6.9338	
BIC	-6.7625	

Note: $*p < 0.1$; $**\ p < 0.05$; $***p < 0.01$;Standard errors in parentheses
Source: Author's computations

Table (6.8) the outcomes of the Augmented model. These results are quite similar to CAC40 model results. GARCH term is significant at 1% level and deploys high value of coefficient. Thus, we can state that the effect of previous shocks on volatility is negligible in comparison with effect of variance effect. Once again we notice, that election preferences variables have no significant effect on the volatility. And its addition to the model does not increase the prediction power, on the contrary worsens it.

The above performed robustness check confirms the results of the model. And convince us in the stability and quality of the produced research.

6.4 Discussion

In this section we are discussing the outcomes of the models. And its economical interpretation. Both of the models: United States and French one, provided the same results in terms of relevance of inclusion of political sentiment. It turned out that both our hypothesis, proposed for examination in the beginning of the thesis, were not rejected. Thus, we do not reject that

- including candidates' ratings into stock prices volatility modeling do not have positive effect on the predictions and do not provide us with more accurate outcomes of the model;
- higher support for a radical candidate does not imply higher price volatility.

However, we can reject our last hypothesis which says, that during the election race period market does not tend to be rising. Since, for the both models the summary statistics presents the positive mean on given period of time.

The non-significance of the political sentiment on the stock prices volatility is an interesting fact and should be discussed further. We have studied a lot of empirical researches on how news sentiments or political biases effect stock markets volatility. Majority of those papers showed the significant effect of investors sentiments on the stock markets volatility. Regardless whether the sentiment was reform proposed by the government or imposed trade tariffs; annual reports of companies with biggest capitalization or news sentiment captured on Twitter.

So why is the research performed has non-significant results? To address this question one should take into account the role of media in this case. It might seem that media exaggerates the level of uncertainty among the market agents. While the model proves, that the news about change in public preferences do not significantly affect their decision-making. The readers might have a feeling that the uncertainty of future political course has big impact. However, during the election race it is only the possible proposals. Once the president is in charge he or she might change the opinion or do not bring to life the promises made during the race. Since, the current political situation shows a lot of populism, market agents react only to action and not to words and promises.

Another possible explanation is the level of globalization. There is enormous amount information from all around the world which has to be reflected in market agents daily decision-making. Hence, each piece of information can not be possibly displayed in change in stock price. Also there is a increasing amount of market shared owned by passive funds. The funds, that do not actively trade, thus they do not react to the news and political sentiments daily. Overall level of market reaction decreasing according to JPMorgan (Megan Greene (2018)) only 10% of US equity investment is currently trading in a traditional way. The left 90% is traded by AI quant funds or passive funds. The first ones do not care why markets move, they only care that they move. Thus, the news sentiments like FED press conference, Donald Trump tweet or earnings report are not taking into account. What they do, is implementing the successful trading strategies until the better one comes around. They do so regardless the fundamentals. The second option, passive funds, ignore fundamentals in the same manner. Usually they simply mimic the index, hence do not follow the news or political changes.

Not all the market agents see Donald Trump as a radical candidate. Some of the reforms proposed by him during the election campaign, might work in favor of investors. Thus, some of them might not associate the rise in his public support with rising level of uncertainty. Thus do not react to the change in election preferences in a predicted way.

Out of all fundamentals, the effect of the company specific factors have the biggest effects. Since they might influence companies with the biggest capitalization on the market, the whole market depends on it. Thus, this companies' news sentiments have much bigger effect than the political ones. For example, if Trump has relevantly significant increase in the public support, but the same day Apple posts a significant increase in revenues market will boom.

Chapter 7

Conclusion

The theory of financial markets has been changing over the last few decades. More and more approaches were specified in order to increase the prediction power of the models forecasting. Market agents try to decrease the level of uncertainty, which they associate with the risk. Efficient Market Theory is not a standartized approach anymore. The market agents have started to account with irrational behavior and trying to include the behavior finance biases to the forecasting models. More and more sentiments are discovered and studied, proving the relationship of different factors on the market volatility.

In this research we analyse the effect of the political bias on stock market volatility. Specifically, the effect of change in support of radical candidate during the presidential campaign. Since it is the first paper to analyse this exact period in political cycle, our ultimate goal is to check for the relevance of the prediction at all. For this purpose we create two models: United States and French one to check our hypothesis.

In the first part of the thesis we focus on finalization of our hypothesis and determination of the radical candidate. For this reason we use different techniques of lexicon-based sentiment analyses approach. First, we study the speeches of the candidates on sentiment orientation, in order to determine the polarity of the text. Secondly, we apply different predefined dictionaries to study the sentiments of the text. Further, we manually create a radical dictionary in order to construct the radical index. The index helps us to determine the radical candidate between two and finalize the hypothesis. For United States model Donald Trump is determined to be the radical candidate, while for the French model it is Marie Le Pen.

The second part of the paper examines the effect of the change in election preferences on the stock market volatility using GARCH modeling. We create two augmented GARCH models for United States and French data sets, which include the relevant election preferences variables. Also we present election preferences separately as positive and negative numeric vectors of preferences change in order to catch and study the asymmetry effect. Afterward, we perform the robustness checks in order to check the stability of our model and confirm the results.

The results of the research suggest, that inclusion of the election preferences to the model do not increase the prediction power of the model. Both the negative and positive change in election preferences have no significant effect on the index volatility. For both, United States and French models results are the same in terms of exogenous variables significance. In addition, the attachment of the exogenous variables to the model worsens its results and the prediction power. Thus it is irrelevant to include the political bias to the market index volatility modleing.

Firstly, I would like to draw your attention to the difference with various news sentiments models. The majority of the empirical studies prove the significant effect of news sentiments on the stock market volatility. Also, a lot of papers examine political sentiments and its influence on stock market volatility. However, all of the models studying the political sentiment examines the time frame which does not align with election race but with a time between elections. Secondly, in Chapter 6 we discuss the possible explanations of non-significant results of change in public preferences on stock market volatility. Among them: amount of daily information that has to be reflected in stock prices, share of market traded by AI quant funds and passive funds, exaggeration of the effect of a candidate's win on the market by media, etc.

The primary contribution of this thesis is that it is the very first work to address this topic - analyses of the effect of change in election preferences on stock market volatility during the election campaign. This work brings the important knowledge of non-significance and irrelevancy of inclusion of the change in election preferences during the election campaign to the volatility modeling.

Thus, we believe it would be useful for market agents which are trying to build the prediction models in order to trace the future stock volatility.

Finally, we present suggestions for further research. The data set can be extended to bring more robust results. In addition, forecast for the stock market volatility for the period following the election date can be constructed. Also similar model can be employed on other election campaigns, for example, the recent general election in Italy. Last but not least, a more candidate specific analysis can be conducted, for instance analysis of the effect of candidate Trump's Tweets on the stock market volatility. Furthermore, instead of an analysis of a general market (S&P500) volatility, one could narrow his focus on specific segments of the stock market, e.g. the drug manufacturers or a stock index of private prison operators. It was widely known that candidate Clinton planned to create a federal oversight group which would monitor drug prices and that should candidate Trump be elected, he was expected to reverse some of the Obama's administration decisions such as to stop using private prison facilities by the federal government.

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Appendix A

Title of Appendix One

Table A.1: ADF test for positive and negative change in election preferences

	pos_change	neg_change
Dickey-Fuller	-14.759	-6.332
lag order	1	7
p-value	0.01	0.01
alternative hypothesis: stationary		

Table A.2: KPSS test for positive and negative change in election preferences

	pos_change	neg_change
KPSS level	0.458	1.301
lag order	5	5
p-value	0.052	0.01
alternative hypothesis: non-stationary		

Table A.3: ADF test for S&P Index and logreturns

	Close	logreturns
Dickey-Fuller	-2.441	-7.287
lag order	6	6
p-value	0.3905	0.01
alternative hypothesis: stationary		

Table A.4: KPSS test for S&P Index and logreturns

	Close	logreturns
KPSS level	2.2272	0.0689
lag order	5	5
p-value	0.01	0.1
alternative hypothesis: non-stationary		

Table A.5: Ljung-Box test S&P logreturns

	logreturns
X-squared	-2.441
df	20
p-value	0.6722
alternative hypothesis: autocorrelatin	

Table A.6: ADF test for positive and negative change in French election preferences

	pos_change	neg_change
Dickey-Fuller	-8.1899	-4.9211
lag order	1	4
p-value	0.01	0.01
alternative hypothesis: stationary		

Table A.7: KPSS test for positive and negative change in French election preferences

	pos_change	neg_change
KPSS level	0.14015	0.0954
lag order	4	4
p-value	0.1	0.1
alternative hypothesis: non-stationary		

Table A.8: ADF test for CAC Index and logreturns

	Close	logreturns
Dickey-Fuller	-0.9263	-4.951
lag order	4	4
p-value	0.9445	0.01
alternative hypothesis: stationary		

Table A.9: KPSS test for CAC Index and logreturns

	Close	logreturns
KPSS level	0.33016	0.33781
lag order	3	3
p-value	0.01	0.1
alternative hypothesis: non-stationary		

Table A.10: Ljung-Box test CAC logreturns

	logreturns
X-squared	17.009
df	20
p-value	0.6524
alternative hypothesis: autocorrelatin	

Figure A.1: LM-ARCH test for S&P

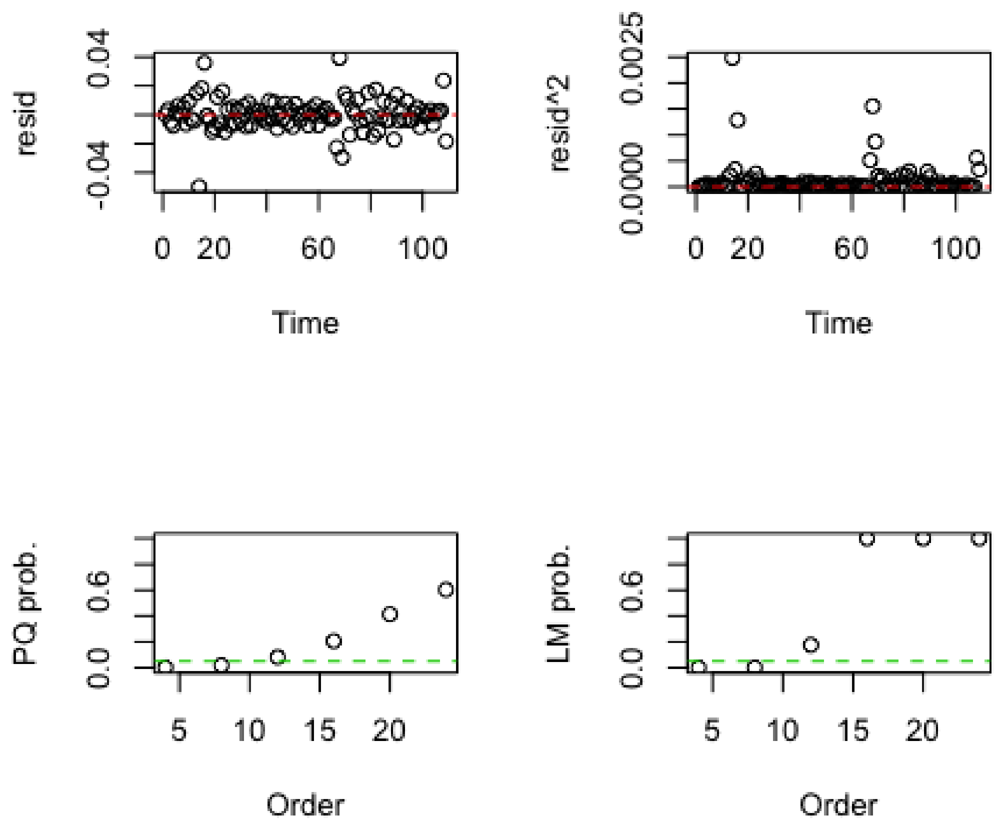

Figure A.2: LM-ARCH test for CAC40