# Impact of major brexit events on various financial markets

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## I. Introduction

In this case-study we set out to statistically test whether any Brexit major event has an impact on financial markets. In our empirical study we investigated the following market: Foreign Exchange (GBP/EUR, GBP/USD, GBP/USD), Cryptocurrencies (BTC/GBP, ETH/GBP), Equity (FTSE100, FTSE250) and Commodities (XAU/GBP, OIL/GBP) markets. Each major Brexit event shown in Table II is tested individually against each asset pair.

We used a parametric approach to test the abnormal mean returns around an event date. From the results obtained we statically show that some events do have an impact on some assets. According to our results XAU/GBP price was impacted by the first time that Brexit was mentioned by David Cameron (event #1) with a p-value of 0.0319 (5%); GBP/EUR price was impacted by the confirmation of a Brexit referendum (event #2) with a p-value of 0.0626 (10%); GBP/EUR, GBP/USD, XAU/GBP prices were impacted by the vote to leave the EU (event #4) with p-values of 0.0351 (5%), 0.0793 (10%) and 0.0812 (10%), respectively; GBP/EUR, GBP/JPY, FTSE100, XAU/GBP were impacted by Theresa May plan for Brexit (event #5) with p-values of 0.0101 (5%), 0.0051 (1%), 0.0862 (10%) and 0.0158 (5%), respectively; XAU/GBP was impacted by the UK and EU agreeing on several key issues (event #6) with a p-value of 0.0879 (10%).

From the results obtained the vote to leave the EU (event #4) and Theresa May plan for Brexit (event #5) had the most impact on the financial markets specified. GBP/EUR and XAU/GBP were impacted the most from our statistical findings.

All the code used for this project is well commented/documented and publicly available on the project's GitHub repository page *datascience-brexit*. In the next sections we will describe the techniques and procedures used to obtain the final results.

## II. Data Collection

In this section we will describe the data collection procedure in detail. For this case study various datasets from different sources were collected to be able to test our hypothesis.

Firstly, we collected data for Brexit major events from two well-known news agencies, Associated Press and Al Jazzera. Brexit event data was collected using web scraping techniques. Two published articles, one from each news agency, included a timeline of key events around Brexit. The Associated Press article [1] was published on 7/06/2019 and outlined events from the range of 7/05/2015 to 7/06/2019, while the Al Jazzera article [2] was published on 15/01/2019 and outlined events from the range of 23/01/2013 to 31/12/2020. The Al Jazzera article also included some upcoming events, that is why it ranges up to the year 2020. These articles were collected and two variables/columns, the date of the event (date/time) and a description of the event (textual) were extracted. The script *'data_collection_events.R'* was used to scrap off the data from these sources and a library called *'vrest'* was used to accommodate the web scrapping functionality in R.

After the events data, the FX (Foreign Exchange) rates were collected from Yahoo Finance. The following FX rates were collected GBP/EUR, GBP/USD and GBP/JPY. This data was collected through a web API call. To interact with the web API (Yahoo Finance) a library called *'quantmod'* was used and the following ticker symbols were specified for each pair; GBPEUR=X [3], GBPUSD=X [4] and GBPJPY=X [5]. The samples collected are within the range of 02/01/2012 to 30/05/2019 and this range was selected to cover all the event dates collected from the new agencies. The data consists of OHLC (Open-High-Low-Close), adjusted-close and volume for daily prices within the range specified. It must be noted that the daily prices have 5 observations per week, and this is because the FX market is open from Sunday till Friday. So, in the end we ended up with data for the following FX rates, Pound Sterling (GBP) against Euro (EUR), United States Dollar (USD) and Japanese Yen (JPY).

Cryptocurrency prices were also collected from Yahoo Finance (Web API) via *'quantmod'* library in R, using the following ticker symbols BTC-GBP [6] and ETH-

GBP [7]. The top two cryptocurrencies by market cap (according to CoinMarketCap [8] on June 2019) were chosen to be tested against GBP, which are Bitcoin (BTC) [9] and Ethereum (ETH) [10]. The same script used for FX rates data collection was used to obtain these datasets. Again, the variables contained in both datasets are the same as the FX rate datasets. The range for BTC/GBP is between 01/01/2012 to 31/05/2019 which covers all the event dates collected from the previous datasets, on the other hand, the range for ETH/GBP is between 06/08/2015 to 31/05/2019. Unlike the other financial data, ETH/GBP does not cover all the event dates due to Ethereum being released on the 30/07/2015, which is after some of the dates found in the events dataset. Unlike the FX market the cryptocurrency market is open 24/7 meaning that there are no skipping dates in the dataset for the specified range, and all daily prices are included between this range.

Equity daily historical prices were collected/downloaded manually from ShareCast. For the equity market we choose to gather data for two indices, instead of gathering data for a single stock. An index is a weighted market capitalization for a group of stocks/companies. In our case, we decided to gather data for the FTSE100 [11] index which is made up of the largest 100 companies (by market cap) listed on the London Stock exchange and for the FTSE250 [12] which is made up of the largest 101-350 companies (by market cap) listed on the London Stock Exchange. The datasets consist of all the variables described in the other financial datasets except for the adjusted close price. Both datasets are from the range of 3/01/2012 to 31/05/2019 and the prices are in GBP. Like the FX market the London Stock Exchange is not open during the weekend and a trading week consists of 5 trading days.

Finally, data for the commodities market was collected via web scraping from Exchange Rates using *'rvest'* library. Two types of commodities were chosen which are Gold (XAU) and oil (OIL), both priced in GBP. These commodities were chosen since gold is the number one commodity exported in the UK, while crude oil is the second most imported commodity in the UK, according to Commodity.com. Both the XAU [13] and OIL [14] datasets have the same variables as each other, which include date and the price on that date. The dates for these datasets are in the range of 14/11/2010 to 31/05/2019.

In summary all the datasets described above (except those datasets which are collected manually) were collected in the following manner: collect the data from source, convert the dataset into a dataframe and then persist the dataframe to disk. All the procedures described above are well documented/commented in their respective scripts, *'data_collection_events.R'* for collecting Brexit events from news agencies and *'data_collection_finance.R'* for collecting financial data from various sources. A more detailed specification for all the datasets collected is shown in Table I.

| Dataset | Source | Type | Range | Freq. | Total |
|---|---|---|---|---|---|
| Brexit Major Events | Associated Press | Date / Textutal | 7/05/2015 to 7/06/2019 | Varies | 23 |
| Brexit Major Events | Al Jazzera | Date / Textutal | 23/01/2013 to 31/12/2020 | Varies | 22 |
| FX Rates GBP/EUR | Yahoo Finance | Date / Numerical (Continuous) | 02/01/2012 to 30/05/2019 | Daily | 1935 |
| FX Rates GBP/USD | Yahoo Finance | Date / Numerical (Continuous) | 02/01/2012 to 30/05/2019 | Daily | 1935 |
| FX Rates GBP/JPY | Yahoo Finance | Date / Numerical (Continuous) | 02/01/2012 to 30/05/2019 | Daily | 1935 |
| Crypto Prices BTC/GBP | Yahoo Finance | Date / Numerical (Continuous) | 01/01/2012 to 31/05/2019 | Daily | 2709 |
| Crypto Prices ETH/GBP | Yahoo Finance | Date / Numerical (Continuous) | 06/08/2015 to 31/05/2019 | Daily | 1398 |
| Index Prices FTSE100 | ShareCast | Date / Numerical (Continuous) | 03/01/2012 to 31/05/2019 | Daily | 1873 |
| Index Prices FTSE250 | ShareCast | Date / Numerical (Continuous) | 03/01/2012 to 31/05/2019 | Daily | 1871 |
| Commodity Prices XAU/GBP | Exchange Rates.org.uk | Date / Numerical (Continuous) | 14/11/2010 to 31/05/2019 | Daily | 3122 |
| Commodity Prices OIL/GBP | Exchange Rates.org.uk | Date / Numerical (Continuous) | 14/11/2010 to 31/05/2019 | Daily | 3116 |

*TABLE I: Detailed specification for the raw dataset collected. Includes source from where the data was collected, the type of variables in the dataset, the range of dates, the sampling frequency and the total number of observations.*

## III. Data Cleansing

In this section we will discuss in detail the techniques and procedures used to clean up the raw datasets described in Section. II. All the code used for the data cleaning process can be found in the following script *'data_cleansing.R'*.

### A. Cleaning Events Datasets

One problem which had to be tackled, is that there were intersecting events from the two datasets (duplicate event for the same date). Another issue was that one of the datasets (Al Jazzera) contained empty rows which had to be removed. One key issue which also had to be resolved is that the event dates in each dataset had a different format and these dates needed to be converted into one standardized format.

To clean up these raw datasets, they were loaded from disk and parse to two dataframes (one for each dataset). Since both datasets were previously saved as one event per line and contained both the event description and event date per line, each line (as a string) was split by *':'* character to make a distinction between the date of an event and the description. After doing so we ended up with two columns (date, description). Then each row was cleaned from unwanted special characters (e.g: " ,\, etc). After doing so any rows with an empty value were removed and the event dates were converted into a standardized format *'yyyy-mm-dd'*. We decided to remove any duplicate events intersecting with the other dataset, by removing duplicate events found in the Al Jazzera data. Finally, both datasets were merged/augmented into one single dataframe, and any events which had the event date greater than 1/06/2019 was removed (one of the datasets contained upcoming events). The dataframe was then persisted as a single dataset which contained major Brexit events (augmented from two datasets).

In a later stage the events dataset was filtered to use only events with at least 100 days difference between the event date. The reasons for this procedure will be discussed in Section V. The total number of events before any filtering was applied was 34 observations.

### *B. Cleaning Financial Datasets*

For the raw financial datasets, the same data cleaning techniques were applied. First the raw dataset was loaded from disk and converted to a dataframe. After doing so we remove any other columns described in Section II and kept only the date and closing price variables. The date variable was then converted to a date with the following format *'yyyy-mm-dd'*, and this was done to have a consistent date format throughout all the datasets. Any duplicate entries (rows with the same date) or entries with an empty variable (closing price or date) were removed. Finally, we created a new column for each dataframe, which is the log return based on the closing price. Log returns are computed using Formula 1. The reasons for this will be discussed in Section V.

Finally, the raw datasets were persisted to disk. It must be noted that the cleaned dataset for FX rates were saved into one single file (augmented datasets), this could be achieved since all the dates for the different FX pairs were aligned.

$$R_t = \ln(\frac{C_t}{C_{t-1}}) \tag{1}$$

*1: Log returns are computed by taking the difference between the natural log for the closing price at time $t$ and subtracting it by the natural log for the closing price at time $t-1$. This will output the log return at time $t$ ($R_t$).*

## IV. DATA STORAGE

In this section we will describe how data was stored prior to data analysis.

All the datasets described in previous Sections II, III were saved as *'.csv'* format. Raw datasets (pre-cleansing) were saved in the following path *'/data/raw'* and a total of 11 files were persisted, on the other hand, cleaned datasets (post-cleansing) were saved in the following path *'/data/cleansed'* and a total of 8 files were persisted.

The following files were persisted in the *'/data/raw'* folder:

- raw_events_ap
- raw_events_aljazzera
- raw_crypto_btcgbp
- raw_crypto_ethgbp
- raw_index_ftse100
- raw_index_ftse250
- raw_commodity_xau
- raw_commodity_oil
- raw_fx_gbpeur
- raw_fx_gbpusd
- raw_fx_gbpjpy

On the other hand, the following files were persisted in the *'/data/cleansed'* folder:

- brexit_events
- btc_prices
- eth_prices
- ftse100_prices
- ftse250_prices
- xau_prices
- oil_prices
- fx_rates

These datasets were also uploaded to a GitHub repository and can be viewed/downloaded from the following link *https://github.com/achmand/datascience-brexit/tree/master/src/data*.

## V. DATA ANALYSIS

In this section we will be showing descriptive statistics for our datasets, visualisations, explain our statistical model and show the results obtained when applying hypothesis testing.

### A. *Objectives of Data Analysis*

The data analysis was conducted to achieve the following objectives:

1) To examine the impact of major brexit events on foreign exchange rates (GBP/EUR, GBP/USD, GBP/JPY).
2) To examine the impact of major brexit events on cryptocurrency prices (BTC/GBP, ETH/GBP).
3) To examine the impact of major brexit events on stock market prices (FTSE100, FTSE250).
4) To examine the impact of major brexit events on commodity prices (GOLD, OIL).

### B. *Descriptive Statistics & Visualisations*

The events which were tested in our case study are shown in Table II.

| No. | Date | Description |
|---|---|---|
| #1 | 23-01-2013 | Cameron mentions Brexit in speech. |
| #2 | 07-05-2015 | British voters elect a majority Conservative government. Then-Prime Minister David Cameron confirms in his victory speech that there will be an in/out referendum on Britain's EU membership. |
| #3 | 20-02-2016 | Cameron confirms that he will campaign for Britain to remain in the 28-nation bloc. The referendum date is set for June. |
| #4 | 23-06-2016 | Britain votes 52 per cent to 48 per cent to leave the EU. |
| #5 | 17-01-2017 | May sets out plan for Brexit. |
| #6 | 19-03-2018 | UK and EU agree on several key issues. |
| #7 | 07-07-2018 | May and her Cabinet endorse the so-called Chequers Plan worked out at a fractious session at the prime minister's country retreat. It leads to the resignations of Brexit Secretary David Davis, Foreign Secretary Boris Johnson and others who favour a more complete break with the EU. |
| #8 | 14-11-2018 | Withdrawal agreement published. |

*TABLE II: Brexit Major Events extracted from Associated Press and Al Jazzera. This table shows the events which have at least 100 days difference between the event date.*

Financial data was then filtered to the date range between 06-10-2012 to 02-12-2018, to cover all the events shown in Table II. Descriptive statistics were then gathered from all the financial datasets. Table III shows the descriptive statistics for all the financial datasets for the closing price variable, while Table IV shows the descriptive statistics for the log returns variable. Figures 1, 2, 3, 4, 5, 6, 7, 8, 9 show the closing price and log return over time for GBP/EUR, GBP/USD, GBP/JPY, BTC/GBP, ETH/GBP, FTSE100, FTSE250, XAU/GBP and OIL/GBP, respectively.

Figures 10, 11, 12 and 13 show the probability distribution for both the closing price and log return variables for each asset in the FX market, cryptocurrency market, equity market and commodity market, respectively.

### C. *Hypothesis of the Study*

The hypothesis which was tested in this study across various financial markets is as follows:

$H_0$: There is no significant difference between the abnormal mean returns before a major brexit event and after it. ($\mu_0 = \mu_1$)
$H_1$: There is a significant difference between the abnormal mean returns before a major brexit event and after it. ($\mu_0 \neq \mu_1$)

### D. *Statistical Model*

There is extensive research on the impact of political events on different financial markets. One common way to investigate the impact of an event on a specific asset or a group of assets (FX rates, stock prices or commodity prices) is to investigate a time window around an event. This window is commonly referred to as an event window. There are many variables which are investigated, some of which are prices, returns (or log returns) and price volatility. The concept of event windowing can be viewed as a range of days ($-t$ days [pre-event] to $+t$ days [post-event], when $t = 0$ thats the date for the event) around an event. This concept is better visualised in Figure 14.

Researchers use different number of days for the event window, for example [15] applied statistical modelling using two event windows of *(-15, +15)* and *(-7, +7)* to investigate the impact of Brexit referendum on the Indian Equity market, [16] used three event windows of *(-15, +15)*, *(-5, +5)* and *(-2, +2)* to investigate political events in relation with the stock market and [17] used *(-10, +10)* to investigate the 1995 Quebec referendum on the equity market. Once an event window is specified an estimation period/window needs to be defined. This window is used to compute the expected return (daily, weekly, monthly or annually) based on that period. There are various methods to compute the expected return (sometimes referred to as normal return), some researchers use the mean adjusted return model [15], while others use CAPM (also known as Market Model) [18]. The number of days used in the estimation period is up to the researcher and various days were tested; [19] used 180 days before the event window to investigate the reaction of the market in relation to DDoS attack announcements, [20] used 100 days prior the event window to investigate politcal events in relation to emerging stock markets and [21] used three different estimation periods 240 days, 120 days and 60 days when

| Asset | Min. | 1st Qu. | Median | 3rd Qu. | Max. | Var. | Std. | Skewness | Kurtosis | Samples |
|---|---|---|---|---|---|---|---|---|---|---|
| GBP/EUR | 1.0795 | 1.1454 | 1.1893 | 1.2671 | 1.4403 | 0.0078 | 0.0882 | 0.8204 | -0.3809 | 1601 |
| GBP/USD | 1.2039 | 1.3194 | 1.4936 | 1.5745 | 1.7161 | 0.0202 | 0.1421 | -0.0853 | -1.3171 | 1601 |
| GBP/JPY | 124.9450 | 144.3230 | 152.3900 | 172.4400 | 195.7420 | 314.3978 | 17.7313 | 0.3486 | -0.9803 | 1601 |
| BTC/GBP | 6.3200 | 159.7025 | 330.1750 | 1500.9850 | 14943.4199 | 6166028.5558 | 2483.1489 | 2.1036 | 4.3805 | 2242 |
| ETH/GBP | 0.4000 | 7.7250 | 37.0000 | 244.9750 | 1073.0000 | 41622.4790 | 204.0159 | 1.5218 | 2.1575 | 1211 |
| FTSE100 | 5536.9700 | 6427.6400 | 6757.1500 | 7224.5100 | 7877.4500 | 255116.7297 | 505.0908 | 0.0123 | -0.7751 | 1557 |
| FTSE250 | 11576.9800 | 15616.5350 | 17066.4500 | 19066.5200 | 21324.0200 | 5149011.8977 | 2269.1434 | -0.1949 | -0.5681 | 1555 |
| XAU/GBP | 695.8022 | 775.6071 | 908.2115 | 971.7441 | 1107.7725 | 11752.9311 | 108.4109 | -0.0216 | -1.3270 | 2250 |
| OIL/GBP | 18.8397 | 35.3447 | 43.5547 | 57.8620 | 71.3218 | 158.5781 | 12.5928 | 0.0454 | -1.1614 | 2250 |

*TABLE III: Descriptive Statistics for all financial datasets using the close price variable, this data is filtered between the date range of 06-10-2012 to 02-12-2018. The following statistics are included: minimum value, first quartile, median, third quartile, maximum value, variance, standard deviation, skewness, kurtosis and the number of samples.*

| Asset | Min. | 1st Qu. | Median | 3rd Qu. | Max. | Var. | Std. | Skewness | Kurtosis | Samples |
|---|---|---|---|---|---|---|---|---|---|---|
| GBP/EUR | -0.053203 | -0.002832 | 0.000000 | 0.002821 | 0.022388 | 0.000027 | 0.005233 | -0.648637 | 7.712632 | 1601 |
| GBP/USD | -0.079085 | -0.002942 | -0.000069 | 0.002832 | 0.028480 | 0.000031 | 0.005568 | -1.743059 | 26.355998 | 1601 |
| GBP/JPY | -0.105833 | -0.003680 | 0.000163 | 0.004162 | 0.044188 | 0.000056 | 0.007510 | -1.554991 | 26.647111 | 1601 |
| BTC/GBP | -0.860084 | -0.015646 | 0.002034 | 0.023366 | 1.543774 | 0.005219 | 0.072243 | 4.027193 | 114.857074 | 2242 |
| ETH/GBP | -1.223775 | -0.028299 | 0.000000 | 0.031129 | 0.693147 | 0.010241 | 0.101199 | -1.170823 | 26.719994 | 1210 |
| FTSE100 | -0.047795 | -0.004360 | 0.000501 | 0.004512 | 0.035150 | 0.000070 | 0.008380 | -0.179624 | 2.495105 | 1557 |
| FTSE250 | -0.074565 | -0.003816 | 0.000585 | 0.004818 | 0.035132 | 0.000064 | 0.008005 | -1.066375 | 10.337410 | 1555 |
| XAU/GBP | -0.089826 | -0.003140 | 0.000000 | 0.003044 | 0.128173 | 0.000066 | 0.008151 | 0.982736 | 35.957671 | 2250 |
| OIL/GBP | -0.084114 | -0.006739 | 0.000000 | 0.006169 | 0.143239 | 0.000281 | 0.016775 | 0.317059 | 5.936580 | 2250 |

*TABLE IV: Descriptive Statistics for all financial datasets using the log returns variable, this data is filtered between the date range of 06-10-2012 to 02-12-2018. The following statistics are included: minimum value, first quartile, median, third quartile, maximum value, variance, standard deviation, skewness, kurtosis and the number of samples.*

investigating the EMH (Efficient Market Hypothesis) in relation to the Turkish Parliament rejecting deployment of the United States army (01/03/2003). It is important that the estimation period do not intersect within another events window as this period is used as a "benchmark" to get the expected return when the market is in it's "normal state", if this happens you would be adding the abnormalities of another event when computing the expected return. This is the reason why events were filtered out if the difference in days between them is smaller than 100 days.

In our model we used an event window of 8 days and an estimation period of 100 days. The expected daily return was computed using the mean of the log returns in the estimation period as shown in Formula 2. Log returns (computed using Formula 1) were used in our statistical model, since they are a measure of change between the price at time $t$ and the price at time $t-1$. Closing prices are also considered to be log-normally distributed [22], so utilising the log returns, we will be working with a normally distributed variable.

$$R^* = \frac{1}{T}\sum_{t=1}^{t} R_t \tag{2}$$

*2: Expected returns were computed using the mean for the daily log prices in the estimation period. In our case $T = 100$ $(-108, -8)$, so the mean for 100 daily log returns prior the event date was used as the expected return.*

In our model we investigated each financial asset individually in relation to each event shown in Table II. The abnormal returns were then computed for each time $t$ prior and after an event, given that they are in the range of the event window. In our case the abnormal returns for the pre-event window *(-8, -1)* and the post-event window *(+1, +8)* was computed, which is equal

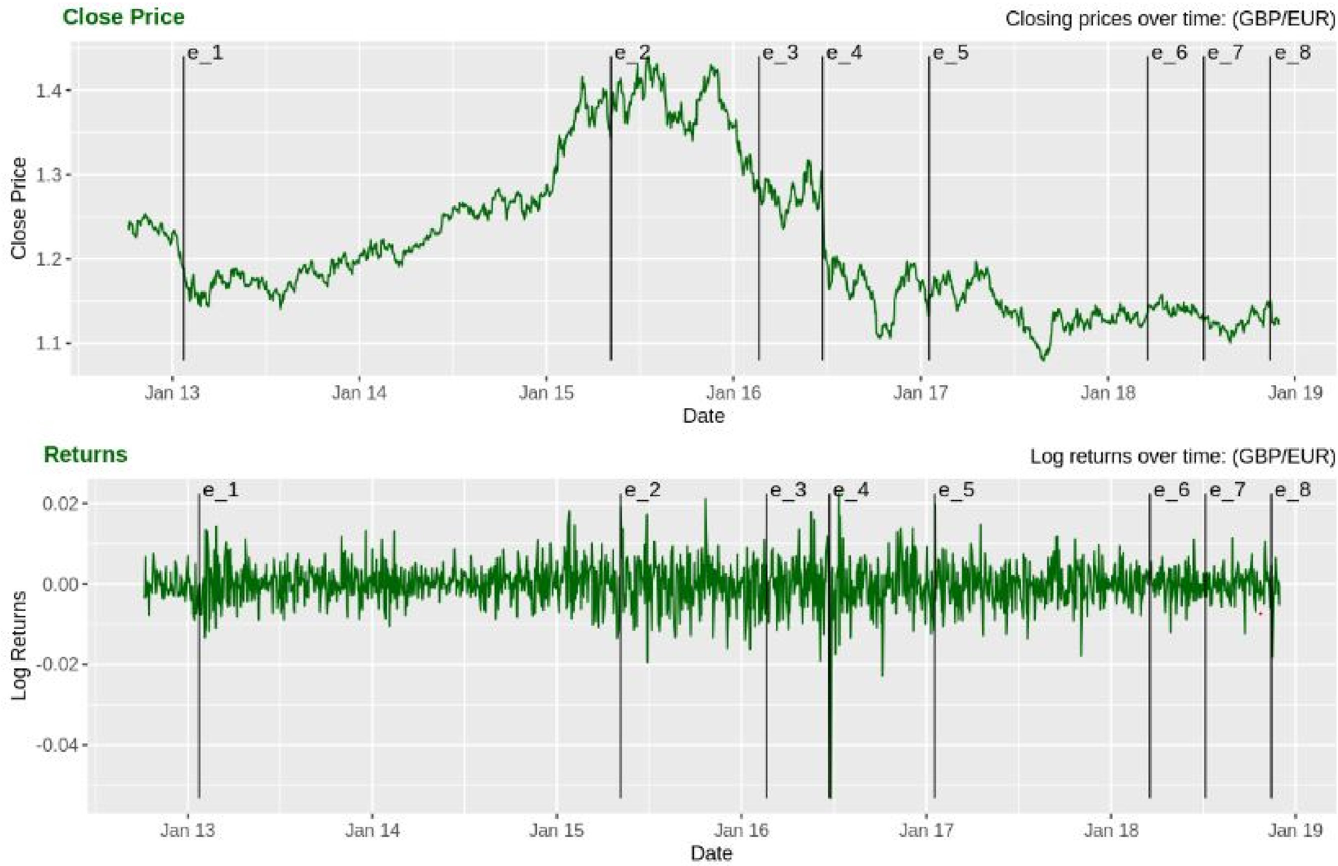


*Fig. 1: Two plots showing the close price and log returns over time for the GBP/EUR pair. The black segments represent an event from the Table II denoted as $e\_n$, $n$ being the event no. in the events table.*

to 16 abnormal returns. Abnormal returns are computed using Formula 3. The abnormal return variable gives as an indication of any abnormalities in the returns by taking the difference of the actual return and the expected return, this variable is also referred to as the expectation error.

$$AR = R_t - R^* \tag{3}$$

*3: Abnormal returns are computed by taking the difference between the actual return at time $t$ and the expected return which is computed using Formula 2. Abnormal returns for each event at time $t$ in the event window (-8, -1) (+1, +8) was computed.*

Now after computing all these variables we needed a way to test the significance of these abnormal returns around an event. There are various techniques to test the significance of this variable (abnormal returns), some of which are: [23] devised a parametric test called the Standardized Cross-Sectional Test which tests if the cumulative abnormal return is equal to 0, Corrado Rank Test which is non-parametric test proposed by [24] to test whether the AAR (Average Abnormal Return) is equal to 0 and the AR Test which is a parametric test which tests whether the abnormal return is equal to 0. All of these techniques have their own assumptions and should be used for a specific use case, for example some are used to test an individual event, others are used to test a sample of events, some test one financial instrument at a time while others test a collection of instruments (portfolio). For our case study we used the same hypothesis testing model as [16]. We tested for significant differences between the abnormal mean returns in the pre-event window and the post-event window around an event, as described in Section V-C. To test for significance, the mean abnormal return or AAR (Average Abnomral Return) for both the pre-event window and the post-event window was computed. These values were computed using Formula 4 and Formula 5, respectively.

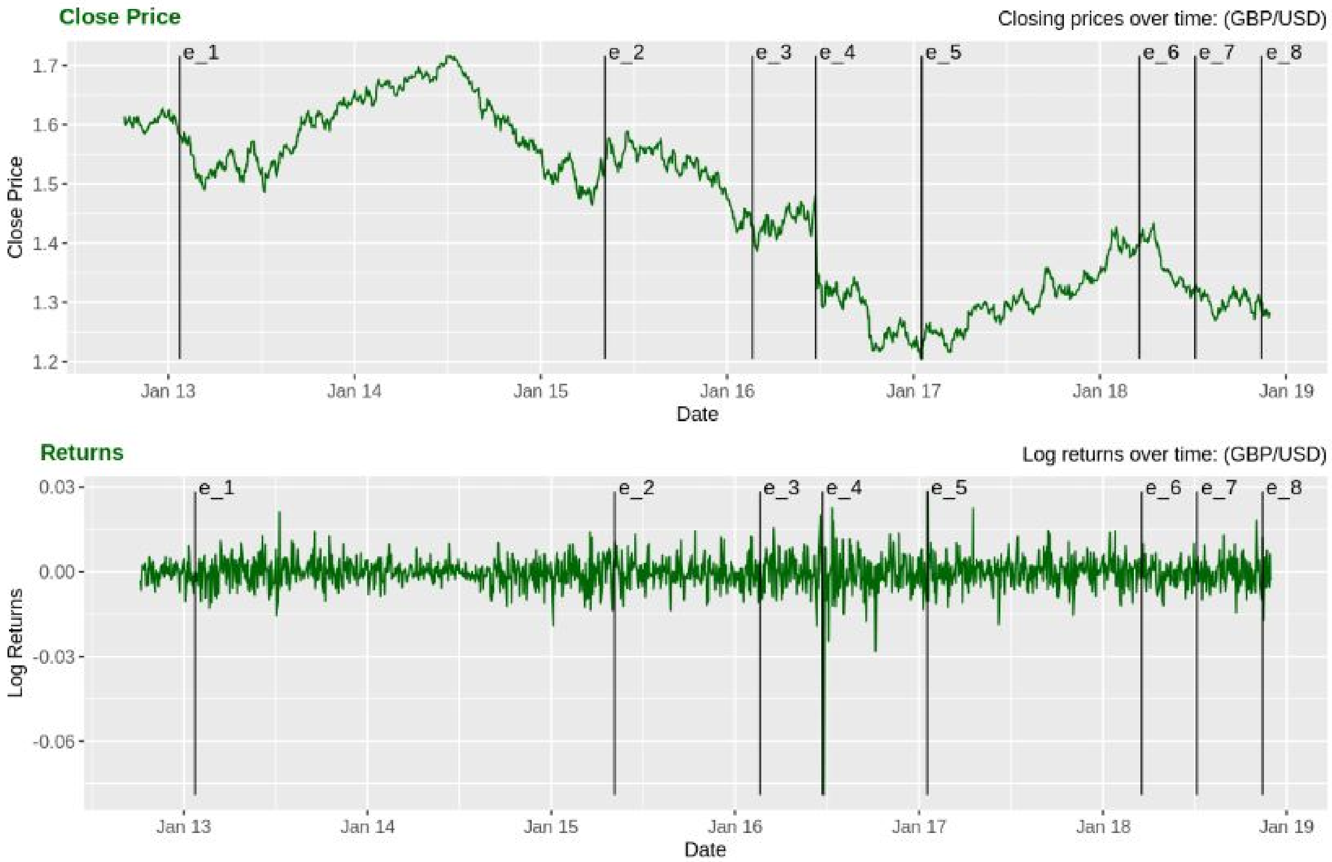


*Fig. 2: Two plots showing the close price and log returns over time for the GBP/USD pair. The black segments represent an event from the Table II denoted as e_n, $n$ being the event no. in the events table.*

$$AAR_{before} = \frac{\sum_{t=-k}^{t=-1} AR_{before,t}}{n} \tag{4}$$

*4: The Abnormal Average Return (AAR) for the pre-event window is computed by taking the summation for all abnormal returns found in the pre-event window (-8, -1) and dividing it by the number of abnormal return found in that pre-event window, which in our case was 8 abnormal returns.*

$$AAR_{after} = \frac{\sum_{t=1}^{t=k} AR_{after,t}}{n} \tag{5}$$

*5: The Abnormal Average Return (AAR) for the post-event window is computed by taking the summation for all abnormal returns found in the post-event window (+1, +8) and dividing it by the number of abnormal return found in that post-event window, which in our case was 8 abnormal returns.*

Moreover, the standard error for the difference in means between the pre-event and post-event window had to be computed to test for any differences in means. Formula 6 shows how the standard of error for the difference in mean between these two samples was computed.

$$\sigma_{pre-post} = \sqrt{\frac{(n_1-1)\sigma_1 + (n_2-1)\sigma_2}{(n_1+n_2-1)(\frac{1}{n_1}+\frac{1}{n_2})}} \tag{6}$$

*6: The formula shows how to compute the standard error. $\sigma_1$ is the variance for the pre-event window/period, while $\sigma_2$ is the variance for the post-event window/period. $n_1$ and $n_2$ are the number of days found in the pre-event period and post-event period, respectively.*

The *t*-value was then computed using Formula 7, which is the measure used to test for the significance between the difference in abnormal means (pre and post event) for a specific event.

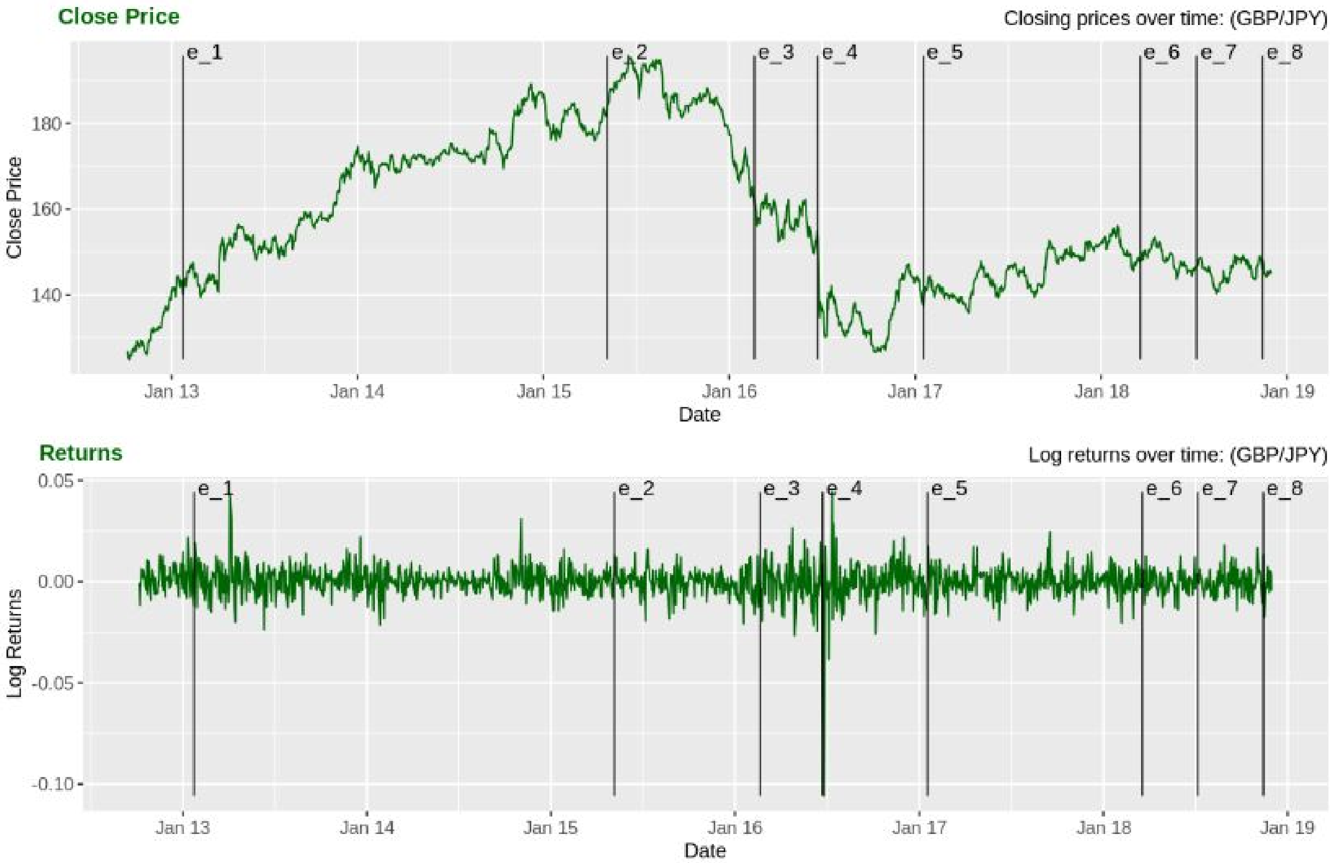


*Fig. 3: Two plots showing the close price and log returns over time for the GBP/JPY pair. The black segments represent an event from the Table II denoted as* $e\_n$, $n$ *being the event no. in the events table.*

$$t = \frac{AAR_{after} - AAR_{before}}{\sigma_{pre-post}} \tag{7}$$

*7: This formula is used to compute the t-statistic. We take the* $AAR_{after}$ *and subtract it with* $AAR_{before}$ *divided by the standard error.* $AAR_{after}$*,* $AAR_{before}$ *and the* $SE$*, are computed using Formula 5, Formula 4 and Formula 6, respectively.*

The following assumptions were taken when conducting hypothesis testing (two-sided test):

- Normality of data distribution (log-returns) due to the nature of the parametric test.
- The variance between the abnormal returns for the pre and post event window is equal/similar.
- Sample size is below 30 samples.
- The scale of measurement is a continuous numerical variable.
- The Brexit events tested are indeed major political events and the source where they where extracted from are not biased towards one political party.
- The market is efficient enough to absorb the event information in an 8-day period and no further changes to the price is due to that specific event after 8 days from an event.

### E. Empirical Results

The code for hypothesis testing can be found in the *"Impact of Major Brexit Events on Various Financial Markets"* jupyter notebook. The following tables show the results obtained when conducting the hypothesis test described in Section V-D: Table V shows the results for FX market, Table VI shows the results for the Cryptocurrency Market, Table VII shows the results for the Equity market and lastly Table VIII shows the results for the Commodity market.

For the GBP/EUR pair we fail to reject the hypothesis when testing events #1, #3, #6, #7 and #8. Although there is statistical significance in event #2, #4 and #5 with p-values of 0.0626 (10%), 0.0351 (5%) and 0.0101 (5%), respectively, so the null hypothesis is rejected for these events in relation to GBP/EUR. When testing the GBP/USD pair there is only one event tested which had statistical significance, which is event #4 with a p-value of 0.0793 (10%). For the other events we failed to reject the null hypothesis in relation to GBP/USD. We also failed to reject the null hypothesis for all events when

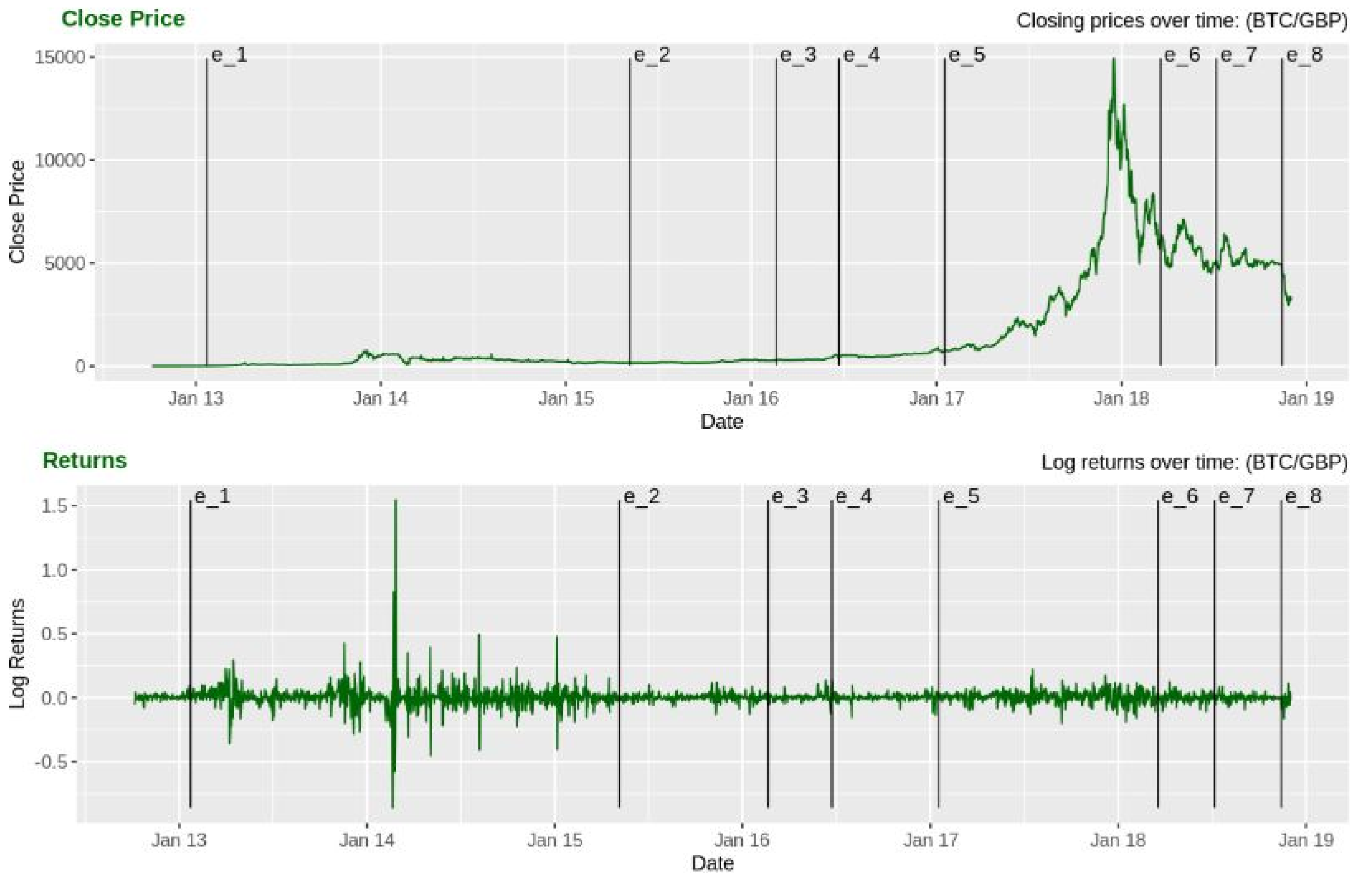


*Fig. 4: Two plots showing the close price and log returns over time for the BTC/GBP pair. The black segments represent an event from the Table II denoted as $e\_n$, $n$ being the event no. in the events table.*

| Event | GBP/EUR | | GBP/USD | | GBP/JPY | |
|---|---|---|---|---|---|---|
| | $p$-values | $t$-values | $p$-values | $t$-values | $p$-values | $t$-values |
| #1 | 0.9026 | 0.1246 | 0.8952 | -0.1341 | 0.4189 | -0.8329 |
| #2 | 0.0626* | -2.0234 | 0.9179 | -0.1050 | 0.7187 | -0.3676 |
| #3 | 0.6987 | -0.3951 | 0.8115 | 0.2430 | 0.5523 | -0.6090 |
| #4 | 0.0351** | 2.3321 | 0.0793* | 1.8925 | 0.1405 | 1.5626 |
| #5 | 0.0101** | -2.9714 | 0.1354 | -1.5846 | 0.0051*** | -3.3120 |
| #6 | 0.8598 | 0.1799 | 0.8628 | -0.1760 | 0.6868 | -0.4117 |
| #7 | 0.7299 | 0.3522 | 0.5322 | 0.6405 | 0.9823 | -0.0226 |
| #8 | 0.1845 | 1.3958 | 0.5008 | 0.6912 | 0.2507 | 1.1982 |

*TABLE V: Results for t-values and p-values when testing abnormal mean returns (pre & post event using 8 day event window) using foreign exchange returns. Events are numbered/labelled according to the event shown in Table V.*
****,**,*Significance at 1, 5 and 10 percent, respectively (p-values)*

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testing the GBP/JPY except for event #5 which had a p-value of 0.0051 (1%). These results are shown in Table V.

Contrary to the previous results discussed, there were no statistical significant results in all the events tested when using the crypto currency pairs. We failed to reject the null hypothesis for all the events when tested using the BTC/GBP and ETH/GBP pairs. The results for the crypto currency tests are shown in Table VI.

| Event | BTC/GBP | | ETH/GBP | |
|---|---|---|---|---|
| | $p$-values | $t$-values | $p$-values | $t$-values |
| #1 | 0.6925 | 0.4037 | N/A | N/A |
| #2 | 0.1913 | 1.3731 | N/A | N/A |
| #3 | 0.2795 | 1.1251 | 0.7456 | -0.3309 |
| #4 | 0.2988 | -1.0790 | 0.5006 | -0.6914 |
| #5 | 0.8634 | -0.1752 | 0.9126 | -0.118 |
| #6 | 0.9921 | 0.0101 | 0.8252 | -0.2250 |
| #7 | 0.4754 | 0.7335 | 0.5599 | 0.5937 |
| #8 | 0.1885 | 1.3826 | 0.1276 | 1.6196 |

*TABLE VI: Results for t-values and p-values when testing abnormal mean returns (pre & post event using 8 day event window) using cryptocurrencies returns. ETH/GBP does not have any stats for event 1 and 2, since Ethereum [10] was released after those particular event dates. Events are numbered/labelled according to the event shown in Table II.*
****,**,*Significance at 1, 5 and 10 percent, respectively (p-values)*

When testing the FTSE100 and FTSE250 indices we failed to reject the null hypothesis for all events except for event #5 when tested using FTSE100 as it had a p-value of 0.0862 (10%). The results for the equity market tests are shown in Table VII.

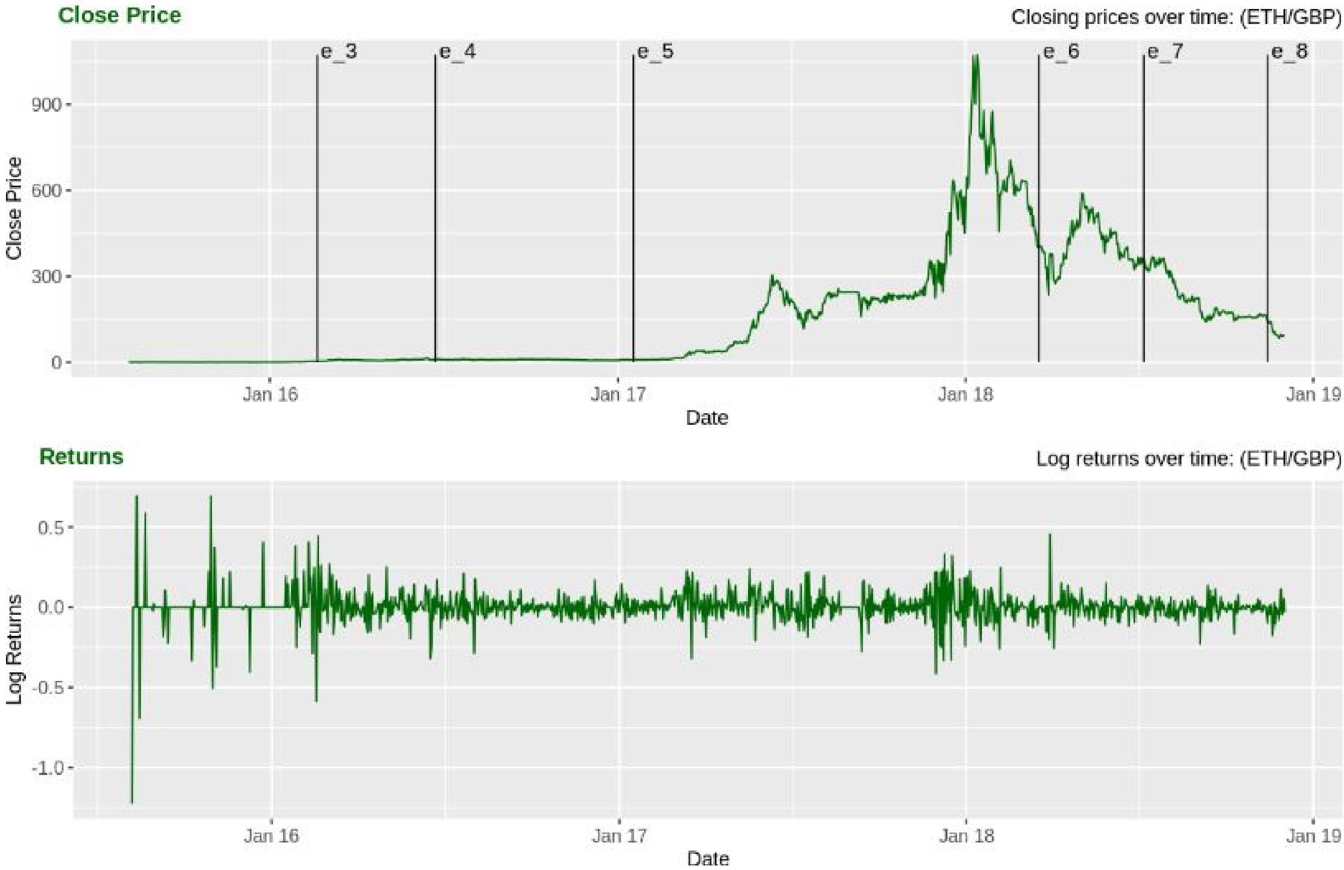


*Fig. 5: Two plots showing the close price and log returns over time for the ETH/GBP pair. The black segments represent an event from the Table II denoted as* $e\_n$, $n$ *being the event no. in the events table.*

| Event | FTSE100 | | FTSE250 | |
|---|---|---|---|---|
| | *p*-values | *t*-values | *p*-values | *t*-values |
| #1 | 0.8860 | 0.1718 | 0.9745 | -0.0326 |
| #2 | 0.3629 | -0.9405 | 0.1208 | -1.6520 |
| #3 | 0.5569 | 0.6018 | 0.6183 | 0.5096 |
| #4 | 0.9167 | -0.1065 | 0.4294 | 0.8138 |
| #5 | 0.0862* | 1.8459 | 0.4623 | 0.7557 |
| #6 | 0.9863 | 0.0174 | 0.5417 | 0.6254 |
| #7 | 0.6959 | 0.3990 | 0.6414 | -0.4761 |
| #8 | 0.7831 | -0.2807 | 0.9917 | 0.0106 |

*TABLE VII: Results for t-values and p-values when testing abnormal mean returns (pre & post event using 8 day event window) using equity indices returns. Events are numbered/labelled according to the event shown in Table II.*
****,**,*Significance at 1, 5 and 10 percent, respectively (p-values)*

| Event | XAU/GBP | | OIL/GBP | |
|---|---|---|---|---|
| | *p*-values | *t*-values | *p*-values | *t*-values |
| #1 | 0.0319** | 2.3836 | 0.4195 | 0.8317 |
| #2 | 0.5310 | -0.6424 | 0.3334 | 1.0018 |
| #3 | 0.3362 | -0.9959 | 0.6022 | 0.5332 |
| #4 | 0.0812* | -1.8789 | 0.1216 | -1.6479 |
| #5 | 0.0158** | 2.7448 | 0.7379 | 0.3413 |
| #6 | 0.0879* | -1.8349 | 0.4715 | -0.7401 |
| #7 | 0.8123 | -0.2420 | 0.5474 | 0.6166 |
| #8 | 0.1263 | -1.6255 | 0.4294 | -0.8139 |

*TABLE VIII: Results for t-values and p-values when testing abnormal mean returns (pre & post event using 8 day event window) using commodities returns. Events are numbered/labelled according to the event shown in Table II.*
****,**,*Significance at 1, 5 and 10 percent, respectively (p-values)*

The XAU/GBP pair (Gold) had 4 statistically significant p-values 0.0319 (5%), 0.0812 (10%), 0.0158 (5%) and 0.0879 (10%) for events #1, #4, #5 and #6, respectively, so the null hypothesis was rejected for these particular events. On the other hand, the OIL/GBP pair had no statistically significant p-values and we failed to reject the null hypothesis for all events tested. Table VIII shows the results for the tests conducted on the commodity market.

## VI. Conclusion

In this section we will give a critical review for the results obtained in Section V-E, discuss any shortcomings in our statistical model and discuss possible future work

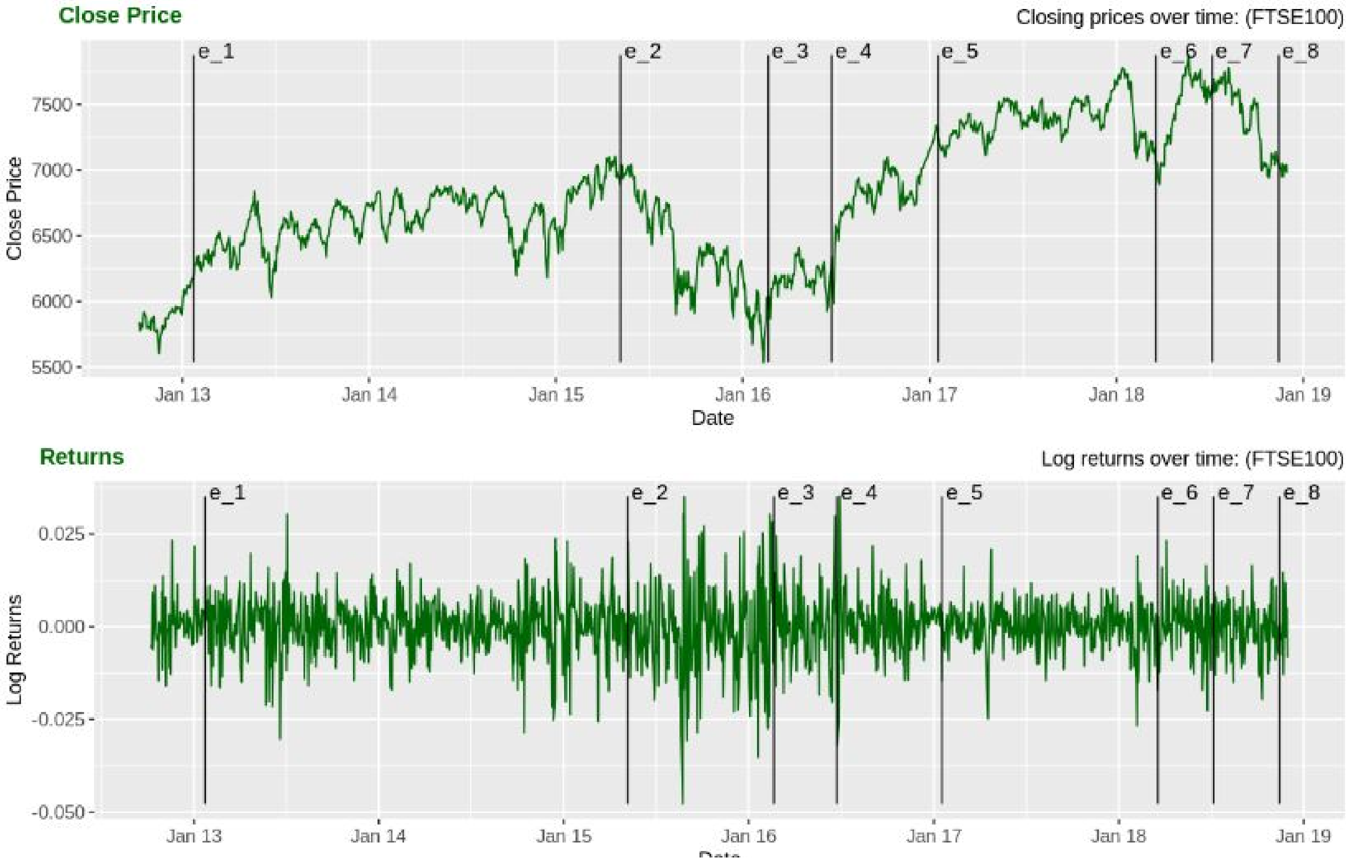


*Fig. 6: Two plots showing the close price and log returns over time for the FTSE100. The black segments represent an event from the Table II denoted as $e\_n$, $n$ being the event no. in the events table.*

### A. Discussion of Results

From the analysis conducted in Section V, it is apparent that not all the events have the same impact and the impact of a specific event is relative to the specific financial instrument (not all the assets are impacted in the same manner). It must be noted that we used three different significance level for the p-values which is 10%, 5% and 1%.

From all the tests conducted on FX currency pairs, the GBP/EUR pair seems to be the most sensitive to Brexit events and this could be because the Brexit campaign was about Britain leaving the European Union. Surprisingly, the most significant p-value obtained in all the assets tested (for every market) was the GBP/JPY in event #5 (May sets out plan for Brexit). The GBP/USD pair seemed to be impacted by the vote to leave the EU (event #4).

The cryptocurrency market seems to be robust from Brexit events from the evidence gathered using our statistical model as there was no statistical significance when testing both the BTC/GBP and ETH/GBP pair. Another surprising result is that both the FTSE100 and FTSE250 seems to be robust to these events as the only statistically significant value obtained is in event #5 (May sets out plan for Brexit) and only when testing FTSE100.

Lastly, some interesting results were obtained in the commodity market. Although OIL/GBP seems to have no statistically significant results, the XAU/GBP had the most statistically significant values with a total of 5 statistically significant p-values. Given that Gold is the number one commodity exported in the UK it makes sense that XAU/GBP is sensitive to Brexit events. Overall the events which had the most impact on the financial markets tested were, event #4 (Britain votes to leave the EU) and event #5 (May sets out plan for Brexit) with a total of 3 and 4 significant p-values, respectively.

These results should not be taken as facts and the statistical tests conducted do not prove any hypothesis, we just showed that there are some statistically significant values for some events investigated. Also, further tests should be required to back up the results obtained in this study; in the next section we will discuss the shortcomings for our proposed method.

### B. Shortcomings for our Statistical Model

- Hypothesis testing was applied to each individual

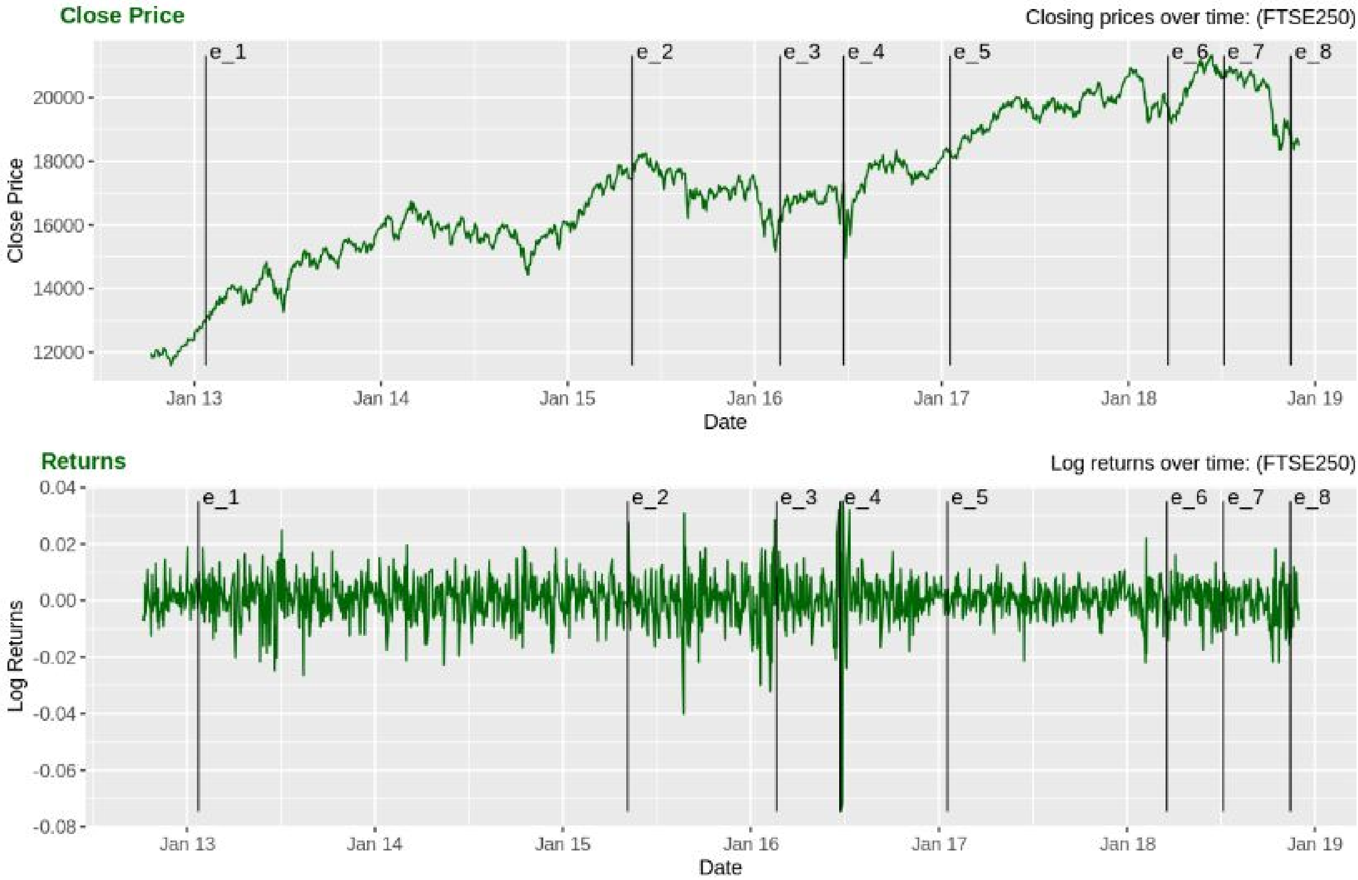


*Fig. 7: Two plots showing the close price and log returns over time for the FTSE250. The black segments represent an event from the Table II denoted as $e\_n$, $n$ being the event no. in the events table.*

event, no tests on sample of events was applied to determine if Brexit events in general have a statistical impact on the assets tested.

- Hypothesis testing was applied to each individual asset, no tests on sample of assets (portfolio) was applied to determine if Brexit events in general have a statistical impact on a group of assets.
- The statistical model applied to test our hypothesis does not take into consideration the event date itself ($t_0$), instead focuses on the differences in mean in the pre-event and post-event window. Some drastic abnormal returns could occur in the event date itself and this was not captured with our model.
- It is common to complement the hypothesis test with a nonparametric test to verify the result and make sure that the results obtained are not cause by an outlier [25]. Our statistical model only applies a parametric test.
- The Brexit events investigated were extracted from two news agencies and there are no statistical backings to check if in fact these events are major events.

Prior to the statistical model mentioned in Section V, we tried to use one different strategy which was not successful. The strategy is very similar to the one implemented, and it was applied before thorough research was done. This strategy also used the same mechanism of event windowing and checked the difference in means across all events, meaning that there would be no distinction between one event and another when tested, and the mean of log returns (no abnormal returns were used) for the pre-window and post-window for all events would be tested in one single test. After doing some research we found out that there are special tests used to test a sample of events which require more sophisticated techniques to test for statistical significance.

### C. Improvements/Future Work

- Apply the same tests using different values for the estimation window and the event window, as it is common to test your hypothesis using different days for both the estimation and event window.
- Use a different hypothesis which takes into consideration the event date itself, for example the AR Test, tests if the abnormal return at each day in

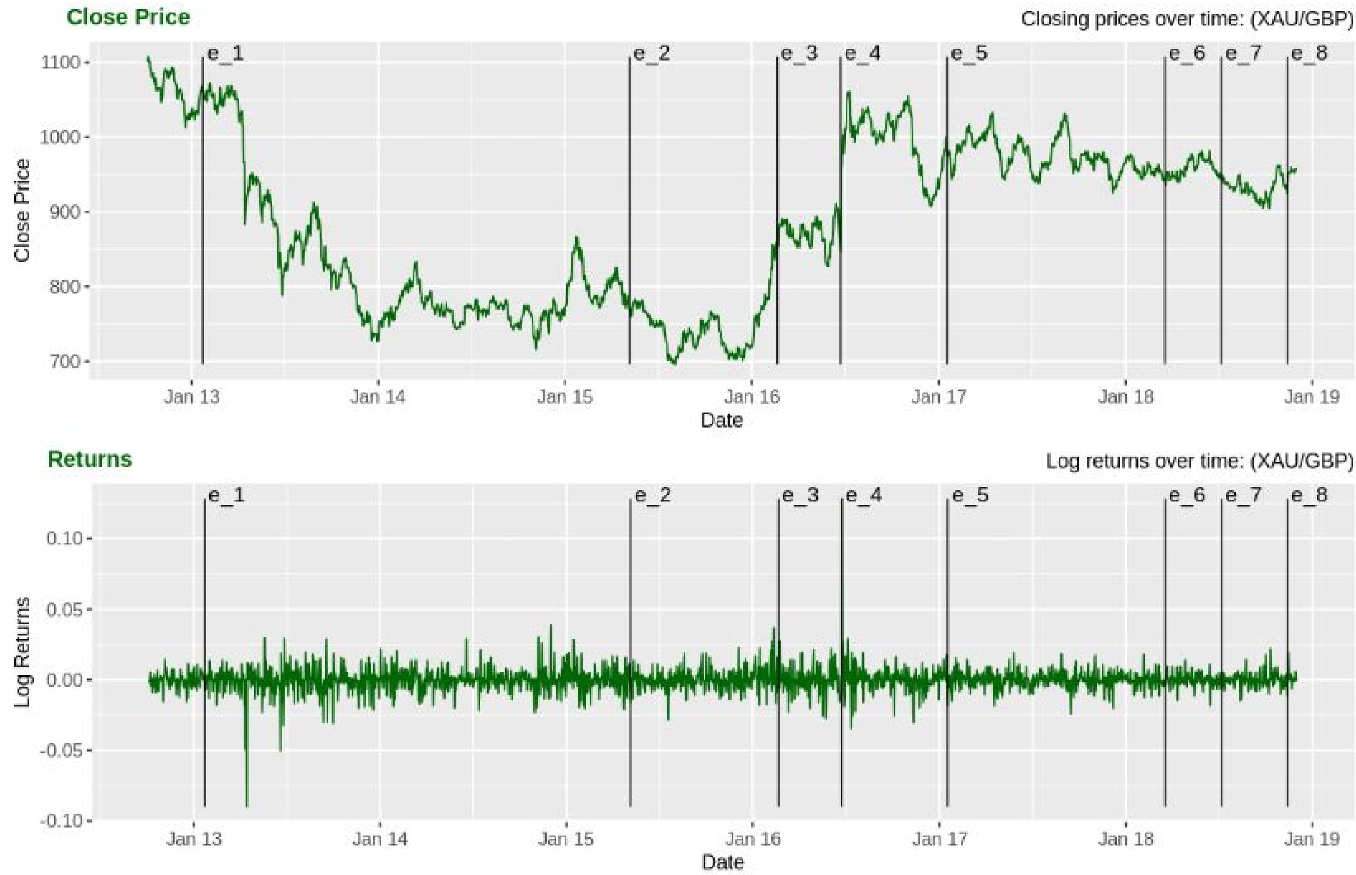


*Fig. 8: Two plots showing the close price and log returns over time for the XAU/GBP pair. The black segments represent an event from the Table II denoted as $e\_n$, $n$ being the event no. in the events table.*

the event period is equal to 0. The formula used to obtain the t-value for each day in the time period is shown in Formula 8.

$$t_{AR_{i,t}} = \frac{AR_{i,t}}{S_{AR_i}} \tag{8}$$

*8: This formula returns the t-value to test if the abnormal return at any $t$ including the event date $t_0$ is equal to 0. It is computed by taking the abnormal at time $t$ and divided it by the standard deviation of the daily log returns in the estimation period $S_{AR_i}$*

- Apply non-parametric test to further confirm our findings. One example is to apply the Cowan Generalized Sign Test [26], which can also be used to test for a sample of events rather than one individual event.

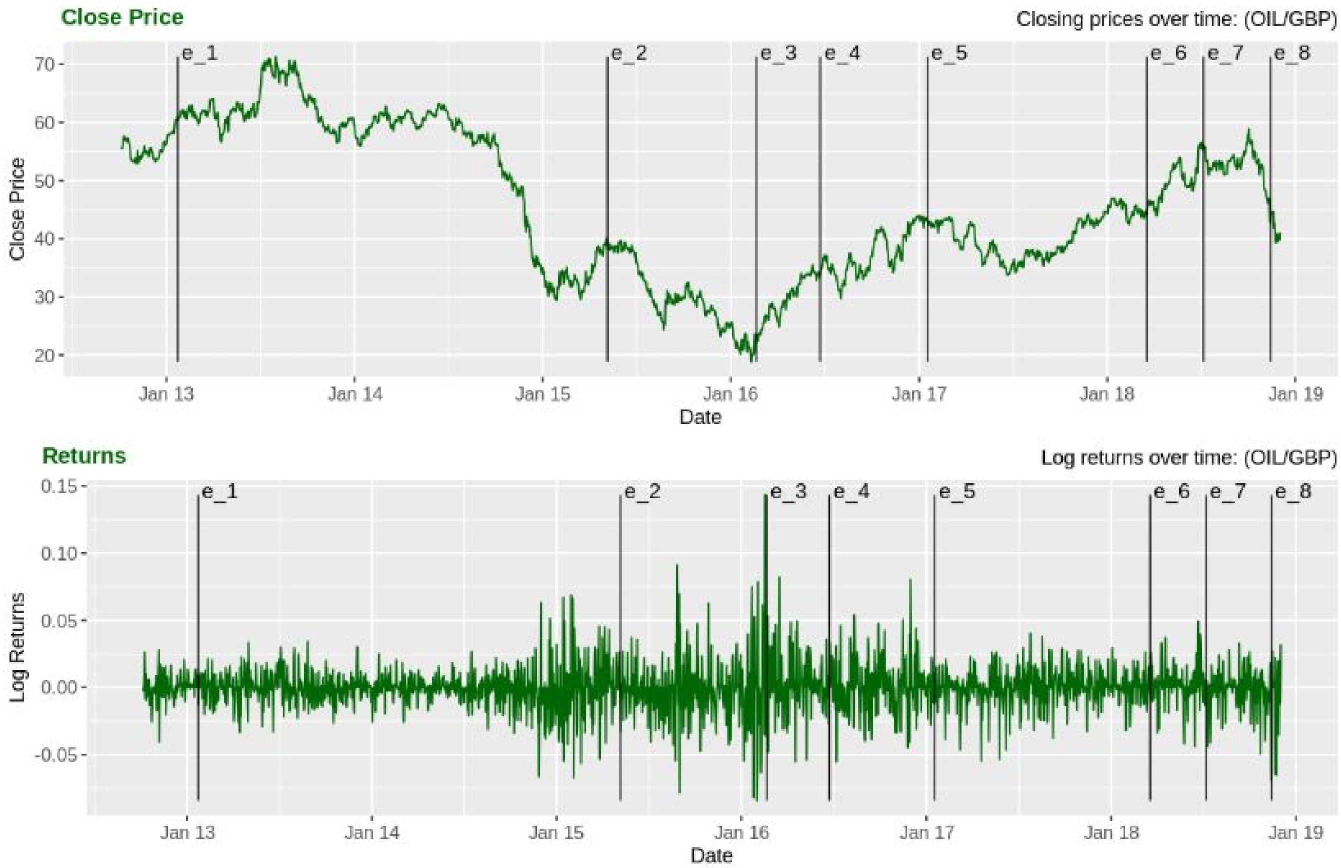


*Fig. 9: Two plots showing the close price and log returns over time for the OIL/GBP pair. The black segments represent an event from the Table II denoted as* $e\_n$*,* $n$ *being the event no. in the events table.*

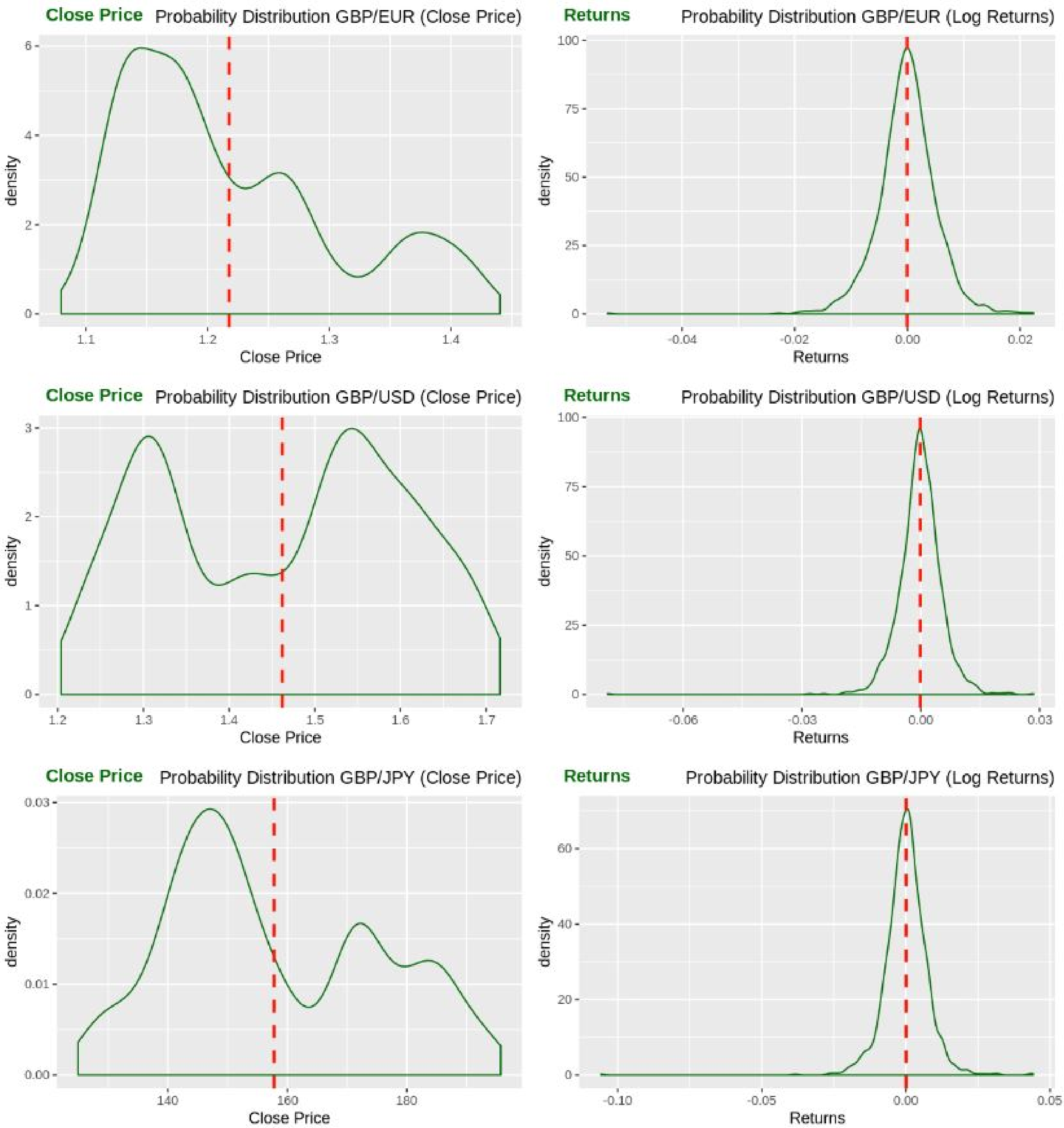


*Fig. 10: Probability distribution plots for the closing prices and log returns for each foreign exchange pair. The red dashed line indicates the mean for that variable.*

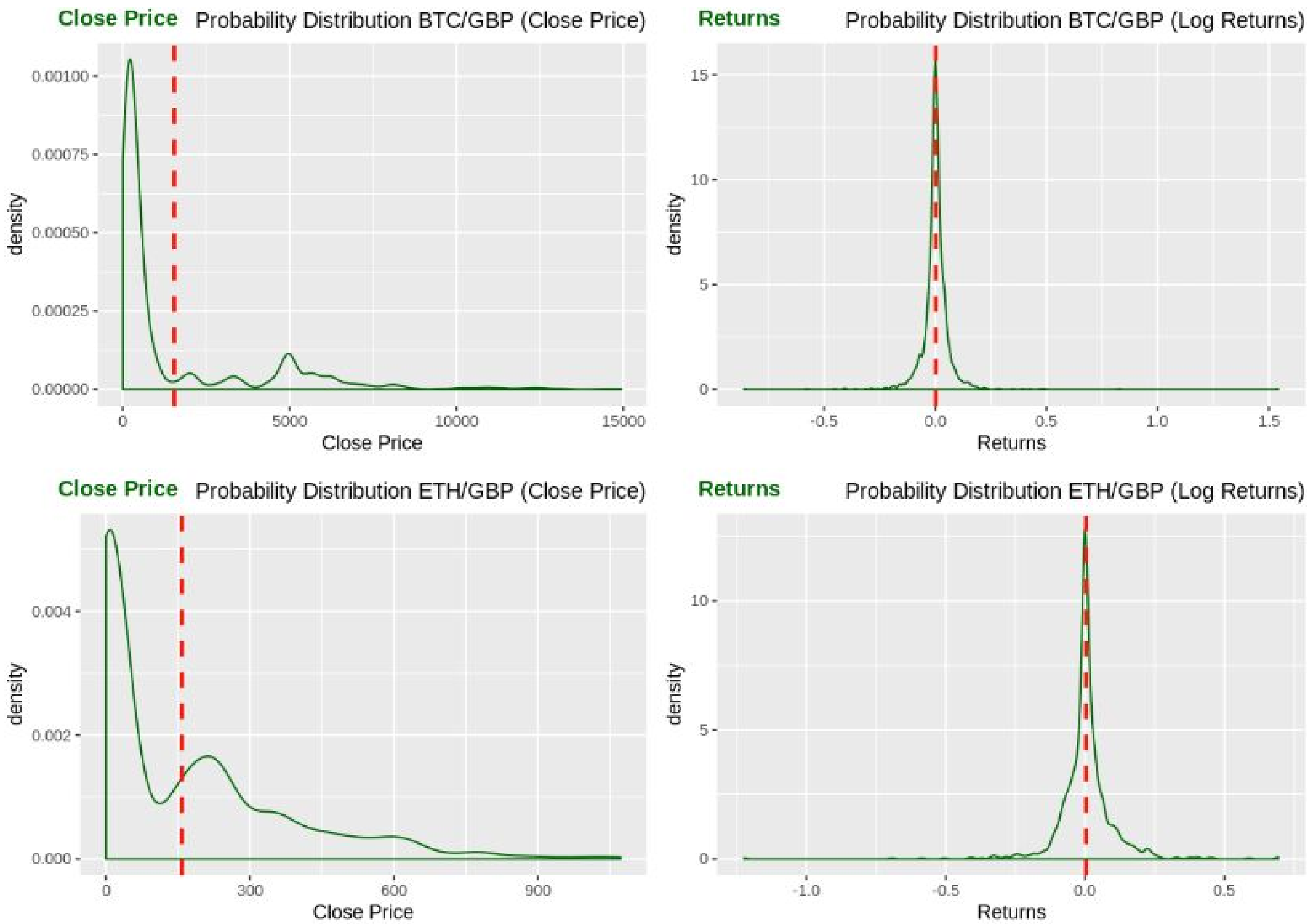


*Fig. 11: Probability distribution plots for the closing prices and log returns for each cryptocurrency pair. The red dashed line indicates the mean for that variable.*

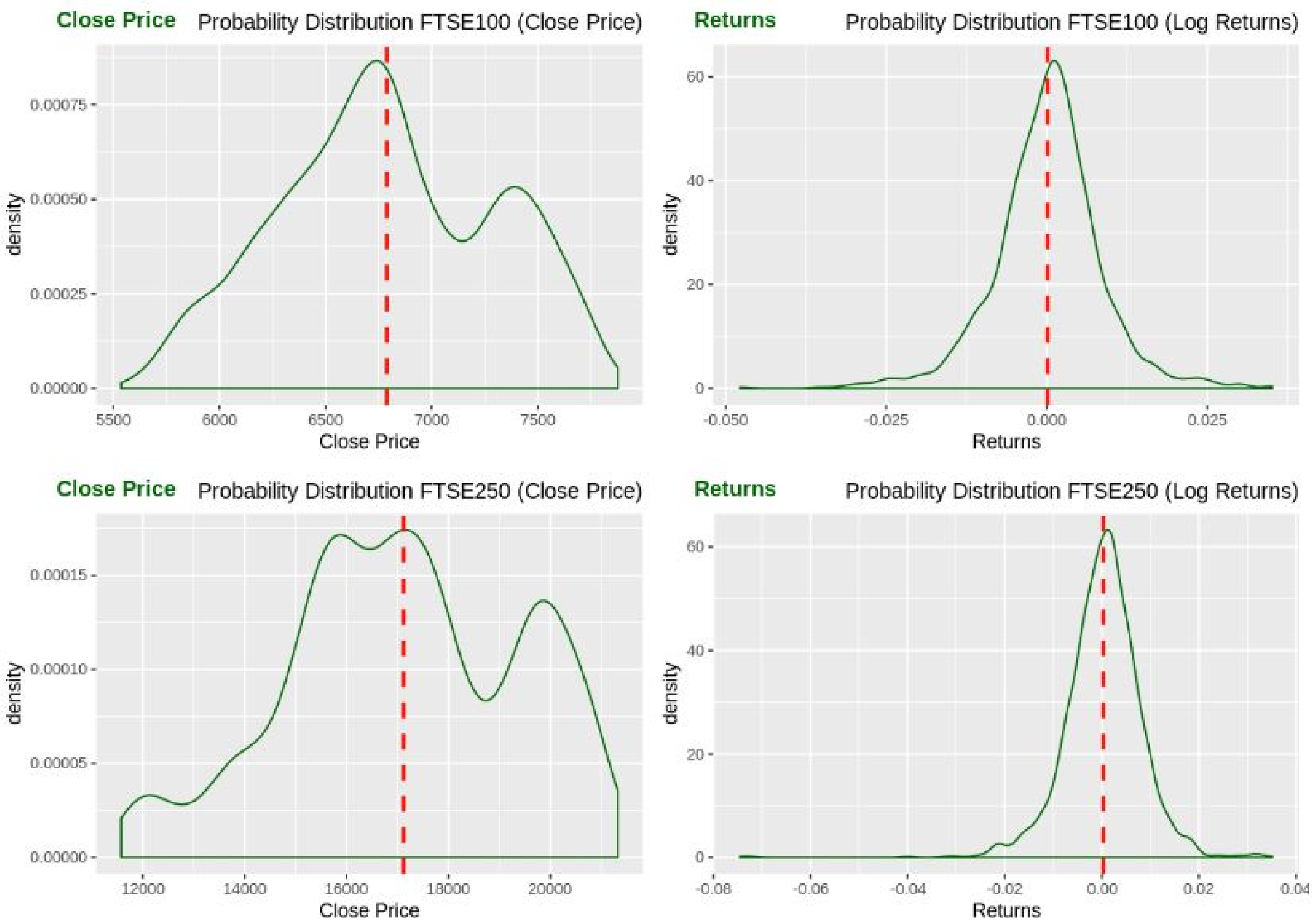


*Fig. 12: Probability distribution plots for the closing prices and log returns for each FTSE index. The red dashed line indicates the mean for that variable.*

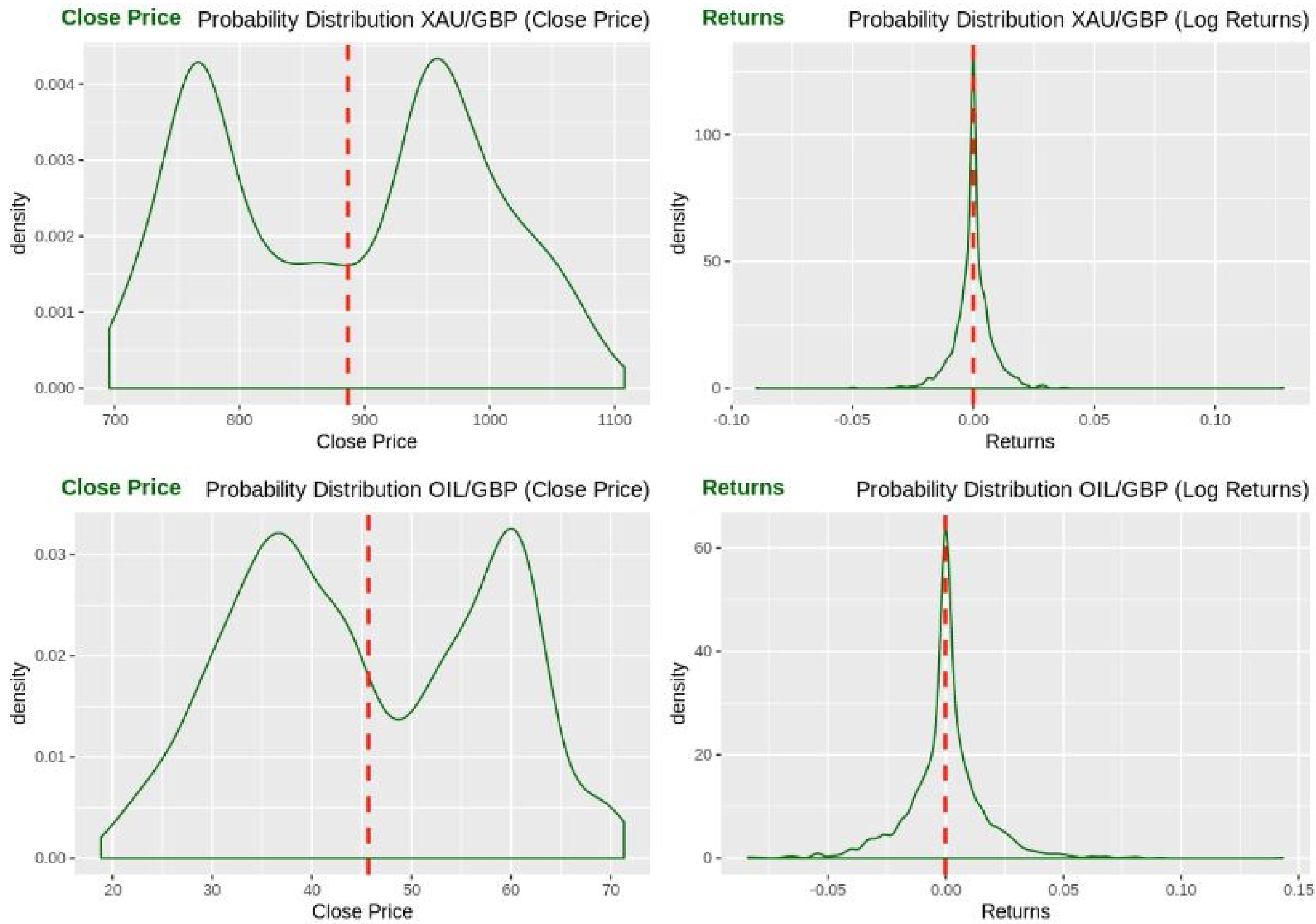


*Fig. 13: Probability distribution plots for the closing prices and log returns for each commodity pair. The red dashed line indicates the mean for that variable.*

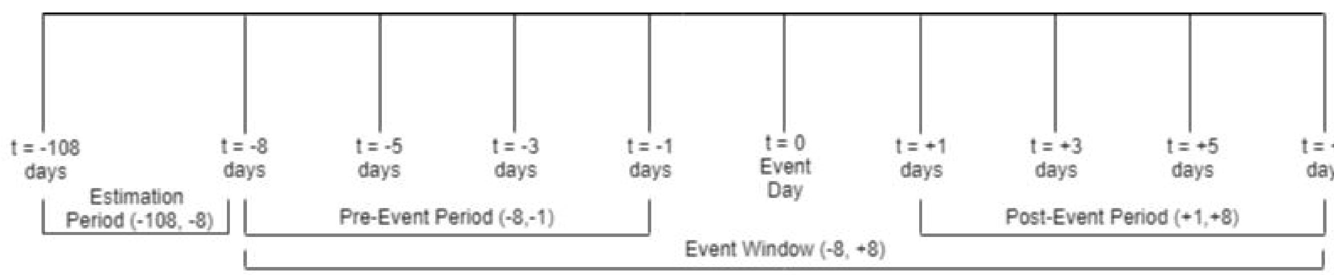


*Fig. 14: Event windowing example with 8 days window (-8 to +8 day, with a total of 16 days including the event date) and 100 days for the estimation period.*

## References


[1] "Associated Press: Timeline of brexit and events leading to may's departure." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.bnnbloomberg.ca/timeline-of-brexit-and-events-leading-to-may-s-departure-1.1270161

[2] "Al Jazzera: Al jazeera recaps the major developments on britain's path to brexit since it was first proposed by ex-pm david cameron." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.aljazeera.com/news/2019/01/brexit-timeline-190115164043103.html

[3] "GBP/EUR: Historical foreign exchange rates. retrieved from *Yahoo! Finance*." 2019, [Online; accessed June 2019]. [Online]. Available: https://finance.yahoo.com/quote/GBPEUR=X/

[4] "GBP/USD: Historical foreign exchange rates. retrieved from *Yahoo! Finance*." 2019, [Online; accessed June 2019]. [Online]. Available: https://finance.yahoo.com/quote/GBPUSD=X/

[5] "GBP/JPY: Historical foreign exchange rates. retrieved from *Yahoo! Finance*." 2019, [Online; accessed June 2019]. [Online]. Available: https://finance.yahoo.com/quote/GBPJPY=X/

[6] "BTC/GBP: Historical crypto currency prices. retrieved from *Yahoo! Finance*." 2019, [Online; accessed June 2019]. [Online]. Available: https://finance.yahoo.com/quote/BTC-GBP/

[7] "ETH/GBP: Historical crypto currency prices. retrieved from *Yahoo! Finance*." 2019, [Online; accessed June 2019]. [Online]. Available: https://finance.yahoo.com/quote/ETH-GBP/

[8] "CoinMarketCap: Top 100 cryptocurrencies by market capitalization," 2019, [Online; accessed June 2019]. [Online]. Available: https://coinmarketcap.com/

[9] S. Nakamoto *et al.*, "Bitcoin: A peer-to-peer electronic cash system," 2008.

[10] G. Wood *et al.*, "Ethereum: A secure decentralised generalised transaction ledger," *Ethereum project yellow paper*, vol. 151, pp. 1–32, 2014.

[11] "FTSE100: Historical index prices. retrieved from *ShareCast*." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.sharecast.com/index/FTSE_100/prices/download

[12] "FTSE250: Historical index prices. retrieved from *ShareCast*." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.sharecast.com/index/FTSE_250/prices/download

[13] "XAU/GBP: Historical commodity prices. retrieved from *Exchange Rates*." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.exchangerates.org.uk/commodities/XAU-GBP-history.html

[14] "OIL/GBP: Historical commodity prices. retrieved from *Exchange Rates*." 2019, [Online; accessed June 2019]. [Online]. Available: https://www.exchangerates.org.uk/commodities/OIL-GBP-history.html

[15] S. Sathyanarayana and S. Gargesha, "Impact of brexit referendum on indian stock market," *Social Sciences*, vol. 5, no. 01, p. 2016, 2016.

[16] M. Sajid Nazir, H. Younus, A. Kaleem, and Z. Anwar, "Impact of political events on stock market returns: empirical evidence from pakistan," *Journal of Economic and Administrative Sciences*, vol. 30, no. 1, pp. 60–78, 2014.

[17] M.-C. Beaulieu, J.-C. Cosset, and N. Essaddam, "Political uncertainty and stock market returns: evidence from the 1995 quebec referendum," *Canadian Journal of Economics/Revue canadienne d'économique*, vol. 39, no. 2, pp. 621–642, 2006.

[18] J. Dangol *et al.*, "Unanticipated political events and stock returns: An event study," *Economic Review*, vol. 20, pp. 86–110, 2008.

[19] A. Hovav and J. D'Arcy, "The impact of denial-of-service attack announcements on the market value of firms," *Risk Management and Insurance Review*, vol. 6, no. 2, pp. 97–121, 2003.

[20] H. Suhardjo, "The impact of domestic political events on an emerging stock market: the case of indonesia," Ph.D. dissertation, University of Malaya, 2001.

[21] H. Aktas and S. Oncu, "The stock market reaction to extreme events: the evidence from turkey," *International Research Journal of Finance and Economics*, vol. 6, no. 6, pp. 78–85, 2006.

[22] W. A. Rosenkrantz, "Why stock prices have a lognormal distribution," 2003.

[23] E. Boehmer, J. Masumeci, and A. B. Poulsen, "Event-study methodology under conditions of event-induced variance," *Journal of financial economics*, vol. 30, no. 2, pp. 253–272, 1991.

[24] C. J. Corrado, "A nonparametric test for abnormal security-price performance in event studies," *Journal of financial economics*, vol. 23, no. 2, pp. 385–395, 1989.

[25] K. Schipper and A. Smith, "Effects of recontracting on shareholder wealth: The case of voluntary spin-offs," *Journal of financial Economics*, vol. 12, no. 4, pp. 437–467, 1983.

[26] A. R. Cowan, "Nonparametric event study tests," *Review of Quantitative Finance and Accounting*, vol. 2, no. 4, pp. 343–358, 1992.