Determining Influence of Major Events in Brexit on Financial Markets

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***Abstract*—This paper demonstrates the impact that major news relating to Brexit has on the GBP/EUR market. Google Trends is used to identify major events by applying the Relative Strength Index indicator, with a standard T Test verifying the statistical significance of the abnormal returns generated by the events.**

I. Introduction

An event can be considered as having an impact on the financial market if that market's returns during the particular event window are abnormal to what is expected. In this study, it is shown that when a major event related to Brexit occurs, the GBP/EUR financial market is indeed impacted, and the price for that particular event window does either rise or fall significantly. With a p-value of 0.00, we also can conclude that these events did not occur by chance. When repeating the test on cryptocurrencies, it is shown that there is no impact on the prices when events relating to Brexit occur. This further supports the previous conclusion that the impact on the GBP/EUR market did not occur by chance.

Google Trends was used to define major events relating to Brexit, by using the Relative Strength Index (RSI) to determine spikes in the number of searches. When cross-referenced with news articles, it turned out to be quite effective in detecting these events.

A. Literature Review

Measuring the impact of news headlines on stock prices is something which has caught the interest of a few researchers. One such researcher is W. Chan, who in [7] examines the returns to a number of stocks after news about them emerges, and compares them to similar stocks where no news headlines emerge. The author discovers that stocks do react to news, however are sometimes a bit slow to react, especially to bad news. This period of time is referred to as drift.

Some authors in fact argue that it might be more beneficial to split news between positive and negative, and thus calculate positive and negative abnormal returns seperately [9]. However this is not always possible, and so researchers generally compare the absolute value of earnings surprise against the absolute value of abnormal returns [9].

The idea of letting the market decide on what constitutes as news has also been explored. In fact, the authors in [8] go a step further and generate labelled examples for sentiment analysis for news stories based on companies stock price movements.

When studying the impact of events, [10] stresses the importance of carrying out hypothesis testing to ensure that any abnormal returns discovered are not due to pure chance. The author also compares and contrasts a number of different parametric and non-parametric tests that can be used for hypothesis testing.

II. Data Collection

The data sources used for this experiment were the following:

1) GBP/EUR Financial Market Historical Data
2) Google Trends Search Volume Index (SVI)
3) Bitcoin and Ethereum Historical Data

Due to both the Brexit referendum being annonced and it taking place in 2016, historical data from the period 1st Jan 2016 - 23 May 2019 was collected. The Financial Market data was collected from *investing.com*, a website which provides historical data for financial markets. The Google Trends data was collected from *trends.google.com*, a service provided by Google based on their search engine usage. Finally the Bitcoin and Ethereum historical data were collected from *coinmarketcap.com*, a popular cryptocurrency news website that aggregates news and prices about a vast majority of cryptocurrencies. All datasets were conveniently provided in CSV file formats.

The timeframe of the collected data was set to daily. Daily data is both the most effective and convenient option - collecting data of a higher frequency (such as minute or hourly data) would be much more difficult to collect and usually only provided by paid services in the case of Financial Data. Data with a lower frequency on the other hand (such as weekly data), would not be appropriate for this particular study. This is due to the highly volatile nature of financial markets, making weekly data too long a timeframe to analyse any events or changes within the market. Daily data remains the perfect balance, as it is effective enough to derive analysis from, while at the same time remains relatively easy to collect.

With regards to cryptocurrencies, the two selected were Bitcoin and Ethereum, two of the largest cryptocurrencies according to market share. The price taken was that of the cryptocurrency against the USD. The reason for this is that taking the price against the GBP or EUR might lead to misleading results, because if these currencies are impacted by the events, it would consequentially affect the exchange rate between them and the cryptocurrency. Here, we are assuming that the USD will be unaffected by Brexit events and therefore can analyse the effects on these cryptocurrencies independently.

III. Data Cleansing

A. Financial Market Data

The financial market data required minimal adjustments. A number of different parameters are provided, including daily open, closing, highest and lowest prices, as well as the volume of trades for that day. For this study the daily closing prices were considered. Using daily closing prices is a standard practice when performing studies in the financial industry, and is generally a good reflection of that day's price. Using the high or low price might not be a true reflection of the day's price due to any anomalies that might occur and be corrected shortly after. Volume is also not a great indicator, as a high volume could be indicative of both buy or sell positions taken.

B. Google Trends Data

Working with Google Trends data provided a number of challenges which needed to be dealt with in order to generate a dataset that would be suitable for the purpose of this study.

The first issue is that when querying the searches on Google Trends over a long period of time, Google Trends will present the results in weekly data format. This is an issue since as previously mentioned, weekly data is too broad a timeframe to derive significant analyses in the context of financial market data. Therefore, a workaround had to be undertaken in order to extract the necessary informtion in a daily format. The process is listed below and explained underneath.

1) Collect the data in 90 day intervals for the whole time period.
2) Collect the weekly data for the same period.
3) Aggregate the daily data into weekly data by summing the values for each week.
4) Compare the aggregated weekly data to the actual weekly data to derive an adjustment value for each week.
5) Modify all daily values according to that week's adjustment value.

A more detailed explanation of the above points is explained below.

When querying Google Trends data for a period of 90 days or less, Google Trends will provide daily data instead of weekly data. Therefore, collecting the data in 90 day blocks allowed us to gather the whole dataset in daily format.

The issue is that Google Trends will scale each 90 day block between 0 - 100. This causes an issue as we cannot compare the different 90 day blocks together and therefore cannot utilize the dataset as a whole. Each 90 day block is scaled with a different degree, so a relative value of say 100 in one 90 day block would not in fact be the same absolute value as another relative value of 100 in another 90 day block.

Therefore, to solve this what we need is an adjustment value for each data point, to scale each datapoint relative to the full time period as opposed to it's 90 day window. To achieve this,

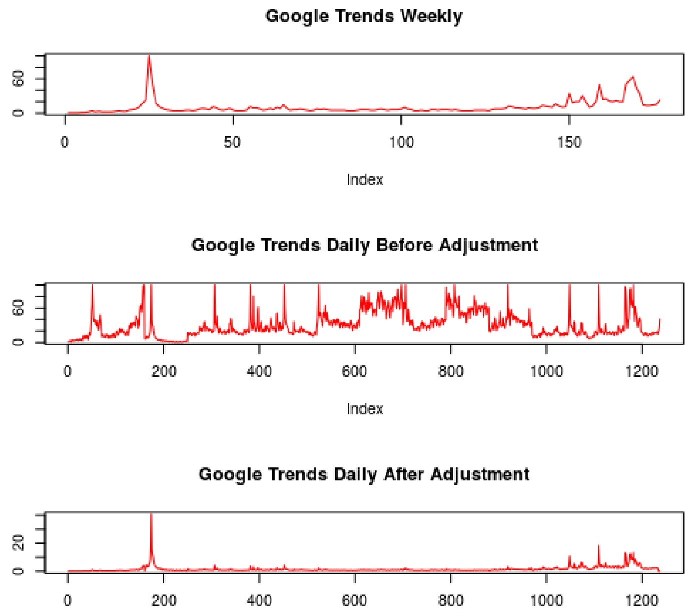

Fig. 1. Google Trends Adjustment

we first collect the weekly data for the whole time period, which is given at one go and all on the same scale by Google Trends. We then aggregate all the daily data into weekly data, taking the sum of all values for each day that week.

The next step is to compare each data point of the weekly aggregated data to the actual weekly data. This will allow us to determine an adjustment factor, meaning the value with which we need to modify the daily data to scale up or down to the appropriate value according to the whole dataset. We then apply each week's respective adjustment factor to the days during that week, and will end up with a daily dataset scaled appropriately.

C. Data Storage

Since the dataset is relatively small (circa 64KB combined), keeping the dataset within CSV files on the local machine sufficed. This also made it easier and quicker to analyse the data, as well as making it easily portable.

D. Data Analysis

*1) **Visualise Data**:* The first thing we need to do is plot the data. Overlaying the two time series graphs over each other and bringing them to within the same scale, as shown in Figure 2, we can begin visually looking for any patterns or correlations.

The trend within the financial time series however makes it more difficult to analyze the effect that the Google Trends data could be having on it. In order to visualise better the effects at each point in time, using the returns at each point rather than the actual price could come in very useful, both for visualisation as well as calculation purposes.

In fact, Figure 3 shows the relationship between the two time series much more prominently.

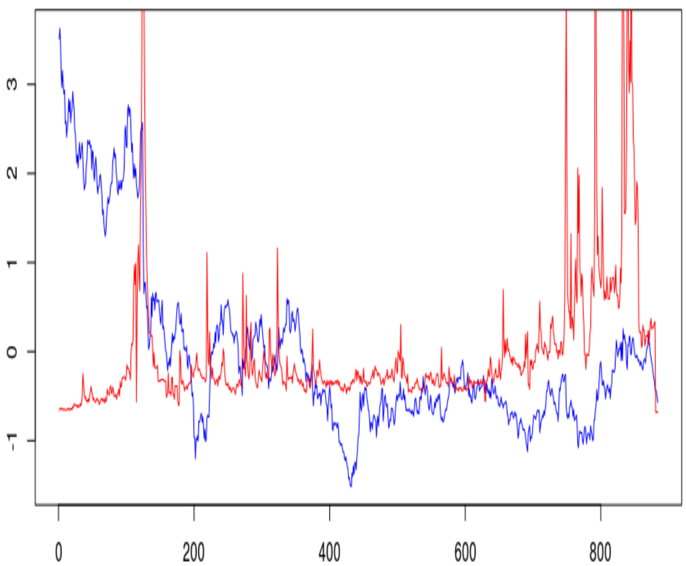

Fig. 2. Price vs Trends time series

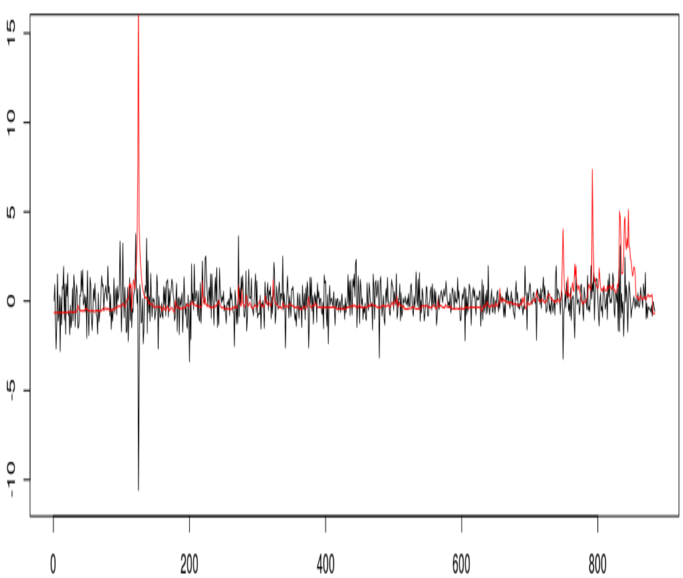

Fig. 3. Returns vs Trends time series

We finally convert these returns into **absolute returns**. The reason for doing so is twofold. Firstly, for the purpose of this study, we are not interested in whether the impact of the news is positive or negative, and in fact we do not even have the sentiment related to each event. The second reason is that combining all positive and negative abnormal returns when calculating the cumulative abnormal return could result in a value of zero as they cancel each other out. This will therefore hide the potential abnormal returns that are being generated.

*2) **Building a hypothesis**:* The next step is to build a hypothesis to define what exactly we need to test for. In theory, what we expect to occur is that when an abnormal event occurs within the Brexit time series, an abnormal return occurs in the GBP/EUR time series. Therefore:

Null hypothesis: There is no abnormal return within the event window.

Alternative hypothesis: There is an abnormal return within the event window.

We can define an event as a spike in the time series. In this scenario, this spike would represent a spike in the number of searches related to Brexit on Google Trends, which probably indicates that some sort of real world event had occurred during that period of time.

*3) **Determining Events**:* The next challenge faced would be that of actually defining a spike within the time series, and where to draw the threshold of what counts as a spike as opposed to a small increase.

In an attempt to achieve this, we can borrow a technical indicator commonly used in the financial world, known as the Relative Strength Indicator (RSI). RSI is generally used to measure the momentum of a stock's price, the strength with which it rose up or down relative to the previous few price observations [6]. This in turn will indicate whether the stock is either currently overbought or oversold. The RSI will be a value between 0 and 100. Values above 70 are considered as overbought, whilst values under 30 are considered as oversold.

To calculate the RSI value at each point, the past 14 values are analyzed. Whenever the value increases in relation to the previous value, it is marked as up, whilst when it decreases, it is marked as down. The average for all the values marked as up, as well as of those marked as down is calculated, and entered into the following formula:

$$RS = \frac{average(up)}{average(down)} \tag{1}$$

The value of this is then used to calculate the RSI:

$$RSI = 100 - \frac{100}{1 + RS} \tag{2}$$

Using the RSI will therefore allow us to define an event. If the RSI value of the Google Trends time series is above 70, this will indicate that it has suddenly risen very sharply, and thus indicates a 'spike'. Here, we are only taking into consideration upward spikes, as this would indicate that some major event related to Brexit has occurred. Figure 4 demonstrates the Google Trends RSI.

In order to **cross-validate** the outcome of the defined events, the dates of the events declared by the RSI process (*Appendix A*) are compared to a list of major events regarding Brexit extracted from online news sources. *Appendix B* includes a table that lists the major Brexit events, and marks down all those that have been identified by the Google Trends RSI.

The result of this seems to be quite satisfactory. On the one hand, all events declared by Google Trends RSI do in fact correlate to real-world events that happened on the same day, or at most 1 day before in a few cases. The only exception to this is the period before the election in June 2019, where a lot

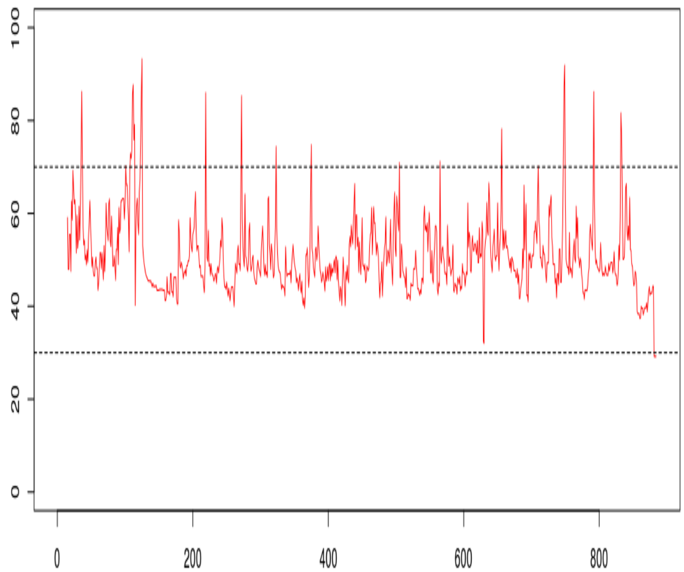

Fig. 4. Google Trends Relative Strength Index (RSI)

of searches occurred despite no specific event occurring. On the other hand however, there were a few real-world events that were not identified by the Google Trends RSI. This indicates that although the Google Trends RSI works quite well, it is not completely accurate in capturing all major events.

*4) **Calculating Abnormal Returns**:* Having defined our events, we now need to determine whether any abnormal returns occur within the specified event time windows. We first split the financial market time series into a *'sample window'* and an *'event window'*. Whenever an event occurs, that particular day as well as the following two days will form part of the event window. All other observations within the time series fall within the sample window.

The reason for having an event window of 3 days (as opposed to simply using the same day) is due to the notion of drift, meaning the slow reaction that investors sometimes have to news, especially bad news [7]. The time series cross-correlation discussed later and shown in Figure 7 also seems to indicate an element of lag present. We are also taking the assumption that 3 days is the maximum time for the market to react to news.

We then calculate the mean return for the sample window. This will serve as our **expected return** when calculating abnormal returns during the event window. We also calculate the standard deviation of the sample window to help us test for significance.

We then calculated all the abnormal returns during the event window as follows:

$$AR_t = R_t - E[R_t|\Omega_t] \tag{3}$$

Where *AR* is the Abnormal Return for day *t*, *R* is the return for day *t*, and *E[R]* is the expect return when an event Ω has not occurred.

We then sum the abnormal returns for each day to the find the Cumulative Abnormal Return (CAR) as follows:

$$CAR = \sum_{t=1}^{L_2}(AR_t) \tag{4}$$

where *L2* is the event window size.

*5) **Testing for Significance**:* The final step is to test whether these abnormal returns are statistically significant, or whether they occured by chance. To do this, we can use a t-test. A t-test is a hypothesis test where the test statistic follows a Student's t-distribution under the null hypothesis. The main advantage and reason for choosing this test is it's simplicity and popularity.

Given the number of samples within the event window in our scenario amount to 57, plotting our t distribution results in the graph shown in figure X.

Our bounds on whether to accept or reject the null hypothesis lie between -1.672522 and 1.672522.

The t-score is then calculated using the following formula:

$$t_{CAR} = \frac{CAR_i}{S_{CAR}} \tag{5}$$

where the standard deviation S_{CAR} can be found as follows:

$$S^2_{CAR} = L_2 S^2_{AR} \tag{6}$$

The **t value** for our test results to **8.3491**. We therefore reject the null hypothesis and accept the alternative hypothesis, meaning that major events in Brexit do influence the financial markets.

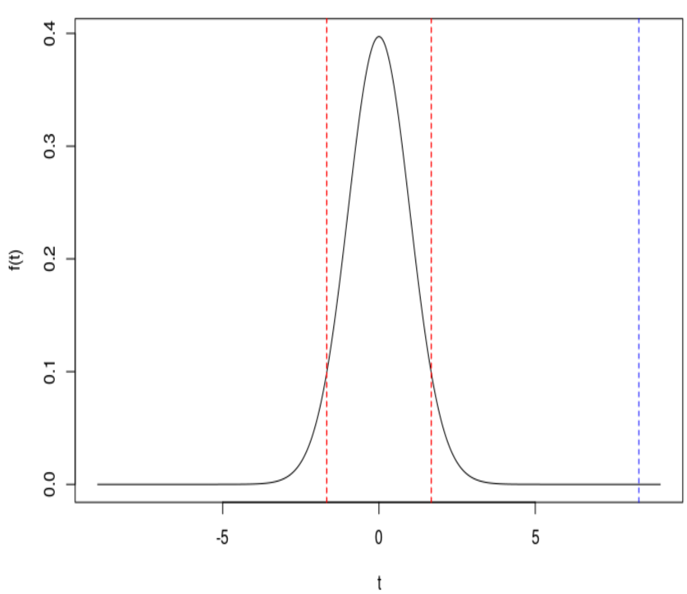

Fig. 5. T Statistic for abnormal returns for GBP/EUR during event windows

*6) **Repeating Tests on Cryptocurrencies:*** The exact same tests and procedures where then performed on cryptocurrencies. The results for crypotcurrencies were signficiantly different. The bounds for the acceptance/rejection of the null hypothesis remain at -1.672522 and 1.672522, since we are using a dataset of the exact same size. However now the **t-values** for Bitcoin and Ethereum resulted to **0.4209** and **0.6239** respectively. Since they fall within the aforementioned bounds (as shown in Figure 6), we accept the null hypothesis, and conclude that major events in Brexit do not generate any abnormal returns for cryptocurrencies.

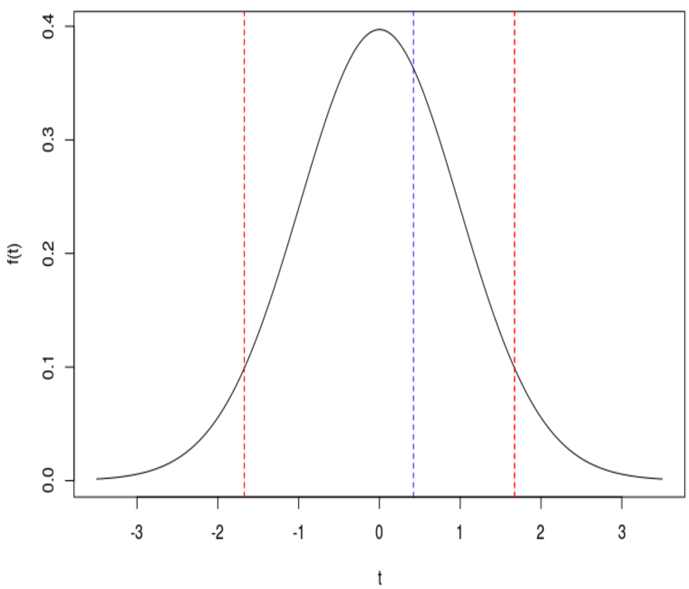

Fig. 6. T Statistic for abnormal returns for Bitcoin during event windows

IV. Other Attempted Procedures

A. Data Collection - News Api

During the initial data collection process, one method that was looked into when determining major events related to Brexit was through the use of News Api [3]. News API is an API service which aggregates news articles from a vast range of sources, and allows one to easily search and filter through these articles to retrieve those related to a particular subject or within a particular time frame. The user may then sort the results by a number of diffferent critera. One such criteria is that of popularity, meaning how many views that particular article got.

The main issue faced was that the free version of this API only provides information for 30 days in the past, which is not sufficient for the purpose of our study. Retrieving data further back in the past would require a paid subscription.

B. Time Series Correlation

Once the two time series had been super imposed, an attempt to find a correlation between the two different time series was made. A cross-correlation was calculated to also determine whether any lag was present between the time series.

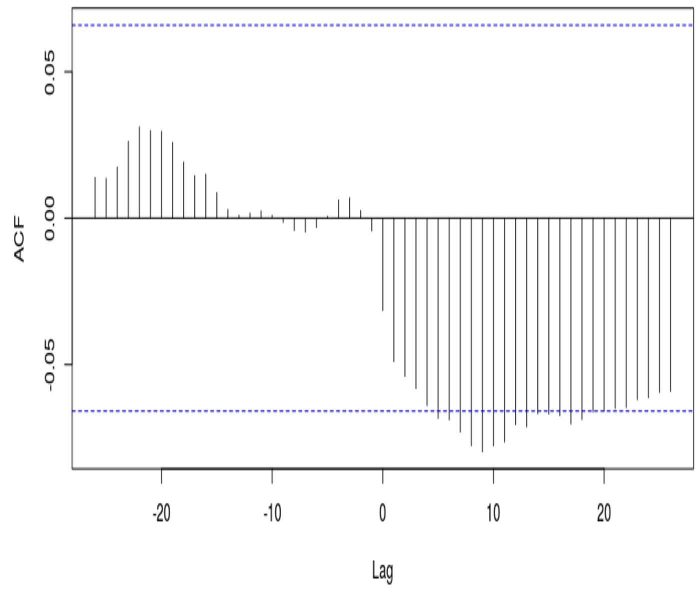

Fig. 7. Cross Correlation between time series

Figure 7 demonstrates that the correlation is in fact very low, with the highest being at just -0.0798. This does in fact make sense, since the financial market is influenced by a variety of different factors, and it would therefore be unreasonable to think that the two time series would consistently move together.

What we can draw from this however, is that there seems to be a small lag present within the time series. This could be useful when determining our event window, as an event occurring in one time series might seem to have a delayed effect on the other.

C. Determining Abnormal Returns Using CAPM

Currently, we are calculating the expected return of the financial market based on the overall mean return of the sample window. This is reasonable because of the sufficient size of our sample data, however the estimate could definately be more accurate if we took more data into consideration.

The Capital Asset Pricing Model (CAPM) is used to determine the estimated rate of return of a particular asset, and therefore is widely used in scenarios such as this to determine abnormal returns [5], [7]. The main issue is that CAPM is generally used for assets such as stocks or bonds, and can therefore consider indices such as the S&P500 as market expected returns or treasury bills as the risk free rate. Since currencies are a different asset class, CAPM is generally not recommended and not as well suited for this task. It is also more difficult to determine the mean market expected returns and risk free rate for this asset class.

V. Assumptions

- The financial market abnormal returns follow a normal distribution. Taking this assumptions allows us to utilize the CAR t-test.
- The market will not take more than 3 days to react to news.
- When taking the cryptocurrency exchange rates, it is assumed that the USD will not be affected by Brexit events. This allows us to analyse the effects on the cryptocurrencies independantly.
- We are assuming that internet searches for information regarding Brexit are being carried out on Google and not other search engines. However this is a reasonable assumption as according to the latest netmarketshare [1, May 2019] report, Google dominates the search engine market with 75% of searches on desktop and 81% of searches on mobile. Next in line are Baidu and Bing with 9.85% and 8.42% respectively, a substantial difference.

VI. Conclusion and Future Work

The results presented above clearly indicate that major news or events regarding Brexit do seem to have a significant effect on the financial markets. The main contributions of this work is that it not only identifies the statistical signifiance of the impact of Brexit events on the financial markets, but also proposes an interesting and effective way of automatically detecting major events through Google Trends.

The power of using Google Trends for such a study is that it allows people themselves to dictate what constitutes as a major event or not through their increased interest in the subject as the event occurs or has been announced. The RSI method also proved to be effective in detecting spikes in the number of searches, and consequently outlining major events when they occur. This prevents the author having to define a major event, which could lead to bias on the author's side. The major downside of this of course is that there is no indication of the people's sentiment in relation to the event, meaning it will not help us predict the direction in which the financial market will move.

Another similar study could be done, using social media instead of Google Trends. However, although social media would be beneficial as it also provides sentiment, the dynamics of social media might be more particular, and not as representative of events. This is because people's interactions with the post might be based on their own personal bias. For example, if users are happy about a particular piece of news, they would be more inclined to like and share, whereas those who dissapprove would not. Therefore it might be more challenging to derive the extent of the signifiance of a particular event. The outreach of particular news pieces would also be dependant upon the popularity of the source that is sharing the news, and significant work might need to be undertaken to aggregate all the different views generated from all the different sources posting about this news. In this case, using specific social media platforms catering specifically for finance, such as *Seeking Alpha* [2], would probably generate more accurate results.

The repeated experiment on Cryptocurrencies show that major events in Brexit do not in fact have any effect on them, and remained robust throughout. This further confirms that our previous results on the GBP/EUR prices were not due to chance.

Another critical analysis to point out is that ideally more than 1 hypothesis test should have been used, to further support the conclusion. Other parametric tests could be included which could correct any weaknesses of the t-test. The Patell test for example standardizes the abnormal returns in the event window, which which limits the impact of stocks with high standard deviations [11]. The Cross-Sectional test could help ignore any cross-sectional correlation and ensure that each event's direct impact is immediately felt within the same event window [12]. A Sign test, which is a type of non-parametric test, could also be advantageous as the author's claim that it is effective in determining small levels of abnormal returns within the event windows [13].

Another improvement could be that of using a more robust pricing model, such as CAPM, to calculate the expected returns. The current expected return is calculated using the sample window returns throughout the time period used within the study. This method does not factor in other details relating to the market as a whole, such as the market risk or the current risk free rate.

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APPENDIX A: EVENT DATES DECLARED BY GOOGLE TRENDS RSI

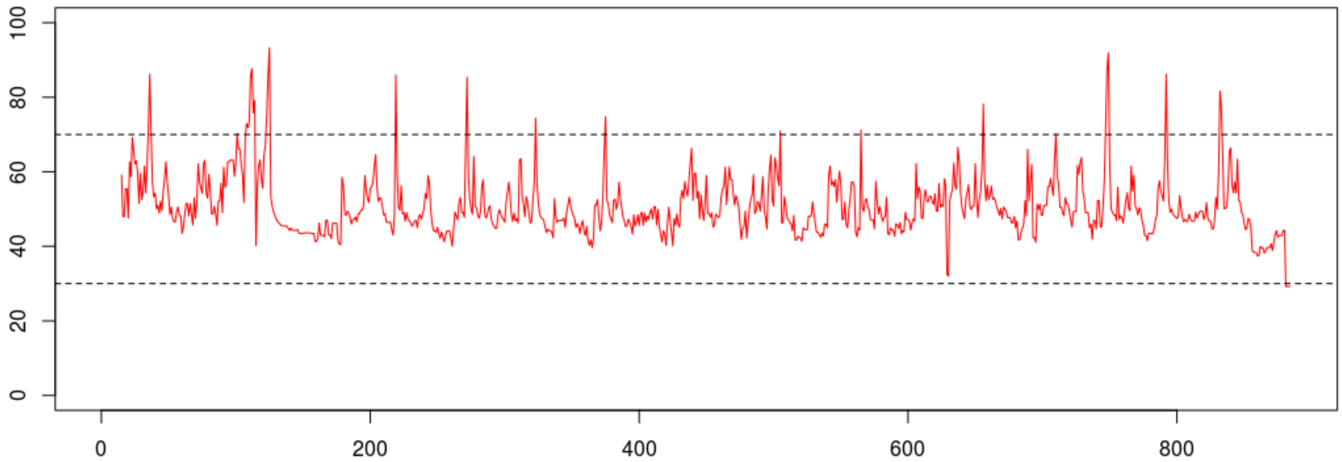

Fig. 8. Google Trends Relative Strength Index (RSI)

2016	2017	2018	2019
02/19/2016	01/17/2017	03/02/2018	01/15/2019
02/22/2016	03/29/2017	07/09/2018	03/12/2019
05/23/2016	06/09/2017	09/21/2018	03/13/2019
06/01/2016	12/08/2017	11/13/2018	
06/02/2016		11/14/2018	
06/03/2016		11/15/2018	
06/06/2016			
06/07/2016			
06/08/2016			
06/09/2016			
06/22/2016			
06/23/2016			
06/24/2016			
11/03/2016			

APPENDIX B: TIMELINE OF BREXIT EVENTS COMPILED FROM NEWS SOURCES

The following list of major events in Brexit was compiled from the following sources:

- https://www.politico.eu/pro/brexit-timeline-from-referendum-to-eu-exit-archive-2016/
- https://apnews.com/563aa3d5a3f5485893b1e50cd8089f74
- https://about-britain.com/institutions/brexit-process-timeline.htm

The events that were detected by the Google Trends RSI are marked in the table below.

Events Identified by Google Trends RSI	Timeline	Real World Event
	2016	
✓	20 Feb	Cameron confirms that he will campaign for Britain to remain in the 28-nation bloc. The referendum date is set for June.
✓	23 June	The UK holds a referendum on whether to leave the European Union. 51.9% of voters vote to leave.
✓	24 June	David Cameron announces his resignation as Prime Minister.
	13 July	Theresa May accepts the Queen's invitation to form a government. David Davis is appointed the newly created Secretary of State for Exiting the European Union to oversee withdrawal negotiations.
	27 July	The European Commission nominates French politician Michel Barnier as European Chief Negotiator for the United Kingdom Exiting the European Union.
	2 Oct	May says that Britain will begin the formal process of leaving the EU by the end of March 2017. In order to do this, the British government would have to invoke Article 50 of the EUs Lisbon Treaty.
✓	3 Nov	The High Court upholds a legal challenge brought by Gina Miller and others and rules the Westminster government must hold a vote in parliament before starting the Brexit process. Three days later, May says the government will appeal the ruling.
	7 December	The UK House of Commons votes 461 to 89 in favour of Theresa Mays plan to trigger Article 50 by the end of March 2017.[142]
	2017	
✓	17 Jan	May lays out her ambitions and 12 negotiating priorities for Brexit at a speech at Londons Lancaster House. She says the U.K. is likely to leave the single market and seek a completely new trading relationship with the EU.
	24 January	The UK Supreme Court rules in the Miller case that Parliament must pass legislation to authorise the triggering of Article 50.
	26 January	The UK Government introduces a 137-word bill in Parliament to empower Theresa May to initiate Brexit by triggering Article 50. Labour leader Jeremy Corbyn instructs his MPs to support it.
	16 March	The bill receives Royal Assent.
✓	29 March	A letter from Theresa May is handed to President of the European Council Donald Tusk to invoke Article 50, starting a two year process with the UK due to leave the EU on 29 March 2019.
	18 April	Theresa May announces that a general election is to take place on 8 June.
✓	8 June	A general election is held in the UK. The Conservative Party remains the largest single party in the House of Commons but loses its majority, resulting in the formation of a minority government with a confidence-and-supply arrangement with the Democratic Unionist Party (DUP) of Northern Ireland.
	19 June	Brexit negotiations commence.
✓	8 Dec	The European Commission recommends that Brexit talks move on to Phase 2, or talks on the future EU-U.K. relationship
	2018	
✓	2 Mar	Theresa May delivers a Brexit speech at the 18th century Mansion House in the City of London, in which she challenges Brussels and her own partys hard-line Brexiteers to face up to the unpleasant realities of Britains imminent divorce from Europe and seek a compromise.
	6 July	A UK White paper on The future relationship between the United Kingdom and the European Union is finalised.
✓	8 July	Davis resigns as Secretary of State for Exiting the European Union. Dominic Raab is appointed as his successor the following day.
✓	21 September	EU reject the UK white paper.
✓	14 November	Brexit withdrawal agreement published.
✓	15 November	Raab resigns as Secretary of State for Exiting the European Union. Stephen Barclay is appointed as his successor the following day.
	25 November	Other 27 EU Member States endorse the Withdrawal Agreement.
	12 December	Conservative lawmakers who back a clean break from the EU trigger a no-confidence vote in May over her handling of Brexit. She wins by 200 votes to 117, making her safe from another such challenge for a year.
	2019	
✓	15 January	First meaningful vote held on the Withdrawal Agreement in the UK House of Commons. The UK Government is defeated by 432 votes to 202.
✓	12 March	Second meaningful vote on the Withdrawal Agreement with the UK Government defeated again by 391 votes to 242.
✓	14 March	UK Government motion passes 412 to 202 to extend the Article 50 period.
	20 March	Theresa May requests the EU extend the Article 50 period until 30 June 2019.
	21 March	The European Council offers to extend the Article 50 period until 22 May 2019 if the Withdrawal Agreement is passed by 29 March 2019 but, if it does not, then the UK has until 12 April 2019 to indicate a way forward. The extension is formally agreed the following day.
	29 March	The original end of the Article 50 period and the original planned date for Brexit. Third vote on the Withdrawal Agreement after being separated from the Political Declaration. UK Government defeated again by 344 votes to 286.
	5 April	Theresa May requests for a second time that the EU extend the Article 50 period until 30 June 2019.
	10 April	The European Council grants another extension to the Article 50 period to 31 October 2019, or the first day of the month after that in which the Withdrawal Agreement is passed, whichever comes first. However, the UK must hold European Parliament elections in May 2019; otherwise it will leave on 1 June 2019.
	24 May	Theresa May announces that she will resign as Conservative Party leader, effective 7 June, due to being unable to pass her Brexit plans through parliament and several votes of no-confidence, while continuing as prime minister while a Conservative leadership contest takes place.