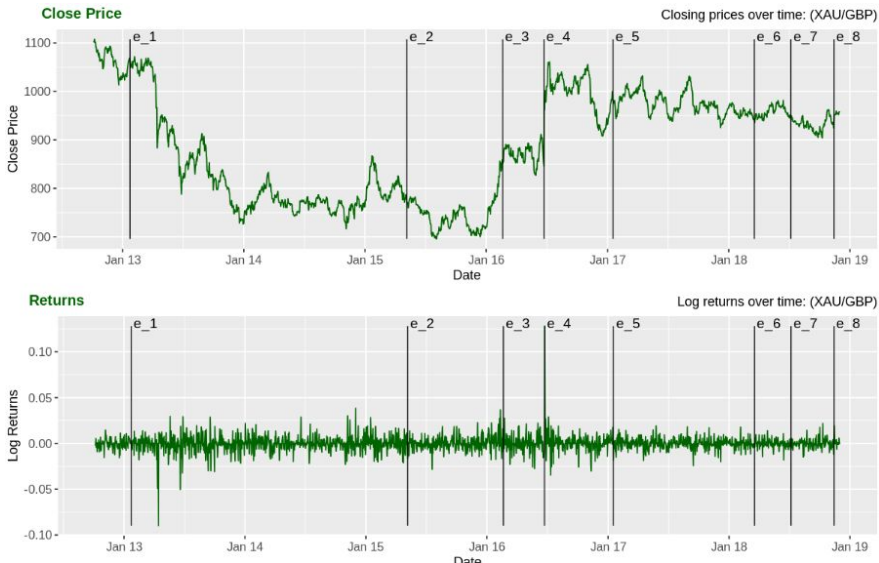




# Brexit Influence on Financial Markets

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26 June 2019

# Data Collection

Exchange Rates.org.uk  
The UK's Favourite Currency Site.



ShareCast

YAHOO!  
FINANCE

Dataset	Source	Type	Range	Freq.	Total
● Brexit Major Events	Associated Press	Date / Textual	7/05/2015 to 7/06/2019	Varies	23
● Brexit Major Events	Al Jazeera	Date / Textual	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

Web Scraping

Web API

Downloaded manually

R Libraries used:

- vrest (web scraping)
- quantmod (web api)

Brexit Events

- Two Articles
- Timeline of events

Financial Markets

- Foreign Exchange
- Cryptocurrencies
- Stock Market
- Commodities

# Data Cleansing



## Cleaning Events Dataset

- Remove duplicates (kept AP), events with the same date & empty rows
- Split date and event description for each event
- Format dates in to one standard 'yyyy-mm-dd'
- Augment into one dataset

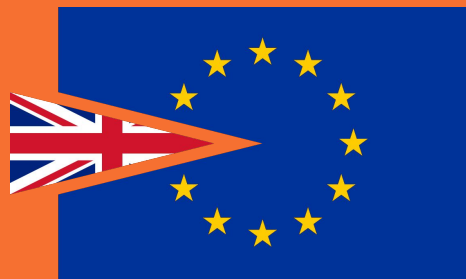
## Cleaning Financial Datasets

- All sets included daily OHLC prices except of commodities (only close)
- Remove other variables except for the close price
- Format dates in to one standard 'yyyy-mm-dd'
- Compute log returns using the close price
- The FX dataset was augmented into one dataset (dates aligned)

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

*Log Returns Formula*

# Data Analysis - Events



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 Jazeera. This table shows the events which have at least 100 days difference between the event date.*

# Data Analysis - Financial (1)

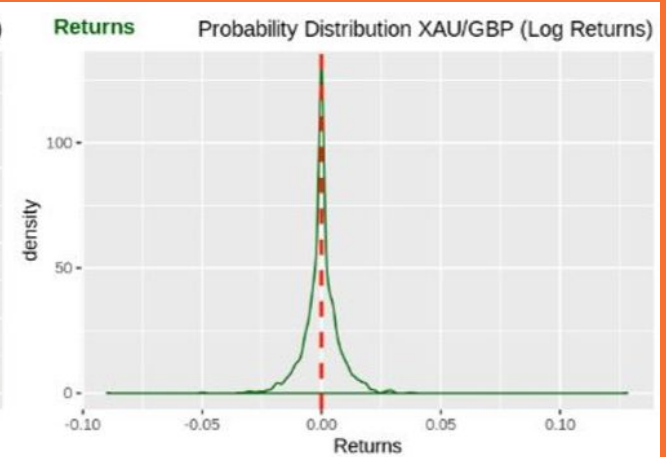
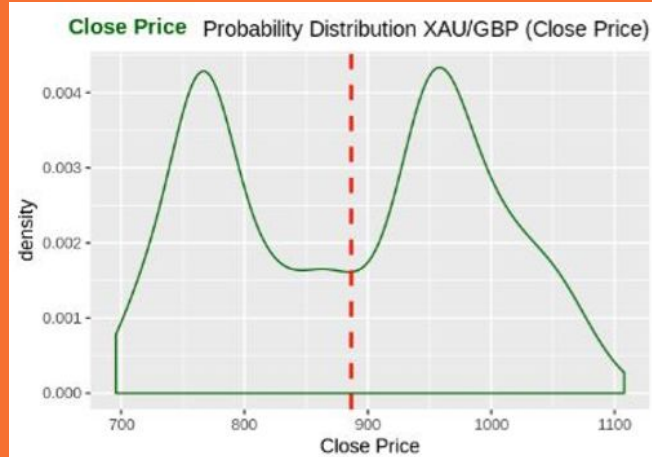
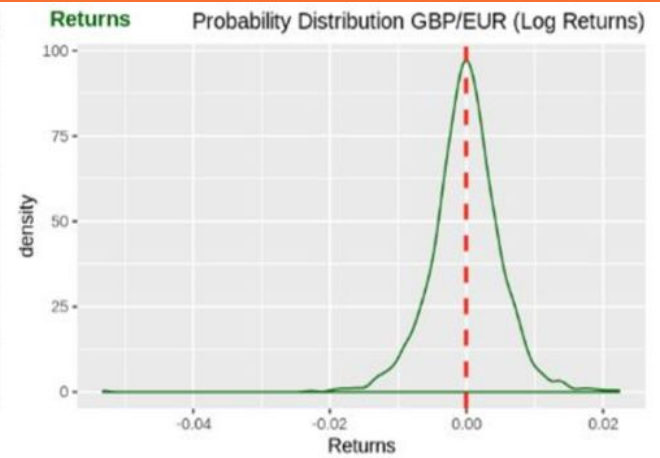


- Financial asset prices are considered to be log-normally distributed
- Financial datasets were filtered to be aligned with the events
- Most log returns are skewed towards negative returns
- FTSE100 has the closest kurtosis value of a normal distribution (which is around 3).

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.

# Data Analysis - Financial (2)





# Data Analysis - Financial (3)

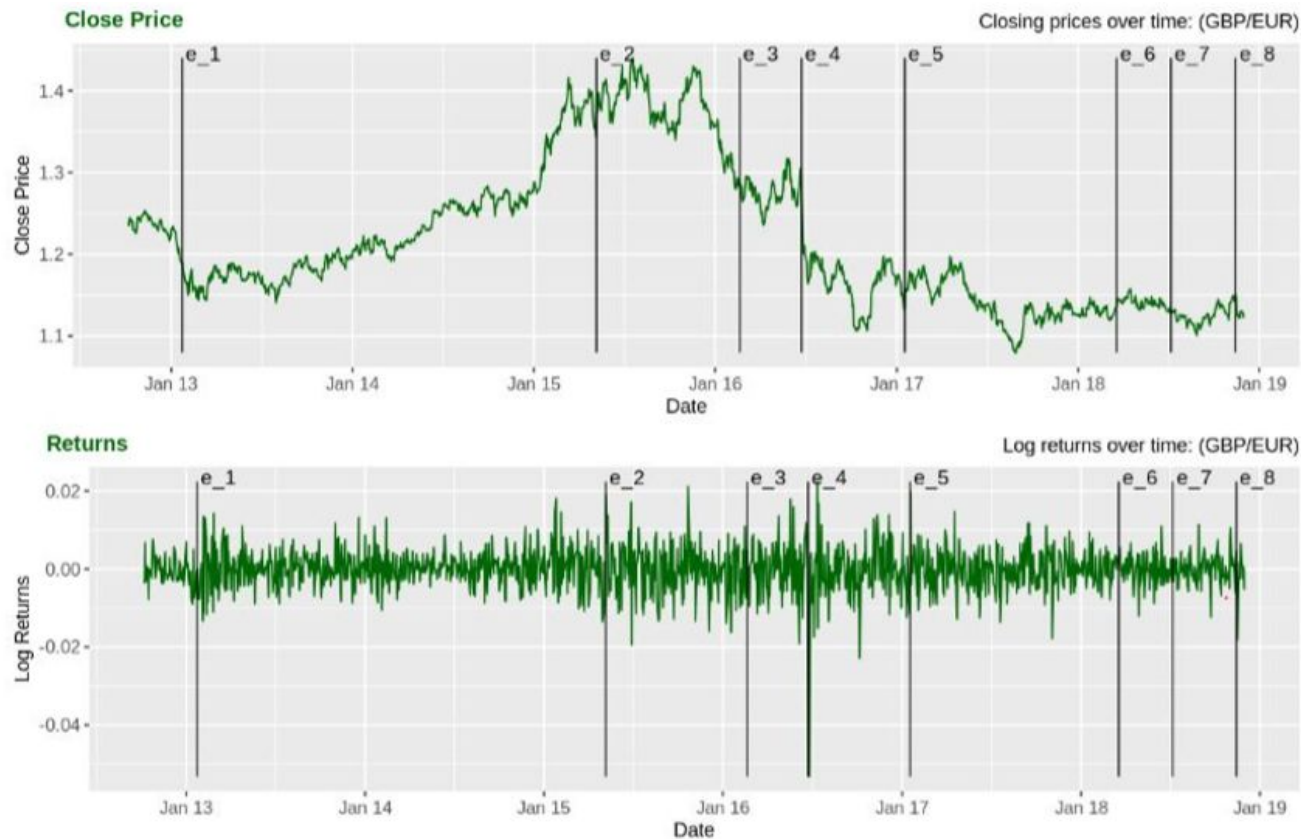


Fig. 1: Two plots showing the close price and log returns over time for the GBP/EUR pair. The black segments represent an event from the Table II denoted as  $e_n$ ,  $n$  being the event no. in the events table.

# Data Analysis - Proposed Model

- Each event will be tested individually
- Make sure there are no intersecting events in the estimation period
- Split event into 3 windows: estimation, pre-event and post-event
- Compute the expected returns from the estimation period  $R^* = \frac{1}{T} \sum_{t=1}^t R_t$
- Compute abnormal returns for each point pre and post event  $AR = R_t - R^*$

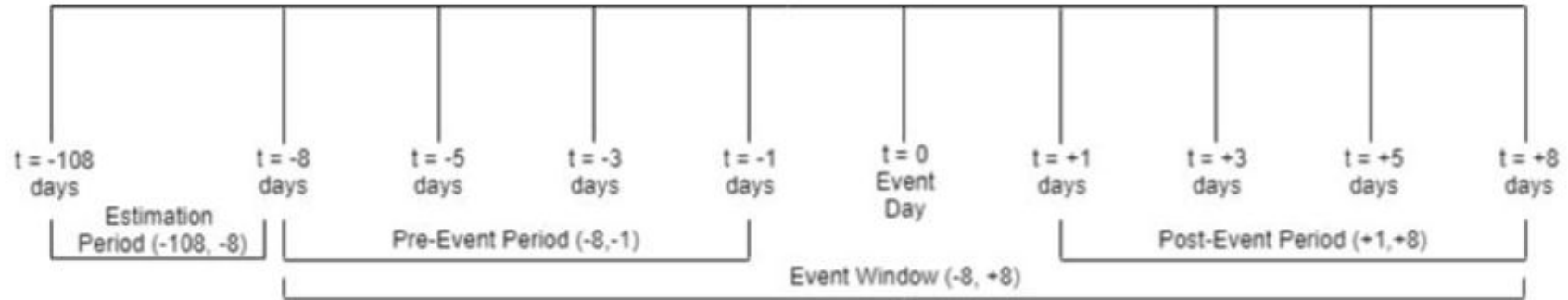


Fig. 14: Event windowing example with 8 days window (-8 to +8 day, with a total of 16 days including the event date) and 100 days for the estimation period.



# Data Analysis - Hypothesis

- **Null Hypothesis:** There is no significant difference between the abnormal mean returns before a major brexit event and after it (pre-mean = post-mean)
- **Alternative Hypothesis:** There is a significant difference between the abnormal mean returns before a major brexit event and after it (pre-mean  $\neq$  post-mean)
- Hypothesis tested using **T-Test** and some of the assumptions included:
  - Variance between the pre and post event window are equal/similar
  - The market is efficient enough to absorb information in an 8 day period
  - The scale of measurement is a continuous numerical variable (log returns)

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

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

# Results

\*\*\*, \*\*, \*Significance at 1, 5 and 10 percent, respectively

Event	BTC/GBP		ETH/GBP	
	<i>p</i> -values	<i>t</i> -values	<i>p</i> -values	<i>t</i> -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

Event	GBP/EUR		GBP/USD		GBP/JPY	
	<i>p</i> -values	<i>t</i> -values	<i>p</i> -values	<i>t</i> -values	<i>p</i> -values	<i>t</i> -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

Event	FTSE100		FTSE250	
	<i>p</i> -values	<i>t</i> -values	<i>p</i> -values	<i>t</i> -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

Event	XAU/GBP		OIL/GBP	
	<i>p</i> -values	<i>t</i> -values	<i>p</i> -values	<i>t</i> -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

# Critical Analysis & Future Work



## Critical analysis for our methodology

- It is common to complement the hypothesis test with a nonparametric test to verify the results obtained are not caused by an outlier
- The events tested are extracted from online articles, there were no statistical backing to check if they are in fact major
- Each financial asset was tested on their own, no tests on a set of assets were conducted (portfolio)
- Our model does not take into consideration the event date itself but we investigated the aftermath (post-event window)

## Future work

- Test the significance on the abnormal returns on the event date itself
- Apply nonparametric approach to further verify results (Cowan Generalised Sign Test)
- Apply different values for the estimation window and event window, which is quite common to do in events studies

All the code used in this case study was written using R

- Final results were shown on a Jupyter Notebook which can be viewed using the following link

[https://nbviewer.jupyter.org/github/achmand/datascience-brexite/blob/master/src/impact\\_of\\_major\\_brexit\\_events\\_on\\_various\\_financial\\_markets.ipynb](https://nbviewer.jupyter.org/github/achmand/datascience-brexite/blob/master/src/impact_of_major_brexit_events_on_various_financial_markets.ipynb)

- All the code used and setup required to run the code is well explained in this project's public GitHub repository

<https://github.com/achmand/datascience-brexite>