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The political power of twitter

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Brexit Insights

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ABSTRACT

In June 2016, the British voted by 52 per cent to leave the EU, a club the UK joined in 1973. This paper examines Twitter public and political party discourse surrounding the BREXIT withdrawal agreement. In particular, we focus on tweets from four different BREXIT exit strategies known as "Norway", "Article 50", the "Backstop" and "No Deal" and their effect on the pound and FTSE 100 index from the period of December 10th 2018 to February 24th 2019. Our approach focuses on using a Naive Bayes classification algorithm to assess political party and public Twitter sentiment. A Granger causality analysis is then introduced to investigate the hypothesis that BREXIT public sentiment, as measured by the twitter sentiment time series, is indicative of changes in the GBP/EUR Fx and FTSE 100 Index. Our results from the Twitter public sentiment indicate that the accuracy of the "Article 50" scenario had the single biggest effect on short run dynamics on the FTSE 100 index, additionally the "Norway" BREXIT strategy has a marginal effect on the FTSE 100 index whilst there was no significant causation to the GBP/EUR Fx. The BREXIT Political party sentiment for the "No Deal" was indicative of short-term dynamics on the GBP/EUR Fx at a marginal rate. Our test concluded that there was no causality on the FTSE 100.

CCS CONCEPTS

• Collaborative and Social Computing Theory • Concepts and Paradigms • Web Mining

KEYWORDS

Behavioral Finance, World Wide Web, Data Mining,

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1 Introduction

Twitter has grown rapidly in recent years and has become an indispensable political communication tool for political parties and is used as an important source of information about political issues as well as influencing public mood. More than that, Twitter has attracted an audience which political leaders could find valuable. Most politicians use social media as the easiest and quickest tool to influence policies and the public. Since the 2008 U.S. Presidential elections the impact of social media on politics marked an historic episode in the political realm, when social networking sites allowed users to share their support for a specific candidate or interact with others on political issues. However, social media (Twitter and Facebook) have positively influenced political participation and more recently research has shown that the use of social media has a strong influence in the political arena. Since the historic referendum on June 23rd, 2016, when Britain voted to leave the European Union, BREXIT has become the single biggest geopolitical event discussed politically and publicly. The outcome remains uncertain in terms of how the European withdrawal decision will affect the UK from a political, economic and social perspective. This uncertainty could have a profound impact on financial markets, investments and the value of the pound that will ultimately affect the wider UK economy. BREXIT tweets might unveil significant political division, this coupled with Twitter sentiment and capital market data has the potential to provide major insights into the implications for the UK economy and its engagement with the EU and other economies.

However, sentiment analysis of Twitter messages has been used to study behavioral finance, specifically, the effect of sentiments driven from social media on financial and economic decisions. Twitter sentiment analysis in particular, is a challenging task because its text contains many misspelled words, abbreviations, grammatical errors and made up words. Therefore, it contains limited contextual information [27].

Sentiment analysis studies have focused on using Twitter chatter sentiment for predicting behaviour. [6] argued that although each tweet represents an individual opinion, an aggregate sample should provide an accurate representation of public mood. A growing group of researchers have looked at the presence of political discussions within Twitter by politicians, campaigners and the public in a variety of countries and over a plethora of political issues but the relative newness of the discipline and use of mixed methodology has meant that patterns of behaviour are yet to be established [20]. [12] show that the volume of Twitter messages discussing politics rises in reaction to a political event. In addition to this [26] find that the level of Twitter activity serves as a predictor of changes in topics in the media event and the number of tweets varied depending on the stage of the event with the bulk of messages posted in the hours directly after an event. Other studies have focused on evaluating whether Twitter is used for political propaganda or to stir up political debates.[2] investigated Twitter chatter in regards to the German Federal Elections in 2009 and found that Twitter is used as a platform for political discussions based on a large number (over a third) of their sample tweets consisting of replies. Thus, the purpose of this paper is to empirically evaluate the effects of the BREXIT political party sentiment and British public sentiment tweets on the FTSE 100 Index and the GBP/USD Fx rate specifically.

2 Related Work

The influence of political uncertainty on economic outcomes has a long history of public debate and research. Nowadays, with populism gaining followers, President Trump unexpectedly getting elected as the president of the United States, the more recent Arab Spring, national elections in four European countries in 2017 and BREXIT, the influence of political uncertainty on the economy is widely discussed again [31]. The topic of political uncertainty has drawn increased attention from policy makers, academics and the media [3]. As this uncertainty could have a profound impact on financial markets, investments, and the value of the currency that will ultimately affect the wider economy. However, research on political risk shows that political news affects financial markets. Stock markets especially respond more to new information regarding political decisions that may affect domestic and foreign policy. The reaction of the stock exchange depends on the political news, prices should increase if the news leads to upward revision of investor's expectation and similarly it can lead to downward if the investors respond to news in the opposite way [28]. [21] developed a general equilibrium model in which stock prices react to political news. They argue that volatility and correlation between stocks is higher when political uncertainty is higher. The reasoning behind this is that high political uncertainty means high uncertainty in political costs that makes asset prices more volatile. Furthermore, [15] study the impact of political uncertainty on stock returns and volatility on the Hong Kong market using a components jump-volatility filter with surprise or jump return movements, which are connected to the announcements of political events. [13] find that stock market volatility is influenced by political news. The influence of negative political news is larger than for positive news [13]. [14] focus on rising political uncertainty around general elections and document that high political uncertainty causes lower investment and consumption around these events. These findings suggest that political uncertainty is an important channel through which the political process affects real economic outcomes. [5] with their analysis of the impact of the uncertainty caused by BREXIT on both the UK and international financial markets show that BREXIT-induced policy uncertainty will continue to cause instability in key financial markets and has the potential to damage the real economy in both the UK and other European countries, even in the medium run. On the other hand, [18] study the initial impact of BREXIT on the main stock markets in the Greater China Region (GCR) using augmented market models that integrate Economic Policy Uncertainty (EPU) and implied volatility (VIX). The main findings of their research suggest that BREXIT does not appear to have an impact on the performance of market returns in the region and the influence of economic policy uncertainty in the GCR appears to be insignificant, except for Hong Kong. Overall, China's stock markets do not seem to be overreacting to unfolding events in the UK and market instability in the region appears to be more associated with global and regional events. [16] focuses on the reactions of selected Central and Eastern European (CEE) and South and Eastern European (SEE) stock markets to the BREXIT vote on 23 June 2016. The results of the study indicate mixed results regarding the abnormal cumulative return series, but the volatility series were found to be significantly affected by the BREXIT. This is important for international investors and gives information on the reaction of these markets to big political and economic events in order to tailor international portfolios in a way to hedge from risk.

2.1 Stock Market Clairvoyance

The ability to reliably predict stock market values can be likened to the search for the Holy Grail or the Philosopher's Stone. Both are items or renown that offer untold riches and immortality, however, they are destined to remain mythologically unattainable. Academics and business leaders have continually been developing and employing theoretical models and quantitative statistical analysis algorithms in a bid to produce verifiably predictive results on stock market fluctuations. Efficient Market Hypothesis (EMH) and random walk theory are two of the methods utilised by early researchers [11]. EMH holds that new information is the key driver of stock market prices more so than historical or current prices. Such information can be termed as News and due to its unpredictability will therefore follow a random walk pattern. There are however, some studies which have shown a degree of predictability in stock market prices and furthermore, reveal that stock market prices do not follow a random walk [6],[8].

Time series analysis and use of historical prices have been well documented as a method of stock market predictability [29],[9]. This method of technical analysis forms the first philosophical branch of stock market prediction. The use of traditional media news articles would fall into the second branch as fundamental analysis of stock market prediction. This analysis requires input of quantitative and qualitative information relating to financial conditions, macro-economic indicators and economic wellbeing for securities, companies or currencies. Numerous studies have sought to harness the information contained in micro-blogging platforms as an additional input to the traditional methods for forecasting stock market fluctuations [19],[22],[10],[20],[24].

[22] used sentiment analysis and applied a Granger causality test to determine that the "excitedness" on Twitter will result in an increase in trading volume on the NASDAQ approximately 62 hours later. The study by [20] is seemingly close to this paper in its attempts and scope. Whereas their study sought to investigate the relationship between public mood in relation to elections and market performance based on Twitter data covering a six-day period, this paper seeks to hone in on the specificities around correlative events over a much longer time period (i.e. the period from December 10th 2018 to February 24th 2019 furthermore lag periods are measured in seconds in our study.

2.2 Twitter as a medium of communication

The advent of social media platforms as a rapid information delivery system may be partly responsible for its phenomenal growth. For investors and traders operating in securities and currencies, quick access to reliable information will undoubtedly provide a competitive advantage. Twitter is a micro-blogging and social networking service with approximately 321 million monthly active users. The arguably main difference between Twitter and other social media platforms is that the data is open to public view whilst other platforms have a private communication function [31]. The method of communication on Twitter via "Tweets" was limited to 140 characters but since November 2017, this has been increased to 280 characters. The cap placed on the number of characters forces users to be more concise in their message content. Twitter makes use of keywords within the tweet that can expand the topic of discussion. These keywords are preceded by the "# "character which allows other users to locate a thread of conversation and also increases the tweets visibility [25]. The hashtag feature presents opportunities for researchers to gather, analyse and process the relevant data pertaining to exchanges of opinions, knowledge and information. A typical method employed is that of sentiment analysis which seeks to ascertain the valence of the content creator.

2.3 Sentiment Analysis

A basic assertion within behavioural economics is that investors are susceptible to emotion and sentiment [13]. There is a growing body of research utilising sentiment analysis derived from social media platforms as a predictive measure on a wide range of topics such as elections [30], [25] and online sales [4]. Difficulties arise when attempting to gauge the influential effect of sentiment via a platform that is restrictive in its character allowance. A tool commonly employed during sentiment analysis studies is OpinionFinder. It allows the user to select terms that help identify subjective sentences and sentiment expressions [6],[17],[25].

2.4 Twitters role in macro- events

Twitter, like most social media platforms, has low economic and technological barriers. It is a method of near instantaneous communication that provides a "back channel" for users to debate and share information outside of the mainstream media [12]. During the 2016 US Presidential elections, Twitter played a central role in the dissemination of information. Not only across its network of users but also to other traditional media outlets and social media platforms, with reports of up to 27,000 election related tweets every minute. Indeed, [12] contend that social media is an influencer on both local and national politics but note the requirements for political parties to deploy resources such as employed staff to fully realise any impact of political influence via social media. So the question arises, what or who is a typical influencer on Twitter? And what or whom are they influencing? There is continuing research into questions such as those just posed that employ various methods of classification or PageRank algorithms [24] furthered this by developing a trust management framework that specifically takes into account the originator or author of the tweet and their standing within the community. A series of tests performed on the data, which covered an eight-month period resulted in a framework that shows promising results regarding abnormal stock returns. However, in the case of this paper, we examine the bifurcation of Twitter based BREXIT tweets from political and public sources and their potential impact on the FTSE 100 Index and sterling market.

3 Data Collection

3.1 Political Background

We have considered the period from December 10th 2018 to February 24th 2019 surrounding the EU Withdrawal Agreement as context for extracting the political sentiment from Twitter which required the full support of Parliament in the House of Commons. This is an important period in the BREXIT negotiations as the Withdrawal agreement required the full support of the House of Parliament to agree on an exit strategy. Numerous strategies were debated such as the "Norway", "Article 50", "Backstop" and "No Deal" exit strategies. Numerous attempts to secure agreement failed. What ensued was complete disharmony across the political spectrum resulting in political divides and market volatility.

3.2 Python -Tweepy Library Public and Private streams

The data is received based upon the data requirements received from the user. We utilise the "Tweepy" python library. For this study we are concerned with BREXIT public streams (which consist of tweets from the public and tweets from the political establishment combined) and the BREXIT Political party streams (which consist of tweets only by the parties in the House of Parliament). The political parties include Labour, the Conservatives, Democratic Unionist Party, the Scottish National Party, Liberal Democrats, the Green Party and Plaid Cymru. We captured the incoming tweets from the BREXIT #Hashtags contained in Table 1

Table 1: #Hashtags and Sample Tweets

#Hashtags	Sample
#BREXIT	RT @IsolatedBrit: To avoid a fascist revolution. That's why we're leaving the EU? #BREXIT
#BREXITCHAOS	No-deal BREXIT could put public at risk, warns Met chief #BREXIT #BREXITChaos #BREXITCrisis
#BREXITSHAMBLES	New Labour Leader desperately needed. Preference would be Yvette Cooper, David Lammy or Chuka #BREXITShambles

We have extracted approximately 3.6 million tweets from the BREXIT public Twitter streams. For each tweet these records provide a tweet identifier, the date-time-seconds of the submission (GMT), location, verified indictor, the text content and a sentiment score derived from the Native Bayes machine learning algorithm which ranges from -1 = negative. 0 = Neutral and 1= positive for each collected tweet. Using an additional python library, we have also extracted the associated capital markets data from Yahoo! Finance for the same period. This includes GBP/EUR Fx rates and the FTSE 100 index. The time series frequency is measured in terms of seconds. To extract our data, we have considered the three key BREXIT hashtags mentioned in Table 1. They are as follows: #BREXIT, #BREXITCHAOS and #BREXITSHAMBLES. Both the public and the politicians were tweeting to these #Hashtags. We then data mined the #Hashtags collectively using SQL LITE queries to determine the strategies which had the most weight in terms of discussion. The following key BREXIT exit government strategies, "Norway", "Article 50", "Backstop" and "No Deal" were identified as being most relevant in terms of count.

3.3 Python -Naïve Bayes using Textblob

Naive Bayes is a straightforward model for classification. It is simple and works well on text categoration. We adopt multinomial Naive Bayes in our project expressed in equation 1. It assumes each feature is conditional independent to other features given the class. That is

$$P\left(\frac{C}{T}\right) = \frac{P\,(C)\;P\,(T/C)}{P\,(T)} \quad (1)$$

Where c is a specific class and t is text we want to classify. P(c) and P(t) is the prior probabilities of this class and this text. And P(t|c) is the probability the text appears given this class. In our case, the value of class c might be POSITIVE or NEGATIVE, and t is just a sentence. The goal is choosing value of c to maximize P(c|t): Where P(wi|c) is the probability of the ith feature in text t appears given class c. We need to train parameters of P(c) and P(wi |c). It is relatively easy for getting these parameters in the Naive Bayes model. They are just the maximum likelihood estimation of each one. When making prediction to a new sentence t, we calculate the log likelihood log P(c) + ΣilogP(wi|c) of different classes, and take the class with highest log likelihood as prediction. We also extract the capital market data from Yahoo! Finance using a python library

3.4 Granger Analysis

The Granger Analysis was carried out using the EViews 10 application. The EViews application is an econometric, forecasting and simulation application.

4 Econometric Method

We have established the political BREXIT exit strategies ("Norway". "Article 50", "Backstop" and "No Deal" and the "Backstop) which lead to the disagreement in the House of Parliament concerning the Meaning Vote. We then wanted to understand if the public and political party Twitter sentiment from these BREXIT strategies correlated with the changes in the GBP/EUR FX and FTSE 100 Index. We now introduce and apply the econometric metric known as the Granger Causality analysis to the time series from the Twitter BREXIT #Hashtags in conjunction with the GBP/EUR FX and FTSE 100 Index variations from Yahoo! Finance in a frequency of seconds. In the Granger-sense χ is a cause of γ if it is useful in forecasting γ1 In this framework "useful" means that χ is able to increase the accuracy of the prediction of γ with respect to a forecast, considering only past values of γ. The FTSE time series is denoted as $ftset$ this essentially defines the daily net increase and decreases in the FTSE 100 index, essentially this is the delta between $ftset$ - $ftset$ -1 similarly, we use $gbp/eurt$ - $gbp/eurt{-}1$ for sterling/ Euro FX rate. To facilitate our test as to whether our BREXIT Twitter public and political sentiment analysis for Norway", "Article 50"," Backstop" and "No Deal" time series has a causal effect on changes in the FTSE 100 Index and GBP/EUR FX markets, we firstly checked for non-stationary variables using the log difference below in equation 2 and converted the two financial variables accordingly

$$\Delta Y_t = \frac{\ln(Y_t) - \ln(Y_{t-1})}{\ln(Y_{t-1})} \quad (2)$$

We then computed the FTSE 100 index and the GBP/EUR FX Granger model illustrated in equation (3) and (4) with lag values of 9 and 52 for both Twitter and the FTSE 100 index from the period 10th December 2018 to February 24th 2019 split out per BREXIT strategy. Where $X1$, $X2$, $X3$ and $X4$ represent the Twitter sentiment from the respective BREXIT strategies

Norway", "Article 50", "Backstop" and "No Deal". This included all tweets pertaining to each BREXIT exit strategy and the associated FTSE 100 index and GBP/EUR FX price movements in 1-minute intervals. We then mined and computed the data for the House of Commons Political parties separately (Labour, Conservatives, Democratic Unionist Party, the Scottish National Party, Liberal Democrats, the Green Party and Plaid Cymru) for the same dates 10th December 2018 to February 24th 2019 split out per BREXIT strategy using the same methodology outlined in equation (3) and (4) with lag values of 3 and 93 for both Twitter and the FTSE 100 index respectively.

$$ftse_t = \alpha + \sum_{i=1}^{n} \beta_i ftse_{t-p} + \sum_{i=0}^{n} \gamma_i X_{t-q} + \epsilon_t \quad (3)$$

$$gbp/eur_t = \alpha + \sum_{i=1}^{n} \beta_i gbp/eur_{t-p} + \sum_{i=0}^{n} \gamma_i X_{t-q} + \epsilon_t \quad (4)$$

5 Results

Table 2 shows the results of the public Granger Causality tests. ADF tests were implemented for stationarity, the variables checked for cointegration and a VAR done to identify the optimal number of lags according to basic steps in time series analysis. The series were identified as I(1) processes. We can reject the null hypothesis that Twitter public sentiment time series does not have a causal effect on FTSE returns such that $\beta1$, 2.. $\eta \neq 0$ Evidence presented herein confirms a short run relationship relates to sentiment impacting the FTSE 100 index changes in the case of the tweets for $X1$, $X2$, where $X2$ ("Article 50") exhibits the highest Granger Causality with the FTSE 100 index for lags ranging from 9 to 52 seconds (***p-value < 0.01) and $X1$, ("Norway") exhibits a Granger Causality with the FTSE 100 index for lags ranging from 9 to 52 seconds (* p-value < 0.10) $X3$ and $X4$ ("Backstop" and "No Deal") do not have any significant causations with the FTSE 100 Index. We fail to reject the null hypothesis that the Twitter political time series does not cause GBP/EUR Fx rate changes such that $\beta1$, $\beta2$, $\beta3$, $\beta4$,... $\eta \neq 0$. Our evidence shows that $X1$, $X2$, $X3$, $X4$ " do not have any significant causations with GBP/EUR Fx changes.

Table 2: Public Granger Causality

Variables	Norway	Article 50	Backstop	No Deal
FTSE 100	1.6277 (0.092)	1.7826 (0.0169)	0.5090 (0.9836)	0.6078 (0.9835)
GBP EUR FX	0.90678 (0.5181)	0.4811 (0.9745)	0.4025 (0.9748)	1.1635 (0.1901)

Table 3: Political Party Granger Causality

Variables	Norway	Article 50	Backstop	No Deal
FTSE 100	1.1098 (0.3450)	1.2444 (0.1252)	1.4753 (0.1412)	1.6349 (0.8701)
GBP EUR FX	1.7527 (0.8610)	1.30216 (0.1931)	0.73442 (0.4633)	1.6827 (0.0925)

Table 3 show the results of the political Granger Causality tests. ADF tests were implemented for stationarity, the variables checked for cointegration and a VAR done to identify the optimal number of lags according to basic steps in time series analysis. The series were identified as I(1) processes. We fail to reject the null hypothesis that the Twitter political party time series does not cause FTSE changes such that $\beta1$, $\beta2$, $\beta3$, $\beta4$,... $\eta \neq 0$. Our evidence shows that $X1$, $X2$, $X3$, $X4$ " do not have any significant causations with FTSE changes, however cointegration exists for $X3$, *and* $X4$ but not significant. We can reject the null hypothesis that Twitter political party sentiment time series does not have a causal effect on GBP/EUR Fx changes such that $\beta4$, ... $\eta \neq 0$. Evidence presented herein confirms a short run relationship relates to sentiment impacting the GBP/EUR changes in the case of the tweets for $X4$, where $X4$ *("No Deal")* exhibits a Granger Causality with the GBP/EUR Fx for lags ranging from 3 to 93 seconds (***p-value < 0.10) $X1$, $X2$ and $X3$ (*"Norway" "Article 50" and "Backstop")* do not have any significant causations with the GBP/EUR Fx.

6 Conclusions and Future Work

In this paper, we conducted a number of tests to establish if Twitter public and political party sentiment associated with four BREXIT exit strategies was indicative of FTSE 100 index changes and of GBP/EUR Fx rate changes. The results confirmed that sentiment tracked using a Naive Bayes machine learning algorithm indicative of public sentiment for "Article 50" and Norway" BREXIT exit strategies for the period 10th December 2018 to the 24th February 2019 was indicative of short-term dynamics on the FTSE 100 Index, whilst the "Backstop" and "No Deal" exit strategies had no causal effects on the FTSE 100 Index changes. Twitter public sentiment for each of the four BREXIT strategies concerning GBP/EUR Fx changes had no causal relationship. We established that Twitter political party sentiment for the "No Deal" was indicative of short-term dynamics on the GBP/EUR Fx. Our test concluded that there was no causality on the FTSE 100 Index however there was cointegration on the "Backstop" and "No Deal" but not significant. The fact these BREXIT strategies are the source of geopolitical instability in the euro zone thus providing market volatility, the sentiment analysis could also be applied to the commodity markets. With ongoing operations by a number of European, Middle East and Asian countries to move away from the dominate reserve currencies such as the US$, GBP and EUR in an effort to cut their exposure [32]. The sentiment and Granger causation analysis could provide important insights for investment decision making into the rise of safe haven commodities such as gold or crypto- currencies as a move away from traditional currency reserves in times of geopolitical risk and euro zone uncertainty. These insights could signal the decline of standard reserve currencies and propel investment decisions globally and at a government level. Future research will look at the effect of BREXIT tweets on crypto currencies.

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