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Impact of Brexit on STOXX Europe 600 Constituents: A Complex Network Analysis

Anna Maria D'Arcangelis [1,†], Arianna Pierdomenico [2,†] and Giulia Rotundo [3,*,†]

1 Department of Economics and Business, University of Tuscia, Via del Paradiso 47, 01100 Viterbo, Italy; adarcangelis@unitus.it
2 BancoBPM, Piazza Filippo Meda 4, 20121 Milan, Italy; ariannapierdomenico@libero.it
3 Department of Statistical Sciences, Sapienza University of Rome, P.le A. Moro 5, 00185 Rome, Italy
* Correspondence: giulia.rotundo@uniroma1.it
† These authors contributed equally to this work.

Abstract: Political events play a significant role in exerting their influence on financial markets globally. This paper aims to investigate the long term effect of Brexit on European stock markets using Complex Network methods as a starting point. The media has heavily emphasized the connection between this major political event and its economic and financial impact. To analyse this, we created two samples of companies based on the geographical allocation of their revenues to the UK. The first sample consists of companies that are either British or financially linked to the United Kingdom. The second sample serves as a control group and includes other European companies that are conveniently matched in terms of economic sector and firm size to those in the first sample. Each analysis is repeated over three non-overlapping periods: before the 2016 Referendum, between the Referendum and the 2019 General Elections, and after the 2019 General Elections. After an event study aimed at verifying the short-term response of idiosyncratic daily returns to the referendum result, we analysed the topological evolution of the networks through the MST (Minimum Spanning Trees) of the various samples. Finally, after the computation of the centrality measures pertaining to each network, our attention was directed towards the examination of the persistence of the levels of degree and eigenvector centralities over time. Our target was the investigation on whether the events that determined the evolution of the MST had also brought about structural modifications to the centrality of the most connected companies within the network. The findings demonstrate the unexpected impact of the referendum outcome, which is more noticeable on European equities compared to those of the UK, and the lack of influence from the elections that marked the beginning of the hard Brexit phase in 2019. The modifications in the MST indicate a restructuring of the network of British companies, particularly evident in the third period with a repositioning of the UK nodes. The dynamics of the MSTs around the referendum date is associated with the persistence in the relative rank of the centrality measures (relative to the median). Conversely, the arrival of hard Brexit does alter the relative ranking of the nodes in accord to the the degree centrality. The ranking in accord to the eigenvector centrality keeps the persistence. However, such movements are not statistically significant. An analysis of this kind points out relevant insights for investors, as it equips them to have a comprehensive view of political events, while also assisting policymakers in their endeavour to uphold stability by closely monitoring the ever-changing influence and interconnectedness of global stock markets during similar political events.

Keywords: Brexit; event study; complex networks; Minimum Spanning Tree; centrality persistence

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1. Introduction

On the 23 June 2016, in spite of media predictions and prevailing public opinion, the Brexit referendum paved the way for the "leave" decision. The United Kingdom, having joined the European Union at a later stage, retained its own currency and a certain level of independence. Despite the advantages of participating in a unified market, the constraints imposed by Union membership were not well received, indicating an underlying emotional motivation behind the votes of UK citizens. The announcement of Brexit had a negative impact on financial markets, as evidenced by significant declines in major indices returns on the 24 June 2016 (FTSE 100 −3.15%, FTSE Mib −12.48%, Ibex −12.35%). However, the whole path from 'Get Brexit done' to 'Make Brexit work' has been extremely complex and multifaceted. After a series of political events, the General Election on 12 December 2019 yielded a substantial majority for the Conservative Party, prompting the Prime Minister Boris Johnson to reassert his dedication to accomplishing Brexit by 31 January 2020, a goal that had previously been failed by former Prime minister Theresa May. Johnson succeeded, albeit at great cost. He established a new relationship with the EU based on uncertain and incomplete foundations, embarking on uncharted territory with little clarity on the way forward. The first two years outside the Single Market were marked by obstacles and problems. Although the entire world economy slowed down significantly, partly due to the COVID-19 pandemic, the UK was the country with the lowest growth among G20 members. Undoubtedly, the outcome of the general elections paved the way for a new chapter in the history of Great Britain, characterised by greater independence from EU regulations, but it is equally true that it has created uncertainties in the economic and financial field that only time can fill.

Following the timeline of the main events leading up to the exit of the UK from the EU's Single Market, this paper aims to analyse the impact of the above events on a selection of European companies. More properly, we grouped together in one sample the UK companies of the STOXX Europe 600 index and the European companies that, according to IFRS 8 reporting disclosure, were denoted by a strong exposure of their revenues to the UK.

The choice to focus on the constituents of a European index is associated with acknowledging the significance of the event being examined for the entirety of the European continent. The objective is achieved using methodologies typical of financial analysis and complex networks. The financial analysis involves a comprehensive event study aimed at identifying and evaluating the effects of the outcome of the referendum and the general election on the stock market around the major events relating to Brexit. The analysis of the correlations offered a means to thoroughly investigate the interconnected variations of returns throughout the various examined historical periods. In order to initiate the implementation of various complex networks analysis techniques, such as the estimation of measures of centrality and the construction of the Minimum Spanning Tree (hereafter referred to as MST) based on distances derived from partial correlations, it was crucial to establish the adjacency matrices based on correlation returns matrices. This specific phase acted as an initial stage that facilitated the subsequent investigation and evaluation of the aforementioned methodologies. Additional analyses intended to validate the persistence and dynamics of the networks over time finalized the analysis.

The contribution of the paper is threefold.

Firstly, we analyse the impact of a significant occurrence in UK politics, encompassing not only the implications associated with the 2016 referendum event, but also extending the examination to the subsequent period, wherein the dynamics have resulted in ramifications of uncertainty and potential instability for Great Britain. To our knowledge, this paper is the first of its kind to analyse the influence of the hard Brexit on financial markets after 2019, in contrast to other studies that have primarily concentrated on the surprising effects stemming from the outcome of the 2016 referendum.

Moreover, the study employs a diverse range of analysis techniques: some well acknowledged in financial analysis, others pertaining to the field of complex networks analyses, and some more statistical tests were used as further support and confirmation of the results. The variety of methodologies leads to a comprehensive and detailed perspective on the impact of the political events under scrutiny.

Lastly, our research does not solely focus on UK stocks. Rather, we acknowledge that the exposure to UK risk is not solely attributed to the mere affiliation with the country, but rather stems from the dependence of revenues on the UK. Therefore, we construct a sample of companies that are exposed to the Brexit event, encompassing both UK and European firms, and compare the results to a control sample of companies whose revenues are not influenced by the British economy.

An examination of this nature is of great significance to investors, as it empowers them to make well-informed judgments over political events, while also aiding policy-makers in their efforts to maintain stability by closely observing the evolving impact and interdependence of worldwide stock markets during comparable political occurrences.

The remainder of the article is organized as follows: Section 2 reviews the existing literature on Brexit, as well as on financial network analyses. Section 3 briefly explains the data and the hypothesis under examination. Section 4 contains a complete description of the methodologies used in the analysis. In Section 5 we present the empirical results. Lastly, Section 6 concludes the paper.

2. Literature Review

BREXIT is commonly acknowledged as the most notable occurrence to impact the English economy in the preceding four decades, with a myriad of scholarly articles delving into its repercussions on financial markets. Without any doubt, the referendum has exerted a noteworthy influence on the worldwide financial markets.

Danielsson [1] highlights novel opportunities and potential hazards for the financial markets in the United Kingdom and the European Union pertaining to protectionism, deficiencies in financial regulations, and systemic risk. This situation prompted reactions from participants in the market, as indicated by Fakhry [2].

Using the Detrended Fluctuation Analysis method, Guedes et al. [3] conclude that the referendum did not substantially affect the level of market efficiency. Furthermore, their study identified a reduction in the cross-correlation coefficient between the stock market in the United Kingdom and other markets within the European Union, indicating that after the referendum the UK index became less integrated with other EU nations.

This research is also related to the literature on the use of networks techniques in finance [4–7]. The field of Complex Networks gained prominence and found numerous applications in the early 2000s. Quite often, it is common to consider each company of the sample as a node. The process of constructing the network typically begins with the availability of the cross-correlation matrix between assets, which is utilized to create the adjacency matrix. When employing the MST, a mathematical function is used to convert the correlations into distances [8,9]. The MST has been first developed for the design of network of wires with the lowest cost, but since the early 2000s found extensive application in the analysis of stock market datasets as a tool for selecting a subset of the networks. In [10] the MST is calculated on a selection of stocks to evidence the amount of the common economic factors impacting the time evolution of prices. In [11] it has been used to evidence that the random market model and the one-factor model are not suitable for modeling the dataset. In [8] it has proved to be a representative tool for giving an immediate visual representation of the phases of expansion or crises of the market, resulting in either an expansion or a shrinkage of the diameter of the tree. The MST is not the only choice for selecting a subset of the network. For instance, a threshold can be selected [5,12,13]. Alternative techniques are proposed in literature and compared to MST [14,15]. Still, the MST extracts the network with a lower number of edges. The act of reducing the dimensionality permits the highlighting of topological alterations that occur during periods of crises, which would not be evidenced in a dense network. Consequently, the topology itself is transformed into an indicator of economic downturns and upturns, as well as the synchronization of stock market movements, as delineated by Onnela et al. [8] for the investigation of the 1987 crisis and in Kumar and Deo for the global financial crisis [16].

Using a network of mutual funds' stock holdings, D'Arcangelis et al. [17] look at how Italian mutual funds pick stocks and how these choices affect the funds' performance. Working on mutual funds correlations in a subsequent paper, D'Arcangelis et al. [12] analyse mutual funds managers' herding, and find that funds are less likely to follow the crowd during market stress. In the realm of pension funds, D'Arcangelis et al. [12] provide evidence that the network of Italian pension funds exhibits a dense network structure, where certain funds hold a more central position.

Complex network applications have additionally been employed to scrutinize the repercussions of Brexit on financial markets. Focusing only on British stocks, Yao and Memon [9] employ the MST technique to examine the dynamics exposed by companies listed on the FTSE 100 index both before and after the referendum. The findings from the post-referendum period reveal the presence of feeble clusters and diminished mean correlations. This can be attributed to the reliance of the stock market's stability on two prominent entities from the financial and consumer services sectors. Moreover, the analysis demonstrates the positive impact of the Brexit referendum, such as an upsurge in revenues, enhancement of the FTSE 100 index value, and an increase of the diameter and average path length of the normalized tree. The present analysis differs from the one performed in Yao [9] for the refinement of both the time frames and the selection of companies.

3. Data Description

The samples were constructed based on the constituents of the STOXX Europe 600 at the most recent event date. The STOXX Europe 600 is a stock index of 600 components representing large, mid and small capitalization companies among 17 European countries (United Kingdom, France, Switzerland, Germany, Austria, Belgium, Denmark, Finland, Ireland, Italy, Luxembourg, the Netherlands, Norway, Poland, Portugal, Spain, and Sweden). The index replicates almost 90% of the underlying investable market. We filtered the constituents that had continuous listing from 11 January 2013 to 23 June 2023.

The first decision was to set the relevant dates for the analysis. The objective was to evaluate the impact of Brexit not only immediately after the referendum but also during subsequent phases characterized by intense political debate. To achieve this, the time period was divided into three parts surrounding the dates of 23 June 2016 (the referendum) and 12 December 2019 (the general political elections in the UK). The elections of 12 December 2019 hold significant importance as they resulted in Prime Minister Boris Johnson obtaining the mandate from the electorate to implement the withdrawal of the United Kingdom from the European Union on 31 January 2020. Furthermore, these elections marked the end of hopes for Brexit opponents seeking a second referendum.

For each given time period, an analysis is conducted on two distinct groups of stocks: Sample 1, representing the primary grouping of companies directly impacted by Brexit, and Sample 2, which serves as a comparative control group composed of companies shielded from the effects of Brexit.

In constructing the first sample, we selected not only the STOXX 600 companies domiciled in the UK, but also those European companies that produce part of their revenues in UK. In this filtering process, the IFRS regulations came to our aid: IFRS 8 Operating Segments requires companies with publicly traded securities to disclose information about their operating segments, products and services, up to a maximum of ten geographical areas in which they operate (all companies declare their country of domicile as the first country in the geographical allocation of profits). Sample 1 is therefore made up of a) 25 UK companies and b) 57 continental companies which indicated the United Kingdom as the 2nd country of revenue allocation.

The decision to extend Sample 1 to include European companies with significant ties to the UK economy was driven by the recognition of a resilient network of interrelations among economic entities in Europe (both originating from and directed towards the UK). As a result, the overall sample size consists of $N = 82$ stocks.

The control sample consists of N stocks, filtered between the constituents of STOXX Europe 600 that do not mention UK in the geographical allocation of revenue required by IFRS 8. The selection of the control sample constituents is based on the matching of specific characteristics such as country, industry, and size with the main sample constituents: for each company in the first sample, a corresponding company is found that shares the same country (except for the 25 UK companies, wherein solely the dimensions and industry were taken into account as parameters for establishing compatibility), industry, and size.

The following stock indexes were similarly gathered: Austrian Traded Index (Austria), Omx Copenhagen Omxc20 (Denmark), Omx Helsinki (Finland), Cac 40 (France), Dax 30 Performance (Germany), Iseq All Share Index (Ireland), FTSE Mib Index (Italy), Luxembourg Se General (Luxembourg), Aex Index (Netherlands), Oslo Se Obx (Norway), Warsaw General Index 20 (Poland), Ibex 35 (Spain), Omx Stockholm 30 (Sweden), Swiss Market Index (Switzerland), FTSE 100 (UK).

Beginning with these three sets, we gathered the prices of stocks on a daily and weekly basis from 11 January 2013 to 23 June 2023. Daily prices are used only in the event study analysis, while weekly ones in all subsequent analyses, which share correlation as a common input. All the data were downloaded from Refinitiv.

4. Methods

As a first step, we computed the set of raw returns

$$R_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1} \tag{1}$$

for the periods from 11 January 2013 to 17 June 2016 (Pre-Referendum Period, hereafter shortened as T1), from 1 July 2016 to 6 December 2019 (Post-Referendum Period, hereafter shortened as T2) and from 13 December 2019 to 23 June 2023 (Post-Elections Period, hereafter denoted also as hard Brexit and shortened as T3). The same measures of the returns were also computed for a representative country index of each stock.

The objective of the authors is to explore the dynamics of corporate connections influenced by Brexit and its chronological sequence. To this end, it was necessary to eliminate the impact attributed to the overall economic (or systematic) factors that link companies to domestic indices. These factors account for the predominant portion of stock dynamics and the correlation between them. What remains after the removal of systematic return is the specific (idiosyncratic) return, which exhibits minimal correlation with risks that signify broader macroeconomic forces. This allows for the investigation of the impact of individual companies' decisions. The financial literature commonly removes this 'market effect' by employing the Single Index Model, pioneered by William Sharpe in 1963 [18], to model the returns of stocks. Since 1963, various versions have been elaborated on and tested on market data. We follow the approach of Campbell et al. [19], which is elaborated from the Sharpe model and it is widely adopted in financial literature [20,21], for calculating the abnormal returns at each time t as the market-adjusted-return by subtracting the country market index returns from the actual returns of the stocks:

$$AR_{i,t} = R_{i,t} - R_{m,t}. \tag{2}$$

In order to avoid the presence of spurious correlations, we carried out the Augmented Dickey-Fuller test for stationarity on $AR_{i,t}$ where the time is either daily or weekly: the results allow us to reject the null hypothesis of non-stationarity [22].

The availability of the daily abnormal returns made it possible to conduct such an event study on the selected event days, 23 June 2016 and 12 December 2019. In two separate studies, Brown and Warner [23,24] analyze how the specific attributes of daily and monthly returns influence event study methodologies. They conclude that using daily data generally poses minimal challenges for conducting event studies. We stress that daily data are selected for the task of detecting the relevance of the specific dates. The aim was to investigate the existence of an effect on the daily abnormal returns of the sampled stocks within an event window (t_1, t_2) around the date ($t = 0$) of an important news. To this end, we further estimate the aggregate daily abnormal returns ($AARs$) by summing daily abnormal returns for each stock to study the aggregate response of each sample. Aggregate abnormal returns are a sum of the abnormal returns from N stocks as follows:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{3}$$

where AAR_t represents the average abnormal returns across the stocks at time t, N is the number of stocks included in the sample. Finally, cumulative abnormal returns ($CAAR$) can be computed over the event window from the day t_1 to t_2 using the following formula:

$$CAAR_{t_1,t_2} = \sum_{t=t_1}^{t_2} AAR_t. \tag{4}$$

The usage of weekly data is a commonly accepted good practice for reducing the random noise always present in daily returns. Therefore, all the next analyses have been performed on the weekly returns.

The exploration of the dataset continued with the calculation of the partial correlation matrices [25], denoted as $C = (\rho_{i,j})$, on weekly abnormal returns for each of the examined samples and time intervals; this allowed to carry out further analyses of the impact of the Brexit event on the risk of the constituents of the examined samples.

The correlation matrix, whose elements indicate connections between pairs of vertices in the network, serves as the basis for determining the adjacent matrix. In order to convert time series of financial data into a network it is proper to calculate a distance among them. Distance measures in statistics quantify dissimilarity between points, essential for statistical analyses. Common measures include Euclidean distance, Manhattan distance, Minkowski distance, and Chebyshev distance. Mahalanobis distance considers data correlations, while cosine similarity is useful for high-dimensional data. Hamming distance is for categorical data. These measures are crucial in clustering, classification, regression, and anomaly detection algorithms, requiring careful selection for model accuracy and effectiveness. In finance, the correlation matrix is widely used to measure the relationship between stocks. In 1999, Mantegna [10] applied a mathematical function to the correlation matrix (which coefficients are ρ_{ij})

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \tag{5}$$

to calculate the distance among the time series. Therefore, the inferred correlation matrices are transformed into distance matrices by employing the distance [8]. This distance varies between 0 and 2, where small values imply strong correlations between stocks. The matrix of distances can be interpreted as adjacency matrix of the network where each node is a company and the weight of the link among them is d_{ij}.

Among the most used centrality measures in literature, we focused only on the node degree and the eigenvector centrality. The first one is by far the most used and has immediate interpretation for the ranking of the nodes; the second one is a prestige measure and integrates the results of the node degree.

In order to have meaningful centrality measures, a proper threshold for the correlation coefficients $\mid c_{i,j} \mid \geq \rho$ has been chosen before calculating the distances, so to keep only the most relevant elements of the correlation matrix. The threshold was selected with the aim of zeroing out 20% of the correlations (the weakest correlations). The threshold value was chosen by setting a condition to zero those correlation values which, in absolute terms, were smaller than this threshold. This means that the remaining links are the ones where the correlation is above the 20%. This selection allows to keep the links with the lower distances. Other methodologies are possible for the selection of a non-complete correlation matrix, among them the Planar Maximally Filtered Graphs [16,26].

Given the adjacency matrix $A = (a_{ij})$, the node degree is

$$d(i) = \sum_{j=1}^{n} a_{ij}. \tag{6}$$

A node has high eigenvector centrality when it is connected to well-connected nodes. Some algebra allows to state that the formalization of this concept leads to the eigenvector corresponding to the highest eigenvalue. In formula:

$$E(i) = \frac{1}{\gamma} \sum_{j \in G(i)} E(j) \tag{7}$$

where γ is the highest eigenvector of the adjacency matrix, $G(i)$ is the set of first neighbours of i, and $E(j)$ is the eigenvector centrality of node j.

We have also calculated the global clustering coefficient, the assortativity and the diameter of the network.

Such quantities cannot be considered a measure of centrality since they provide one value for the entire network as a whole, rather than focusing on individual nodes or vertices within the network.

The global clustering coefficient quantifies the presence of triangles to all potential incomplete triangles, thus providing insight into the level of connections among the neighbors of each node. The formula can be written as

$$Cl = \frac{\sum_{i,j,k} A_{ij} A_{jk} A_{ki}}{\sum_i k_i (k_i - 1)} \tag{8}$$

where $k_i = \sum_j A_{ij}$ and $Cl = 0$ if the denominator is equal to zero.

Networks exhibiting a substantial clustering coefficient are often observed in real-world data. They have played a pivotal role in the advancement of the Watts-Strogatz model, which was initially derived from the random Erdos-Renyi networks [27].

The concept of assortativity, in a broad sense, can be understood as the Pearson correlation coefficient that measures the relationship between the degrees of connected nodes.

The Newman's r assortativity coefficient formula is $r = \frac{\sum_{jk} jk(e_{jk} - q_j q_k)}{\sigma_q^2}$, where:

- j and k are the degrees of the nodes at either end of an edge e. These are the numbers of connections each node has in the network.
- e_{jk} is the fraction of edges in the network that connect nodes with degrees j and k. It represents the joint probability that an edge connects nodes with degrees j and k.
- q_j and q_k are the fractions of stubs (half-edges) that are attached to nodes of degree j and k respectively. In other words, q_j is the probability that a randomly chosen stub is attached to a node of degree j.
- σ_q^2 is the variance of the degree distribution. The wider the variance is, the larger is the span of values of the node degrees in the network. The usual formula for the variance is applied, as it is calculated as the sum of squares of the probabilities q_j minus the square of the sum of q_j.

Social networks are often assortative, while cross-shareholding networks have been proven to be slightly disassortative. The assortativity increases as the number of pairs of connected nodes having the same degree the degrees increases. Additional enhancements to this measure have been suggested in various academic papers [27–29].

The maximum distance − that is the length of the minimal path connecting any two nodes in a network − is the network's diameter. In certain cases, the average distance is used to determine the diameter to minimize the influence of outliers. Considering that networks either dense or complete have necessarily a short diameter, a subset of links has to be extracted for having meaningful results from the measurement of the diameter of the network.

To enhance the comprehension of the dynamics of the networks amidst the Brexit events, the MST was employed to extract the backbone of the various networks. The MST shows the strongest correlations and evidences the network topology. We used the Kruskal's algorithm for constructing it [4,30] on both samples, and three periods for each of them.

The availability of MSTs allowed us to compare the distribution of nodes in the networks on the three periods, observing the evolution of the relationship between them.

Onnela et al. [8] demonstrated that during periods of economic or financial growth, the diameter of the MST of financial networks tends to expand, whereas the opposite trend has been observed during crises.

Literature proposes several methods for assessing the persistence of links and structures in networks [31]. We propose an analysis of persistence of the ranking of the node, where the ranking is given by two measures of centrality (degree and eigenvector centrality). This analysis aims at verifying whether the events of Brexit had changed the role of companies in the network. In each interval of the analysis, a company was designated as "central" if its centrality measure exceeded the median of all companies, and as "peripheral" if it did not. Then we counted the number of companies whose rank has stayed consistent over time (above or below median) or not and conducted a non-parametric persistence test [32] of the two groups C (central companies) and P (peripheral companies) thus identified. To evaluate the time persistence of the position (either above or below the median), we have documented the position of each company in two adjacent periods: CC (central/central), CP (central/peripheral), PC (peripheral/central) and PP (peripheral/peripheral). The frequencies of the four combinations were included in a two-way contingency table. Following Brown and Goetzmann [33], we have subsequently computed the cross product ratio (CPR), which represents the odd ratio of the number of persistent companies to the number of those that don't persist, as illustrated in the subsequent formula:

$$CPR = \frac{CC \times PP}{CP \times PC}. \tag{9}$$

We subsequently employed a log odds ratio examination to assess the statistical significance of the CPR measure. The CPR assumed the natural log form and is divided by the standard error:

$$Z_{statistic} = \frac{\ln(CPR)}{\sigma_{\ln(CPR)}} \tag{10}$$

with

$$\sigma_{\ln(CPR)} = \sqrt{\frac{1}{N_{CC}} + \frac{1}{N_{CP}} + \frac{1}{N_{PC}} + \frac{1}{N_{PP}}}. \tag{11}$$

The Z-statistic assumes the normal distribution under the assumption of independent observations. A Z-value greater or equal to 1.645 at 95% confidence level is used as a test of significance.

As a final step, we also applied the Adjusted Rand Index (ARI) [34] that allows to judge the similarity of the two data clusterings above and below the median. ARI is an improvement of the Rand Index that accounts for the possibility that some agreement between two clusterings can occur by chance. The higher the ARI value, the closer the two clusterings are to one another. The range spans from -1 to 1, with a value of 1 denoting a state of complete concordance between the two clusterings, a value of 0 denoting a state of random concordance, and a value of -1 denoting a state where the two clusterings are entirely dissimilar. The ARI is widely used in machine learning, data mining, and pattern recognition, especially for the evaluation of clustering algorithms.

5. Results

This section is organized in four subsections: event study, correlation analysis, MST analysis, centrality measures and persistence analysis.

5.1. Event Study

The findings for the two examined samples are displayed in Figure 1, which illustrates the fluctuations of the AARs within the event window. The numbers on the x-axis identify the distance from the event date (day 0, set at the Referendum on 23 June 2016). The outcome of the Referendum significantly influenced both samples, as indicated by the negative and statistically significant abnormal return on the event date 1 (the day after the event). It is noteworthy to mention that there is a clear "surprise effect" for both groups, as the abnormal returns are not statistically significant around zero prior to the referendum, to dramatically drop on the event date.

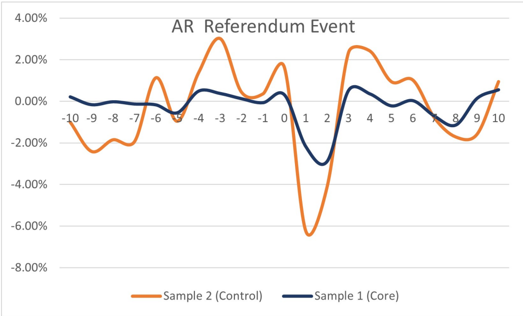

Figure 1. The y-axis shows the Average Abnormal Returns for Sample 1 and Sample 2. The x-axis reports the distance from the event date (day 0, set at the Referendum on 23 June 2016). The Microsoft Excel smoothing function has been used to guide the eye.

The interesting observation that arises from the abnormal returns curves is that the impact is more pronounced in the control sample (Sample 2, consisting of European companies not economically tied to the UK) compared to Sample 1 (which includes companies with the greatest connection to British events, both in the UK and Europe).

The conclusion we can draw is that the element of surprise was more noticeable outside of the UK. Investors from other European countries who dealt with their own securities reacted more strongly compared to British investors when it came to UK companies. It seems like this effect was partially expected and therefore less surprising for those who voted, in contrast to investors who relied on media sources for information.

Figure 2 permits to compare the abnormal returns of the two subgroups UK (dark blue curve) and non-UK (light blue curve curve) that form Sample 1. Again, the analysis of AARs shows that excess returns remain around zero, until the date of the event (day 0), and then fall sharply following the negative impact of the news on stock prices. However, the downward impact is quickly compensated by a positive return effect two days after the event. Starting from this date, albeit with more pronounced volatility, the AARs start to swing again around zero, which indicates that the news has been quickly absorbed by prices.

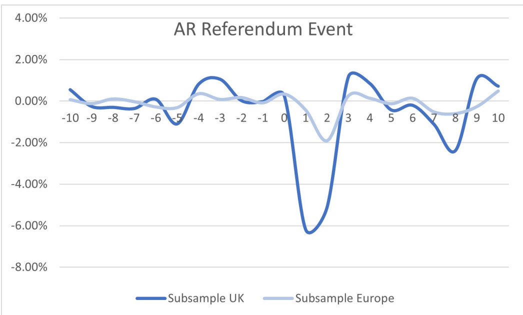

Figure 2. The y−axis shows the Average Abnormal Returns for the UK and non−UK Subsamples. The x−axis reports the distance from the event date (day 0, set at the Referendum on 23 June 2016). The Microsoft Excel smoothing function has been used to guide the eye.

It is worth mentioning that the dynamics of the subset of securities from countries other than the United Kingdom exhibit a similar albeit less prominent pattern. This observation further validates the susceptibility of the returns from the companies included in Sample 1, in addition to those from the United Kingdom.

Finally, the fluctuations in the Abnormal Absolute Returns (AARs) surrounding the second date of the event, namely the General Political Elections that took place on 12 December 2019, exhibit a contrasting pattern (Figure 3): there is a significant surge in the abnormal returns on the day of the election and the subsequent day, followed by a decline. It is worth noting that, in this particular scenario, the short-term impact captured by an event study analysis on the two samples is negligible.

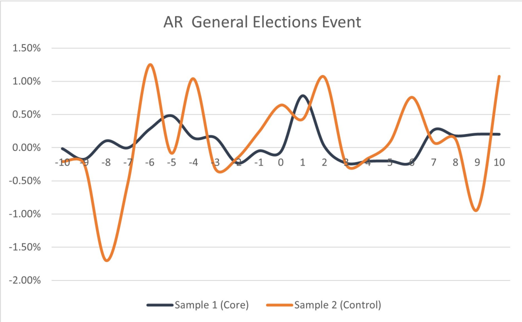

Figure 3. The y−axis shows the Average Abnormal Returns for Sample 1 and Sample 2. The x−axis reports the distance from the event date (day 0, set at General Political Elections that took place on 12 December 2019).

5.2. Correlation Analysis

Summary statistics on the partial correlation coefficients are shown in Table 1.

Table 1. Correlation coefficients of the two samples (average and percentiles).

	Sample 1				Sample 2			
	Min	**Median**	**Max**	**Avg**	**Min**	**Median**	**Max**	**Avg**
T1	−0.4438	0.0023	0.4275	0.0034	−0.3607	0.0031	0.5639	0.0011
T2	−0.3328	0.0008	0.5238	0.0035	−0.3750	0.0019	0.4508	0.0035
T3	−0.3313	0.0044	0.5619	0.0062	−0.3714	0.0000	0.5807	0.0028

The average values are very close to zero, which means that, within each sample and each period, we are matching positive with negative correlations. The average correlation in Sample 1 shows a slight increase after the referendum (0.0035), and an upward shift in the range between minimum and maximum (particularly noticeable in deciles within the median). This is in line with the literature [35–38] which shows that the correlation between stocks tends to increase during financial crises. This phenomenon is well-documented in financial literature and can be attributed to several factors, including market contagion, increased investor risk aversion, and synchronized market reactions to macroeconomic shocks. This has important implications for portfolio diversification, risk management, and financial stability.

The result confirms the negative immediate effect shown in the previous examination of the event study (even if a comparison between a short-term analysis, such as the event study, and a historical analysis focused on the relationship between joint returns on a weekly basis is not immediate).

A comparable but more pronounced trend is observed in Sample 2, where the average correlation increases by 0.0024. However, upon closer examination, it is evident that all deciles decrease except for the last one (Table 1 only presents the median and minimum data). Consequently, the rise in the mean can be attributed to its sensitivity to the maximum value, which is the only data point that increased. This indicates that Sample 1 shows a spike in the perceived risk level, which is not supported by the return dynamics of "continental" companies. The occurrence of a hard Brexit phase (the period after date T3) results in a different situation. In Sample 1, the average correlation shows an increase of

+0.0273, a change that is not observed in Sample 2. While the spread in Sample 2 increases significantly due to the upward movement of the extreme decile, the average correlation decreases by −0.00075.

Details can be evidenced by examining Figure 4 (Sample 1) and Figure 5 (Sample 2). In the case of the first sample, the correlations between before and after the referendum show a negligible dynamics; in contrast, the period after the election (hard Brexit) exhibits a noteworthy amplification of the correlations, which increase in absolute value.

This situation draws attention to the fact that there is a difference in the perspectives on the consequences of Brexit within European companies. But the predominant effect remains the one linked to the December 2019 general elections. The outcome of the election, which introduced the possibility of a hard Brexit, had a large impact on the returns of UK companies, but companies not linked by commercial relations with the UK remain extraneous to this dynamic. This effect was clearly a result of the uncertainty surrounding the uncharted path the country was about to embark on. Even though the voters' expressed preferences, this development has set the stage for a potential escalation of uncertainty within the country. The asset allocation involving the companies participating in this process will potentially face significant penalties as an immediate consequence. The impact of the elections, although expected, has caused a considerable amount of volatility in the European stock market, especially for British businesses and European companies heavily influenced by British political matters.

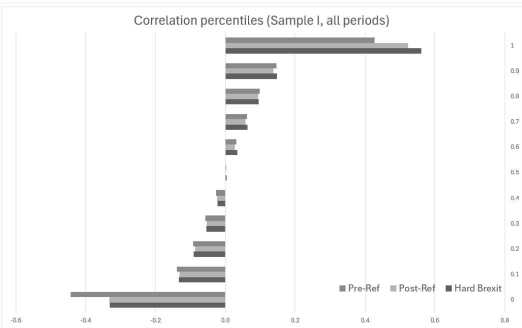

Figure 4. Distribution of correlation coefficients in Sample 1.

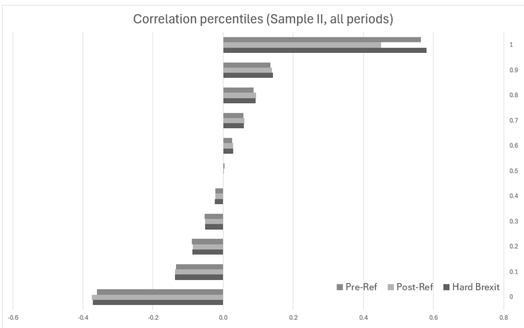

Figure 5. Distribution of correlation coefficients in Sample 2.

In view of the all the elements reported above, it is important to note that the dynamics of volatility and correlations cannot be attributed to global factors such as COVID-19, which emerged in 2020, as the correlations were calculated based on the partial correlations computed on excess returns. Stock excess returns are very often used in finance precisely for the purpose of correcting returns for the systematic factors present in indices: the correlation between assets or stocks is in fact largely explained by common factors such as indices. The subtraction of the market return factor removes the effect of all systematic factors in the dynamics of stocks. The use of partial correlation further enhances this effect: given the significance of systemic factors present in market indices, it is likely that the impact of the removed variables is predominantly due to these systemic factors, and COVID-19 has clearly been a global factor. This assertion is supported by the widespread economic disruption caused by the sharp decline in global economic activity and the massive fiscal and monetary stimulus measures implemented worldwide. In summary, COVID-19 has indeed been a systematic factor influencing stock market indices, introducing new patterns of volatility, reshaping sector dynamics, and prompting significant government and central bank interventions to stabilize economies and markets.

5.3. MST Analysis

The analysis of the MST proves to be advantageous in elucidating the pattern of interconnectivity, the distinct positioning of individual companies, as well as the dynamic influence within said companies. The segmentation of the data, encompassing two samples and three subsets based on time, grants the opportunity for numerous remarks. Initially, we present the findings obtained from Sample 1, as depicted in Figure 6 (Pre Referendum), Figure 7 (Post Referendum) and Figure 8 (hard Brexit). The Mnemonic datatype in Refinitiv is used for the labels of the nodes. Table 2 sums up the global clustering coefficient, the assortativity and the diameter of the MST.

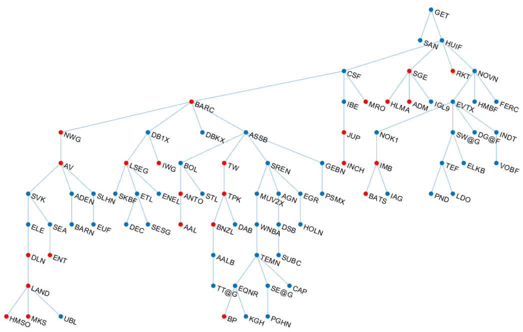

Figure 6. MST of Sample 1 (T1, Pre-Referendum).

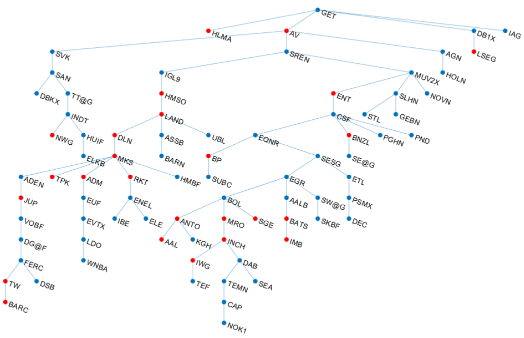

Figure 7. MST of Sample 1 (T2, Post-Referendum).

Table 2. Measures of global clustering coefficient, assortativity and diameter of MSTs.

	Sample 1			Sample 2		
	T1	**T2**	**T3**	**T1**	**T2**	**T3**
Global clustering	0.8111	0.8098	0.8094	0.8115	0.8116	0.8107
Assortativity	−0.0173	−0.0273	−0.0346	−0.0358	−0.0299	−0.0302
Diameter	17.036	29.832	24.441	29.102	30.161	26.517

The MST during the period prior to the referendum (referred to as T1) indicates that a significant proportion of companies located in the United Kingdom possess the smallest geographical proximity to other domestic companies (red points).

Figure 6 visually displays the MST of Sample 1 companies, which includes UK (red dots) and not-UK (blue dots) companies. The nodes with high degree have correlation with the other companies higher than the other nodes of the network. The UK companies tend to have at least one connection to other UK companies. We remark that both UK and not-UK companies keep high correlations. For instance, in Figure 6 BARC (UK), and HUIF, EVTX, ASSB (not-UK) have higher degrees. In Figure 7 MKS (UK) is the most connected, closely followed by CSF (not UK). The high connected nodes in T1 (BARC, HUIF, EVTX, and ASSB) are now close to the extremities of the branches they belong to. We also note that MKS was in a leave of the tree Figure 6. CSF, instead, had a good number of connections. This evidences that the centrality of the UK nodes in the period T1 is quite different from the one in the period T2; the effect is less pronounced for the not-UK companies. It is remarkable that in T2 the MST tree has longer chains than in T1. The chains give a good contribution to the increase of the diameter of the tree. The clustering coefficient is not decreasing much, and the tree maintains an overall good balance. The increase of negativity of the assortativity –that is disassortative mixing– in T2 compared to T1 is in line with an augmented maximal node degree, and with the increase of the diameter.

Figure 8 refers to the period T3 and depicts a distinct assemblage of UK companies. Remarkably, the diameter is still higher than in T1, but lower than T2. The clustering coefficient is substantially stable, but the increase of the negative values of the assortativity witness for a higher presence of nodes with higher degree (two nodes with degree six, AAL and HMSO, instead of the only node MKS with degree six in T2). It is worth to point out that AAL and HMSO are both UK. AAL was in the leaves of the MST trees in T1 and T2; HMSO was in a leaf in T2 and in a chain in T2. Their relevance is totally changed. Overall, new structure of correlations in T3 is quite different than in T1 and T2.

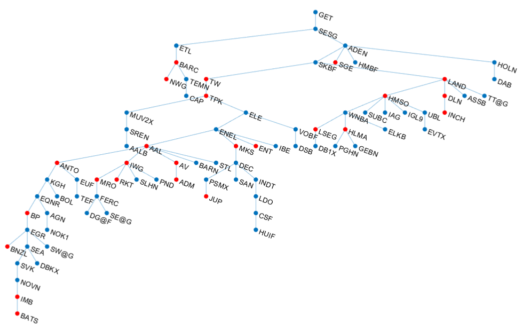

Figure 8. MST of Sample 1 (T3, hard Brexit).

Figure 9 (Pre-Referendum, referred to as T1), Figure 10 (Post-Referendum, referred to as T2), Figure 11 (hard Brexit, referred to as T3) present the results of the MST calculation for the control sample (Sample 2).

In the Sample 2, the MST starts with a value of the diameter comparable to the maximal diameter of the Sample 1. Also in this case, the chains contribute to this value. In T2, the increase of the diameter of the MST of the Sample 2 is lower than in the Sample 1. The chains show sequences different from T1, and a long chain appears (SBMO−ACS). The number of nodes with high degrees increases in T2, but also the assortativity increases, although the network is still disassortative. This is the opposite behavior than the Sample 1, and the most dissimilarity in the behavior of Sample 1 against Sample 2. The behavior of Sample 2 in T3 is similar to the one of the Sample 1: the clustering remains substantially stable, the assortativity and the diameter decrease. This indicates a contraction of the network and a raise in correlations, as highlighted in [8] during times of crisis.

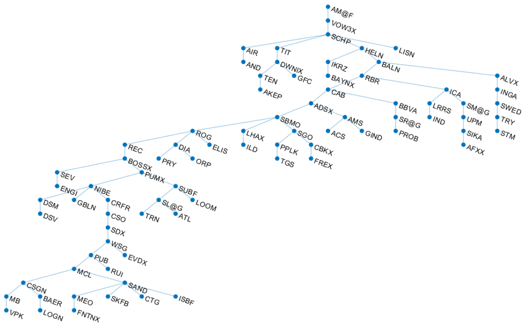

Figure 9. MST of Sample 2 (T1, Pre-Referendum).

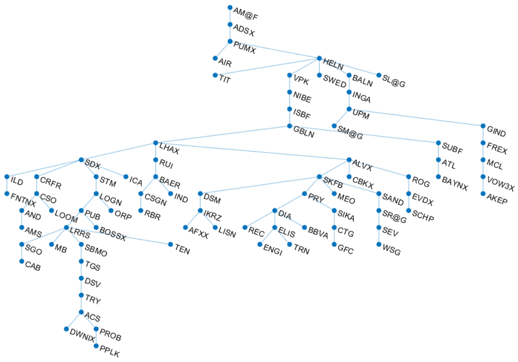

Figure 10. MST of Sample 2 (T2, Post-Referendum).

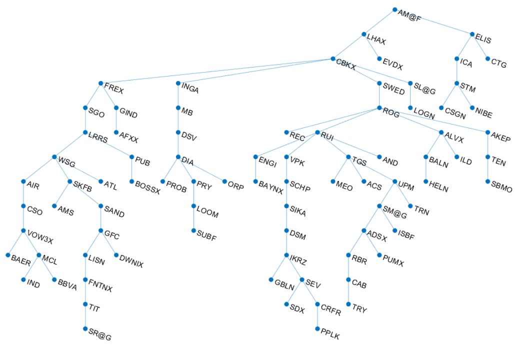

Figure 11. MST of Sample 2 (T3, hard Brexit).

Summing up, the analysis uncovers the establishment of a different ranking of correlations in the network, resulting in an increase of the diameter in T2 if compared to T1, in line with the results of [9]. In all the cases the global clustering coefficient remains quite stable. After the turmoil of the hard Brexit period the set of companies reshape their correlations showing an overall frame similar to the T1 period, although through different links.

5.4. Centrality Measures and Persistence Analysis

We applied the non-parametric persistence test of Brown and Goetzmann (1995) [33] and Goetzmann and Ibbotson (2010) [32] to analyze the ranking of the centrality measures (degree and eigenvector centrality) for the two samples and the two consecutive periods from the dates of the 2016 referendum to the 2019 UK political elections. The goal is to ascertain if, after categorizing the centralities as either central (C) or peripheral (P) based on their placement above or below the median, these same centralities exhibit consistency within their respective categories. The CPR metric captures the proportion of companies that exhibit persistence compared to those that do not: if the centralities in the initial period cannot predict centralities in the next period, then the odds ratio would be 1 (one would expect that each of the four categories denoted by CC, CP, PC, PP to have 25% of the total number of companies). A CPR larger than 1 reveals persistence in centrality positioning of the company, and a value less than 1 implies reversals. Table 3 reports the CPRs and their associated Z-statistic (as detailed in Christensen [39]) for the two samples.

Table 3. Cross Product Ratio CPR - Non-parametric persistence test (in parentheses the Z-statistic). T_1: Pre-Referendum; T_2: Post-Referendum; T_3: hard Brexit.

	Sample 1		**Sample 2**	
Centrality	$\mathbf{T_1 - T_2}$	$\mathbf{T_2 - T_3}$	$\mathbf{T_1 - T_2}$	$\mathbf{T_2 - T_3}$
Degree	1.739 (1.228)	0.813 (−0.452)	1.913 (1.432)	0.478 (−1.581)
Eigenvector	1.341 (0.662)	1.341 (0.662)	1.633 (1.102)	1.341 (0.662)

The CPR ratio values in Table 3 (1.739 and 1.341 respectively for degree and eigenvector in period $T_1 - T_2$) demonstrate that the referendum did not exert a substantial influence on the centralities. This event caused a reordering of the nodes (companies) in the sample, highlighted the persistence of most companies in the sample. However, it is important to note that the resulting impact is not statistically significant. In contrast, if we focus on the impact of the election that opened the hard Brexit phase, the conclusion partially changes: for the degree centrality the CPR is below 1 (Z-statistic not significant): this implies that the 2019 General Elections have had an impact on the centrality of the companies in Sample 1, so that the most connected lose centrality, while the least connected gain it. This is not observable when we define centrality via eigenvector centrality. Moreover, all values are similar to those observed in the control group of companies without economic or financial ties with the United Kingdom (Sample 2): after the referendum there is a persistence of the centrality ranking while the hard Brexit modifies the roles of companies in terms of degree centrality: this event causes a significant change in the groups above and below the median degree.

The Adjusted Rand Index (ARI) presented in Table 4 calculates the mean value of the Rand Index (RI) for random clusterings across a range of possibilities. Consequently, a positive ARI indicates that a dataset exceeds the average expectation, while a negative ARI suggests a lower level of persistence than what would be expected through random pairing. It is noteworthy that the positive Adjusted Rand Index (ARI) for the degree in Sample 1 confirms the persistence of centralities (both above and below the median) subsequent to the 2016 Referendum, provided that centrality is here defined as a metric solely based on the number of connections.

Table 4. Adjusted Rand Index.

	Sample 1		**Sample 2**	
Centrality	$\mathbf{T_1 - T_2}$	$\mathbf{T_2 - T_3}$	$\mathbf{T_1 - T_2}$	$\mathbf{T_2 - T_3}$
Degree	0.0093	−0.0116	0.0172	0.0092
Eigenvector	−0.0071	−0.0071	0.0026	−0.0071

We are unable to arrive at the same conclusion when employing eigenvector centrality for the identical time frame and sample. The presence of a negative value in the Adjusted Rand index signifies a reorganization in the hierarchy of central companies, when the emphasis is placed on the quality rather than the quantity of connections. A comparable effect of reordering the centrality hierarchy is observed following the General Elections held in December 2019, irrespective of the specific centrality metric utilized.

On the other hand, sample 2 (control sample) shows a general persistence of large and small centralities around the two events studied, except for the post-2019 elections, which sees a negative value of the Adjusted Rand index.

6. Discussion and Conclusions

The departure of the United Kingdom from the European Union, commonly referred to as Brexit, had a substantial influence on both the financial markets within the UK and the EU. The objective of this study is to empirically examine whether Brexit, along with the subsequent events leading to a hard Brexit, had a diversified impact on the European stock markets. To achieve this goal, UK companies in the STOXX 600 were combined with European companies whose profit and loss depend on UK macroeconomic factors. These two groups formed the multi-country core sample, referred to as Sample 1. Additionally, all analyses were repeated for a control sample, referred to as Sample 2, consisting of STOXX 600 European companies that do not report any UK dependence in their revenues' figures.

The analysis focuses on two key events: the referendum held on 23 June 2019, which resulted in the majority of voters supporting Brexit, and the general election held on 12 December 2019, which granted PM Johnson's party a strong majority and facilitated a swift, economically termed hard Brexit.

The event study around the referendum date reveals a significant and negative impact on abnormal daily returns for all stocks included in the samples. Moreover, it provides evidence of a surprise effect, as the abnormal returns observed prior to the events were close to zero and lacked statistical significance. Contrary to expectations, the impact on continental companies is even more pronounced than that on other samples.

The fluctuations in the Abnormal Absolute Returns (AARs) that revolve around the second date of the event (the General Political Elections that occurred on 12 December 2019), showcase a contrasting pattern that is worth mentioning: there is a noteworthy surge in the abnormal returns on the day of the election as well as the subsequent day, which is then followed by a decline. We can therefore conclude that the short-term impact captured by the event study on the two samples is practically insignificant.

The analysis continued with a Complex Networks analysis based on partial correlation coefficients matrices. The correlation matrix provided the foundation for creating a network of distances. This network was then used to implement the MST, which reveals the shifting nature of the closest connections over time. The outcomes of this phase enable us to argue that the occurrence of Brexit had a substantial impact on the interconnectedness of companies.

The calculation of centrality measures of the networks additionally permitted the assignment of roles to companies within the network, as well as the measurement of their connections. We focused on the node degree and we added the eigenvector centrality for a more comprehensive view of the centrality of companies. These measures also allowed for the identification of the most central and least central companies in the system, as well as the verification of their persistence in these roles in the three phases examined by the analysis.

Given a relative positioning of companies, through the entity of centrality compared to the median, we have analysed the impact of Brexit events on this relative positioning. The outcome of the referendum has disrupted the situation, leading to a rearrangement of the companies, where some companies have remained while others have experienced reversals. However, the statistical impact is not significant. On the other hand, the electoral shift towards a hard Brexit is statistically stronger and indicates a significant persistence of companies involved in the ongoing political process, regardless of whether their belonging to United Kingdom. These companies continue to play a central role within the median, suggesting that the uncertainty caused by the hard Brexit event was already anticipated in both market returns and the relationships examined through centrality measures.

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& Editing, A.M.D., A.P. and G.R.; Visualization, A.P.; Supervision, A.M.D. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

Sample 1

Name	**Label**
GETLINK	GET
NATWEST GROUP	NWG
BARCLAYS	BARC
ANTOFAGASTA	ANTO
ANGLO AMERICAN	AAL
TAYLOR WIMPEY	TW
BP	BP
JUPITER FUND MANAGEMENT	JUP
MELROSE INDUSTRIES	MRO
LONDON STOCK EXCHANGE GROUP	LSEG
IMPERIAL BRANDS	IMB
BRITISH AMERICAN TOBACCO	BATS
IWG	IWG
TRAVIS PERKINS	TPK
BUNZL	BNZL
HALMA	HLMA
ADMIRAL GROUP	ADM
AVIVA	AV
RECKITT BENCKISER GROUP	RKT
HAMMERSON	HMSO
DERWENT LONDON	DLN
LAND SECURITIES GROUP	LAND
INCHCAPE	INCH
MARKS & SPENCER GROUP	MKS
SAGE GROUP	SGE
ENTAIN	ENT
AALBERTS	AALB
SUBSEA 7	SUBC
WIENERBERGER	WNBA
PARTNERS GROUP HOLDING	PGHN
DEUTSCHE BOERSE	DB1X
HANDELSBANKEN	SVK
SVENSKA CELLULOSA	SW@G
SWISS RE	SREN
DEUTSCHE BANK	DBKX
MUENCHENER RUCK.	MUV2X
INTL.CONS.AIRL.GP.	IAG
IBERDROLA	IBE
JCDECAUX	DEC
AEGON	AGN
KGHM	KGH
PROSIEBENSAT 1	PSMX
BANCO SANTANDER	SAN
TELEFONICA	TEF
HUHTAMAKI	HUIF
CAPGEMINI	CAP
GLANBIA	IGL9
BOLIDEN ORD SHS	BOL
SKANSKA B	SKBF
HENNES & MAURITZ B	HMBF
ADECCO GROUP	ADEN

SWISS LIFE HOLDING	SLHN
EVOTEC	EVTX
DANSKE BANK	DAB
PANDORA	PND
FERROVIAL	FERC
VINCI	DG@F
LEONARDO	LDO
SES FDR	SESG
ASSA ABLOY B	ASSB
INDUTRADE	INDT
HOLCIM	HOLN
BARRY CALLEBAUT	BARN
A P MOLLER MAERSK B	DSB
EUROFINS SCIEN.	EUF
THALES	CSF
ELEKTA B	ELKB
TRELLEBORG B	TT@G
NOVARTIS 'R'	NOVN
ENDESA	ELE
NOKIA	NOK1
EUTELSAT COMMUNICATIONS	ETL
EQUINOR	EQNR
TEMENOS N	TEMN
STORA ENSO R	EGR
UNIBAIL RODAMCO WESTFIELD	UBL
ENEL	ENEL
STELLANTIS	STL
SKANDINAVISKA ENSKILDA BANKEN A	SEA
ELECTROLUX B	SE@G
VOLVO B	VOBF
GEBERIT 'R'	GEBN

Sample 2

Name	**Label**
DASSAULT AVIATION	AM@F
VOLKSWAGEN PREF.	VOW3X
AIR LIQUIDE	AIR
RECORDATI INDUA.CHIMICA	REC
ENGIE	ENGI
DEUTSCHE LUFTHANSA	LHAX
WOLTERS KLUWER	WSG
FREENET	FNTNX
ROYAL DSM	DSM
CARLSBERG B	CAB
GBL NEW	GBLN
BAYER	BAYNX
CASINO GUICHARD-P	CSO
SODEXO	SDX
MEDIOBANCA BC.FIN	MB
SUEZ	SEV
TELECOM ITALIA	TIT
MICHELIN	MCL
ADIDAS	ADSX
DIASORIN	DIA
RUBIS	RUI
CARREFOUR	CRFR
HUGO BOSS	BOSSX
SBM OFFSHORE	SBMO
CARL ZEISS MEDITEC	AFXX
PUMA	PUMX
ROYAL VOPAK	VPK
TGS	TGS
ANDRITZ	AND
CREDIT SUISSE GROUP	CSGN
DEUTSCHE WOHNEN	DWNIX
SWEDBANK A	SWED
SKF B	SKFB
BALOISE HOLDING	BALN
COMMERZBANK	CBKX
ALLIANZ	ALVX
INDITEX	IND
GRIFOLS ORD CL A	PROB
PUBLICIS GROUPE	PUB
ING GROEP	INGA
ORLEN	PPLK
CTS EVENTIM	EVDX
BBV.ARGENTARIA	BBVA
AMADEUS IT GROUP	AMS
NELES	MEO
STMICROELECTRONICS	STM
KERRY GROUP 'A'	IKRZ

HOLMEN B	SM@G
NIBE INDUSTRIER	NIBE
ICA GRUPPEN	ICA
SCHINDLER ‘P’	SCHP
HELVETIA HOLDING N	HELN
FRESENIUS	FREX
TRYG	TRY
ROYAL UNIBREW	RBR
ACS	ACS
SAINT GOBAIN	SGO
PRYSMIAN	PRY
TENARIS	TEN
SECURITAS B	SUBF
SANDVIK	SAND
SIKA	SIKA
LINDT & SPRUENGLI	LISN
DSV	DSV
ORPEA	ORP
LEGRAND	LRRS
GETINGE B	GIND
ATLAS COPCO A	SR@G
ROCHE HOLDING	ROG
NATURGY ENERGY	CTG
ELISA	ELIS
ILIAD	ILD
AKER BP	AKEP
LOGITECH ‘R’	LOGN
UPM-KYMMENE	UPM
GECINA	GFC
TERNA	TRN
ATLANTIA	ATL
INVESTOR B	ISBF
ERICSSON B	SL@G
LOOMIS	LOOM
JULIUS BAER GRUPPE	BAER

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