GESTÃO & PRODUÇÃO

ISSN 0104-530X (Print)
ISSN 1806-9649 (Online)

ORIGINAL ARTICLE

# S&P500 volatility and Brexit contagion

*Volatilidade do S&P500 e o contágio do Brexit*

Matheus Vinicius Gomes[1], Maria Paula Vieira Cicogna[1]

[1]Faculdades de Campinas – FACAMP, Escola de Economia, Campinas, SP, Brasil. E-mail: matheus.vinicius97@hotmail.com; maria.cicogna@facamp.com.br

**How to cite:** Gomes, M. V., & Cicogna, M. P. V. (2023). S&P500 volatility and Brexit contagion. *Gestão & Produção*, 30, e8422. https://doi.org/10.1590/1806-9649-2022v30e8422

**Abstract:** This paper investigated the existence of contagion between S&P500 and FTSE100 stock indexes, the two major stock exchange markets in the world, due to Brexit. Brexit caused a wave of volatility in international financial markets and the immediate reaction in US market has brought instability among investors, who remained cautious regarding the unexpected unfolds over the global economy. Dynamic conditional correlation model (DCC GARCH) was applied to analyze the shift-contagion phenomenon in the time series data. The results showed that there was no evidence of shift-contagion between the two markets during the Brexit period. It was possible to observe a moderate increase in the conditional correlation during the month of the Brexit referendum, which may be due to the high interdependence between the two asset markets.

**Keywords:** Brexit; S&P 500; FTSE100; Contagion; Volatility.

**Resumo:** O presente artigo investiga a existência de contágio entre os índices de ações S&P e FTSE100, dois dos maiores mercados de ações do mundo, devido ao Brexit. O Brexit causou uma onda de volatilidade nos mercados financeiros internacionais e a imediata reação nos mercados dos Estados Unidos levou instabilidade instantaneamente aos investidores, os quais se mantiveram cautelosos sobre desdobramentos não esperados na economia global. Foi utilizado o modelo de correlação dinâmica condicional (DCC GARCH) para analisar a existência de *shift-contagion* nos dados em série de tempo. Os resultados mostraram que não há evidência de shift-contágio entre os dois mercados durante o período do Brexit. Foi possível observar um aumento moderado na correlação condicional durante o mês do referendo do Brexit, o que pode ser devido à elevada interdependência entre os dois mercados de ativos.

**Palavras-chave:** Brexit; S&P 500; FTSE100; Contágio; Volatilidade.

## 1 Introduction

The relations among financial markets has been deepening over time, as financial markets become increasingly interconnected. One event that highlighted this trend was Brexit, the United Kingdom (UK) decision to leave the European Union (EU) on June 23, 2016. Most of the British population voted in favor of withdrawing from the European Union, in a referendum, on the understanding that the economic bloc did not bring the expected social and economic benefits.

Received Jan. 6, 2023 – Accepted Mar. 21, 2023
Financial support: None.

As shown in Davies et al. (2017), in 2017, the London financial market was quite representative in the world and dominated financial services in the European Union. The paper data show that the London financial market accounted for more than 35% of asset management in Europe, concentrated about 38% global exchange rate trading, and was responsible for nearly 40% of global transactions in derivatives markets. By comparison, Euronext Paris, the second largest derivatives market in the EU, accounted for less than 5% of global transactions. Howarth & Quaglia (2017) argue that a successful Europe results from a successful United Kingdom, once more than one third of UK's private equity investment funds go to companies in other EU nations and English banks lend more than $2 trillion to eurozone countries in an annual basis.

The referendum's result immediately brought uncertainty to investors and volatility in international financial markets could soon be observed. The uncertainty about the future led investors to take short positions against the pound sterling, leading to a 10% drop against the dollar. It was the biggest devaluation in 31 years (Allen et al., 2016). Caporale et al. (2018) portrays the deterioration of the British pound sterling against the euro and the dollar has evidenced investors' fear about the Brexit consequences, which was already reflected in asset prices. The authors highlighted higher risk perception reflected on sovereign risk spreads – measured by the 5-year CDS – which brought greater volatility to the asset prices.

The sell-off movement caused an increase in volatility in the European markets between June and July 2016. One workday after the referendum, on 27 June 2016, there was an increase in the risk premium between the British pound and the euro that resulted in the devaluation of the pound. UK listed firms share prices were affected by the depreciation of pound right after Brexit, and investors were expecting an economic downturn or even a recession in the days after the referendum (Breinlich et al., 2018). Sita (2017) mentioned the Brexit day as a day of extreme and showed that the market sentiment – measured as stock, exchange rate and excess residual volatility – damped a U-shaped pattern on portfolio composition due to rational investors that acquired large stocks and floated small stocks.

The close economic, commercial and financial relations and dependency within the European Union made the high volatility in financial markets across the economic bloc an expected result. When analyzing intraday high-frequency data, Nishimura & Sun (2018) showed that the volatility spillover among five major European stock markets first largely increase, then largely decrease, and three months after the Brexit referendum there was no change in volatility patterns among these markets. However, looking at short periods, volatility spillover on the first trading day after the event unexpectedly decrease, but the authors did not investigate what mechanism caused such phenomena.

Li (2020) argued that UK was a net volatility transmitter to other European countries in 2015, but its influence decreased since the Brexit referendum in 2016. The author investigated the volatility relations from five European countries under the uncertainty of Brexit in a multivariate time-varying setting. The results show that Brexit referendum exerted diverse instantaneous impacts on markets interactions during the first five days after the event, although the impacts of referendum result continued to be substantial and persist by day 5.

In the USA, the S&P500 (Standard & Poor's 500 Index) fell by about 2.4%, the yield on the government's 10-year Treasuries fell to its lowest level since 2009, and the VIX Index (volatility measure of S&P500 index) reached its peak for the month of June, evidencing the increase in investor uncertainty regarding the British decision to leave the EU (Wells & Fahey, 2016).

What is striking in this case is that the S&P500 is the stock index measured by the main American exchanges (NYSE, NASDAQ and CBOE), which together are much larger than the London stock exchange. As of October 2022, in market capitalization (in trillion US dollars), the value of the New York Stock Exchange (NYSE) was equal to US$22.11, NASDAQ market cap was US$17.23, while same figure for London Stock Exchange (LSE Group) was US$2.82. Therefore, was there a contagion effect from FTSE100 – which represents the top 100 companies listed on the LSE –, to S&P500, or this joint movement is a result from the growing interdependence among international stock exchange markets?

NYSE and NASDAQ are, respectively, the first and second largest stock exchanges in the world by market capitalization, while the LSE occupies the tenth position, however, they are two important trading exchanges on the world stage. Moreover, according to Walker & Palumbo (2018), in 2016 the USA was the second largest exporter of goods and services to the UK (around £63 billion) and the main destination for British exports (around £100 billion). The main industries that benefit from the dynamic commercial relationship between the two countries are aeronautics, capital goods, pharmaceuticals and automotive. In addition, the UK is the country that leads the flow of foreign direct investment (FDI) in the USA and the second main destination for USA direct investment.

The strong correlation between USA and European stock markets was found by Morana & Beltratti (2006). The authors applied factor model for 1973-2004 daily returns and found evidence of a trend towards an increase in correlation coefficients over time, which was explained by two dominant factors (correlation and volatility). Moreover, it was identified that the positive dependence of correlation is robust, maintaining itself for markets with bullish and bearish trends.

Hui & Chan (2021) examined the Brexit referendum contagion among general equity and securitized real estate markets of the U.K., France, Germany, USA, Hong Kong, and Japan. The study combines the case-resampling bootstrap method with linear regression, skewness, and kurtosis tests. Results showed that there is evidence in favor of contagion, but less significant compared to the median of all bootstrap standard methods. The evidence of contagion becomes even less significant when taking the interquartile mean as the estimator. Besides, the contagion effect is larger for general equity markets than for securitized real estate markets, and considering the countries in the sample, contagion effect was larger for UK, France, Germany, and the US.

In this research, the objective is to apply the definition of "shift-contagion" mentioned for the first time by Forbes & Rigobon (1999) to verify if the effect of Brexit transmission to the US stock market was a result of contagion, or just the continuation of the interdependence between two very representative asset markets in the world. According to the authors, "shift-contagion" is a significant increase in cross-market linkages after a shock occurred in one country, which is different from pre-existing contagion conceptions considered by other.

Shift-contagion definition avoids measures of contagion mechanisms difficult to quantify, as fundamentals transmission, trades, or investors behavior. Although shift-contagion does not indicate which transmission mechanisms are predominant, it provides a straightforward method for contagion test (Forbes & Rigobon, 1999).

Therefore, the contribution to the literature is to focus on a simple measure of contagion, preventing the interdependence effect from being confused with contagion, since the lights are on two relevant financial markets in the world (United States and United Kingdom). Our results are important for portfolio diversification management, as well as for financial supervision and regulation, and complement the results of previous research that identify contagion or strong correlation between the two developed economies.

The tests were performed considering the returns of S&P500 in response to fluctuations in the returns of the FTSE100 index. To verify the contagion, it was applied the Generalized Autoregressive Conditional Heteroscedasticity model, considering Dynamic Conditional Correlation (DCC GARCH), as Forbes & Rigobon (2002) model.

The paper is organized as follows. The next section presents a bibliographic review of contagion literature, focusing in recent results and models. The data and econometric model are described in the third section. Section 4 brings the descriptive statistics of the returns of S&P500 and FTSE100 and model results. Finally, section 5 concludes the research.

## 2 Contagion literature

The financial markets of the United States and England are important indicators of investor expectations about the performance of the global economy. Potential shocks in one of these markets could trigger increases in the volatility of stock exchanges around the world due to the contagion effect between economies.

Pritsker (2001) points out that contagion occurs when the information flows freely between financial markets, leading to oscillations of one market to impact, to a greater or lesser extent, the volatility of the other. When agents receive information, they can try to rebalance their assets portfolio by adjusting the risk-return ratio through hedging or increasing their exposure to a certain risk related to the event. From the uncertainty that a shock causes, markets tend to follow protection strategies independent of macroeconomic fundamentals, reflecting the degree of irrationality that the search for liquidity can cause in the adjustment process between markets during contagion.

There are four contagion channels within the financial markets. The first occurs through correlation, i.e., there are common macroeconomic trends that influence the price of assets among economies, which allow the financial markets to be interconnected. The second is related to agent's response to a given shock based on his/her seek for protection in another market. This may trigger the third channel, which is the cross-market hedging, i.e., the contagion effect is a response from investors to the readjustment of their risk appetite through macroeconomic uncertainties. The last channel refers to contagion due to wealth shocks. In other words, this occurs when an investor changes the assets within its portfolio (basket of currencies, bonds, stocks, etc.) towards other less riskier assets, which can provoke a correlated liquidity shock between assets when the settlement of one position occurs at the expense of another (Kodres & Pritsker, 2001).

However, the change in investors’ risk aversion levels may contribute more to the contagion effect than the agents' financial expectations. An increase in risk perception can lead investors to sell their positions in riskier assets and flow into liquid assets, causing this trend to spread over other markets (Boyer et al., 2006; Dimitriou et al., 2013). The portfolio and risk management are relevant sources of contagion, as wealth constraints are the contagion channel during crisis (Wang et al., 2021).

The change in portfolio risk assets is called safe-haven effect and is more prominent during financial crisis and contagion effect. To address this issue, Chang et al. (2021) performed an empirical analysis to verify the contagion among volatility and safe-haven role of gold in the United States, the United Kingdom, Germany, Australia, and Japan during 2002–2018. The results confirmed that after a financial crisis, the inverted asymmetric effects in the high-volatility regime generally coincide with the safe-haven ability of gold for all countries, indicating that volatility regimes influence the volatility of gold, which has an asymmetric nature.

The increase in global financial markets volatility results in a greater influence on the joint movement of assets during crises. Caporin et al. (2018) analyzed European sovereign shift-contagion using bond yield spreads and concluded that the shift-contagion did not occur in the sample periods considered (2003–2006, Nov. 2008–Nov. 2011, Dec. 2011–Apr. 2013). The research applied a Bayesian quantile regression approach allowing for heteroskedasticity, and US crisis resulted in reduction of the intensity of the propagation of shocks coefficients, which was a surprisingly result. The authors argued that the increases in correlation results from larger shocks and the heteroskedasticity in the data, not from similar shocks propagated with higher intensity across Europe.

Dornbusch et al. (2001) add to the discussion the fact that the transmission of shocks between countries can occur in or out crisis periods, and they are related to movements in exchange rates, stocks, sovereign spreads, and capital flows. According to the authors, there are factors that can worsen the effect of shocks between countries, such as the depth of commercial and financial relations. Investors estimate the impacts of the shock on the bilateral trades, which can deepen the crisis by reducing the capital flow and spread the liquidity to other markets.

According to Ammer & Mei (1996), the abandonment of fixed exchange rates and the relaxation of capital controls increased the volatility in stock market returns significantly over time, both in developed and emerging markets. The covariance of returns between 1957-1972 and 1973-1989 increased from 5.6 to 17.5 and the conditional correlation more than quadrupled in the last period due to the acceleration of the global financial integration process that increased the degree of interdependence between markets.

Connoly & Wang (1998) studied the impact of macroeconomic news on the return and volatility of indices from 1985 to 1996. Applying a conditional volatility GARCH model, the authors identified asymmetries in the impact of volatility of returns of the S&P500, FTSE100 and the Nikkei indices. The impact of the FTSE100 on the S&P500 is ten times the size of the effect of the S&P500 on the FTSE100 index returns for the period. They have pointed out that there are intrinsic factors in the markets, such as economic and corporate news related to companies listed, that can influence the volatility and the joint movements between the indices. However, they argue that macroeconomic news plays a key role in explaining volatility between markets better than returns.

In a joint modelling of contagion, which combines bilateral-based and market-based financial network analyses, considering financial market prices and bank lending, Ahelegbey et al. (2021) argue that both channels explain contagion over countries. The authors show that bilateral-based transmission of shocks is more stable in time, and market-based financial contagion channel is more volatile. The results pointed that equity markets contagion is stronger during financial crises with the US as a leading contributor, while bank lending becomes more relevant in the European sovereign crisis (during and after).

Banks excessive on-balance-sheet liquidity increases systemic risk. Moreover, when banks are deeply connected to each other, the relationship between liquidity creation and systemic risk can be strengthened and illiquidity risk can easily spread to the entire financial system (Zhang et al., 2021). Aligned to this point, Covi et al. (2021) showed that banks specific characteristics are less relevant than banking network structure, however the system shift comes from the non-linear interaction.

Connoly & Wang (1998) and Morana & Beltratti (2006) analyzed the contagion between S&P500 and FTSE100. Connoly & Wang (1998) evaluated the impact of macroeconomic news on the return and volatility of the stock indices and found that those announcements accounted for little impact on the direct return and volatility spillovers in the US, UK, and Japan markets. Morana & Beltratti (2006) estimated the impact of commercial and financial integration in the movements between the stock indices and their results have shown a growing integration process, resulting in the enhancement of comovements in prices, returns, volatility and correlation over time, especially for US and Europe. The model of the present research follows the one proposed by Forbes & Rigobon (2002) to evaluate the contagion from FTSE100 to S&P500, as described in the next section.

## 3 Methodology

In order to evaluate the contagion between FTSE100 and S&P500 returns during the Brexit, it was applied the Generalized Autoregressive Model with Conditional Heteroscedasticity considering Dynamic Conditional Correlation (DCC GARCH).

The chosen model follows the suggestion of Forbes & Rigobon (2002). The authors have shown that the presence of heteroscedasticity in asset price returns is due to changes in the series variance in times of stress and calmness in the financial markets, so there are conditional correlations regardless of the structural transmission of shocks between these assets' changes. For the authors, because the financial series have heteroscedasticity, the calculation of variances is biased and naturally their correlations change over time. Therefore, they indicate the application of the DCC GARCH model to financial series.

Paula (2006) compared several econometric methodologies to identify the presence or absence of contagion between series of indicators, and mentions the following advantages of DCC models: (i) it preserves the parsimony of univariate GARCH models using a time-varying correlation structure; (ii) reduces the order of parameters estimated by maximum likelihood to N, producing more consistent estimates compared to the VEC and BEKK models; (iii) the number of parameters with simultaneous estimation drops to 1.

The GARCH model was first introduced by Robert Engle in 1982 (Engle, 1982) to estimate the variance of UK inflation. This model is indicated for non-linear series, a striking characteristic of financial time series, since they present the evolution of their variances conditioned by time (Morettin & Toloi, 2004). The purpose of statistical modeling is to understand the behavior of the time series when exposed to extreme events or marked volatility in certain time intervals.

DCC models do not aim to directly estimate the conditional covariance matrix, but rather the covariance and the conditional correlation between the variables (Orskaug, 2009). In this specification, the covariance matrix $H_t$ can be decomposed into conditional standard deviations, $D_t$, and a correlation matrix, $R_t$, which varies over time, as showed by Equations 1, 2 and 3.

For Orskaug (2009), considering returns, $a_t$, of each stock index (S&P500 and FTSE100) with an expected value of zero and covariance matrix $H_t$, the DCC model is defined as:

$$r_t = \mu_t + a_t \tag{1}$$

$$\text{at} = H_t^{1/2} z_t \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

Where:

$r_t$: $\mathrm{n} \times 1$ vector of logarithmic returns of each index (S&P and FTSE) at time t;

$a_t$: $\mathrm{n} \times 1$ vector of returns corrected by the mean of n assets at time t, i.e., $E[a_t] = 0$. Cov[$a_t$] = $H_t$;

$\mu_t$: $\mathrm{n} \times 1$ vector of the expected value of conditional $r_t$;

$H_t$: $\mathrm{n} \times \mathrm{n}$ matrix of conditional variances of $a_t$ at time t;

$H_t^{1/2}$: matrix n × n at time t. $H_t$ is the conditional variance matrix of $a_t$. $H_t^{1/2}$can be obtained by a Cholesky factorization of $H_t$;

$D_t$: $\mathrm{n} \times \mathrm{n}$, diagonal matrix of conditional standard deviations of $a_t$ at time t;

$R_t$: $\mathrm{n} \times \mathrm{n}$, matrix of conditional correlation of $a_t$ at time t;

$z_t$: $\mathrm{n} \times 1$ independent and identically distributed error vector, such as $E[z_t] = 0$ e as $E[z_t z_t^T] = I$.

The elements in the diagonal matrix, $D_t$, are the standard deviations of the univariate GARCH models, as indicated by Equation 4.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & 0 & \cdots & 0 \\ 0 & \sqrt{h_{2t}} & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sqrt{h_{nt}} \end{bmatrix} \tag{4}$$

Where: $\boldsymbol{h}_{it} = a_{i0} + \sum_{q=1}^{Q_t} a_{iq}\, a_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{ip}\, h_{i,t-p}$.

Moreover, $R_t$ is the conditional correlation matrix for the standard errors $e_t$: $\boldsymbol{\epsilon}_t = D_t^{-1} a_t \sim N(0, R_t)$, where: $R_t$ is a symmetric correlation matrix.

The components of $H_t = D_t R_t D_t$ are $[H_t]_{ij} = \sqrt{h_{it}} h_{jt} \rho_{ij}$.

Then, $R_t$ can be decomposed into: $\boldsymbol{R}_t = Q_t^{*-1} Q_t Q_t^{*-1}$; where $\boldsymbol{Q}_t = (1 - a - b)\bar{Q} + a\epsilon_{t-1}\epsilon_{t-1}^T + bQ_{t-1}$, and $\bar{Q} = Cov[\epsilon_t \epsilon_t^T] = E[\epsilon_t \epsilon_t^T]$ is the absolute covariance matrix of standard errors $e_t$. It can be estimated as $\bar{Q} = \frac{1}{T} \sum_{t=1}^{T} \epsilon_t \epsilon_t^T$.

The variables $a$ and $b$ are scalars and $Q_t^*$ is a diagonal matrix with the square root of the diagonal elements of $Q_t$. Therefore $Q_0$, i.e., the initial value of $Q_t$, must be positive to guarantee $H_t$ to be defined positive. Then, $Q_t$ must be positive to ensure $R_t$ is defined positively. There are some conditions imposed on parameters $a$ and $b$ to satisfy the condition that $H_t$is positive. Thus, $a$ and $b$ must satisfy the following conditions $\mathrm{a} \geq 0, \mathrm{b} \geq 0$ e $\mathrm{a} + \mathrm{b} < 1$.

The equation that defines the dynamic correlation structure can be extended to the general DCC (m, n) GARCH model as defined in Equation 5:

$$Q = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\overline{Q_t} + \sum_{m=1}^{M} a_m\, a_{t-n} a_{t-n}^T + \sum_{n=1}^{N} b_n\, Q_{t-n} \tag{5}$$

## 4 Data and results

In this section, the data analysis, and the results of the DCC GARCH model will be presented, following the order and structure expressed in Paula (2006).

Database considers daily returns for the S&P 500 and FTSE 100 between 06/25/2013 and 06/30/2019, obtained from Bloomberg database. This period was considered to use three years before and after the Brexit referendum and includes events in the markets of clustered volatility, such as the European debt crisis, which ran from 2011 to 2015, USA presidential election in 2016 and the Brexit negotiations (2016-2019). The data used corresponds to the closing prices of the FTSE100 and S&P500 indices.

There are differences on workdays in the USA and in the United Kingdom. From 06/25/2013 to 06/30/2019, the FTSE100 presented 1521 observations and 1514 S&P500 observations. The non-corresponding dates were discarded, leaving only the workdays presented in the two markets. After adjusting observations, 1470 observations were considered from the two indices (3.35% of data was dropped).

Once data was collected, the statistical software R was used to perform the descriptive statistics of the time series variables, as well as model estimations.

FTSE100 daily returns and the volatility of the index is presented in Figure 1, where more volatile periods are highlighted. The red dashed lines indicate periods of greater stress in the market, while the blue line points out the day after the results of Brexit referendum.

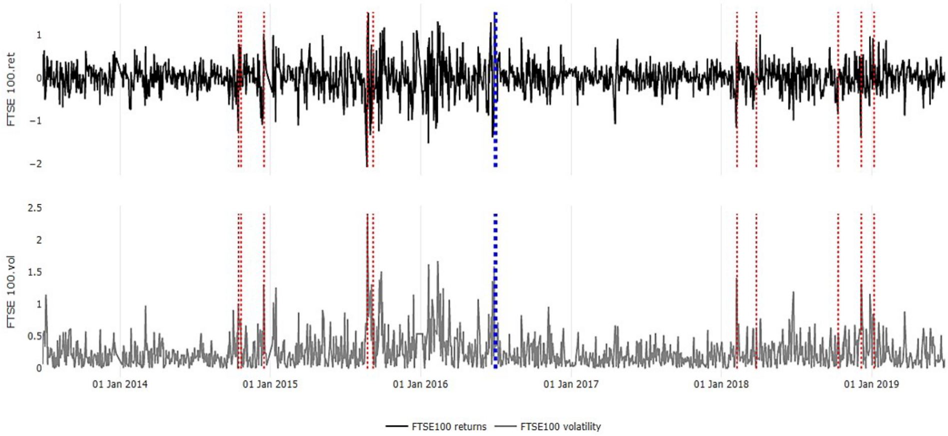


**Figure 1.** FTSE100 returns and volatility (%) from 06/25/2013 to 06/30/2019 (On top: returns; At the bottom: volatility).

In June 2016, the preliminaries, and the official referendum for leaving the EU by the UK took place. Consequently, due to the Brexit effect, the sharp drop in the FTSE100 and S&P500 indices dragged returns downwards causing high volatility and uncertainty for the month of July as well.

Due to the markets short-term response (sharp depreciation of the pound and fall of the FTSE100) the Bank of England (BOE) emergency reduction of the interest rate on an annual basis from 0.5% to 0.25% was a key act in calming the market down. Nonetheless, in the following months there was many sources of uncertainties regarding the Brexit and its impact on the European economy, and whether there would be an agreement by both parties to formalize the leaving. USA endogenous factors, such as the financial volatility created by the presidential election, from July to November 2016, had a greater impact on the North American stock market, while the debate in Europe was based on Brexit unfolds. Figure 2 shows the S&P financial returns. During 2016 there was in increase in S&P volatility, including the Brexit peak highlighted in blue.

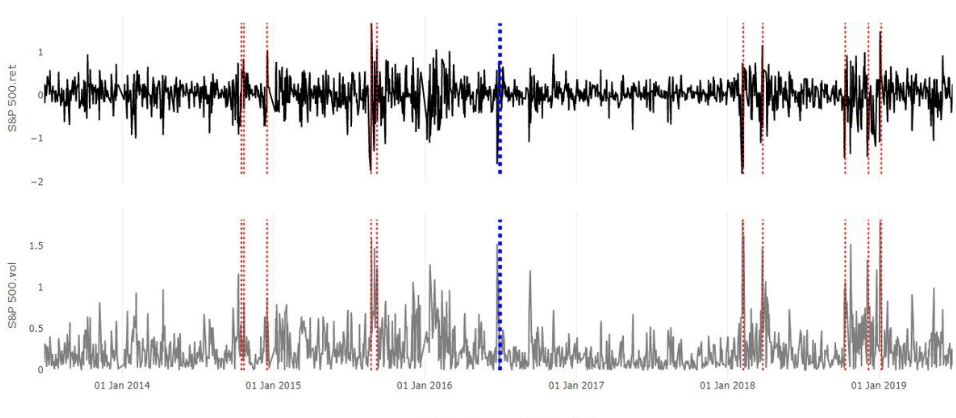


**Figure 2.** SP500 returns and volatility (%) from 06/25/2013 to 06/30/2019 (On top: returns; At the bottom: volatility).

From January 2018 to March 2019 there was an increase in volatility in the S&P500 regarding the FTSE100 due to the uncertainties caused by the beginning of the trade war between China and the USA, whose consequences could negatively impact the returns to the S&P500, since the trade barriers imposed by both countries put the growth of the global economy at risk. Only in March 2019 there was a preliminary agreement signed by both parts aiming to stabilize their trade relations and then to provide a truce to the trade conflict. In sum, as new sanctions and tariffs were imposed by both sides, the returns of the S&P500 proved to be increasingly volatile due to the uncertain environment.

It is needed to emphasize that the FTSE100 from January 2018 to March 2019 also showed negative returns and high volatility due not only to the forementioned reasons, but also because of Brexit negotiation imbroglios. In other words, the disagreement between the British government and the European bloc regarding the costs of the exit increased the risk of a unilateral exit from the British side (Hard Brexit), which kept the uncertainty in European markets up.

To assess the behavior trend of returns between time series, a correlation analysis was made between the S&P500 index and the FTSE100 index. From 06/2/2013 to 06/30/2019 the correlation was 0.51, i.e., moderate. Even though international stock exchanges and investors were apprehensive about the preliminary and official results of the referendum, the forementioned correlation for the period shows that there is no evidence of a contagious effect between the S&P500 index and the FTSE100.

Table 1 shows the descriptive statistics for both indices returns:

**Table 1.** Descriptive statistics.

| **Period** | **25/06/2013 - 30/06/2019** | |
|---|---|---|
| **Indices** | **FTSE100 (%)** | **S&P500(%)** |
| Minimum | -2.07582 | -1.81720 |
| 1º Quartile | -0.19179 | -0.12669 |
| Median | 0.01932 | 0.02200 |
| Mean | 0.00550 | 0.01749 |
| 3º Quartile | 0.19876 | 0.20123 |
| Maximum | 1.52673 | 1.66297 |
| Std. Deviation | 0.36337 | 0.35079 |
| Asymmetry | -0.17757 | -0.59533 |
| Kurtosis | 2.55650 | 3.26560 |

The unit root test indicates rejection of the null hypothesis with 5% significance. Thus, the indices series are stationary. The Augmented Dickey Fuller (ADF) test results in a negative test statistic number: the lower the test statistic, the greater the test evidence to reject the null hypothesis ($H_0$) of the existence of a unit root and therefore the non-presence of stationarity in the time series. The test results are shown in Table 2:

**Table 2.** Augmented Dickey-Fuller test.

| | Dickey Fuller | Lag Order | P-valor |
|---|---|---|---|
| FTSE100 | -11.99554 | 11 | 0.0100** |
| S&P500 | -11.72786 | 11 | 0.0100** |

**1% significance. Both series reject the null hypothesis of the existence of a unit root and therefore the non-presence of stationarity in the time series.

The autocorrelation functions of the logarithmic returns and their squared returns for the FTSE100 and S&P500 indices is in Figure 3. The serial autocorrelation function (ACF) of the index's returns is slightly close to zero for a test with 40 lags, not being statistically significant. However, for the serial correlation of the squared returns, an autocorrelation greater than 0 is found for the first 10 lags. Although the autocorrelation is small, it is statistically significant and, therefore, it was necessary to perform a data filtering process.

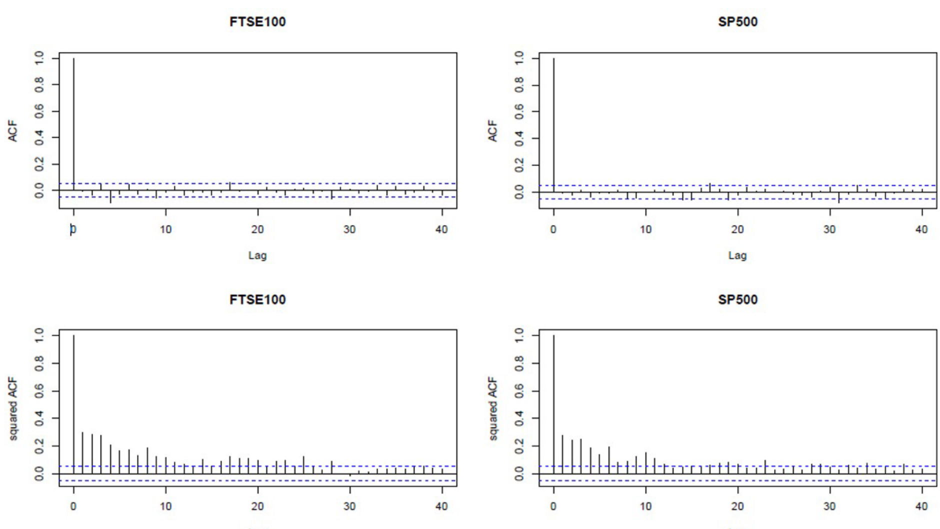


**Figure 3.** Returns and squared returns autocorrelation function (ACF) for the FTSE100 and S&P500 indexes.

For this purpose, two AR [AR(1) and AR(2)] and four ARMA [ARMA (1,1), ARMA (1,2), ARMA (2,1) and ARMA (2,2)] filters were performed for each time series of the specified indices. As the filtering process, the target was to obtain the average of the residual closest to zero. The models with the best mean-effect were AR(1) for FTSE100 and AR(2) for S&P500.

Table 3 shows the descriptive statistics of residual from the filtering process. Note that the extreme values (maximum and minimum) remained practically stable in comparison with the descriptive statistics before filtering. Likewise, small variations were seen for asymmetry, kurtosis, and standard deviation, but none were significantly important.

**Table 3.** Descriptive statistics of time series after the filtering process.

| | **FTSE100 AR(1)** | **S&P500 AR(2)** |
|---|---|---|
| Minimum | -2.09014 | -1.84114 |
| 1º Quartile | -0.19816 | -0.14486 |
| Median | 0.01469 | 0.00489 |
| Mean | 0.00000 | -0.00000 |
| 3º Quartile | 0.19093 | 0.18586 |
| Maximum | 1.52918 | 1.60056 |
| Std. Deviation | 0.36336 | 0.35069 |
| Asymmetry | -0.18377 | -0.62186 |
| Kurtosis | 2.55940 | 3.25585 |

Figure 4 depicts the autocorrelation functions of residuals and the squared residuals after the filtering process. Even after the filtering process there was little change related to Figure 3. The FTSE100 autocorrelation function of the residual had slightly decreased while the S&P500 remained stable, mainly in the first lags (filtering objective). In the autocorrelation function of squared residuals, even after the filtering process, no significant change was evidenced.

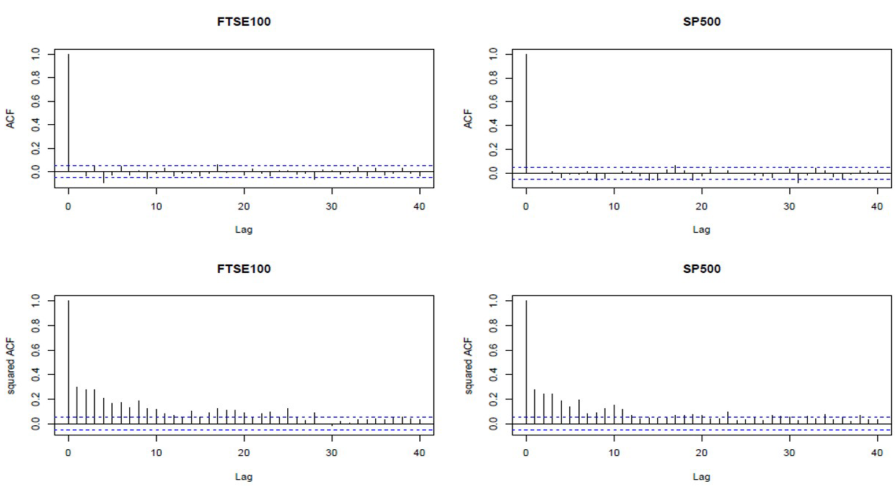


**Figure 4.** Returns and squared returns autocorrelation function (ACF) for the FTSE100 and S&P500 indices after the filtering process.

Therefore, estimations for FTSE100 and S&P500 were, respectively:

$$r_t = \emptyset_0 + \emptyset_1 r_{t-1} + \epsilon_t \quad (6)$$

$$r_t = \emptyset_0 + \emptyset_1 r_{t-1} + \emptyset_2 r_{t-2} + \epsilon_t \quad (7)$$

Where $\epsilon_t \sim N(0,1)$.

Table 4 presents the estimated results for the parameters of Equations 6-7. To estimate the following models, only the filtered data was considered.

**Table 4.** Filtered parameters and variances estimations for AR (1) and AR (2).

| | FTSE100 AR(1) | S&P500 AR(2) |
|---|---|---|
| $\hat{\phi}_0$ | 0.00550 | 0.01749 |
| $\hat{\sigma}^2_{\phi 0}$ | 0.00068 | 0.00008 |
| $\hat{\phi}_1$ | -0.00705 | -0.00568 |
| $\hat{\sigma}^2_{\phi 1}$ | 0.00009 | 0.00068 |
| $\hat{\phi}_2$ | - | -0.02350 |
| $\hat{\sigma}^2_{\phi 2}$ | - | 0.00068 |

Given the results of Table 4, it was considered the following model specifications for the FTSE100 and S&P500 returns: DCC GARCH (1,1), DCC GARCH (2,1), DCC GARCH (1,2) and DCC GARCH (2,2).

Akaike (AIC) and Bayes (BIC) criteria for specification testes were carried out and the results are reported in Table 5. There was no conflict between the results, and the DCC GARCH (1,1) specification had the best information criteria according to the Akaike and Bayesian criteria in relation to the others.

**Table 5.** Akaike (AIC) and Bayes (BIC) specification tests*.

| Model | Parameters | Akaike | BIC |
|---|---|---|---|
| DCC (1,1) | 13 | 0.82157 | 0.86837 |
| DCC (1,2) | 14 | 0.82286 | 0.87327 |
| DCC (2,1) | 14 | 0.82293 | 0.87334 |
| DCC (2,2) | 15 | 0.82422 | 0.87823 |

*GARCH models with normal distribution and 1470 observations. The lowest values of the estimates of the BIC and AIC specification tests indicate that the DCC GARCH (1,1) specification had the best information criteria.

The Table 6 shows the parameters estimation for the DCC GARCH (1,1). The t-test shows that the model is well specified.

**Table 6.** DCC GARCH (1,1) estimation.

| Parameters | Estimative | Std. Error | t-test | P-value |
|---|---|---|---|---|
| FTSE100ω | 0.00880 | 0.00317 | 2.77121 | 0.00558* |
| FTSE100α | 0.13682 | 0.03112 | 4.39658 | 0.00001* |
| FTSE100β | 0.79268 | 0.04813 | 16.46866 | 0.00000* |
| S&P500ω | 0.00838 | 0.00242 | 3.45633 | 0.00054* |
| S&P500α | 0.17584 | 0.03586 | 4.90321 | 0.00000* |
| S&P500β | 0.75766 | 0.03930 | 19.27448 | 0.00000* |
| ρ1 | 0.00263 | 0.00211 | 1.24359 | 0.21364 |
| ρ2 | 0.99224 | 0.00682 | 145.38229 | 0.00000* |

*Significant at 1%. All variables are statistically significant.

The Table 7 stresses out the descriptive statistics for the standardized residuals of the DCC GARCH (1,1). It is necessary to emphasize that the date of occurrence of the minimum values of the residuals for the S&P500 was on 10-10-2018 and for the FTSE100 was on 04-18-2017. On the other hand, the maximum values of the residuals were found for the S&P500 on 07-11-2016 and for FTSE100 on 02-09-2016. Besides that, the residuals of the S&P500 had a slightly heavier tail on the left regarding to the FTSE100 residuals which also had a slightly asymmetric tail. In terms of the curve's flattening (kurtosis), the S&P500 had a curve closer to the shape of a normal distribution, while the FTSE100 still had a more flattened (platykurtic) distribution function.

**Table 7.** DCC GARCH (1,1) residuals descriptive statistics.

| | **S&P500** | **FTSE100** |
|---|---|---|
| Minimum | -6.37936 | -4.87454 |
| 1º Quartile | -0.51668 | -0.59042 |
| Median | 0.03340 | 0.02061 |
| Mean | -0.00896 | -0.02102 |
| 3º Quartile | 0.56780 | 0.57540 |
| Maximum | 3.37933 | 3.84937 |
| Std. Deviation | 0.99706 | 1.00244 |
| Asymmetry | 2.95997 | 1.32373 |
| Kurtosis | -0.78235 | -0.27844 |

The adequacy of the model was tested using the Ljung-Box test. The null hypothesis is the absence of the serial correlation in the residuals and in its squared residuals. Table 8 shows that the null hypothesis was rejected for all residuals and its squared residuals for the FTSE100 and S&P500 indices at 1% and 5% significance. This means that the model may not be effective in eliminating the serial correlation of the residual returns and their respective squared ones.

**Table 8.** Ljung-**Box for** the residuals of the DCC GARCH model (1,1) and the squared residuals, with a maximum of 20 lags.

| | **Residuals** | | **Squared residuals** | |
|---|---|---|---|---|
| | **Statistic** | **P-value** | **Statistic** | **P-value** |
| S&P500 | 42.02672 | 0.00274* | 578.12240 | 2.2e-16* |
| FTSE100 | 43.60160 | 0.00170* | 766.26090 | 2.2e-16* |

*Significant at 1%. Ljung-Box null hypothesis was rejected at 1% significance level for both variables.

Then for the model specification tests, heteroscedasticity (Breusch-Pagan), residual autocorrelation (Durbin-Watson) and the lagged variable factor (regression of the S&P500 against its previous lag) were performed. Based on Table 9, the Breusch-Pagan test for heteroscedasticity pointed out that there was evidence of this specification problem with 1% significance (rejection of the null hypothesis of absence) for the residuals regarding the standardized residuals. As for the residuals autocorrelation test, the Durbin-Watson test did not provide enough evidence to reject the null hypothesis (presence of residual autocorrelation). The previous variable's lag factor test pointed out that there is no evidence to reject the hypothesis that the lagged variable of the residuals has explanatory power over its previous one. In short, adopting a significance of 5%, the model presents specification problems with respect to heteroscedasticity and autocorrelation. This indicates that the DCC model was able to explain the heteroscedasticity and residual autocorrelation present in the series.

The test results are shown in the following table:

**Table 9.** Specification tests for the DCC GARCH (1,1) residuals.

| | **Residuals** | | **Standardized residuals** | |
|---|---|---|---|---|
| | **Statistic** | **P-value** | **Statistic** | **P-value** |
| Breusch-Pagan | 6.93203 | 0.00846* | 1.38246 | 0.23968 |
| Durbin-Watson | 2.22153 | 0.99998 | 2.07777 | 0.93233 |
| Lagged S&P500 | 1.96991 | 0.04903** | -1.35676 | 0.17506 |

*Statistic rejected at 5% of significance. **Statistic rejected at 1% significance. Breuch-Pagan null hypothesis of absence of heteroscedasticity was rejected at 1% significance level. Durbin-Watson statistic will always have a value ranging between 0 and 4: values below 2.0 mean there is positive autocorrelation and above 2.0 indicates negative autocorrelation. Lag Factor Test null hypothesis of lagged residuals has explanatory power over its previous one was rejected at 5% significance level.

Finally, it was necessary to analyze the volatility between the returns of the FTSE100 and S&P500 indices based on the dynamic conditional correlation model. In Figure 5, it is possible to note that there was a more pronounced volatility conglomerate during the week of the Brexit referendum, and it reached a mark higher than 0.8% on the business day following the voting result (June 27, 2016).

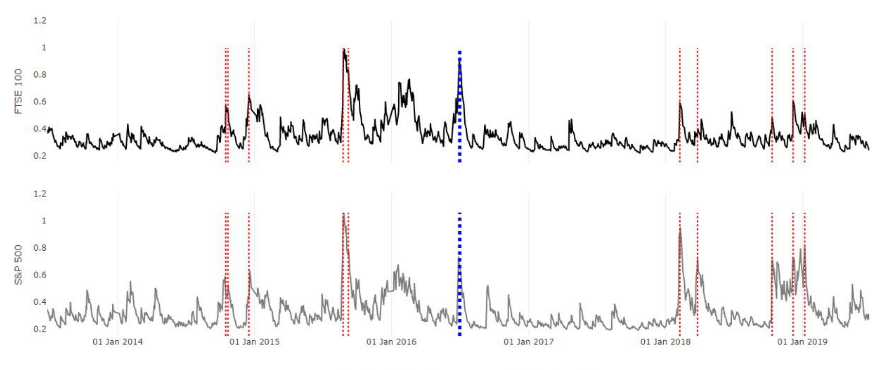


**Figure 5.** DCC GARCH (1,1) dynamic conditional volatility for the S&P500 and FTSE100 indexes.

In Figure 6, following the line of the most accentuated conditional volatility it is found that on the day after the referendum, the covariance also increased and reached the second highest mark in the time series with 0.35. It is necessary to stress out that in the weeks following Brexit, the BOE applied an expansionary monetary policy to reduce volatility in the market and therefore calm down the investors euphoria. Then, is possible to observe a significant reduction in the series volatility in the second half of 2017.

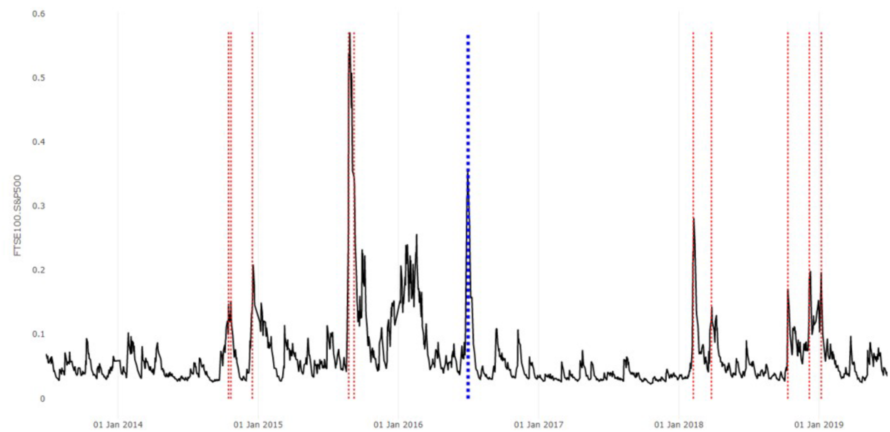


**Figure 6.** DCC GARCH (1,1) dynamic conditional covariance for the S&P500 and FTSE100 indexes.

To identify the presence or absence of shift-contagion in the returns of the S&P500 index by the FTSE100, it is necessary to observe the dynamic and accumulated conditional correlation matrix modelled by the DCC GARCH (1,1). Through the analysis of Figure 7, the dynamic conditional correlation of the time series reached its peak in the Brexit event (0.57) and decreasing after that. If we use the concept of shift-contagion expressed by Forbes & Rigobon (2002), contagion is defined by the relevant increase in correlations in periods of crisis, it is noted that there was no evidence of contagion between the S&P500 and FTSE100 index during Brexit, in spite of the fact that it can be observed an increase in dynamic conditional correlation.


**Figure 7.** DCC GARCH (1,1) Dynamic and Cumulative Conditional Correlation for the S&P500 and FTSE100 indexes.

To investigate the increase in the conditional correlation between the two indicators on the date of the event, the Granger Causality test was performed. The objective of the causality test if to verify whether it can be stated that the FTSE100 granger-causes the S&P500 in the period analyzed for Brexit. The term “Granger-causes” means that knowing the value of FTSE100 time series is useful to predict the value of S&P500 time series at a later time period. With 1 lag, 1473 observations, the F-statistic value is 2.9607, and P-value (Pr>F) equal to 0.08552, so the null hypothesis cannot be rejected, indicating that FTSE100 returns do not Granger-cause S&P500, corroborating with previous results.

The global results indicate that there was no evidence of shift-contagion between the two markets during the Brexit period, however, it is possible to observe the presence of a moderate increase in the conditional correlation during the Brexit referendum. This contrasts with the results of Hui & Chan (2021), which can be explained by different methodologies, or by the high interdependence between the two asset markets, which can result in a positive contagion test depending on the definition of contagion.

## 5 Conclusion

The volatility in financial markets is an important thermometer for investors over market expectations. The sell-off movement arising from the Brexit event spread over other financial markets in a response to the insecurity about the future on the United Kingdom and Europe.

This research investigated the contagion between S&P500 and FTSE100, two very important stock exchange markets in the world, due to Brexit. Many studies have investigated the occurrence of contagion between economies in the same geographic region, same economic bloc or even contagion from developed economies to other developing ones. In this research, contagion was investigated between two major world economies, whose financial markets are among the most important in terms of market value and number of transactions.

There are few studies that have analyzed the contagion effect between the US and London stock markets. Relationships were found between the movements of stock indices in these markets and, specifically for Brexit, Hui & Chan (2021) showed evidence in favor of the contagion effect.

However, it is expected a strong interdependence between these two relevant worldwide stock markets. Therefore, in this research we tested for the existence of contagion applying the concept defined by Forbes & Rigobon (1999), called “shift-contagion”. It is a simple measure that identifies the transmission of financial crises from one region to another by the increasing the correlation between asset prices in periods of crisis.

It was tested the contagion from FTSE100 to S&P500 by a DCC GARCH model for the from 25-06-2013 to 30-06-2019. The DCC GARCH (1,1) was efficient to measure fluctuations and volatility clusters between the returns of the S&P500 and FTSE100 indexes, and the results showed that there was no evidence of contagion between the two markets during the Brexit period, however, it is possible to observe the presence of a moderate increase in conditional correlation during the Brexit referendum month.

The results indicate that there was no relevant change in the correlation between the two stock indices. As these are two very representative stock markets in the world, it can be inferred that the international diversification of assets between the two markets can be effective and bring gains to the portfolios, but they may not be good assets for risk protection between the markets. For international regulatory institutions, the interdependence observed before the crisis did not change significantly, indicating that policies to protect developed markets in times of crisis can be predictable in relation to the structure of dependence between markets.

Future research may apply other contagion definition and econometric tests as an attempted to identify possible channels for contagion between the two stock markets.

## References

Ahelegbey, D. F., Giudici, P., & Hashem, S. Q. (2021). Network VAR models to measure financial contagion. *The North American Journal of Economics and Finance*, 55, 101318. http://dx.doi.org/10.1016/j.najef.2020.101318.

Allen, K., Treanor, J., & Goodley, S. (2016). *Pound slumps to 31-year low following Brexit vote*. Retrieved in 2020, October 16, from https://www.theguardian.com/business/2016/jun/23/british-pound-given-boost-by-projected-remain-win-in-eu-referendum

Ammer, J., & Mei, J. (1996). Measuring international economic linkages with stock market data. *The Journal of Finance*, 51(5), 1743-1763. http://dx.doi.org/10.1111/j.1540-6261.1996.tb05224.x.

Boyer, B. H., Kumagai, T., & Yuan, K. (2006). How do crises spread? Evidence from accessible and inaccessible stock indices. *The Journal of Finance*, 61(2), 957-1003. http://dx.doi.org/10.1111/j.1540-6261.2006.00860.x.

Breinlich, H., Leromain, E., Novy, D., Sampson, T., & Usman, A. (2018). The economic effects of Brexit: evidence from the stock market. *Institute for Fiscal Studies*, 39(4), 581-623. http://dx.doi.org/10.1111/1475-5890.12175.

Caporale, G. M., Gil-Alana, L., & Trani, T. (2018). Brexit and uncertainty in financial markets. *International Journal of Financial Studies*, 6(1), 21. http://dx.doi.org/10.3390/ijfs6010021.

Caporin, M., Pelizzon, L., Ravazzolo, F., & Rigobon, R. (2018). Measuring sovereign contagion in Europe. *Journal of Financial Stability*, 34, 150-181. http://dx.doi.org/10.1016/j.jfs.2017.12.004.

Chang, M.-S., Kung, C.-C., Chen, M.-W., & Tian, Y. (2021). Volatility regime, inverted asymmetry, contagion, and flights in the gold market. *Pacific-Basin Finance Journal*, 67, 101522. http://dx.doi.org/10.1016/j.pacfin.2021.101522.

Connoly, R. A., & Wang, F. A. (1998). Economic news and stock market linkages: evidence from the U.S., U.K., and Japan. In *Proceedings of the Second Joint Central Bank Research Conference on Risk Management and Systemic Risk* (pp. 2-31). Tokyo: The Bank of Japan. Retrieved in 2020, April 5, from https://www.researchgate.net/publication/254745273_Economic_News_and_Stock_Market_Linkages_Evidence_from_the_US_UK_and_Japan

Covi, G., Gorpe, M. Z., & Kok, C. (2021). CoMap: mapping contagion in the Euro area banking sector. *Journal of Financial Stability*, 53, 100814. http://dx.doi.org/10.1016/j.jfs.2020.100814.

Davies, A., Jones, H., & MacAskill, A. (2017). *How Brexit is set to hurt Europe's financial systems*. Retrieved in 2020, February 23, from https://www.reuters.com/investigates/special-report/britain-europe-cost/

Dimitriou, D., Kenourgios, D., & Simos, T. (2013). Global financial crisis and emerging stock market contagion: a multivariate FIAPARCH–DCC approach. *International Review of Financial Analysis*, 30, 46-56. http://dx.doi.org/10.1016/j.irfa.2013.05.008.

Dornbusch, R., Park, Y. C., & Claessens, S. (2001). Contagion: why crises spread and how this can be stopped. In S. Claessens & K. J. Forbes (Eds.), *International financial contagion* (pp. 19-42). New York: Springer.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, 50(4), 987-1007. http://dx.doi.org/10.2307/1912773.

Forbes, K., & Rigobon, R. (1999). Measuring contagion: conceptual and empirical issues. In S. Claessens & K. J. Forbes (Eds.), *International financial contagion* (pp. 43-66). New York: Springer.

Forbes, K., & Rigobon, R. (2002). No contagion, only interdependence: measuring stock market co-movements. *The Journal of Finance*, 57(5), 2223-2261. http://dx.doi.org/10.1111/0022-1082.00494.

Howarth, D., & Quaglia, L. (2017). Brexit and the single European financial market. *Journal of Common Market Studies*, 55, 149-164. http://dx.doi.org/10.1111/jcms.12589.

Hui, E. C. M., & Chan, K. K. K. (2021). New test of contagion with application on the Brexit referendum. *Physica A*, 564, 125474. http://dx.doi.org/10.1016/j.physa.2020.125474.

Kodres, L. E., & Pritsker, M. (2001). *A rational expectations model of financial contagion*. Washington, D.C.: Federal Reserve Board. Federal Reserve Board Working Paper.

Li, H. (2020). Volatility spillovers across European stock markets under the uncertainty of Brexit. *Economic Modelling*, 84, 1-12. http://dx.doi.org/10.1016/j.econmod.2019.03.001.

Morana, C., & Beltratti, A. (2006). Comovements in international stock markets. *International Centre for Economic Research*, 3, 1-29.

Morettin, P. A., & Toloi, C. M. C. (2004). *Análise de séries temporais*. São Paulo: Edgard Blucher.

Nishimura, Y., & Sun, B. (2018). The intraday volatility spillover index approach and an application in the Brexit vote. *Journal of International Financial Markets, Institutions and Money*, 55, 241-253. http://dx.doi.org/10.1016/j.intfin.2018.01.004.

Orskaug, E. (2009). *Multivariate DCC-GARCH model-with various error distributions* (Master's thesis). Department of Mathematical Sciences, Norwegian University of Science and Technology, Trondheim. Retrieved in 2020, August 23, from https://ntnuopen.ntnu.no/ntnu-xmlui/bitstream/handle/11250/259296/724505_FULLTEXT01.pdf?sequence=2&isAllowed=y

Paula, J. F. (2006). *Contágio em mercados financeiros emergentes* (Master's thesis). Instituto de Matemática, Estatística e Computação Cientifica, Universidade Estadual de Campinas, Campinas. http://dx.doi.org/10.47749/T/UNICAMP.2006.363053.

Pritsker, M. (2001). The channels for financial contagion. In S. Claessens & K. J. Forbes (Eds.), *International financial contagion* (pp. 67-95). New York: Springer.

Sita, B. B. (2017). Volatility patterns of the constituents of FTSE100 in the aftermath of the U.K. Brexit referendum. *Finance Research Letters*, 23, 137-146. http://dx.doi.org/10.1016/j.frl.2017.02.011.

Walker, A., & Palumbo, D. (2018). *The UK-US trade relationship in five charts*. Retrieved in 2020, May 17, from https://www.bbc.com/news/business-44802666

Wang, H., Yuan, Y., Li, Y., & Wang, X. (2021). Financial contagion and contagion channels in the forex market: a new approach via the dynamic mixture copula-extreme value theory. *Economic Modelling*, 94, 401-414. http://dx.doi.org/10.1016/j.econmod.2020.10.002. PMid:33071422.

Wells, N., & Fahey, M. (2016). *The US company being hit hardest by brexit vote*. CNBC. Retrieved in 2020, May 17, from https://www.cnbc.com/2016/06/24/the-us-companies-being-hit-hardest-by-brexit-vote.html

Zhang, X., Fu, Q., Lu, L., Wang, Q., & Zhang, S. (2021). Bank liquidity creation, network contagion and systemic risk: evidence from Chinese listed banks. *Journal of Financial Stability*, 53, 100844. http://dx.doi.org/10.1016/j.jfs.2021.100844.

**Authors contribution:**

Data collection was coordinated by Matheus Gomes, as well as data analysis and theoretical-methodological approach. Maria Paula Vieira Cicogna worked on the conceptualization and theoretical. All authors worked together in the writing and final revision of the manuscript.