ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Bachelor Thesis [IBEB]

Can the UK Economic Policy Uncertainty predict the EU stock market?

Study on the aftermath of the first Brexit referendum.

Date final version: 10-06-2020

Name student: Yuzhe Chen

Student ID number: 474827

Abstract

This paper analyses the predictability of the economic policy uncertainty (EPU) in the UK before and during the first Brexit referendum in forecasting the financial market movements in the EU. The study is designed to provide investors on the European market with more insightful information whether the political factors in the UK need to be counted as a crucial point when making investment decisions on the EU financial market. The basic forecasting models of European stock price indices are built according to the Autoregressive Integrated Moving Average (ARIMA) structure. By comparing the out-of-sample R-squared, the forecasting ability of the models with- or without the UK EPU is investigated and compared. It is found that the inclusion of British EPU as an explanatory factor effectively improves the forecasting results of European stock price index at a general level. Around a 2% increase in the R-squared is observed when the factor of the UK EPU is considered. More specifically, the most influenced one is DAX index on Frankfurt stock exchange while other markets including those in France and Belgium are not significantly affected by the UK EPU. Overall, the British political economic factor after the Brexit event should be counted as an important issue when building the investment strategy on the European market.

1. Introduction

The Brexit, claim of the UK leaving the European Union (EU), has raised immense attention throughout the last few years. The prolonged process beginning in late June 2016 finally came to an end on the 31st Jan 2020, meaning the official departure of the UK from the EU. Despite leaving Europe, the UK still needs to follow the EU regulation until the end of 2020 (BBC News, 2020). It is reasonable to consider that the Brexit event cast much influence on the political and economic environment. Evidently, economic policy-related factors have generated intensive financial crisis globally, such as those serial crises in the EU (Baker, Bloom, and Davis, 2016).

Intuitively, several pieces of research have been conducted regarding stock market trends during the first Brexit referendum. The linkage between the EU stock market and the uncertainty resulting from the Brexit can be significant (Bohdalova and Greguš, 2017). The negative initial price movement on particular financial markets in the EU can be explained by the fears of economic downturn and depreciation of British ponds right after the referendum (Breinlich, Leromain, Novy, Sampson, and Usman, 2018). Apparently, the potential departure of British community triggered many political and economic uncertainties, which can cause the variations in the investing pattern. Generally, it cost four years for Brexit to reach its final stage followed by a transitional period undergoing now. Intensified policy-related economic uncertainty leads to an unsolved question whether it significantly affects the Eurozone financial indices within and after the lengthy Brexit event. Former research has generally investigated the causal relationship between these two factors during the first Brexit referendum. To advance, this study aims at investigating whether the European financial market indices can be forecasted by the uncertainty before and after the first-round Brexit referendum in the UK. Thus, the central research question of this paper is constructed:

How well can the British economic policy uncertainty predict the EU stock market indices from Jun 2017 to Jan 2020?

The European stock market indices selected compose of three country-specific indices, namely, CAC 40 index (France), BEL20 index (Belgium), DAX index (Germany), and S&P Europe 350 index in the general European market level. The economic policy uncertainty is presented by the economic policy uncertainty (EPU) index in the UK and EU from the daily-renewed dataset provided by Baker, Bloom, and Davis (2016). Past EPU data before and after one year of the first-round UK-EU exit negotiation is used to forecast the future stock performance on the EU market thereafter until recent.

Inspired by the prediction model built by Li, Balcilar, Gupta, and Chang (2016) and the positive correlations between the UK EPU and major European stock market indices claimed by Bohdalova and Greguš (2017), this paper is made to focus on two sub-questions. Firstly, it investigates whether the EPU of European countries is effective in forecasting the EU stock price indices. Secondly, further prediction models with additional UK EPU factors are built to investigate the question whether the British policy-related economic uncertainty during the Brexit can give a better prediction of stock price variations in the EU. Compared with statistics applied in previous studies, an up-to-date monthly dataset is used to measure the process of Brexit until recent. Instead of using the quantile regression model that presents the in-sample relationships, the causality relation is built under the Autoregressive Integrated Moving Average (ARIMA) model. From scientific aspects, this study examines the ability of the EPU index in the UK in forecasting the European stock price indices in the future. The progressive ARIMA models provide evidence whether the British EPU has an effective role in influencing the trend on the European financial market. Differing from previous studies, forecasting models with- and without the UK EPU are compared both in the country level (France, Germany, and Belgium) and union level (EU), giving more insightful predictions of the national stock trading. Meanwhile, this study is socially relevant since it gives useful information for investors on the European stock market to what extend the economic policy-related factors in the UK need to be considered to make investments.

In the rest of this paper, the literature relevance behind the relation between policy-related economic factors and stock market movements will be deliberated first. Then, the data and methodology sections are to be demonstrated respectively to give a clear presentation of forecasts, followed by the demonstration and interpretation of the results. Lastly, the conclusion, together with the limitations of this research will be elaborated.

2. Literature Review

Research surrounding the EPU and stock returns have been made frequently on global markets. Since Baker, Bloom, and Davis initially uncovered the definition of EPU to the public, the correlation studies between the EPU index and stock market volatility or return has been a heated research topic (Liu and Zhang, 2015). Pioneers like Mensi et al. (2014) included the US EPU as an influential global factor to examine its interdependence with the emerging financial markets in the BRICS countries. Furthermore, Ko and Lee (2015) found the relationship between the US EPU and stock price both in time length and frequency aspects. Empirical results from their wavelet analysis showed that the EPU and stock price are negatively related. A cohesive conclusion was also found in the study made by Arouri et al. (2016), who claimed the increase in the EPU reduces the stock market returns in the US significantly. Additionally, the effect turned out to be stronger and more persistent when extreme volatility exists. In the same manner, Bohdalova and Greguš (2017) researched the impact of Brexit on the EU equity markets by referring to the EPU index during the Brexit referendum as Brexit uncertainty. Both Mensi et al. (2014) and Bohdalova and Greguš (2017) applied quantile regression but discovered opposite relations. The latter argued that the daily data indicates the positive correlation between the selected EU stock price and Brexit EPU index. Adding more complications, a recently written report by Ringe (2018) showed the negligible role of Brexit event on the financial market via analysing the past examples in the European financial market integration. Ideas about the implications of EPU and stock price relations in different countries and regions diversify, representing that EPU indicates the area-specific characteristics of economic and political factors.

The development of correlation analysis, revealing contradictory relationships circumstanced to regional policy-related economic characteristics, led to a boom of studies concentrating on the predictability of EPU in forecasting stock return or volatility. The accuracy of out-of-sample prediction generally determines whether the EPU-based model can be effectively implemented by investors in the future. Liu and Zhang (2015) researched on the out-of-sample forecast of stock market volatility in the US predicted by the American EPU. Advancing the previous trial conducted by Pastor and Veronesi (2012) in correlation analysis between volatility and EPU, they built an ARMA forecasting model of volatility using the US EPU. Lately, the study proposed by Mei et al. (2018) furthermore explored whether the US EPU contributes to predicting the European stock market indices. Results showed that the European EPU itself cannot provide an accurate prediction of a stock price index, but the predicting model is significantly improved through adding the US EPU as an independent variable. This research offered a potential of the advancement of current forecasting model investigated by considering the EPU in another region as an additional explanatory factor in predicting European market indices.

As indicated by the report of Bohdalova and Greguš (2017), the policy-related uncertainty in the UK during the 2016 first-round Brexit referendum exerted a substantial influence on the European stock market. However, reactions of global stock markets to the Brexit referendum vary, determining the aftermath of Brexit process, especially after the first-round referendum, is still unpredictable (Amewu, Mensah, and Alagidede, 2016). Indeed, the impact of Brexit has persisted since 2016, which implies that the dataset at that moment was not sufficient for post Brexit referendum studies of the performance of the UK EPU in predicting the European stock market indices during the later part and after Brexit. Whereas, with the latest information available from the EU stock price and recently summarized EU and the UK EPU, the full blueprint of the forecasting ability of UK EPU (including the most influential part of Brexit) can be investigated. According to previous research outcomes (Liu and Zhang, 2015; Bohdalova and Greguš, 2017; Mei et al., 2018), it is logical to assume the economic policy in the UK during the Brexit can effectively help predict trends on the European financial market. In fact, the UK EPU remained significantly large before the first-round UK-EU exit negotiation in June 2017 (Centre for European Reform, 2020). Thus, the European stock market performance in the latter part of Brexit process and after the Brexit possibly rely on British EPU.

3. Data

In this section, the financial data and policy-related uncertainty statistics are described. Considering forecasting models for the EU as a whole and for countries that were most influenced by the Brexit process, financial indices collected are CAC 40 index, BEL 20 index, DAX index, and S&P Europe 350 index.

S&P Europe 350 index is part of the S&P Global 1000 Index and consists of 350 leading blue-chip companies form 16 developed European financial markets. CAC 40 index is the benchmark French stock market index which represents the 40 most significant stocks among the top 100 market caps on the Euronext Paris Exchange. BEL 20 index is also constructed by the Euronext group and consists of 10 to 20 companies traded on Brussel Stock Exchange. DAX index that measures the performance of the Germany stock market consists of 30 major Germany corporations on the Frankfurt Stock exchange. All stock indices are constructed using the capitalization-weighted method. According to the research purpose of this paper, monthly indices statistics from 31st May 2000 to 31st Jan 2020 are extracted from the Compustat database through Wharton Research Data Services (WRDS) platform. In particular, the data for DAX index from 31st May 2000 to 30th June 2006 is missing, which causes fewer samples for the Germany stock price performance. Generally, 237 data points are gathered for each index except for DAX index (163 data points). Statistics from 31st May 2000 to 31st May 2016 (Except for DAX: 30th Jun 2006 to 31st May 2017) are treated as test samples. Thus, the sample size for forecast model formation is 205 (Except for DAX: 131).

Statistics about the EPU are provided by the datasets constructed by Backer, Bloom, and Davis (2016). The UK monthly EPU index is measured based on the newspaper articles concerning the policy uncertainty. 11 UK newspapers are measured in counting the frequency of economic- and policy-relevant words like ‘uncertainty’, ‘policy’, ‘tax’, ‘budget’, deficit, etc. In a similar scenario, the EU EPU, France EPU and Germany EPU are obtained. Since there is no measurement for Belgium EPU, the forecasting model for Belgium stock price uses the EU EPU only. The total number of data points for the obtained EPU indices is 237. The sample size used for building forecasting models is 205 (Except for DAX: 131), matching the sample size of monthly summarized stock market indices under examination.

Table 1: Descriptive statistics for stock market indices and EPU in May 2000 - Jan 2020.

	Observation	**Minimum**	**Maximum**	**Mean**	**Std. Dev.**
CAC40 Index	237	2618.46	6625.42	4428.41	2086.77
DAX Index	163	444.10	3066.61	1375.17	757.31
Belgium20 Index	237	1635.22	4697.86	3055.436	712.08
S&PEurope350 Index	237	719.72	1676.79	1264.17	247.81

EPUFR	237	23.92	574.63	182.55	99.36
EPUDE	237	28.43	454.01	138.29	65.80
EPUEU	237	47.69	433.28	154.36	67.43
EPUUK	237	719.72	1676.79	1264.17	247.81

All the indices are evaluated in the same period except for DAX Index. The absolute value of the indices varies, but the relative changes will be considered in the following section in the form of return. Figure 1 presents the variations of four target indices during the sample timeline. Clearly can be seen that the France index followed a very similar pattern as Belgium 20 index.

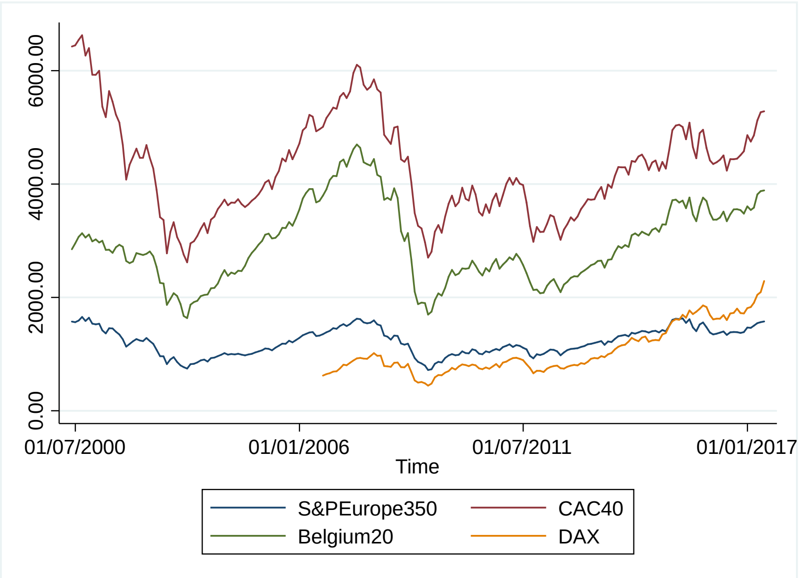


Figure 1 Time plots of CAC 40 index, BEL 20 index, DAX index, and S&P Europe 350 index, 30th Jun 2000 - 31st May 2017.

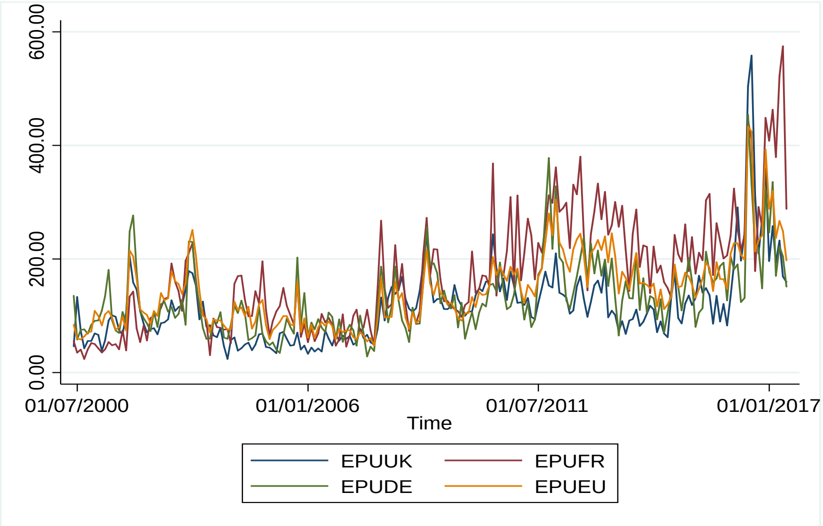


Figure 2 Time plots of EPU in the UK, the EU, France, Belgium and Germany, 30th Jun 2000 - 31st May 2017.

<u>3.1 Stationarity test</u>

In order to guarantee the effectiveness of the ARIMA forecasting model, the stationarity of autoregressive terms needs to be ensured. Considering short-term forecasts are made and compared, the stationarity of mean and variance is guaranteed by taking the difference of variables instead of taking logarithm. The Dickey–Fuller test (Dickey and Fuller, 1979) examines whether unit root exists in the datasets. As can be seen from the graph of the raw stock indices and EPU indices (Appendix A, Figure A.2), there appears no trend in all data series. Then, the Augmented Dickey-Fuller (ADF) test is performed on each variable. At this stage, all dependent and independent variables are taken the first-order difference to improve stationarity and reduce seasonality.

However, the correlograms of indices variables still demonstrate that the S&P Europe 350 index, CAC 40 index and DAX index are still non-stationary since all data points are under 95% confidence bands. Therefore, the second-order differencing is applied on these three indices instead to ensure their stationarity, leaving the Belgium 20 index being the only first order differentiated variable.

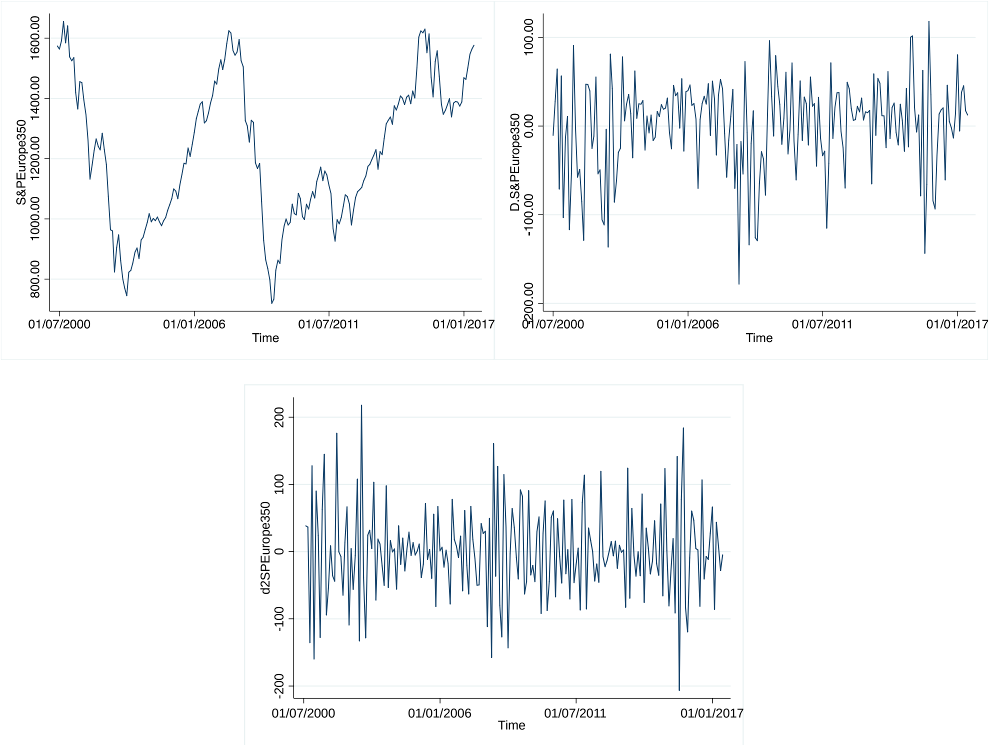


Figure 3 Time plots of S&P Europe 350 index, first and second-order difference of S&P Europe 350 index, 30th Jun 2000- 31st May 2017.

3.2 Autocorrelation and Partial Autocorrelation

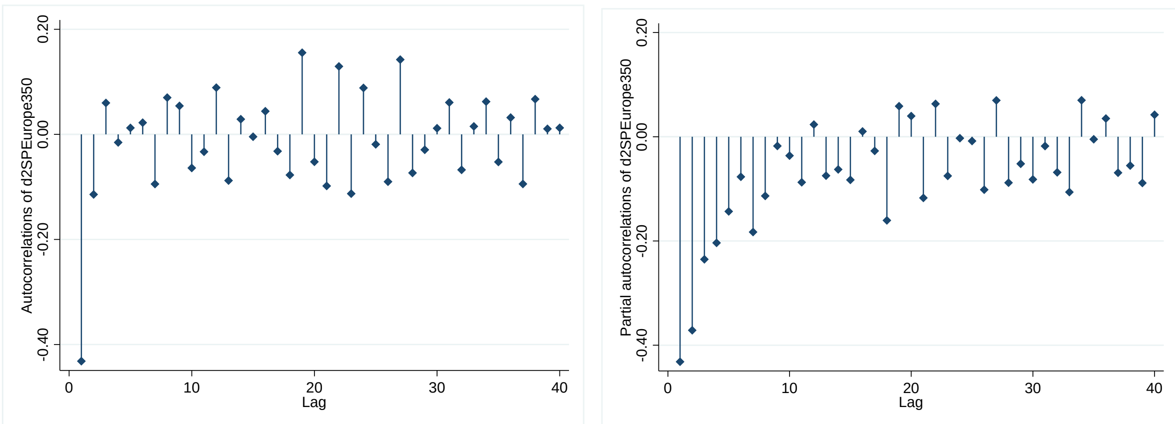


Figure 4 Correlograms of second-order difference of S&P Europe 350 index, 30th Jun 2000- 31st May 2017.

Figure 4 demonstrates the autocorrelation and partial autocorrelation of second-differentiated S&P Europe 350 index. Correlograms for other three indices are presented in Appendix A (Figure A.2). The second-order differentiation of S&P Europe 350 index presents a strong first lag of autocorrelation.

4. Methodology

Predicting models are formed and tested in two steps under the ARIMA model specification which is initially proposed by Whittle (1951). The model was further developed by Box et al. (1970) and became relatively popular in the 1970s. Numerous empirical studies proved the advantages of the ARIMA model over other time-series models in post-sample forecasting. The critical prerequisite for ARIMA to perform decently are ensuring the stationarity and removing the trend of data, which have been done previously in this research. Moreover, the logarithm and power transformations of data are effective in improving the long-term forecasting rather than the short-term one (Makridakis and Hibon, 1997). In this paper, the effectiveness of EPU in European countries in forecasting the short-term European stock market indices is tested initially. Then, the factor of the UK EPU is added to the prediction model. By comparing the two sets of forecasting models with different independent and explanatory variables. Results can be interpreted to determine whether the UK policy-related uncertainty is effective in predicting the price trends on the EU stock markets.

Model formation and selection criteria are based on the Box-Jenkins methodology introduced by Box et al. (1970). Box-Jenkins methodology describes a three-step approach, namely model identification and model selection, parameter estimation and statistical model checking to figure out the best-fitted ARIMA model for time series data. Firstly, the ARIMA estimation models with p autoregressive lags, d differences and q moving-average lags for the country-level and the EU-level stock indices are built:

$$\Delta^d SI_t = \mu + \Delta^d \sum_{i=1}^{p} \beta_i SI_{t-i} + \Delta^d EPUX + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad \text{(Equation 1)}$$

Where:

- $SI_t =$ stock price index (CAC 40 index, BEL 20 index, DAX index, and S&P Europe 350 index independently) in time t;
- $EPUX =$ economic policy uncertainty in country or region X (France, Belgium, Germany, and the EU);
- $\mu =$ constant or intercept;
- $\beta_i =$ coefficient of each parameter p;
- $\theta_j =$ coefficient of each parameter q;
- $\varepsilon_t =$ error term in time t;
- $\Delta^d =$ difference d times;

Furthermore, to test the predictability of the UK EPU in improving the model written above, an additional term is added:

$$\Delta^d SI_t = \mu + \Delta^d \sum_{i=1}^{p} \beta_i SI_{t-i} + \Delta^d EPUX + \Delta^d EPUUK + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \qquad \text{(Equation 2)}$$

Where:

- $SI_t =$ stock price index (CAC 40 index, BEL 20 index, DAX index, and S&P Europe 350 index independently) in time t;
- $EPUUK =$ economic policy uncertainty in the UK;
- $EPUX =$ economic policy uncertainty in country or region X (France, Belgium, Germany, and the EU);
- $\mu =$ constant or intercept;
- $\beta_i =$ coefficient of each parameter p;
- $\theta_j =$ coefficient of each parameter q;
- $\varepsilon_t =$ error term in time t;
- $\Delta^d =$ difference d times;

Lastly, the out-of-sample R-squared is adopted as the measurement to evaluate the forecasting performance of different models selected. This evaluation approach is well-performed in testing the forecasting accuracy of time-series models. Clark and McCracken (2001) performed numerical simulations to test the power and size of a bunch of equal forecasting accuracy and encompassing tests. The results strongly confirmed the validity of out-of-sample R-Squared as an evaluation tool, which is constructed below:

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{T}(\Delta^d SI_t - \widehat{\Delta^d SI_t})}{\sum_{t=1}^{T}(\Delta^d SI_t - \overline{\Delta^d SI_t})}$$

Where,

- $R^2_{oos} =$ out-of-sample R-Squared;
- $\Delta^d SI_t =$ d times differentiated Stock index in time t;
- $\widehat{\Delta^d SI_t} =$ out-of-sample forecast of d times differentiated Stock index in time t;

5. Results

This section elaborates the model evaluations and selection results, together with forecasting outcomes on the investigated markets. This study selects Akaike's Information Criterion (AIC) and Bayesian's Information Criterion (BIC) to identify the most suitable ARIMA models. The evaluation process of the most suitable forecasting model basically consists of three steps. Initially, the models without considering the UK EPU are examined. In this stage, the country-level and regional-level EPU are included as an explanatory variable (Equation 1). Then, the models with the UK EPU factor are included further to see whether its inclusion improves the model (Equation 2). Finally, the best-performed model in each group is selected to do the forecasts. The following sections grouped by country or region are based on the three-step approach explained above:

5.1 The EU (S&PEurope350 index)

To evaluate the explanatory power of each ARIMA models considered, the significance level of crucial time-series lags (AR (1) and MA (1)), AIC, and BIC figures are extracted from Stata, presented in Table 2 and Table 3.

5.1.1 Models without the UK EPU

The tested ARIMA models are constructed depended on the correlograms (Figure 3) and the only included control variable is the EU EPU. The ARIMA (2,2,3) model gives both the lowest AIC and BIC, and the coefficients are all significant at 1% significance level. The coefficient of the EU EPU is significantly negative at 1% significance level under all ARIMA models, indicating that the economic policy uncertainty in the EU negatively affects the stock prices in the EU market.

Table 2 ARIMA models of S&PEurope350 index without the UK EPU: AIC, BIC and coefficients of AR (1), MA (1) and the EU EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*
S&PEurope350-EU					
ARIMA (1,2,0)	2233.92	2247.17	-0.4488***		-0.3612***
ARIMA (1,2,1)	2164.52	2181.09	0.0950	-1.0000	-0.3948***

ARIMA (1,2,2)	2166.43	2186.32	-0.2742	-0.6322	-0.3945***
ARIMA (1,2,3)	2168.40	2191.59	-0.4106	-0.4935	-0.3938***
ARIMA (2,2,0)	2204.76	2221,32	-0.6211***		-0.3625***
ARIMA (2,2,1)	2166.52	2186.40	0.0949		-0.3948***
ARIMA (2,2,2)	2168.38	2191.57	-0.3902	-0.5121	-0.3934***
ARIMA (2,2,3)	**2157.76**	**2177.64**	**-1.4617*****	**0.5817*****	**-0.4256*****
ARIMA (0,2,1)	2164.90	2178.15		-0.9372***	-0.4103***
ARIMA (0,2,2)	2164.51	2181.08		-0.9038	-0.3947***
ARIMA (0,2,3)	2166.51	2186.39		-0.9035	-0.3947***

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. S&PEurope350-EU model includes the EU EPU as an explanatory variable;

5.1.2 Models with the UK EPU

Furthermore, the UK EPU is included as another explanatory factor to build a new series of ARIMA models. Apparently, the coefficient of the UK EPU is not significant at 10% significance level and the sign of the coefficient is not consistent among all models. In this manner, the ARIMA (0,2,1) is selected to be the most effective model in presenting the European stock market index.

Table 3 ARIMA models of S&PEurope350 with the UK EPU: AIC, BIC and coefficients of AR (1), MA (1), the EU EPU and the UK EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUUK*
S&PEurope350-EU-UK						
ARIMA (1,2,0)	2235.87	2252.43	-0.4480***		-0.3425***	-0.0228
ARIMA (1,2,1)	2166.52	2186.40	0.0955	-1.0000	-0.3878***	-0.0090
ARIMA (1,2,2)	2166.43	2186.31	-0.2689	-0.6371	-0.3908***	-0.0049
ARIMA (1,2,3)	2170.40	2196.90	-0.4079	-0.4958	-0.3901***	-0.0047
ARIMA (2,2,0)	2206.43	2226.31	-0.6270***		-0.4126***	0.0624
ARIMA (2,2,1)	2166.52	2186.40	0.0954	-1.0000***	-0.3878***	-0.0090
ARIMA (2,2,2)	2170.38	2196.89	-0.3891	-0.5132	-0.3895***	-0.0049

ARIMA (2,2,3)	2169.558	2196.06	-1.4759***	0.5723	-0.3786***	-0.0233
ARIMA (0,2,1)	**2166.40**	**2183.46**		**-0.9372*****	**-0.4154*****	**0.0066**
ARIMA (0,2,2)	2166.51	2186.39		-0.9033	-0.3876***	-0.0091
ARIMA (0,2,3)	2166.50	2186.38		-0.9030***	-0.3879***	-0.0088

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. S&PEurope350-EU model includes the EU EPU and the UK EPU as explanatory variables;

5.1.3 Comparison and Forecast

To evaluate the out-of-sample forecasting ability of proposed models, the out-of-sample R-squared is adopted as the evaluation criterion. Using the samples from 31st May 2000 to 31st May 2017, the out-of-sample forecasts are constructed from 1st June 2017 to 31st Jan 2020. The out-of-sample R-squared of the ARIMA (2,2,3) model with the EU EPU as the explanatory variable is about 0.5226, indicating that the forecasts explain approximately 52.26% of the actual value after the sample period. Then, the ARIMA (0,2,1) model with the EU EPU and the UK EPU is investigated. It is apparent that both R-Squared are significant under 1% significance level, which means the value predicted by the past values, residuals and EPUs well coincides with the out-of-sample real statistics. The out-of-sample R-squared of the expanded model including the UK factor (around 0.5419) is relatively higher than the simple model, though a higher mean squared error is also found in the expanded model.

Table 4 Out-of-sample forecasting results of second-order differentiated S&PEurope350

	R^2_{oos}	P-value	MSE
S&PEurope350-EU	0.5226***	0.000	2258.34
S&PEurope350-EU-UK	0.5419***	0.000	2464.81

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. MSE: Mean Squared Error;

c. S&PEurope350-EU model includes the EU EPU as an explanatory variable;

d. S&PEurope350-EU model includes the EU EPU and the UK EPU as explanatory variables;

Despite the coefficient of the UK EPU being insignificant at 10% level, the forecasting ability of the model including the British policy-related factors improves the predictability of the original model, reflected by the out-of-sample R-squared.

5.2 France, Belgium, and Germany (CAC 40 index, BEL 20 index and DAX index)

In a similar scenario, the results for three European countries are generated and summarized below. Differing from the previous set of models for the EU, the country-based analysis considers country-specific EPUs as an additional explanatory factor (except for Belgium). In general, the three-steps approach mentioned before is applied to three countries, respectively.

5.2.1 Models without the UK EPU

According to the correlograms (Appendix A, Figure A.1) of the second-order difference of the CAC 40 index, the variable presents strong first- and second-order autocorrelation and three lags of partial autocorrelation. Alongside, the DAX index presents a rather mimic pattern to the CAC 40 index. Being the only first-order difference variable, the Belgium index shows a comparatively complicated movement of autocorrelation and partial autocorrelation.

The investigated ARIMA models are built based on the autocorrelations and partial autocorrelations observed. Results of CAC 40 index show that the ARIMA (2,2,3) model has the best fit under the AIC evaluation, though the coefficients of MA lags are insignificant at 10% significance level. The coefficient of the EU EPU is significantly negative under all forecasting models (at 1% significance level). Seen from Table 5, under the ARIMA (2,2,3) best fit, the France EPU is significantly positively related to the second-order differentiated CAC 40 index at 5% significance level. In the case of Belgium 20 index (Table B.1, Appendix B), the ARIMA (1,1,3) model has the lowest AIC (around 2552.15) whose AR (1) lag and MA (1) lag are 1% statistically significant (p-value = 0.0000). The number of lags of the best-fitted model of the Germany market is the same as that of the Belgium market, though having a higher degree of difference. Noticeably, the France EPU is 5% statistically significant in the ARIMA (2,2,3) model while the Germany EPU is not. The European EPU always remains the most influential explanatory variable in predicting the financial market indices in European countries since the negative relationship is always significant at 1% significance level.

Table 5 ARIMA models of CAC 40 index without the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1), the EU EPU and FR EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUFR*
CAC40-EU-FR						
ARIMA (1,2,0)	2820.40	2836.97	-0.4261***		-2.0162***	0.4813
ARIMA (1,2,1)	2737.41	2757.29	0.0474	-1.0000	-2.3141***	0.54501
ARIMA (1,2,2)	2738.25	2761.44	-0.4306	-0.4881	-2.2726***	0.5386
ARIMA (1,2,3)	2739.46	2765.97	-0.1174	-0.8075	-2.3515***	0.5568
ARIMA (2,2,0)	2780.74	2800.61	-0.6113***		-2.0216***	0.4726
ARIMA (2,2,1)	2736.98	2760.17	-0.0204	-0.9112***	-2.4025***	0.5706*
ARIMA (2,2,2)	2738.77	2765.28	-0.1770	-0.7511	-2.3726***	0.5640*
ARIMA (2,2,3)	**2732.37**	**2762.19**	**-1.3188*****	**0.4268**	**-2.6849*****	**0.7848****
ARIMA (0,2,1)	2735.85	2752.42		-1.0000	-2.3645***	0.5512
ARIMA (0,2,2)	2737.31	3757.19		-0.9412	-2.3036***	0.5451
ARIMA (0,2,3)	2737.58	2760.78		-0.9202***	-2.3634***	0.5628*

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. CAC40-EU-FR model includes the EU EPU and France EPU as an explanatory variables;

5.2.2 Models with the UK EPU

By adding the UK EPU, the best fitted ARIMA model of the French stock market turns out to be the same as that of without the UK EPU. The AIC of the new ARIMA (2,2,3) is 2731.02, which is the lowest among all tested models. Besides, the inclusion of the UK EPU improves the statistical significance level of all the MA lags (reaching the 1% significance level). Differently, the best-of-fit ARIMA models changed to ARIMA (2,1,3) and ARIMA (1,2,2) in Belgium and Germany respectively. The UK EPU is only 1% significant in the Belgium 20 ARIMA (2,1,3) model.

Table 6 ARIMA models of CAC 40 index with the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1), the EU EPU and FR EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUFR*	*EPUUK*
CAC40-EU-FR-UK							
ARIMA (1,2,0)	2822.14	2842.02	-0.4287***		-2.2168***	0.4995	0.2204
ARIMA (1,2,1)	2739.04	2762.234	0.0427	-1.0000	-2.5663***	0.5658*	0.2835
ARIMA (1,2,2)	2739.90	2766.40	-0.4469	-0.4748	-2.5141***	0.5619*	0.2780
ARIMA (1,2,3)	2741.00	2770.81	-0.1428	-0.7869	-2.6334***	0.5816*	0.3248
ARIMA (2,2,0)	2781.26	2804.45	-0.6249***		-2.4882***	0.5004	0.5478
ARIMA (2,2,1)	2738.57	2765.08	-0.0288	-0.9081***	-2.6658***	0.5940*	0.3024
ARIMA (2,2,2)	2740.30	2770.12	-0.2115	-0.7219	-2.6519***	0.5868*	0.3273
ARIMA (2,2,3)	**2731.02**	**2760.83**	**-1.3201*** **	**0.4213*** **	**-3.1200*** **	**0.8287*** **	**0.5244**
ARIMA (0,2,1)	2737.40	2757.28		-0.1000	-2.6434***	0.5766*	0.3175
ARIMA (0,2,2)	2738.96	2762.16		-0.9470	-2.5486***	0.5669*	0.2750
ARIMA (0,2,3)	2739.17	2765.68		-0.9237	-2.628***	0.5869*	0.3023

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. CAC40-EU-FR model includes the EU EPU, France EPU and the UK EPU as an explanatory variables;

5.2.3 Comparison and Forecasts

The forecasting outcomes of three countries are listed in Table 6. Explicitly, the models of Belgium 20 index (with or without the UK EPU factor) fail to give a significant out-of-sample prediction of the stock prices after 31st May 2017. Meanwhile, the models of CAC 40 index and those of DAX index give significant out-of-sample R-squared. The Belgium models are largely different from models of other countries since they exclude the country-specific economic policy uncertainty factor. By including the UK EPU variable, the out-of-sample R-squared of the ARIMA (2,2,3) model in France gets lower (from around 0.5039 to 0.4768). The mean squared error also increases. Contrarily, the addition of the UK EPU factor improves the R-squared (from 0.5989 to 0.6106) of the DAX index prediction model, lowering the mean squared error as well.

Table 6 Out-of-sample forecasting results of first or second order differentiated CAC 40 index, BEL 20 index and DAX index.

	R^2_{oos}	**P-value**	**MSE**
CAC40-EU-FR	0.5039***	0.0000	48123.20
CAC40-EU-FR-UK	0.4768***	0.0000	50760.09
BEL20-EU	0.0289	0.3619	20124.26
BEL20-EU-UK	0.0254	0.3833	20198.09
DAX-EU-DE	0.5989***	0.0000	15725.16
DAX-EU-DE-UK	0.6106***	0.0000	15398.33

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. MSE: Mean Squared Error;

c. CAC40-EU-FR model includes the EU EPU and the France EPU as explanatory variables;

d. CAC40-EU-FR-UK model includes the EU EPU, France EPU and the UK EPU as explanatory variables;

e. BEL20-EU model includes the EU EPU as an explanatory variable;

f. BEL20-EU-UK model includes the EU EPU and the UK EPU as explanatory variables;

g. DAX-EU-DE model includes the EU EPU and Germany EPU as explanatory variables;

h. DAX-EU-DE-UK model includes the EU EPU, Germany EPU and the UK EPU as explanatory variables;

To summarize, the European EPU forecasts the European stock market index significantly, whether seen from the EU as a whole or from separative country perspective. The forecasting accuracy results shows that the British EPU is effective in predicting the S&PEurope 350 index and the DAX index, while it fails to give a valid prediction for the Belgium 20 index and fails to improve the prediction of CAC 40 index.

Conclusion

This paper examines the effectiveness of the UK EPU before and during the first Brexit referendum in predicting the European stock market indices one-year after the initial referendum. In summary, the European EPU negatively affects the future stock price movements on the stock market. In the EU level, the model including British economic-related policy uncertainty before and during the Brexit referendum can give a more precise prediction than the basic model that solely considers the EU EPU, represented by a about 2% increase in the R-squared. The advanced model including the UK EPU predicts a significant positive relationship between the UK policy uncertainty and the European stock market index. It is reasonable to interpret this relationship as that the political and economic factor in the UK surrounding the Brexit event is effective in influencing the European stock market movements after the first Brexit referendum. The uncertainty of Brexit, therefore, casts light on the future market trend on the European stock market. In the country-specific level, the inclusion of the UK EPU as a predictive factor only improves the model on the Germany stock market, suggesting it is the most affected financial market in the EU during the Brexit. Inclusion of British EPU does not effectively improve the validity of models on the French and Belgium market.

Therefore, indicated by the study outcomes, investors should consider the political economic factor in the UK as an important issue when building portfolios on the EU stock market, especially in the short-term when the pattern on the European financial market is still significantly affected by the aftermath of Brexit. When making country-level portfolios, investors need to take a cautious attitude on the role of British EPU since different levels of significance of UK EPU is observed in different European countries.

However, this study has a few limitations existing. As mentioned earlier, the data for DAX index from 31st May 2000 to 30th June 2006 is missing and the Belgium EPU is not incorporated to evaluate and compare the country-level forecasting models. The incompletion of datasets can decrease the accuracy of forecasting results in Germany market and Belgium market. Furthermore, the out-of-sample R-squared is treated as the only evaluation method of the forecasting outcomes. This may cause biases because different forecasting evaluation criterion can generate variant outcomes. In addition, this study only focuses on the short-term prediction model rather than long-term outcomes.

For future research, more considered datasets including the missing data points can be used to improve the quality of results. Moreover, inspired by this study, the long-term forecasts can be tested to investigate the power of the UK EPU in predicting the long-term stock market trend in the EU. Lastly, except for ARIMA models, other forecasting models can also be compared to the selected models above to improve the model validity, which is beyond the scope of this research.

Bibliography

Amewu, G., Mensah, J. O., & Alagidede, P. (2016). Reaction of global stock markets to Brexit. *Journal of African Political Economy and Development*, *1*(1), 40-55.

Arouri, M., Estay, C., Rault, C., & Roubaud, D. (2016). Economic policy uncertainty and stock markets: Long-run evidence from the US. *Finance Research Letters*, *18*, 136-141.

BBC News, 2020. *A Really Simple Guide To Brexit*. [online] BBC News. Available at: <https://www.bbc.com/news/uk-politics-32810887> [Accessed 31 March 2020].

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, *131*(4), 1593-1636.

Bakera, S. R., Bloomb, N., & Davisc, S. J. (2013). Measuring Economic Policy Uncertainty.

Bohdalova, M., & Greguš, M. (2017). The Impacts of Brexit on European Equity Markets. *Financial Assets and Investing*, *8*, 5-18.

Box, G. E., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American statistical Association*, *65*(332), 1509-1526.

Box, G. E., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time series analysis: forecasting and control*. John Wiley & Sons.

Breinlich, H., Leromain, E., Novy, D., Sampson, T., & Usman, A. (2018). The economic effects of Brexit: evidence from the stock market. *Fiscal Studies*, *39*(4), 581-623.

Centre for European Reform, 2020. *Brexit Timeline*. [online] Centre for European Reform. Available at: <https://www.cer.eu/brexit-timeline> [Accessed 5 April 2020].

Clark, T. E., & McCracken, M. W. (2001). Tests of equal forecast accuracy and encompassing for nested models. *Journal of econometrics*, *105*(1), 85-110.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Ko, J. H., & Lee, C. M. (2015). International economic policy uncertainty and stock prices: Wavelet approach. *Economics Letters*, *134*, 118-122.

Li, X. L., Balcilar, M., Gupta, R., & Chang, T. (2016). The causal relationship between economic policy uncertainty and stock returns in China and India: evidence from a bootstrap rolling window approach. *Emerging Markets Finance and Trade*, *52*(3), 674-689.

Liu, L., & Zhang, T. (2015). Economic policy uncertainty and stock market volatility. *Finance Research Letters*, *15*, 99-105.

Makridakis, S., & Hibon, M. (1997). ARMA models and the Box–Jenkins methodology. *Journal of Forecasting*, *16*(3), 147-163.

Mei, D., Zeng, Q., Zhang, Y., & Hou, W. (2018). Does US Economic Policy Uncertainty matter for European stock markets volatility?. *Physica A: Statistical Mechanics and its Applications*, *512*, 215-221.

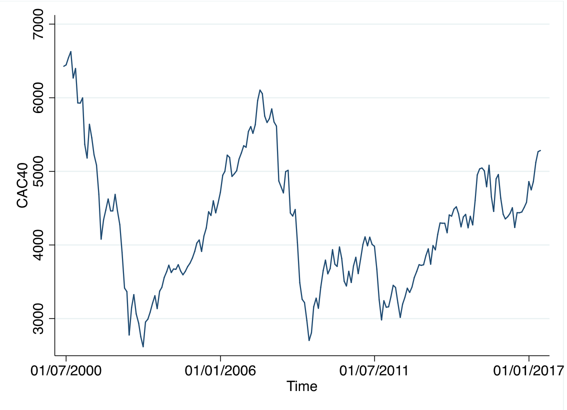
Mensi, W., Hammoudeh, S., Reboredo, J. C., & Nguyen, D. K. (2014). Do global factors impact BRICS stock markets? A quantile regression approach. *Emerging Markets Review*, *19*, 1-17.

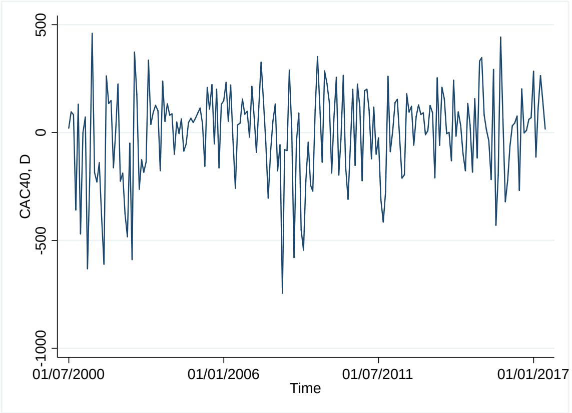
Pastor, L., & Veronesi, P. (2012). Uncertainty about government policy and stock prices. *The journal of Finance*, *67*(4), 1219-1264.

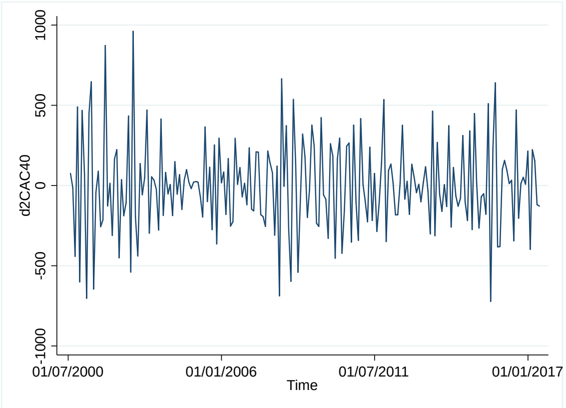
Ringe, W. G. (2018). The irrelevance of Brexit for the European financial market. *European Business Organization Law Review*, *19*(1), 1-34.

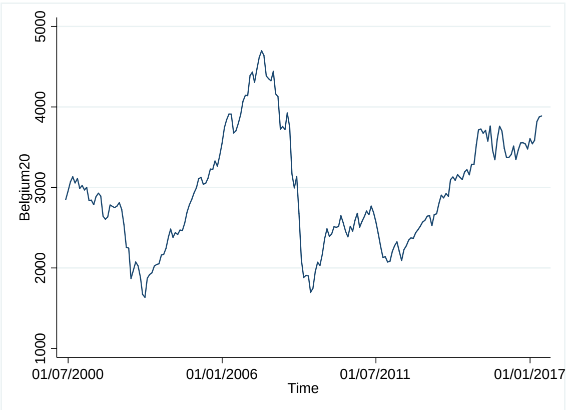
Whittle, P. (1951). *Hypothesis testing in time series analysis* (Vol. 4). Almqvist & Wiksells boktr.

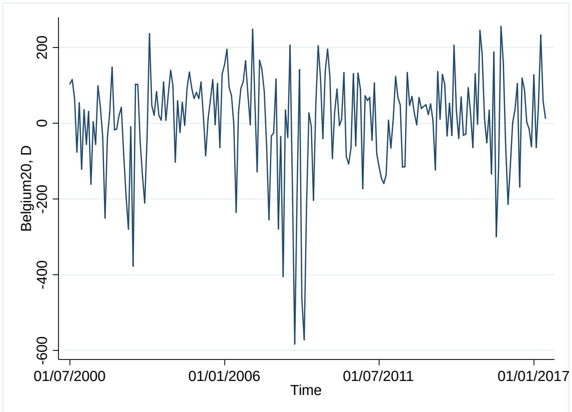
Appendix A

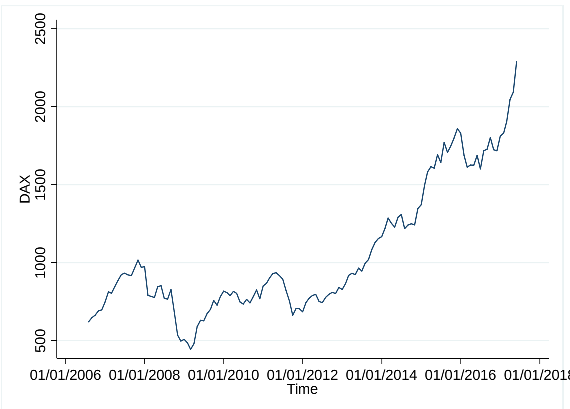

CAC40
3000
4000
5000
6000
7000
01/07/2000
01/01/2006
01/07/2011
01/01/2017
Time

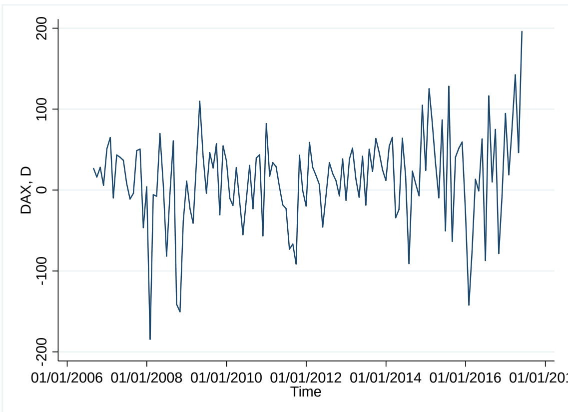

CAC40, D
-1000
-500
0
500
01/07/2000
01/01/2006
01/07/2011
01/01/2017
Time


d2CAC40
-1000
-500
0
500
1000
01/07/2000
01/01/2006
01/07/2011
01/01/2017
Time


Belgium20
1000
2000
3000
4000
5000
01/07/2000
01/01/2006
01/07/2011
01/01/2017
Time


Belgium20, D
-600
-400
-200
0
200
01/07/2000
01/01/2006
01/07/2011
01/01/2017
Time


DAX
500
1000
1500
2000
2500
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014
01/01/2016
01/01/2018
Time


DAX, D
-200
-100
0
100
200
01/01/2006
01/01/2008
01/01/2010
01/01/2012
01/01/2014
01/01/2016
01/01/2018
Time

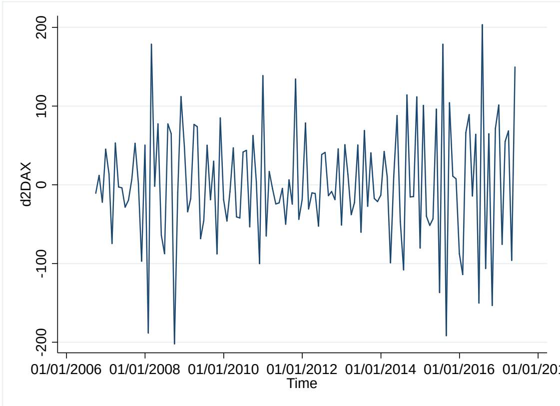
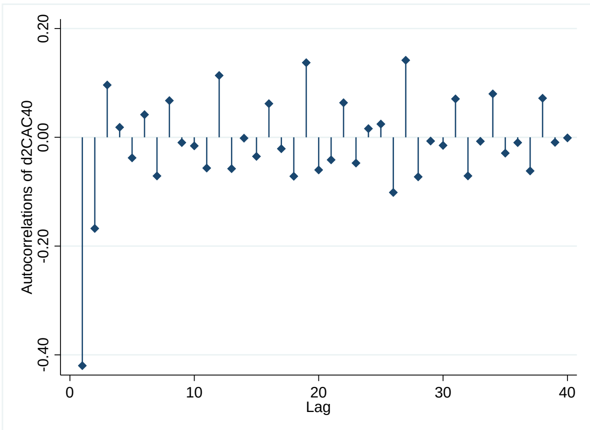
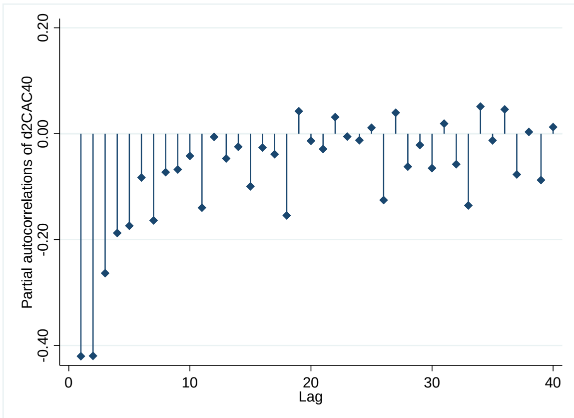
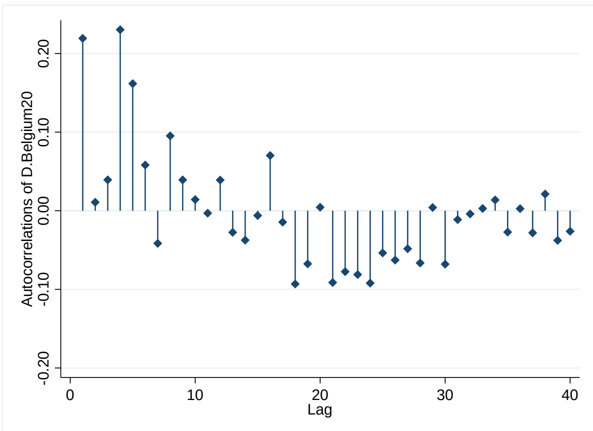
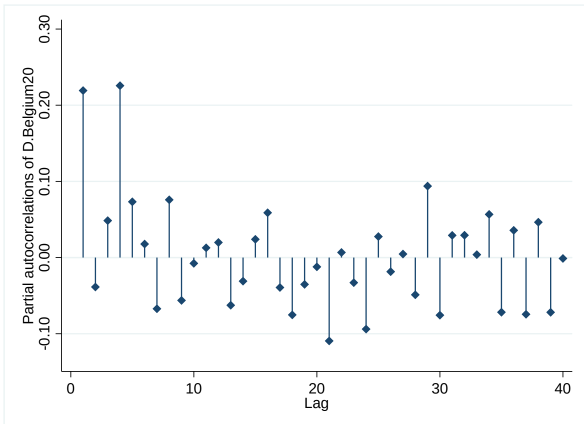


Figure A.1 Time plots of CAC 40 index, BEL 20 index, DAX index, first and second (excluding BEL 20) difference of CAC 40 index, BEL 20 index, DAX index, 30th Jun 2000- 31st May 2017.









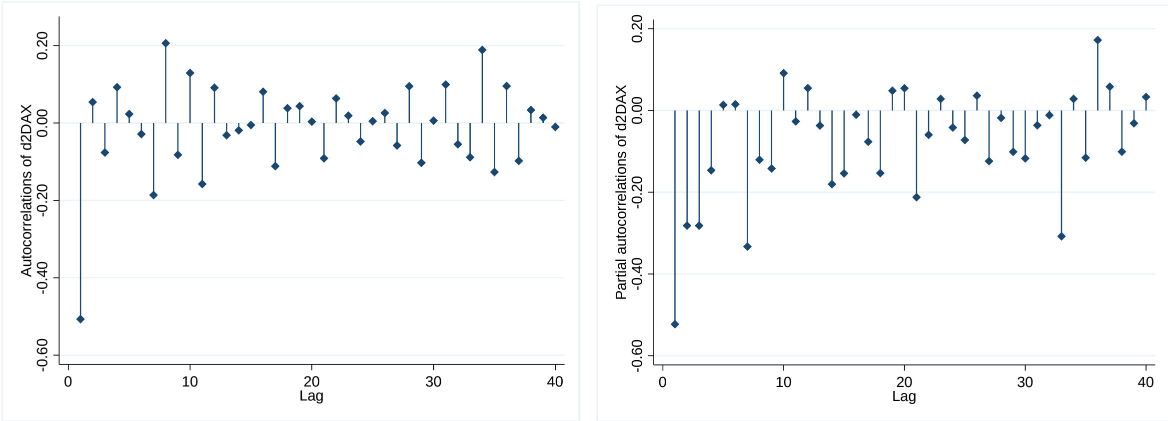


Figure A.2 Correlograms of first or second-order difference of CAC 40 index, BEL 20 index, DAX index, 30th Jun 2000- 31st May 2017.

Appendix B

Table B.1 ARIMA models of BEL 20 index without the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1) and the EU EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*
BEL20-EU					
ARIMA (1,1,0)	2618.00	2631.25	-0.3949***		-0.8690***
ARIMA (1,1,1)	2555.39	2571.96	0.1264***	-0.9229***	-0.9235***
ARIMA (1,1,2)	2556.88	2567.76	-0.1321	-0.6535	-0.9160***
ARIMA (1,1,3)	**2552.15**	**2581.35**	**0.8333*** **	**-0.7102*** **	**-0.9608*** **
ARIMA (2,1,0)	2596.59	2613.15	-0.5270		-0.8574***
ARIMA (2,1,1)	2555.37	2575.25	0.0518	-0.8376***	-0.9258***
ARIMA (2,1,2)	2556.71	2579.90	0.2672	-1.0640***	-0.9426***
ARIMA (2,1,3)	2552.18	2678.69	-0.0780	-0.6926***	-0.9353***
ARIMA (0,1,1)	2555.05	2568.30		-0.8689***	-0.9897***
ARIMA (0,1,2)	2554.82	2571.39		-0.8095	-0.8951***
ARIMA (0,1,3)	2556.44	2676.32		-0.8006***	-0.9337***

a. ** = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. *BEL20-EU model includes the EU EPU as an explanatory variable;*

Table B.2 ARIMA models of BEL 20 index with the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1) and the EU EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUUK*
BEL20-EU-UK						
ARIMA (1,1,0)	2619.85	2636.41	-1.3936***		-0.7874**	-0.1022
ARIMA (1,1,1)	2257.37	2577.25	1.1281*	-0.9238***	-0.8902***	-0.0424
ARIMA (1,1,2)	2558.86	2582.05	-1.1285	-0.6565	-0.8875***	-0.0368
ARIMA (1,1,3)	2554.32	2577.52	0.8333***	-1.7102***	-0.9608***	-0.0366
ARIMA (2,1,0)	2598.58	2618.46	-1.5277***		-0.8756***	0.02315
ARIMA (2,1,1)	2557.37	2580.56	1.0525	-0.8380***	-0.9124***	-0.0174
ARIMA (2,1,2)	2558.71	2585.21	1.2677	-1.0541***	-0.9309***	-0.0156

ARIMA (2,1,3)	**2553.93**	**2583.75**	**1.2589*** **	**-1.1302*** **	**-0.9773*** **	**0.0068*** **
ARIMA (0,1,1)	2557.05	2573.62		-0.8689***	-0.9893***	-0.0008
ARIMA (0,1,2)	2556.79	2576.67		-0.8088	-0.8551**	-0.0526
ARIMA (0,1,3)	2559.44	2581.62		-0.8002***	-0.9209***	-0.1636

a. ** = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. *BEL20-EU-UK model includes the EU EPU and the UK EPU as explanatory variables;*

Table B.3 ARIMA models of DAX index without the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1), the EU EPU and DE EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUDE*
DAX-EU-DE						
ARIMA (1,2,0)	1431.69	1445.99	-0.5771***		-0.2748**	-0.1018
ARIMA (1,2,1)	1408.15	1425.31	0.0506	-1.0000	-0.2024	-0.1611
ARIMA (1,2,2)	1403.19	1423.20	-0.9912***	-0.0553	-0.3437**	-0.1188
ARIMA (1,2,3)	**1401.02**	**1421.03**	**-0.9899*** **	**0.0643**	**-0.2944***	**-0.1347**
ARIMA (2,2,0)	1424.43	1441.59	-0.7247***	-0.2553**	-0.1204	-0.1204
ARIMA (2,2,1)	1405.39	1425.41	0.0355	-1.0000	-0.2757**	-0.1214
ARIMA (2,2,2)	1407.19	1430.07	0.2916	-1.2621	-0.2694*	-0.1250
ARIMA (2,2,3)	1404.24	1427.12	-1.6113***	0.6704***	-0.2498	-0.1737
ARIMA (0,2,1)	1406.42	1420.72		-1.0000	-0.2308	-0.1535
ARIMA (0,2,2)	1406.24	1420.53		-0.9650***	-0.2105	-0.1591
ARIMA (0,2,3)	1406.52	1426.54		-0.9713	-0.2678*	-0.1271

a. ** = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. *DAX-EU-DE model includes the EU EPU and Germany EPU as an explanatory variables;*

Table B.4 ARIMA models of DAX index with the UK EPU: AIC, BIC, and coefficients of AR (1), MA (1), the EU EPU, DE EPU and the UK EPU.

	AIC	*BIC*	*AR (1)*	*MA (1)*	*EPUEU*	*EPUDE*	*EPUUK*
DAX-EU-DE-UK							

ARIMA (1,2,0)	1433.60	1450.76	-0.5777***		-0.3247	-0.0904	0.0400
ARIMA (1,2,1)	1407.87	1425.02	0.0489	-1.0000***	-0.2893	-0.1473	0.0806
ARIMA (1,2,2)	**1405.13**	**1428.01**	**-0.9912*** **	**-0.0545**	**-0.3815**	**-0.1123**	**0.0352**
ARIMA (1,2,3)	1405.02	1430.76	-0.9899***	0.0642	-0.2968	-0.1343	0.0024
ARIMA (2,2,0)	1425.84	1445.86	-0.7319***		-0.3792*	-0.0986	0.1061
ARIMA (2,2,1)	1407.19	1430.07	-0.3530	-0.1059	0.0650	-0.1059	0.0650
ARIMA (2,2,2)	1406.88	1429.76	0.3234	-1.2971***	-0.3634	-0.1076	0.0812
ARIMA (2,2,3)	1406.23	1431.97	-1.6100***	0.6697	-0.2365	-0.1758	-0.0133

*a. * = p-value < 0.10; ** = p-value < 0.05; *** = p-value < 0.01;*

b. DAX-EU-DE-UK model includes the EU EPU, Germany EPU and the UK EPU as an explanatory variables;