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The dynamic relationship between stock market indexes and foreign exchange

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Abstract

This empirical study analyses the dynamic relationship between the FTSE 100 Index and the Euro STOXX 50 Index and the USD/EUR and USD/GBP exchange rates, from January 2007 to April 2017. The Johansen co-integration tests suggest that these variables have a long-term relationship. The Granger causality test was conducted through the use of VECM equations, showing that the FTSE 100 and the Euro STOXX 50 Index both have a causal feedback relationship. A unidirectional relationship was found between the FTSE 100 Index stock prices and the USD/EUR exchange rate. The presence of a unidirectional relationship between the USD/GBP exchange rate and FTSE 100 and Euro STOXX 50 Index stock prices was also detected.

JEL Classification: G15; C22; C51 ; C52

Key Words: cointegration; Granger causality; USD/EUR and USD/GBP exchange rates; European stock indexes

1. Introduction

The relationship between share prices or index stock prices and exchange rates has been a motivation for research for decades. Empirical studies on this relationship have set the stage scene for macro and micro theoretical discussions and for the expansion of new econometric models.

Dornbusch and Fisher (1980) introduced the traditional stock prices and exchange rates approach, which consists of the fact that domestic currency depreciation leads to an increase in stock prices. The argument behind this theory is that firms become more competitive in comparison to other countries as the domestic currency becomes cheaper for foreign investors, and this leads to a rise in exports, and therefore an increase in firms' flows (stock prices). This is considered to be a micro theory based on the flows mechanism.

The other classical economic theory taken into account is the portfolio approach, which considers that exchange rates and stock prices are negatively correlated. Changes in stock prices lead to exchange rate fluctuations. Contrary to the previous approach, this formulation is considered to be a macro theory, which is based on the stocks mechanism.

The purpose of this empirical research is to disentangle the dynamic relationship between the FTSE 100 Index of the London Stock Exchange, the Euro STOXX 50 Index, as a representative of the Eurozone stock market, and USD/EUR and USD/GBP exchange rates, from January 2007 to April 2017. During this time period, two major events took place: the 2008 crisis and the United Kingdom (UK)'s decision in a June 23, 2016 referendum to leave the European Union (EU).

Nowadays, individual financial investors or corporate firms are more attentive and sensitive to the economic, social, and financial news from around the world. In the era of globalisation, available local and international information changes rapidly, at the rate of seconds. Consequently, investments decisions are influenced accordingly.

This paper is organised as the following. First, a literature review on this topic is presented. In section three, more details are described about the data used, and in section four, the methodology is thoroughly explained. Section five presents the empirical findings. The last section presents the conclusions.

2. Literature Review

The literature developed over the last 40 years regarding the relationship between exchange rates and stock prices or the stock index values is very wide and extensive.

In the early 1970s, Frank and Young (1972) aimed to understand how to interpret the earnings fluctuations of multinational companies with respect to exchange rates and whether their profit position was influenced by their international activities. They show that there is no significant relationship between the stocks prices of multinationals and exchange rates.

Later on, in the 1980s, Aggarwal (1981) studied the New York Exchange Index (NYSE), the Standard and Poor's 500 Stock Index, the Department of Commerce Index of 500 Stocks (DC500), and the USD relationship, with monthly data from between 1974 and 1978, given the fact that the USD dollar exchange rate adopted a floating regime as from mid-1974. He showed that there is a positive correlation among these Indexes, and that exchange rates cause multinational firms' potential profits and losses through stock prices fluctuations, which corroborates the traditional approach.

Soenen and Hennigar (1988) also proved that there is a significant relationship between stock prices and the exchange rates, albeit negative, for the period between 1980 and 1986.

In the 1990s, Bahmani-Oskooee and Soharian (1992) applied the co-integration test and the Granger causality test to study the relationship between the S&P500 index and the effective exchange rate of the dollar. Adopting the portfolio approach, they demonstrated no evidence of a long-run relationship between these two variables, although there was bidirectional causality among them in the short-run.

Up until the end of the 1990s, almost all of these studies were related to the U.S.A., analysing whether one of the indexes was related with the effective USD exchange rate. With the shift of the monetary policy to adopting floating exchange rates from different countries in the world and also due to the influence of new technologies in the financial markets, new studies were produced that reveal how diverse indexes from the rest of the world are influenced or caused by different exchange rates.

Ajayi and Mougoue (1996) are one of the main references for this topic, as theirs was one of the first studies to consider how stock prices and exchange rates relate to each other for Canada, France, Germany, Italy, Japan, Netherlands, the United Kingdom and the U.S.A, using daily data, from 1985 to 1991, and the Error Correction Model and co-integration tests. The conclusion was that there is short-run and long-run feedback among these two variables. Indeed, the results show that an increase in aggregate domestic stock price has a negative short-run effect on domestic currency value. In the long-run, however, increases in stock prices have a positive effect on the value of domestic currency. On the other hand, currency depreciation has a negative short-run and long-run effect on the stock market.

Nieh and Lee (2001) examine the long and short-run dynamic relationship between stock prices and exchange rates for the G-7 countries, concluding that there is no statistical evidence of a long-run relationship between these two variables for any of the G-7 countries. They also conclude that currency depreciation has a positive effect on the Canadian and UK stock indexes, and that the increase of the value of Italian and Japan stock indexes do indeed have a negative effect on their currency.

Granger *et al.* (2000) conclude that Taiwan stock prices have a negative effect on exchange rates, which is in line with the portfolio approach. On the contrary, in the case of Japan and Thailand, exchange rates and stock prices show a positive correlation. Singapore showed no short or long-term relationship between the two variables, whilst feedback relations were detected for Indonesia, Korea, Malaysia and the Philippines.

Stavárek (2005) analysed the causal relationship between stock prices and effective exchange rates in four of the older EU member countries (Austria, France, Germany, and the UK), four new EU member countries (the Czech Republic, Hungary, Poland, and Slovakia), and in the United States. The findings suggest that causalities seem to be predominantly unidirectional, with the direction running from stock prices to exchange rates. Furthermore, the results show much stronger causality in countries with developed capital and foreign-exchange markets.

Islami and Welfens (2013) examine any potential links between nominal stock market index and nominal exchange rate in four Eastern European countries. The results show that significant links exist between the stock market index and the foreign exchange rate for three countries, where for Poland, both long-term and short-term links exist.

Bhuvaneshwari and Ranger (2017) analyse the impact and relationship between USD-INR exchange rate and Indian stock prices during the period 2006-2015. They find that there is no long term co-movement between the variables and none of the variables is predictable on the basis of past values of other variable and that there is causality running from Indian stock prices to INR/USD exchange rate and vice versa.

Chen et al. (2018) conduct a comparative analysis of pairwise dynamic integration and causality of US, UK, and Eurozone stock markets, measured in common and domestic currency terms, to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among stock market indices, from 1980 to 2015. They conclude that the degree of dynamic correlation and cointegration between pairs of stock markets rises in periods of high volatility and uncertainty, especially under the influence of economic, financial and political shocks, suggesting that the potential for diversifying risk by investing in the US, UK and Eurozone stock markets is limited during the periods of those shocks.

This paper revisits the dynamic relationship between the FTSE 100 Index of the London Stock Exchange, the EURO STOXX50 Index, and USD/EUR and USD/GBP exchange rates, from 2007 to 2017, a period that includes the 2008 financial crisis and the Brexit, the withdrawal of the UK from the EU, following a referendum held on 23 June 2016. These two shocks constitute the motivation to consider the analysis of that relationship.

3. Data

The data consist of the historical daily closing prices of stock market indexes from United Kingdom and Eurozone, the FSTE 100 Index from London Stock Exchange and the EURO STOXX50 Index, respectively, and both the USD/EUR and USD/GBP nominal exchange rates, from January 2007 to April 2017.

Data from both stock indexes are from the Thomson Reuters Eikon database. The USD/EUR exchange rate comes from the Eurosystem database and the USD/GBP exchange rate is from the Bank of England statistical interactive database.

4. Methodology

This study uses multivariate time series analysis. Firstly, it conducts stationarity tests and examines optimal lag length and time series autocorrelation. Secondly, we perform co-integration analysis, and use an Error Correction Model (ECM) when needed. Finally, the Granger Causality test is applied.

The time series stationarity is the key for successful data modelling, as explored by Granger and Newbold (1974). If this condition is not verified, then we are dealing with spurious regressions with no statistical evidence between their variables, and therefore they have no economic meaning. The Augmented Dickey-Fuller (1979, 1981) (ADF) test and the Phillips and Perron (1988) (PP) test are performed to find unit roots.

The general ADF(p) model regression is provided by following equation (Tsay, 2005):

$$\Delta y_t = \beta_{1+} \beta_2 \, t + \delta \, y_{t-1} + \sum_{i=1}^{m} \alpha_i \, \Delta y_{t-i} + \mu_t \qquad (1)$$

Where y is the variable used to check the time series data features, Δ is the difference operator, for example, $\Delta y_t = y_t - y_{t-1}$, β_1 is the constant term, t is the trend variable, and m is the optimum lag length. This regression error term is a white noise error and is represented by μ_t.

The general PP model test regression follows a first order auto-regressive process, AR (1), as shown below:

$$\Delta Y_t = \alpha + \delta \, Y_{t-1} + \varepsilon_t \qquad (2)$$

where Δ is the difference operator, α is the constant term, the Y_{t-1} term corresponds to our variable's first lag, and ε_t is white noise error.

The main difference between the PP and ADF unit root test is that the first one follows a non-parametric statistical method and therefore it does not consider the time lag difference. In other words, time is not considered for the serial correlation within the error term.

The hypothesis of both tests considers that $\delta = (p - 1)$, and the null hypothesis contemplates that our variable time series have the presence of unit roots and has an order of integration equal to one, $I(1)$.

$$H_0: p = 1 \; one \; unit \; root, non \; stationary, Y{\sim}I(1)$$

$$H_1: p \leq 1 \; no \; unit \; root, stationary, Y{\sim}I(0)$$

After ensuring our time series are stationarity, the next step is to test their co-integration relationship. For this we first need to estimate the Vector Auto-Regressive Regression (VAR), using a multivariate time series model.

The co-integration test used follows the Johansen procedure researched by Johansen (1988, 1995) and Johansen and Juselius (1990), to search for a long-run relationship among our variables, which is achieved by testing the co-integration presence on VAR vectors through using the maximum likelihood technique.

The VAR model was first introduced by Sims (1980), who understood that business behaviour not only depends on demand and supply at current prices, but also on other factors related to this sector. This behaviour results from the dynamic around the market, and vice versa. This model is characterised by the linear function of each variable having its own past lags and the past lags from other variables, contradicting with the models of unidirectional relationship between two or more variables. Inn our study, each of our four variables are considered as being endogenous or dependent, and the constant term as being exogenous or independent.

The following definitions are from Tsay (2005). The reduced-form VAR model of order 1, VAR(1), of a multivariate time series r_t is:

$$r_t = \emptyset_0 + \Phi r_{t-1} + \mathrm{a}_t \quad (3)$$

$\emptyset_0$ is k $dimensional\ vector$

Φ is k x k matrix, which measures the dynamic dependence of r_t

$\{\mathrm{a}_t\}$ $is\ a\ multivariate\ normal, sequence\ of\ serially\ uncorrelated\ randon$

$vectors\ with\ mean\ zero\ and\ covariance\ matrix\ \sum = \ Cov(r_t, \mathrm{a}_t)$.

$\sum$ is required to be positive.

Let us use an example of a VAR(1) with two variables (bivariate case), with k=2, and $r_t = (r_{1t}, r_{2t})'$ and $a_t = (a_{1t}, a_{2t})'$. This model has two equations:

$$r_{1t} = \emptyset_{10} + \Phi_{11} r_{1,t-1} + \Phi_{12} r_{2,t-1} \mathrm{a}_{1t} \quad (4)$$

$$r_{2t} = \emptyset_{20} + \Phi_{21} r_{1,t-1} + \Phi_{22} r_{2,t-1} \mathrm{a}_{2t} \quad (5)$$

From the first equation, we can interpret Φ_{12} as being the linear dependence of r_{1t} on $r_{2,t-1}$ in the presence of $r_{1,t-1}$. If the coefficient value is equal to zero, then this means that this model shows that r_{1t} only depends on its own past.

If we consider the coefficients values jointly, we can come to very interesting conclusions, as: if $\Phi_{12} = 0$ and $\Phi_{21} \neq 0$, then there is a unidirectional relationship from r_{1t} to r_{2t}, whereas if both coefficients are different from zero, then our time series have a feedback relationship between them.

Is true that the reduced form of VAR model does not show the concurrent relationship between the two variables, which is the diagonal element σ_{12} of the covariance matrix $\sum$ of α_t. However, it is the most commonly-used form in econometric literature, due to its easy estimation and the fact that correlation cannot be used in forecasting, which is not the purpose of this study.

If r_t is weakly stationary, then $\tilde{r}_t = r_t - \mu$, [where $\mu = E(r_t)$], and the general p lag order vector autoregressive VAR(p) can be written as:

$$\tilde{r}_t = \Phi_1 \tilde{r}_{t-1} + \cdots + \Phi_p \tilde{r}_{t-p} + \alpha_t \quad (6)$$

As we are examining four variables and its times series, our VAR(p) model will have four equations.

To choose the optimal lag factor for our VAR model, the Akaike Information Criterion (AIC) is used:

$$AIC(i) = \ln(|\tilde{\sum}_i|) + \frac{2k^2 i}{T} \qquad (7)$$

where, $\tilde{\sum}$ is the maximum likelihood of the residual covariance matrix.

We then look for the lag length, when the AIC value satisfies$AIC(i) = min_{0 \leq i \leq p0}$.

The time series co-integration test suggested by Johansen and Juselius (1990) follows a maximum likelihood procedure for the study of the possible presence of co-integrating vectors.

The maximum likelihood applied to Johansen and Juselius' VAR model in levels can be written as the following:

$$\Delta Y_t = C + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-1} + \Pi\, Y_{t-1} + \varepsilon_t \quad (8)$$

where Y_t is a vector of non-stationary variables, C is the constant term, and $\Pi = \alpha\beta'$.

The Π matrix contains the information on the coefficient matrix between the levels and it can be unfolded in terms of the matrix of adjustment coefficients α, and in terms of the matrix of co-integrating vectors β.

If $\Pi = 0$, then the variables are not co-integrated and the model remains as the first difference VAR (p).

The rank of Π is equal to the number of co-integrating vectors. Our test hypothesis takes this term into consideration.

The co-integration tests carried out are the trace test and the maximum eigenvalue test, and they are likelihood-ratio tests. Their hypotheses are the following:

Table 1. Co-integration tests

Trace test	Maximum eigenvalue test
Null hypothesis = $rank\ (\Pi) = r_0$ = *no co-integration*	Null hypothesis = $rank\ (\Pi) = 0$ = *no co-integration*
The alternative hypothesis is: $r_0 < rank\ (\Pi) < n$*	The alternative hypothesis is: rank (Π) = 1

*n is the maximum number of possible co-integrating vectors.

If this co-integration test demonstrates that there is a long-run relationship between our variables, then an error-correction model (ECM) needs to be estimated for our model.

(ECM) $\Delta x_t = \mu_t + \Pi x_{t-1} + \Phi *_1 \Delta x_{t-1} + \cdots + \Phi *_{p-1} \Delta x_{t-p+1} + \alpha_t$ (9)

where, $\Pi = \alpha\beta' = -\Phi(1)$ (10)

α is the matrix of adjust coefficient

β is the matrix that contains co-integrating vectors

Πx_{t-1} is the error-correction term

If we are testing the Granger causality between our four variables, and if they are considered to be co-integrated, they therefore have a long-run relationship, and we then need to work with the Error Correction Model to look for their causality relationships.

Let us continue with the two bivariate time series explanation for a better understanding, where we have the Y variable and the X variable with *p* lag length, to study in which direction there is evidence of causality, and we need to check a regression of Y regarding its own lags and X lags, and also to check a regression of X regarding its own lags and Y lags.

In this way it is possible to conclude whether the causality is unidirectional, where only X Granger causes Y, but Y does not Granger cause X, or is bidirectional, X Granger causes Y, and Y also Granger causes X. Each variable is tested as a dependent variable, and their coefficients are evaluated using the null hypothesis. As an example, we use the regression regarding variable Y:

$$\Delta Y_t = \emptyset + \delta t + \lambda e_{t-1} + \gamma_1 \Delta Y_{t-1} + \cdots + \gamma_p \Delta Y_{t-p} + \omega_1 \Delta X_{t-1} + \cdots + \omega_q \Delta X_{t-q} + \varepsilon_t$$

(11)

The term λe_{t-1} represents $Y_{t-1} - \alpha - \beta X_{t-1}$.

Our null hypothesis is $H_{o:}\, \omega_1 = \omega_q = \lambda = 0$, which implies that X does not Granger cause Y, and the alternative hypothesis of H_1 implies the opposite.

5. Empirical Results

5.1 Unit root tests results

We test for stationarity in the two stock market indexes and also in the two exchange rates time series. This follows the suggestion made by Engle and Granger (1987) to use the Augmented Dickey-Fuller and Phillips-Perron tests with constant and linear trend. In Table 2 we can check the t-statistic values at level and at first difference and compare with the critical values from MacKinnon (1996) for the 1% level test.

The lag length used for ADF tests was that of the Schwarz Info Criterion, and its value was that suggested by E-views. Furthermore, the bandwith used in the PP test was the Newey-West bandwith, with the specification suggested by the programme.

We conclude that the null hypotheses are not rejected at level tests, meaning that there is statistical evidence at the 99% level of the unit root for all the time series. They are only stationary at $I \sim (0)$, when the first difference is applied.

Table 2. t-statistic values from unit root tests results

Type of test	Tests	Constant		Constant and Linear Trend
	FTSE100			
Augmented Dickey-Fuller	Level	-1.6286		-2.7134
	First Difference	-51.4201		-51.4414
Phillips-Perron	Level	-1.3050		-2.4362
	First Difference	-51.9140		-52.0326

STOXX50			
Augmented Dickey-Fuller	Level	-2.2547	-2.2464
	First Difference	-24.9136	-25.0098
Phillips-Perron	Level	-2.0832	-2.0606
	First Difference	-52.7799	-52.8858

USD/EUR			
Augmented Dickey-Fuller	Level	-1.3232	-2.9534
	First Difference	-51.0312	-51.0288
Phillips-Perron	Level	-1.3818	-3.0388
	First Difference	-51.0305	-51.0277

USD/Libra			
Augmented Dickey-Fuller	Level	-1.3853	-2.0227
	First Difference	-49.0677	-49.0583
Phillips-Perron	Level	-1.3639	-2.0007
	First Difference	-49.0354	-49.0255

5.2 VAR model estimation and checking

We first estimate an unrestricted VAR model, because we are assuming that our variables are not co-integrated and that they do not have a long-run association among them. Data will be displayed in natural logarithm form. This model has as endogenous variables all the four variables of log(STOXX50), log(FTSE100), log(USD/EUR), and log(USD/GDP), and the constant term as the exogenous variable. For the first attempt, the lag intervals 1-2 were used for the first ones. Our VAR model has four equations, and one constant term.

It was verified that the coefficients value, standard errors, and t-statistics values for the two lags from each of our equations were acceptable. Next, the VAR optimal lag order was checked through using the Akaike Information Criterion, and the minimum value of AIC is present in Lag Four (Table 3). Therefore, the optimal lag order chosen for this model is Lag Five.

Table 3. VAR Lag Order Selection Criteria values

Lag	LogL	LR	FPE	AIC	SC	HQ
1	28814.76	NA	6.34e-18	-28.24792	-28.20382*	-28.23174*
2	28841.58	53.43276	6.27e-18	-28.25854	-28.17033	-28.22618
3	28857.77	32.20081	6.27e-18	-28.25873	-28.12642	-28.21020
4	28873.62	31.44319	6.27e-18	-28.25858	-28.08217	-28.19387
5	28898.99	50.24466*	6.22e-18*	-28.26777*	-28.04726	-28.18688

6	28907.55	16.92319	6.26e-18	-28.26047	-27.99586	-28.16341
7	28911.86	8.488204	6.33e-18	-28.24900	-27.94029	-28.13576
8	28923.35	22.63377	6.36e-18	-28.24458	-27.89177	-28.11517

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

The unit root polynomial is analysed. For a non-stationary VAR model we need to have an absolute value unit root of less than one, which means that there is no root outside the unit circle. This is shown in Table 4.

Table 4. Roots of Characteristic Polynominal

Root	Modulus
-0.672871	0.672871
-0.192768 + 0.601051i	0.631207
-0.192768 - 0.601051i	0.631207
0.494648 - 0.385186i	0.626933
0.494648 + 0.385186i	0.626933
0.434347 - 0.376672i	0.574925
0.434347 + 0.376672i	0.574925
-0.190199 - 0.519079i	0.552828
-0.190199 + 0.519079i	0.552828
0.028614 - 0.549978i	0.550722
0.028614 + 0.549978i	0.550722
0.507513 - 0.101842i	0.517630
0.507513 + 0.101842i	0.517630
-0.458780 - 0.139860i	0.479625
-0.458780 + 0.139860i	0.479625
0.208988 + 0.418084i	0.467408
0.208988 - 0.418084i	0.467408
-0.298335 - 0.305787i	0.427211
-0.298335 + 0.305787i	0.427211
-0.396470	0.396470

No root lies outside the unit circle.
VAR satisfies the stability condition.

5.3 Co-integration test

As demonstrated above, our four variables time series are non-stationary at level, but when we convert them to first difference, they then become stationary. It is possible to apply the Johansen co-integration test because our data fulfil the requirement that their time series are integrated of the same order.

The results from the Trace statistic test and the Maximum eigenvalue statistic test demonstrate that null hypothesis of no co-integration at 5% significance level reject the null hypothesis of no co-integration (Table 5).

For the Trace Statistic test, the null hypothesis is the number of co-integrating equations (No. of CE(s)) that are equal to zero or none, meaning that there is no co-integration among our four VAR equations. We can check that the Trace Statistic value is higher than the 5% critical value, at 65.0499 > 47.8561, and that its p-value value is also less than 5%, and thus we can reject the null hypothesis.

This test shows us that there is one co-integrating equation at 0.05 level, and that our four variables are co-integrated, or, in other words, that they have a long-run relationship or in the long-run they move together.

Table 5. Unrestricted Co-integration Rank test (Trace) results

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.021167	65.04992	47.85613	0.0006
At most 1	0.003803	17.27738	29.79707	0.6195
At most 2	0.003476	8.769501	15.49471	0.3871
At most 3	0.000446	0.995027	3.841466	0.3185

Trace test indicates 1 co-integrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Finally, the Maximum Eigenvalue test allows us to discover whether our conclusion regarding the variables relationship is the same. For this second test, the null hypothesis is also the number of co-integrating equations being equal to zero or none, and we can check that the Max-Eigen Statistic value is also higher than the 5% critical value, at 47.7725 > 27.5843. Its p-value value is also less than 5%, and thus we can again reject the null hypothesis (Table 6).

Table 6. Unrestricted Co-integration Rank test (Maximum Eigenvalue) results

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.021167	47.77254	27.58434	0.0000
At most 1	0.003803	8.507881	21.13162	0.8700
At most 2	0.003476	7.774475	14.26460	0.4021
At most 3	0.000446	0.995027	3.841466	0.3185

Max-eigenvalue test indicates 1 co-integrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Both the tests give us the same conclusion, namely that there is a long-term relationship between the Stoxx50 Index, the FTSE100 Index, and the USD/EUR and USD/GDP exchange rates, which means that each of the previous variables values are predictable, based on the past values of the others three variables.

5.4 Vector Error Correction model

As findings suggest that our VAR model has one co-integrating equation, the Vector Error Correction model (VECM) needs to be estimated, in order that we can proceed with the Granger causality tests. By using this model estimation, it is possible to find the Co-integrating equation (CE) (Enders, 2015).

The VECM does not include constant or trend term, but only contains endogenous variables, which are our four variables: log(STOXX50), log(FTSE100), log(USD/EUR), and log(USD/GDP). The estimation sample is the same as that used in the estimation of the VAR model, and the lag intervals for our variables time series are now less one lag than the previous model, being 1-4. The rank number of co-integrating is one, and the deterministic trend specification tested was linear tend in data for intercept in CE and VAR. No restrictions were added.

The four VECM equations are estimated, one for each variable and also the CE. This last equation is needed to perform the Granger causality tests, and therefore they are our only focus.

The Co-integrating equation, which is equivalent to the long-run model, is obtained as follows:

$$CE_{t-1} = 1{,}0000 \log\big(FTSE100(-1)\big) - 1{,}5318 \log\big(STOXX50(-1)\big) \\ - 2{,}13157 \log(USD_{EUR(-1)}) + 2{,}3526 \log(USD_{GBP(-1)}) + 2{,}9171$$

5.5 Granger Causality tests

The Granger Causality/Block Exogeneity Wald test was adopted to analyse the causal relationship between our four variables.

The causality examination is carried out individually by variable and then an equation for each one of our four variables is analysed, and, one by one, they are used as the dependent variable of the equation, which is reliant on the other three independent variables. First, two hypotheses are checked, if the coefficients of each of independent variables are equal to zero and also if the joint-coefficients of all the independent variables are equal to zero. For both hypotheses tests, we look at their p-values. If these are less than 5%, then there is a causality relationship among the variables under analysis.

The first equation under analysis has dlog(FTSE100) as the dependent variable, as shown in Table 7. We analyse whether the past lags of the independent variables dlog(STOXX50), dlog(USD/EUR) and dlog(USD/GBP) Granger causes the value of the FTSE100 variable.

We can check that the hypothesis that all of the four lags of dlog(STOXX50) are equal to zero is rejected, as its p-value is less than 0.05, which means that this independent variable does, indeed, cause dlog(FTSE100). The same logic is true for dlog(USD/GBP). However, we cannot conclude the same for dlog(USD/EUR).

Therefore, at this stage, we can conclude that there is a unidirectional causality relationship between dlog(FTSE100) and dlog(STOXX50), and the first one and dlog(USD/GBP).

Next, when checking the p-value for the joint hypothesis that all the coefficients from all the independent variables causes an effect on log(FTSE100), we can then conclude that they jointly cause an influence on our dependent variable (Table 10).

Table 7. Granger Causality/Block Exogeneity Wald test results for D(LOG(FTSE100))

Dependent variable: D(LOG(FTSE100))

Excluded	Chi-sq	df	Prob.
D(LOG(STOXX50))	17.05089	4	0.0019
D(LOG(USD_EUR))	4.136318	4	0.3879
D(LOG(USD_GBP))	13.95327	4	0.0074
All	35.25479	12	0.0004

Moving forward to our second equation, we now check the p-values from Table 8 for dlog(FTSE100). We conclude whether its null hypothesis is rejected. The p-value is less than 0.05, which means that the null hypothesis is in fact rejected, and that this independent variable does cause dlog(STOXX50). The same logic is true for dlog(USD/GBP). However, we cannot conclude the same for dlog(USD/EUR).

Table 8. Granger Causality/Block Exogeneity Wald test results for D(LOG(STOXX50))

Dependent variable: D(LOG(STOXX50))

Excluded	Chi-sq	df	Prob.
D(LOG(FTSE100))	12.14243	4	0.0163
D(LOG(USD_EUR))	3.629581	4	0.4585
D(LOG(USD_GBP))	14.68881	4	0.0054
All	30.95100	12	0.0020

When analysing our third equation, we check whether the null hypothesis of each independent variable is rejected. The variable D(LOG(USD_EUR)) has a causality relationship with D(LOG(FTSE100)), D(LOG(STOXX50)), and D(LOG(USD_GBP)). Similar to the conclusion of Equation One and Two, this equation show that joint coefficients also cause our dependent variable.

Table 9. Granger Causality/Block Exogeneity Wald test results for D(LOG(USD_EUR))

Dependent variable: D(LOG(USD_EUR))

Excluded	Chi-sq	df	Prob.
D(LOG(FTSE100))	26.98030	4	0.0000
D(LOG(STOXX50))	25.45612	4	0.0000
D(LOG(USD_GBP))	14.09943	4	0.0070
All	44.86045	12	0.0000

Finally, the last of our equations to be examined is that related to the causality relationship between D(LOG(USD_GBP)) and D(LOG(FTSE100)), and also D(LOG(STOXX50)) and D(LOG(USD_EUR)). As the coefficients' p-values presented in Table 10 are all above 0.05, we can quickly conclude that there is no causality relationship between this dependent variable and each of the equation's independent variables.

Table 10. Granger Causality/Block Exogeneity Wald test results for D(LOG(USD_GBP))

Dependent variable: D(LOG(USD_GBP))			
Excluded	Chi-sq	df	Prob.
D(LOG(FTSE100))	8.519282	4	0.0743
D(LOG(STOXX50))	6.059217	4	0.1948
D(LOG(USD_EUR))	7.974952	4	0.0925
All	25.24406	12	0.0137

6. Conclusion

This paper examines the long-term dynamic relationship between the FSTE 100 and Euro STOXX 50 indexes and the USD/EUR and USD/GBP exchange rates.

Result shows that there is a co-integration relationship between the two indexes and the two exchange rates, which indicates that our variables do indeed have a long-run relationship.

The Granger causality test results were obtained through VECM equations and they show that both the FSTE 100 and the Euro STOXX 50 Index are the only variables which have a causal feedback relationship. The FSTE 100 Index, the Euro STOXX 50 Index, and the USD/GBP exchange rate individually cause the USD/EUR variable. Their past values influence the past values of this exchange rate. In addition, it appears that there is a unidirectional relationship between stock index prices and the USD/EUR exchange rate, which is in partial accordance with the portfolio theory.

The presence of a unidirectional relationship between the USD/GBP exchange rate and the FSTE 100 and Euro STOXX 50 Index stock prices was also detected, which is in partial accordance with the traditional theory.

These findings confirm the common belief among investors that an association exists between exchange rates and stock prices, and that these are predictable, on the basis of the values of other variables. Therefore, it appears that investors in the foreign exchange market can use information regarding stock prices to improve the forecast of exchange rates. Moreover, they corroborate the idea that risk diversification by investing in the US, UK and Eurozone stock markets is limited during the periods of financial and political shocks.

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