A Dynamic Analysis of S&P 500, FTSE 100 and EURO STOXX 50 indices under Different Exchange Rates

Yanhua Chen¹, Rosario N. Mantegna²,³, Athanasios A. Pantelous¹,⁴,⁵,⁶*, and Konstantin M. Zuev¹,⁷

¹Institute for Risk and Uncertainty, University of Liverpool, Peach Street, L697ZF Liverpool, UK,
²Center for Network Science and Department of Economics, Central European University, Nadoru. 9,
1051 Budapest, Hungary,
³Dipartimento di Fisica e Chimica, Universita degli Studi di Palermo, Viale delle Scienze, Ed 18. 90128
Palermo, Italy,
⁴Department of Mathematical Sciences, University of Liverpool, Peach Street, L69 7ZL Liverpool, UK,
⁵Department of Econometrics and Business Statistics, Monash University, Wellington Road, Clayton
VIC 3800 Melbourne, Australia,
⁶School of Management, Shanghai University, No.99 Shangda Road, Shanghai 200044, China,
⁷Department of Computing and Mathematical Sciences, California Institute of Technology, 1200 E.
California Blvd. Mail Code 305-16, Pasadena, CA 91125, USA.

Abstract

The persistence analysis of short- and long-term interaction and causality in the international financial markets is a key issue for policy makers and portfolio investors. This paper assesses the dynamic evolution of short-term correlation, long-term cointegration and Error Correction Model (hereafter referred to as ECM)-based long-term Granger causality between each pair of US, UK, and Eurozone stock markets over the period of 1980–2015 using the rolling-window technique. A comparative analysis of pairwise dynamic integration and causality of stock markets, measured in common and domestic currency terms, is conducted to evaluate comprehensively how exchange rate fluctuations affect the time-varying integration among the S&P 500, FTSE 100 and EURO STOXX 50 indices. The results obtained show that the dynamic correlation, cointegration and ECM-based Granger causality vary significantly over the whole sample period. The degree of dynamic cointegration and correlation between pairs of stock markets rises in periods of high volatility and uncertainty, especially under the influence of external and internal economic, financial and political shocks. Meanwhile, weaker and decreasing cointegration and correlation among the three developed stock markets are observed during the recovery periods. Interestingly, the most persistent and significant cointegration among the three developed stock markets exists during the 2007–09 global financial crisis. Finally, the exchange rate fluctuations, also influence the dynamic correlation, cointegration and ECM-based Granger casual relations between all pairs of stock indices, with that influence increasing as the local currency terms are used.

JEL classification: C58; C02; C32; G15; F31

Keywords: Correlation, Cointegration, ECM-based long-run Granger causality, Crises, Exchange Rates, Uncertainty.

*Corresponding author: Dr Athanasios A. Pantelous is with the Department of Mathematical Sciences, and the Institute for Risk and Uncertainty, University of Liverpool, UK, Peach Street, L697ZL, email: A.Pantelous@liverpool.ac.uk, tel: +44 151 79 45079
1 Introduction

The integration among financial markets worldwide has increased markedly of late, due to the rapid flow of capital in the form of direct and indirect investments, and to the globalization of the financial system. In this new era, many countries appear to be more vulnerable than ever before to (global) shocks, as the magnitude and effects of local and international economic, financial and political shocks can be transferred more rapidly in the financial system (Beine et al., 2010; Yu et al., 2010; Lehkonen, 2014). Furthermore, not only the frequency but also the severity of crises in the markets has increased significantly. In particular, the 2007–09 global financial crisis considerably influenced the international stock markets, and the subsequent European sovereign debt crisis in early 2010 not only had significant adverse effect on the European stock markets, but also affected those outside of Europe (Reinhart and Rogoff, 2009; Moro and Beker, 2015). As a consequence, integration and causality among those markets have attracted the attention of academia, policy makers and individual investors, as they unveil the complex structure of the global market and, practically, they can influence monetary and fiscal policy coordination and international portfolio diversification (Umutlu et al., 2010).

Early research focused mainly on the assets’ price correlation based on stationary returns (Panton et al., 1976; Jaffe and Westerfield, 1985), and correlation has been widely applied to study the mutual interdependence of financial asset returns (Mantegna, 1999; Mantegna and Stanley, 2000; Bonanno et al., 2004; Tumminello et al., 2010; Song et al., 2011; Buccheri et al., 2013; Lillo et al., 2015; Iori et al., 2015). Song et al. (2011) studied the dynamic correlations between 57 international stock market indices, and their results reported both fast and slow dynamics. They argued that the fast dynamics of correlations were associated with the internal or external critical events, and economic and financial shocks, while the slow dynamics reflected consolidation and globalization. Buccheri et al. (2013) investigated the correlations between all pairs of stocks traded in the US stock market. They also confirmed that the fast correlations between individual stocks were associated with exogenous or endogenous events, and the slow dynamics indicated that a different degree of diversification of investment was possible. However, linear correlation is an indicator of co-movement of two time series based on synchronous changes. It might therefore miss long-run relationships occurring on a long time scale (Schöllhammer and Sand, 1985; Eun and Shim, 1989; Arshanapalli and Doukas, 1993).

The recognition of the non-stationarity of asset prices led to the exploration of possible long-run relations among international stock markets using the cointegration framework to avoid spurious relationship between financial asset series (Granger, 1969, 1981; Engle and Granger, 1987; Johansen, 1988, 1991, 1995). Cointegration is a statistical concept, pioneered by Granger and Engle (Granger, 1969, 1981; Engle and Granger, 1987). Generally, two variables are said to be cointegrated when a linear combination of the two is stationary, even though each individual variable may not be stationary (Hakkio and Rush, 1989). Empirical studies of the cointegration relationships between some major global stock markets have not provided us with consistent results, since different data samples, time periods, and data frequencies have been used. For instance, Kanas (1998) examined the cointegration relationship between the US and six major European stock markets before and after the 1987 “Black Monday” crash. His results showed no evidence of cointegration among the seven markets. On the other hand, Kasa (1992) tested the degree of integration of the US, Japanese, UK, German and Canadian stock markets from 1974 to 1990, and found a single cointegrating vector among the five markets. When Ar-
shanapalli and Doukas (1993) studied the dynamic interactions among the US, German, French, UK, and Japanese stock markets, they divided the data sample into two periods, pre- and post-October 1987, to better capture the dynamics of cointegration. Their results showed that, in the later period, the degree of cointegration was significantly greater than in the earlier period. We can also emphasize here that, in this paper, the dynamic cointegration among the stock market indices is used, as static cointegration cannot capture the changes in interdependence (Pascual 2003; Gilmore et al. 2008; Yu et al. 2010; Balcilar et al. 2015). Moreover, in most of the time-varying cointegration studies, the Johansen test (Johansen 1988, 1991, 1995) has been applied to examine whether one or more cointegrating vectors exist (generally speaking, for more than three variables), while they have not focused on the pairwise dynamic relationships, which is the main contribution of this paper.

The primary feature of cointegrated variables is that their time paths are affected by the extent of any discrepancies from long-run equilibrium. After all, if the system is to return to the long-run equilibrium, the movements of at least some of the variables must respond to the magnitude of the disequilibrium (Engle and Granger 1987, Enders 2010). The process of adjustment towards an economic equilibrium can be captured by the Error Correction Model (ECM). The Granger’s representation theorem (Engle and Granger 1987; Granger 1988) demonstrates that there must be causation in at least one direction among the cointegrated variables which can be represented within ECMs. Specifically, the sign and magnitude of the ECM coefficients indicate respectively, that the direction and speed of adjustment towards the long-run equilibrium path and the long-term causality are evaluated via the significance of the ECM coefficients (Granger et al. 2000; Andrei et al. 2017). For example, Wahab and Lashgari (1993) employed the cointegration technique and ECMs to show how the magnitude of adjustments towards the long-run equilibrium in both index and future prices for the S&P 500 and FTSE 100 is formulated for the period of 1988 to 1992. Their results indicate that future prices exhibit stronger subsequent responses to disequilibrium in the spot prices. In Arshanapalli and Doukas (1993), despite that the pairwise stock exchange markets of US and France, US and Germany, US and UK are cointegrated in the post-October 1987 period, the insignificant adjustment coefficients of ECM terms implies that the equilibrium error cannot be used to predict next period’s stock market price changes. Olawale and Taofik (2014) showed statistical significant long-run relationship between macroeconomic variables and the FTSE 100 and S&P 500 stock market indices, their results further indicated that US stock market has a quicker speed of adjustment to its long-run equilibrium than that of UK stock market.

Furthermore, Alexander (1999, 2001) and Miao (2014) argued that cointegration and correlation are somewhat related concepts but that some differences exist. For instance, they found that high correlation of asset returns does not necessarily indicate high cointegration in asset prices, and vice versa. Actually, correlation is a short-run measure of co-movement, and is liable to instability over time. On the other hand, cointegration measures the long-run co-movements in asset prices, which may occur even during periods when correlation appears to be low. In this paper, the differences and similarities between the correlation, the cointegration and ECM-based long-run Granger causality of international stock markets are studied using a dynamic framework that considers the various external and internal shocks in the economy.

Since the replacement of fixed exchange rates with floating ones in the 1970s, economic and financial crises in the markets have led currencies to fluctuate substantially. In particular, Eun and Shim (1989) examined the world’s nine developed stock markets’
interactions in terms of local currency units to avoid the effect of currency devaluation and appreciation after the occurrence of crises. Alexander and Thillainathan (1995) found evidence of cointegration when the stock market indices were expressed in local currency terms. Additionally, Voronkova (2004) showed a higher degree of cointegration among stock markets in central Europe, France, Germany, UK and US when the local currencies were used. Furthermore, the effects of currency devaluation or appreciation after the occurrence of crises (or unexpected events) was no longer present when the stock indices they used in their analyses had been converted to the same currency. Hilliard (1979), Chen et al. (2002), Pukthuanthong and Roll (2009), Hyde et al. (2007) found evidence of asymmetries in conditional volatility for local currency returns, while the asymmetry disappeared among the Asian, US and European stock markets when the US dollar currency was used. On the contrary, Roll (1992) argued that such a transformation did not entirely eliminate the influence of exchange rates (see also Koch and Koch (1991) and Bessler and Yang (2003)). Thus, changes in exchange rates might affect the short-term co-movement behavior between two international stock markets but it has not yet been fully investigated how the dynamic framework might influence them. Hence, in the present paper, we intend to fill this gap and answer the following four fundamental questions:

- How is the pairwise dynamic long-run cointegration between international stock indices?
- How is the dynamic long-run ECM-based Granger causality between cointegrated stock indices?
- What are the differences and similarities between the dynamic correlation, cointegration and long-run ECM-based Granger causality?
- How do the different exchange rates affect both dynamic correlation, cointegration and long-run ECM-based Granger causality?

With these concerns in mind, the objective of this work is to study the impact of external and internal shocks (i.e., economic, financial, and political episodes) on the S&P 500, FTSE 100 and EURO STOXX 50 stock market indices, using the correlation, cointegration and ECM-based long-run Granger causality tests in a dynamic framework. Additionally, we study whether changes in the foreign exchange rates affect the pairwise integration and causality behavior of the stock markets. Overall, the contribution of this paper can be divided into four main parts. Firstly, we employ a rolling-window technique by choosing a window size of one year for the correlation and cointegration tests for the S&P 500, FTSE 100 and EURO STOXX 50 indices from January 1st, 1980 to December 29th, 2015. In particular, the rolling-window analysis gives us the opportunity to compare the levels of correlation and cointegration relations before and after specific episodes of financial distress over that period. Second, the rolling-window dynamic ECM-based long-run Granger causality provide more interesting results not only for the interaction detection, but also for the directed causal relations over time. Third, during the periods of internal and external economic, financial and political episodes, the difference and similarity of dynamic correlation, cointegration and ECM-based long-run Granger causality between the pairs

---

1It should be mentioned here that Gilmore et al. (2008) commented that, when all indices are expressed in US dollar terms (which is very common in the finance literature), the results of the study are particularly useful to the US, but also to international investors.

2EURO STOXX 50 was launched on February 26th, 1998
of stock market indices are detected. Finally, unlike previous studies in the corresponding
literature, in this study the dynamic correlation, cointegration and ECM-based long-run
Granger causality are measured using common and domestic currency terms. Thus, we
are able to investigate how the fluctuation of exchange rates influences the integration and
causality behavior between all the combinations of pairs from those three stock market
indices from 1980 to 2015.

2 Materials and Methods

2.1 Data

We choose three international stock market indices in this study, to cover the three major,
most liquid and most developed financial markets in the world, i.e., in the US, UK and
Eurozone. The data consist of two groups: three stock indices, the S&P 500, FTSE 100
and EURO STOXX 50, and three exchange rates, the USD (US dollar), GBP (UK pound)
and EUR (Euro), which are obtained from Thomson Reuters DataStream.

In order to avoid the “non-synchronous trading effect” (Eun and Shim 1989; Kadlec
and Patterson 1999), which is related to the fact that not all the markets are open during
the same hours of the day, we choose to use weekly data. The data range from January
1st, 1980 to December 29th, 2015, apart from that for the EURO STOXX 50 index, for
which data was available from February 26th, 1998. The samples of the S&P 500 and
FTSE 100 consist of 1879 observations each, and that of the EURO STOXX 50 index
contains 932 observations. Fig. 1 plots the original stock price index and returns for the
S&P 500, FTSE 100 and EURO STOXX 50, respectively. Over the past 35 years from
1980 to 2015, the price indices of the S&P 500 and FTSE 100 appear to have stochastic
trends and seem to reveal similar behavior from the beginning until 2009. Two peaks
occurred, in 2000 and 2007, followed by sharp declines in 2001 and 2008 for all three
indices. Then, the S&P 500 recovered strongly from 2009 until the end of December
29th, 2015, while the performance of the FTSE 100 and EURO STOXX 50 indices lagged
behind that of the S&P 500 but exhibited similar increasing trends. Furthermore, from
the movement of the returns in Fig. 1, we can deduce that the downward movements of
the S&P 500, FTSE 100 and EURO STOXX 50 tend to be associated with large returns.

Table 1 provides the name and date of each external and internal economic and financial
shock that occurred around the world between 1980 and 2015. Furthermore, in order
to study how the fluctuation of exchange rates affects the pairwise interdependence of
stock markets, the pairs of stock price indices, namely, S&P 500 with FTSE 100, S&P
500 with EURO STOXX 50, and FTSE 100 with EURO STOXX 50, each of those pairs
are converted using the same currency (i.e., fixing the exchange rates fluctuations) and
their domestic currencies (i.e., permitting exchange rates fluctuations). The details of our
sample are reported in Table 2.

2.2 Methods

The steps to measuring the dynamic pairwise correlation, cointegration and ECM-based
long-run Granger causality of the stock markets are described in this section. For the
rolling-window technique, first, we choose a rolling window of size $l$, which is the number
of observations per rolling window, and then we set the number of increments between
successive rolling windows. Then, the entire sample $T$ is converted into $N = T - l + 1$
sub-samples. Thus, the first rolling window contains observations for the first period through \( l \), the second rolling window contains observations for the second period through \( l + 1 \), and so on (Mylonidis and Kollias, 2010).

### 2.2.1 Rescaling the original stock index series

Since our indices have different scales, they must be rescaled so as to be comparable. Thus, the first step is to calculate the percentage changes of each stock index series, which are given by

\[
\Delta_i(t) = \frac{P_i(t)}{P_i(t-1)}, \quad \text{for all } t \geq 2,
\]

where \( P_i(t) \) is the price of index \( i \) in week \( t \). For the rescaled index series \( R_i(t) \), we set the first entry in each series to be \( R_i(1) = 1 \), and then \( R_i(t) \) is expressed, for all subsequent entries in each series, by

\[
R_i(t) = R_i(t-1) \times \Delta_i(t), \quad \text{for all } t \geq 2.
\]

After rescaling the original stock index series, we finally transform them into their returns and natural logarithms for the correlation and cointegration test, respectively.

### 2.2.2 Rolling-window Correlation Test

For the correlated variables, the standard method of Pearson (1895) correlation is used. The analysis is based on the weekly logarithmic return after rescaling, which is given by Eq (3) for each stock index \( i \):

\[
r_i(t) = \ln P_i(t) - \ln P_i(t-1),
\]

where \( P_i(t) \) is the price of index \( i \) in week \( t \). Then, in each time window, the Pearson correlation coefficient between returns \( i \) and \( j \) is given by

\[
C_{i,j} = \frac{\langle [r_i(t) - \mu_i][r_j(t) - \mu_j] \rangle}{\sigma_i \sigma_j},
\]

where \( \mu_i \) and \( \mu_j \) are the sample means and \( \sigma_i \) and \( \sigma_j \) are the standard deviations of the two returns \( i \) and \( j \).

### 2.2.3 Rolling-window Cointegration Test

The cointegrated variables must obey an equilibrium relationship in the long run, although they may diverge substantially from that equilibrium in the short run. Based on the traditional Engle–Granger (Engle and Granger, 1987, 2003) cointegration test, our methodology consists of the following two steps to examine cointegration for the non-stationary financial asset price series:

**Step 1:** Rolling-window Unit Root Tests

Before we proceed further, we consider the non-stationarity of our transformed series (note that the integration of order one is denoted by \( I(1) \)) (Granger, 1969, 1981; Engle and Granger, 1987). Thus, the stationarity is tested after taking the first difference by

\(^3\)A stationary process (denoted by \( I(0) \)) has the property that the mean, variance and autocorrelation structure do not change over time.
implementing the popular and conventional Augmented Dickey-Fuller (hereafter referred to as ADF) and Dickey-Fuller (hereafter referred to as DF) unit root tests (Dickey and Fuller, 1979). The ADF unit root test model for an order-\(p\) VAR variable \(y\) is given by

\[
\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \varepsilon_t,
\]

where \(y_t\) is the logarithm of the rescaled index series for time period \(t\), \(\Delta y_t = y_t - y_{t-1}\) is the first difference of \(y_t\), \(\alpha\) is an intercept constant representing a drift term, \(\beta\) is the coefficient on a time trend, \(\gamma\) is the coefficient presenting the process root, \(\sum_{i=1}^{p} \delta_i \Delta y_{t-i}\) are lagged values of \(y_t\), \(p\) is the lag order of the auto-regressive process, and \(\varepsilon_t\) is the error term that should be white noise in our case.

The focus of the testing is whether the coefficient \(\gamma\) equals zero, which would mean that the process of \(y_t\) was non-stationary and had a unit root. Hence, the null hypothesis of \(\gamma = 0\) is tested against the alternative hypothesis \(\gamma < 0\) of stationarity. Then, the \(t\)-statistic test of \(\gamma\) in the ADF test for the null hypothesis is defined as

\[
t_{\gamma=0} = \frac{\hat{\gamma}}{SE(\hat{\gamma})},
\]

where \(\hat{\gamma}\) is the ordinary least squares (hereafter referred to as OLS) estimate of \(\gamma\) and \(SE(\hat{\gamma})\) is the usual standard error estimate of \(\gamma\) in Eq (5). The critical values for the test are tabulated by Dickey and Fuller (1979) through Monte Carlo simulations for different levels of significance and for three test models: no constant and no trend; with constant but no trend; with constant but no trend; with constant and with trend. If the \(t\)-statistic exceeds the critical values, the null hypothesis of stationarity is rejected in favor of the unit root alternative.

An important practical issue in the implementation of the ADF test is the specification of the lag length \(p\) in Eq (5). To determine the lag length \(p\), we first set an upper bound \(p_{\text{max}}\) for \(p\), where \(T\) is the sample size of an index series. Then, we set \(p = p_{\text{max}}\) and perform the ADF test to minimize the Schwarz (1978) information criterion (hereafter referred to as SIC). Here, we should note that, if the lag length \(p = 0\), the ADF test model in Eq (5) will be transformed into the DF test:

\[
\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \varepsilon_t.
\]

In that case, the test process is similar to that of the ADF test, and the corresponding critical values are also provided by Dickey and Fuller (1979). Once we have established that all stock indices are \(I(1)\) in each time window, the rolling Engle-Granger cointegration test could be implemented.

**Step 2:** Rolling-window Engle-Granger Two-step Cointegration Tests

Then, we apply the Engle-Granger cointegration test (Engle and Granger, 1987), which is a two-step process. First, the determination of the linear relationship is required, and then the stationarity testing on the residuals follows. As the Engle-Granger cointegration procedure is sensitive to the choice of dependent variable (Dickey et al., 1991; Engle and Granger, 1987), the OLS regressions given by Eqs (8) and (9) are used, which provide the linear long-run equilibrium relationships we assume for the two \(I(1)\) processes.

\[
y_t = \alpha_1 + \beta_1 x_t + u_{1t}, \text{ (when } y_t \text{ is the dependent variable),}
\]

\[\hat{p}_{\text{max}} = \left\lceil 12\left(\frac{T}{100}\right)^{\frac{1}{4}} \right\rceil\]
\[ x_t = \alpha_2 + \beta_2 y_t + u_{2t}, \text{ (when } x_t \text{ is the dependent variable),} \quad (9) \]

where \( y_t \) and \( x_t \) are the logarithms of the rescaled stock index series for time period \( t \), \( \alpha_1 \) and \( \alpha_2 \) are intercept constants, \( \beta_1 \) and \( \beta_2 \) are cointegration coefficients, \( u_{1t} \) and \( u_{2t} \) are long-run equilibrium error as the measurement for the deviation of \( y_t \) and \( x_t \) from the long-term cointegration relationship, respectively. In order to determine if the variables are actually cointegrated, the estimated residuals \( \hat{u}_{1t} \) \((\hat{u}_{1t} = y_t - \hat{\alpha}_1 - \hat{\beta}_1 x_t)\) and \( \hat{u}_{2t} \) \((\hat{u}_{2t} = x_t - \hat{\alpha}_2 - \hat{\beta}_2 y_t)\) must be tested for unit root non stationary by DF tests with no constant and no trend model:

\[ \Delta \hat{u}_{1t} = \gamma_1 \hat{u}_{1,t-1} + \epsilon_{1t}, \quad (10) \]
\[ \Delta \hat{u}_{2t} = \gamma_2 \hat{u}_{2,t-1} + \epsilon_{2t}, \quad (11) \]

where \( \Delta \hat{u}_{1t} \) and \( \Delta \hat{u}_{2t} \) are the first difference of \( \hat{u}_{1t} \) and \( \hat{u}_{2t} \), \( \gamma_1 \) and \( \gamma_2 \) are the coefficients presenting the process root, and \( \epsilon_{1t} \) and \( \epsilon_{2t} \) are error terms, respectively. The null and alternative hypotheses in the DF \( t \)-statistic test for stationarity of residuals are given by:

\[
H_0 : \gamma_1(\gamma_2) = 0 \iff \hat{u}_{1t}(\hat{u}_{2t}) \text{ is non-stationary} \iff y_t(x_t) \text{ does not cointegrate with } x_t(y_t); \\
H_1 : \gamma_1(\gamma_2) < 0 \iff \hat{u}_{1t}(\hat{u}_{2t}) \text{ is stationary} \iff y_t(x_t) \text{ cointegrates with } x_t(y_t). \]

If \( \hat{u}_{1t} \sim I(0) \) and \( \hat{u}_{2t} \sim I(0) \), then two \( I(1) \) variables \( y_t \) and \( x_t \) are said to be cointegrated, and then the rolling-window ECM test can be implemented.

### 2.2.4 Rolling-window Error Correction Model

According to Granger Representation Theorem \cite{Engle1987}, once \( y_t \) and \( x_t \) are found to be cointegrated, there always exists a corresponding error correction representation between two variables, which implies the existence of causality (in the Granger sense) in at least one direction \cite{Granger2000, Andrei2017}

\[
\Delta y_t = \alpha_{10} + \gamma_y ECT_{y,t-1} + \sum_i^p \beta_{11i} \Delta y_{t-i} + \sum_i^q \beta_{12i} \Delta x_{t-i} + \eta_{1t}, \quad (13) \\
\Delta x_t = \alpha_{20} + \gamma_x ECT_{x,t-1} + \sum_i^p \beta_{21i} \Delta y_{t-i} + \sum_i^q \beta_{22i} \Delta x_{t-i} + \eta_{2t}, \quad (14) \\
ECT_{y,t-1} = u_{1,t-1} = y_{t-1} - \alpha_1 - \beta_1 x_{t-1}, \quad (15) \\
ECT_{x,t-1} = u_{2,t-1} = x_{t-1} - \alpha_2 - \beta_2 y_{t-1}, \quad (16)
\]

where the \( ECT_{y,t-1} \) and \( ECT_{x,t-1} \) are the lagged error correction terms (hereafter referred to as ECT) resulting from the verified long-run cointegration relationship in Eq \( [8] \) and \( [9] \), respectively. The ECT coefficients \( \gamma_y \) and \( \gamma_x \) represent the long-run adjustment, whereas \( \beta_{11i}, \beta_{12i}, \beta_{21i} \) and \( \beta_{22i} \) are the coefficients of short-run adjustment, \( \eta_{1t} \) and \( \eta_{2t} \) denote the disturbance terms, assumed to be uncorrelated and have zero mean. It should be noted that the \( p \) is lag length, which have estimated by the different model selection information criteria\(^5\) to determine the number of lags.

Generally, in long-run equilibrium, the ECTs are equal to zero. However, if \( y_t \) and \( x_t \) deviate from the long-run equilibrium in the short run, the ECTs will not equal to

\(^5\)Akaike’s Information Criterion (AIC), Schwarz Criterion (SC) and Hannan-Quinn Criterion (HQ).
zero and each dependent variable adjusts to partially restore the equilibrium relations caused by the disequilibrium of ECTs. In particular, the ECT coefficient $\gamma_y$ and $\gamma_x$, which represent the speed of adjustment towards the long-run equilibrium path following an exogenous shock, are expected to be negative in order to ensure the stability of the model Andrei et al. (2017). According to Granger et al. (2000), the long-term causality is evaluated via the significance of the $\gamma_y$ and $\gamma_x$ using the standard $t$-statistic (Toda and Phillips, 1994), respectively. The null hypothesis of long-run non causality from $x_t$ to $y_t$ is given by $\gamma_y = 0$ in Eq (13), on the contrary, the null hypothesis of long-run non causality from $y_t$ to $x_t$ is given by $\gamma_x = 0$ in Eq (14).

2.2.5 Benjamini and Hochberg False Discovery Rate Control

For each pairwise test of stock market indices, determining whether an observed result is statistically significant, requires comparing the corresponding statistical confidence measure (the $p$-value) to a confidence threshold $\alpha$ (i.e., 0.01, 0.05 and 0.1). However, as the number of hypotheses increases, so does the probability of incorrect rejections of false positives. The false discovery rate (hereafter referred to as FDR) multiple testing procedure was utilized to correct the false significant tests of multiple comparisons. The technique for controlling the FDR was briefly mentioned by Simes (1986) and developed in detail by Benjamini and Hochberg (1995), the Benjamini and Hochberg false discovery rate control (hereafter referred to as BH FDR control) procedure is carried out as follows:

**Step 1:** Calculate the unadjusted $p$-values for $m$ hypotheses tests and sort them in ascending order, $p(1) \leq p(2) \leq \ldots \leq p(m)$. Set the smallest $p$-value has a rank of $i = 1$, then next smallest has $i = 2$, etc.

**Step 2:** Compare each individual $p$-value to its BH critical value, $\alpha \times \frac{i}{m}$, where $i$ is the rank, $m$ is the total number of tests, and $\alpha$ is the FDR you choose.

**Step 3:** Define $k$ to be the largest rank $i$ for which $p(i) \leq \alpha \times \frac{i}{m}$. Declare all tests of rank $1, 2, \ldots, i$ as significant with $p$-values smaller or equal to $p(k)$.

3 Results and Discussion

A rolling window size of $l = 48$ (i.e., 48 weeks per calendar year) is chosen as the frame in the paper Mylonidis and Kollias (2010). By adding one observation at the end and removing the first one, we can divide the full sample into $N = T - 48 + 1$ time windows. Then, for each of those rolling time windows, the dynamic analysis of the correlation, unit root tests, cointegration, ECM-based long-run Granger causality test are implemented, respectively.

3.1 Dynamic Short-run Correlation Analysis

In our study, the first measure of the extent of the financial markets’ integration is provided by the correlations estimated using dynamic Pearson correlation analysis. Fig. 2(a)–2(c) present the dynamic correlation coefficients for each pair of stock market indices from the S&P 500, FTSE 100 and EURO STOXX 50, when measured in the same and local currency terms from 1980 to 2015. A statistical summary is provided in the form of strongest, weakest and average absolute value of correlation coefficients in Table 3.

Observing Fig. 2(a)–2(c), we find that the dynamic correlation coefficients between all pairs of stock market indices tend to rise significantly both with the domestic and
international economic, financial and political shocks under the influence of high market volatility and uncertainty in the system, and then gradually decreasing during the periods of recovery of the stock market after shocks. The observed results indicate that the dynamic integration between US and UK stock markets show a consistently positive trend over 1980–2015, compared with the relatively stable and higher-valued trend between the US and Eurozone, UK and Eurozone. Furthermore, in Table 3, we report that the average correlation coefficient between the S&P 500 and FTSE 100 is 0.544 in USD/USD, 0.545 in GBP/GBP, and 0.586 in local currencies. That between the S&P 500 and EURO STOXX 50 is 0.596 in USD/USD, 0.515 in EUR/EUR, and 0.597 in local currency terms, and that between the FTSE 100 and EURO STOXX 50 is 0.646 in GBP/GBP, 0.621 in EUR/EUR, and 0.652 in local currency units, suggesting that, when measured in local currency terms, the correlation is stronger. What is more, Table 3 reports that the FTSE 100 and EURO STOXX 50 have the strongest correlation compared with the S&P 500 and FTSE 100 or the S&P 500 and EURO STOXX 50, which indicates that economies that are geographically proximate are also connected quite closely. Furthermore, the implementation of some institutional agreements of the European Union concerning stock markets, the exchange rate mechanism that is partly coordinated among the UK and the Eurozone, and intensive trade and other cooperation between national governments have removed many barriers and resulted in a high degree of stock market integration between FTSE 100 and EURO STOXX 50. In addition, the strongest correlation coefficients between the S&P 500 and FTSE 100 or the S&P 500 and EURO STOXX 50, both occur during period 31, i.e., at the beginning of 2004–06 US housing asset bubble period. In particular, when we take into account how the changes of exchange rates influence the dynamic correlation coefficients between all three stock market indices, the weakest correlation between the S&P 500 and FTSE 100 is measured in GBP/GBP during periods 4, and 35–47, all of which saw the USD depreciate against the GBP. For the S&P 500 and EURO STOXX 50, the weakest correlation coefficients can be observed when using EUR/EUR during periods 31–47, which were associated with the USD’s devaluation against the EUR. Furthermore, in periods 42–47, the correlation between the FTSE 100 and EURO STOXX 50 becomes weaker when expressed in EUR/EUR, and again the GBP depreciated against the EUR during that time period.

The linear correlation analysis is performed to ascertain the degree of co-movement among the three developed stock markets based on stationary returns. However, such analysis might miss long-run relationships occurring on a long time scale and lack the information of the direction of interaction between international stock markets. For the non-stationary financial asset price series, the implementation of the dynamic cointegration and ECM tests could be used to verify whether a long-term relationship exists, and to examine the long-run Granger causality, respectively.

### 3.2 Dynamic Unit Root Test Analysis

Before estimating the dynamic cointegration in the long-run, we firstly employ the unit root test model with constant and with trend, and the test model with no constant and no trend, to examine the integration order of the S&P 500, FTSE 100 and EURO STOXX 50 indices in logarithm levels and in logarithm differences. In Fig. 3, we plot the dynamic ADF $t$-statistic of the S&P 500, FTSE 100 and EURO STOXX 50 indices (expressed in
USD, GBP and EUR, respectively) in logarithm levels at the 5% significance level. We observe that the ADF $t$-statistics are above the red line for the vast majority of time windows. Thus, the null hypothesis of $\gamma = 0$ is accepted and the stock indices are found to be non-stationary. However, for those cases in which the ADF $t$-statistics are below the red line, we have to delete the corresponding rolling windows to ensure that all stock index series under all sub-sample windows are $I(1)$, i.e. non-stationary in logarithm levels and stationary in logarithm differences.

Fig. 4 shows that all of the ADF dynamic $t$-statistics for all stock index series and for every rolling window, under logarithm differences, are smaller than the critical value for the 1% statistical significance level (i.e., below the red line), which strongly indicates that, after first differencing, they become stationary. Hence, according to Fig. 3 and Fig. 4, the rolling-window ADF test results suggest that the S&P 500, FTSE 100 and EURO STOXX 50 indices, expressed in terms of USD, GBP and EUR, respectively, can be described as $I(1)$ processes, and therefore the rolling-window cointegration tests can be implemented to examine whether there are long-run cointegration relations between the pairs of processes.

### 3.3 Dynamic Long-run Cointegration Analysis

Pairwise dynamic cointegration of stock indices is indicated by the $p$-values of the DF unit root test of the residual series; see Figs. 5–10 which show the $p$-values after BH FDR control for both $I(1)$ process. In the multiple statistical test, a FDR $p$-value that is consistently less than 0.05 or 0.01 would suggest that the null hypothesis of no cointegration could be rejected. Practically, this would mean that there was a long-run cointegration relationship between that pair of stock indices. Generally, the smaller the obtained $p$-values, the null hypothesis can be rejected at lower values of the chosen statistical threshold. The one-year rolling cointegration estimation and the results for the dynamic $p$-values over the period 1980–2015 are plotted in Figs. 5 and 6 for the S&P 500 and FTSE 100 measured in USD/USD, GBP/GBP, and their domestic currency units. Figs. 7 and 8 show the S&P 500 and EURO STOXX 50 measured in USD/USD, EUR/EUR and their local currency units, and Figs. 9 and 10 show the FTSE 100 and EURO STOXX 50 measured in GBP/GBP, EUR/EUR and their local currency units. Over 1980–2015, we can observe that the dynamic $p$-values fluctuate, indicating significant fluctuation in the degree of integration among the different indices and currencies.

#### 3.3.1 Dynamic Cointegration between S&P 500 and FTSE 100 Indices

The dynamic $p$-values that reflect the extent to which the FTSE 100 cointegrates with the S&P 500, measured in USD/USD, GBP/GBP and GBP/USD, are shown in Fig. 5. Table 4 reports the observed time periods in which the FTSE 100 cointegrates with the S&P 500 at both the 1% and 5% significance levels. Combining the results of Fig. 5 and Table 4, we can report that the FTSE 100 cointegrates with the S&P 500 at the 1% significance level during all the periods associated with internal and external economic, financial and political shocks, from 1980 to 2015. Based on the degree of persistent cointegration, an interesting finding is that, when compared to the exogenous shocks that occurred in the developing countries (e.g., see periods 17, 19, 21), the endogenous shocks to the US market (e.g., see periods 18, 27, 29, 33–35) have greater influence on the FTSE 100’s cointegration behavior with the S&P 500. In particular, the most persistent periods of the FTSE 100’s cointegration with the S&P 500 are periods 33–35,
namely, the recent 2007–09 international financial crisis, which indicates that the US stock market significantly influenced the UK market during that time. On the other hand, the dynamic $p$-values exhibit lasting fluctuation during periods 2, 7, 31, 32, 45 and 46, at the 5% statistical significance level, suggesting that it is the 1985–87 US economic crisis caused by the Palza Accord (Gao et al., 2015), the continuous impact of the US housing asset bubble in 2004–06, and a series of US quantitative easing (hereafter referred to as QE) policies implemented by the Federal Reserve (Fawley and Neely, 2013) that are the most significant causes of the evidence of the FTSE 100’s cointegration with the S&P 500. The comparative analysis of how exchange rate movements affect the cointegration of the FTSE 100 with the S&P 500 is illustrated in Fig. 5(a)–5(c). At first sight, the difference between the cointegration as measured in the same currencies versus local currencies seems relatively small, while in periods 9, 13, 39, 40 and 47 we can observe stronger integration when measured in local currency terms, GBP/USD, which is in line with the findings of Voronkova (2004). During period 24, the evidence that the FTSE 100 cointegrates with the S&P 500 can only be found when measured using local currencies, which is consistent with Alexander and Thillainathan (1995). Furthermore, there is a stronger possibility that the FTSE 100 cointegrates with the S&P 500 when we measure it using USD/USD and domestic currency terms during periods 5, 16 and 31, yet the evidence of cointegration disappears when we measure it using GBP/GBP (note that the GBP depreciated against the USD during these periods). Reverse findings are identified during periods 9 and 40. In these periods, the evidence of the FTSE 100’s cointegration with the S&P 500 vanishes when it is measured in USD/USD (the USD depreciated against the GBP during these periods).

Fig. 6 shows the dynamic $p$-values that indicate the S&P 500’s cointegration with the FTSE 100, measured in USD/USD, GBP/GBP, and USD/GBP, at both 1% and 5% significance levels. Similarly, Table 4 reports the observed times at which the S&P 500 cointegrates with the FTSE 100, all of which are associated with the exogenous and endogenous economic, financial and political episodes that occurred during 1980–2015. The most long-lasting period of cointegration occurs during periods 33–35, i.e., during the 2007–09 global financial crisis, which was also the case for the FTSE 100’s cointegration with the S&P 500. However, when comparing Figs. 5 and 6, one difference we can see is that the dynamic $p$-values are greater for the S&P 500 cointegrating with the FTSE 100 than vice versa, which suggests a lower degree of cointegration. In particular, during period 2, the time of the early-1980s recession in the US market, the evidence of the S&P 500 cointegrating with the FTSE 100 disappears. Furthermore, during periods 45 and 46, when the third and fourth round of US QE policies were implemented, we find evidence that the S&P 500’s long-lasting cointegration with the FTSE 100 is weak and almost disappears. Additionally, the evidence indicates that, since the growth of the FTSE 100 lagged significantly behind that of the S&P 500, following the severe shocks caused by the 2007–09 global financial crisis and 2010 sovereign debt crisis in the European area, the influence of the UK on the US market was weaker than the reverse. On the contrary, the degree of the S&P 500’s cointegration with the FTSE 100 tends to be higher than that of the FTSE 100’s cointegration with the S&P 500 during period 17, namely, the 1994 Mexican debt crisis. Moreover, we notice there is significant evidence of the S&P 500 cointegrating with the FTSE 100 during period 15 (i.e., 1992’s “Black Wednesday” in the UK), while the FTSE 100 does not cointegrate with the S&P 500 during that period (see Fig. 5), which implies that the UK currency crisis on September 16th, 1992 not only affected the UK stock market greatly, but also enhanced the latter’s influence on the US
market.

Finally, taking into account the influence of exchange rate movements on the S&P 500’s dynamic long-lasting cointegration with the FTSE 100 (see Fig. 3(a)–3(c)), we observe that, during periods 5, 9, 31 and 39, the S&P 500 cointegrates more intensely with the FTSE 100 when they are measured in USD/USD and local currency terms, respectively. In particular, the S&P 500’s cointegration with the FTSE 100 can only be identified when using the local currencies during period 40, namely during the 2010 European sovereign debt crisis. Furthermore, our results reveal that, during periods 15, 48, and 49, the evidence that the S&P 500 cointegrates with the FTSE 100 disappears when measured in GBP/GBP (note that there was depreciation of the GBP against the USD during these periods), while it is stronger when measured in USD/USD and local currency terms. The opposite results are observed during period 13, when a higher degree of cointegration is reported under GBP/GBP and the local currencies, yet there is no evidence of cointegration under USD/USD (note the depreciation of the USD against the GBP at this time).

3.3.2 Dynamic Cointegration between the S&P 500 and EURO STOXX 50 Indices

The dynamic p-values indicating the extent to which the EURO STOXX 50 cointegrates with the S&P 500 and the S&P 500 cointegrates with EURO STOXX 5, when they are measured in both common and local currency terms, are only presented from 1998 to 2015 (see Figs. 7 and 8), and the observed periods of cointegration are reported in Table 5 for both the 1% and 5% statistical significance levels. From Figs. 7 and 8 we can observe similar degrees of long-lasting cointegration of the EURO STOXX 50 with the S&P 500 and vice versa, associated with external and internal economic and financial shocks, and once again the cointegration between the S&P 500 and EURO STOXX 50 is most persistent and highest during the 2007–09 global financial crisis, out of the whole sample period. However, a significant distinction is that, during periods 24 and 31, namely after the 2000 bursting of the dot-com bubble and during the 2004–06 US housing asset bubble, there is stronger cointegration of the S&P 500 with the EURO STOXX 50 than vice versa. However, the opposite is true for periods 45 and 46, i.e., when the US QE3 and QE4 policies were implemented.

Now turning our attention to how changes in exchange rates influence the integration behavior between the S&P 500 and EURO STOXX 50, we compare Fig. 7(a)–7(c) and Fig. 8(a)–8(c). There is a stronger probability of the existence of cointegration between the S&P 500 and EURO STOXX 50 when they are measured in their local currencies rather than under a common currency, i.e., USD/USD and EUR/EUR, respectively. Particularly, during periods 26 and 27, there is a larger probability of cointegration between the EURO STOXX 50 and S&P 500 when they are measured in local currency terms. Furthermore, the EURO STOXX 50 appears to cointegrate more strongly with the S&P 500 during periods 31 and 43 when they are measured in USD/USD and local currency terms, yet the evidence of cointegration is weaker under EUR/EUR (note the depreciation of the EUR against the USD during these periods). In addition, from Fig. 7 we can observe that, during period 40, the evidence that the EURO STOXX 50 cointegrates with the S&P 500 is significant only when it is measured in EUR/EUR and the local currencies, while no cointegration appears under USD/USD. On the other hand, as for the evidence of the S&P 500 cointegrating with the EURO STOXX 50, during periods 26, 31, 34, 41, 45, 46, 48 and 49, we observe stronger cointegration when they are measured in local
currency terms.

### 3.3.3 Dynamic Cointegration between the FTSE 100 and EURO STOXX 50 Indices

Figs. [9](#) and [10](#) show the dynamic p-values indicating the extent to which the EURO STOXX 50 cointegrates with the FTSE 100 and vice versa, measured in both common and local currency terms, for 1998–2015. Table [6](#) shows all the periods of integration at both 1% and 5% statistical significance levels. From Table [6](#) we can observe that the periods during which the EURO STOXX 50 cointegrates with the FTSE 100 and the FTSE 100 cointegrates with the EURO STOXX 50 are quite similar during the whole sample period. In particular, for periods 31–39, there is the strongest probability of cointegration existing between the FTSE 100 and EURO STOXX 50, out of the entire sample period. We also observe that the FTSE 100 cointegrates with the EURO STOXX 50 only during periods 24 and 40, while there is no evidence that the EURO STOXX 50 cointegrates with the FTSE 100. The reason might be related to the internal, serious debt crisis in the Eurozone, which led to more shocks moving from the Eurozone to the UK stock market than vice versa. In addition, since the EURO STOXX 50 index covers 50 stocks from 11 Eurozone countries (i.e., Austria, Belgium, Finland, France, Germany, Ireland, Italy, Luxembourg, the Netherlands, Portugal and Spain), it appears that the collapse of the dot-com asset bubble in the US in March 2000 affected the EURO STOXX 50 more than the FTSE 100 index.

In terms of the influence of exchange rate movements, the cointegration between the FTSE 100 and the EURO STOXX 50 is reported in Table [6](#). Of particular note, during periods 40 and 44, we identify stronger cointegration of the EURO STOXX 50 with the FTSE 100 and vice versa when using the local currencies. Furthermore, during periods 45 and 46, when the US QE3 and QE4 policies were implemented, there is strong persistent cointegration of the FTSE 100 and EURO STOXX 50, which indicates that the economic recession in the UK and Eurozone markets and a series of similar monetary and fiscal policies caused these two markets to integrate significantly.

To sum up, based on the dynamic cointegration analysis between all pairs of stock market indices, we conclude that the persistent cointegration periods observed are all associated with external or internal asset bubbles, market crashes, sovereign failures, or wars, while the strongest cointegration occurs in tandem with internal financial shocks. In particular, during the 2007–09 global financial crisis, all three major stock markets exhibited the most persistent and deepest cointegration with each other due to the serious shocks on the US and global stock markets. There is some evidence that, during economic, financial and political shocks, the capitalization of the stock market indices grew quickly and synchronously, and they were highly cointegrated with each other. Meanwhile, when an individual stock market experiences internal economic, financial and political episodes (e.g., see the 2004–06 US housing asset bubble, the 2010 European sovereign debt crisis, etc.), it is significantly affected by other stock markets due to the recession in the former country’s economy. Furthermore, by comparing with dynamic correlation between S&P 500 and FTSE 100, S&P 500 and EURO STOXX 50, FTSE 100 and EURO STOXX 50 in Fig. [2](#), the degree of cointegration changed associated with the rising or decreasing correlation obviously. Additionally, when the indices are measured in local currency terms, the probability of cointegration between all three pairs of stock indices is higher than that when using the same unit of currency for each index in the pair, which is consistent with the findings of Voronkova [2004](#). Evidence of cointegration can only be found...
when using local currencies during some time periods, which is in line with Alexander and Thillainathan (1995), who also found that integration between international equity markets appeared only when stock indices were expressed in local currency terms. Our comparative analysis conducted under common and local currency terms, formulated on a dynamic framework, provides new insights over and above that found in the existing studies.

3.4 Dynamic ECM-based Long-run Granger Causality Analysis

As was described in the previous subsection, the dynamic $p$-values after BH FDR controlling indicate the probability that we can accept the long-run cointegration relationships between the pairs of stock market indices. Then, the ECM is used in order to identify the long-run Granger causality through the error correction coefficients. Only statistical significant error correction coefficients are reported in Figs. 11 to 13 for each pair of stock market indices of S&P 500, FTSE 100 and EURO STOX 50 from 1980 to 2015, respectively. In particular, Table 4–6 report the time periods in which we observe the statistical significantly directional Granger causality between each pair of stock indices in the long run during 1980–2015. Summary statistics are provided in the form of strongest, weakest, and average absolute value of adjustment coefficients in Table 7.

In the case of the long-run Granger causality between S&P 500 and FTSE 100, Fig. 11(a)–11(c) show the dynamic statistical significant error correction coefficients based on the results of the FTSE 100’s cointegration with the S&P 500 and the S&P 500 cointegration with the FTSE 100, calculated using the same and local currencies, respectively. We observe that all the adjustment coefficients for the ECTs are negative for S&P 500 and FTSE 100, confirming the long-run Granger causality running from S&P 500 towards FTSE 100 (shown with a blue bar), from FTSE 100 to S&P 500 (shown with a yellow bar), respectively. As shown in Table 4, the proportion of period in which the S&P 500 long-run Granger causes FTSE 100 is greater than the reverse, namely 50% to 40% when using USD/USD, 58% to 44% when using GBP/GBP, and 52% to 34% when using the local currencies. Specifically, we find that the time periods in which FTSE 100 is strongly long-run Granger caused by S&P 500, namely periods 1–4, 13, 23, 33–34, all accompany economic recession or financial shocks in the US market, whether we measure them in common or local currency terms. In contrast, the significant negative error correction coefficients are found as an evidence of long-run Granger causality running from FTSE 100 to S&P 500 during periods 1, 4, 15–16 40, early 1980s recession in the UK, UK market’s “Black Wednesday” currency crisis in 1992, and the subsequent 1992–93 European currency crisis, significantly Granger caused the US stock market in the long run. Furthermore, significantly directional long-run Granger causality between S&P 500 and FTSE 100 are found during the early 1980s recession in the US and UK, following the 1993 economic recovery of US and UK, the early 1990s recession in the US and UK (only using GBP/GBP and local currencies), the early 2000s recession in the US (only using GBP/GBP and local currencies). Meanwhile, the statistical results in Table 7 show that the dynamic error correction coefficients vary over time. In most of the time periods, the coefficients that show evidence of long-run Granger causality running from S&P 500 to FTSE 100 are stronger than the reverse direction, when measured in USD/USD (average values of 0.387 vs. 0.366) and local currencies (average values of 0.429 vs. 0.377), which indicates that the US stock market is more influential than the UK market. However, contrasting results are found when we use GBP/GBP (average values of 0.336 vs. 0.349).
Moreover, the strongest coefficients for the S&P 500 long-run Granger causes FTSE 100 are 0.970 (using USD/USD during period 42), 0.895 (using GBP/GBP during period 42), and 0.926 (using USD/GBP during period 34). It should be noted that since the high volatility during the 2011 US debt-ceiling crisis and the 2007–2009 global financial crisis, the shock of US stock market exerts a significantly leadership toward UK market.

The statistical significant and negative adjustment coefficients for S&P 500 and EURO STOXX 50 in Fig. 12(a)–12(c) provide evidence of long-run causal relationship running for S&P 500 to EURO STOXX 50 (shown with a blue bar), from EURO STOXX 50 to S&P 500 (shown with a yellow bar) from 1998 to 2015 calculated using the same and local currencies, respectively. From Table 5 we find that the proportion of period in which the S&P 500 long-run Granger causes EURO STOXX 50 is stronger than the reverse, namely 65% to 58% when using USD/USD and 65% to 54% when using EUR/EUR, and 73% to 42% measured in the local currencies. Furthermore, the time periods in which the S&P 500 strongly long-run Granger causes EURO STOXX 50 are particularly during the 1999 Kosovo war, the 2002 stock market downturn, the collapse of US housing bubble, the 2007–2009 global financial crisis, the 2010 European debt crisis, the 2015–2016 US stock market sell-off, all of which are accompanied by economic, financial or political shocks in the US market. However, the reverse direction that EURO STOXX 50 long-run Granger causes S&P 500 is observed during the burst of the 2000 dot-com bubble, the beginning of US housing bubble period, from the early 2000s recession in the US to the 9/11 attack and war in Afghanistan, the beginning period of the US housing price bubble, the 2010 European debt crisis, the period that second round of QE implementation in the UK. It should be noted that, when measured in EUR/EUR, there is strongly long-run Granger causality running from the EURO STOXX 50 to S&P 500 after the Lehman Brother collapse in Sept. 2008 since the significant depreciation of Euro against US dollars, resulting in money inflows and investment shock in the UK stock market and causes changes in S&P 500. Moreover, the average error correction coefficients between the S&P 500 and EURO STOXX 50, using both the same and local currency terms, are displayed in Table 7 and they further prove that the long-run Granger causality between S&P 500 EURO STOXX 50 is similar, with average values of 0.441 vs. 0.416 in USD/USD, 0.339 vs. 0.368 in EUR/EUR and 0.504 vs. 0.511 in USD/EUR, respectively. The maximum error correction coefficients for the S&P 500s causes EURO STOXX 50, 1.668 using USD/USD in period 39, 1.407 using EUR/EUR in period 29, and 1.332 using local currencies in period 29, are associated with the 2009 Dubai debt standstill and the 2002 stock market downturn.

Finally, the estimation of dynamic adjustment coefficients for the ECM-based long-run Granger causality for FTSE 100 and EURO STOXX 50 are presented in Fig. 13(a)–13(c), from 1998 to 2015 in both common and local currency terms, respectively. The statistical significant and negative adjustment coefficients provide an evidence of long-run causal relationship running for FTSE 100 to EURO STOXX 50 (shown with a blue bar), from EURO STOXX 50 to FTSE 100 (shown with a yellow bar) respectively. As shown in Table 6 the proportion of period in which the EURO STOXX long-run Granger causes FTSE 100 is much more compared with the causality running from FTSE 100 to EURO STOXX 50, namely 58% to 50% when using GBP/GBP and 54% to 38% when using EUR/EUR. Moreover, the time periods in which the FTSE 100 strongly long-run Granger causes EURO STOXX 50 are especially during the 1999 Kosovo war, the 2002 stock market downturn, the collapse of US housing bubble, the 2007–2009 global financial crisis, the 2010 European debt crisis, the US recession of Dec 2007-Jun 2009.
the US QE2 from November 4th, the 2010 to June 30th, 2011, the 2015–2016 US stock market selloff. However, the reverse causal direction that EURO STOXX 50 long-run Granger causes FTSE 100 is during the 9/11 Attacks, the 2001 US war in Afghanistan, the 2011 US debt-ceiling crisis, during the 2013 US debt-ceiling crisis, the implementation of US QE3 & QE4 and UK QE2, respectively. Next, from the average error correction coefficients between the FTSE 100 and EURO STOXX 50 shown in Table 7, we notice that the EURO STOXX 50 long-run Granger causes FTSE 100 is slightly stronger than the reverse direction, with average values of 0.498 vs. 0.425 (GBP/GBP), 0.479 vs. 0.504 (EUR/EUR), and 0.553 vs. 0.524 (local currency terms). The strongest coefficients by which the long-run Granger causality running from FTSE 100 to EURO STOXX 50 is 1.225 (with GBP/GBP in period 29), 1.154 (with EUR/EUR in period 29) and 0.930 (with local currency terms in period 29). What is more, the strongest coefficients of the EURO STOXX 50 long-run Granger causality FTSE 100 are 1.119 (with GBP/GBP in periods 27–28), 1.233 (with EUR/EUR in periods 27–28), and 1.050 (with local currency terms in period 42). The results reveal that, although the 9/11 attack, the 2001 US war in Afghanistan, and the 2011 US debt-ceiling crisis all originate from the US market which is associated with high volatility, since various bilateral trade and economic cooperation agreements exist between the US, UK and the Eurozone markets, resulting in significantly long-run Granger causal relation between FTSE 100 and EURO STOXX 50.

3.5 Summary Results of Dynamic Correlation, Cointegration and ECM-based long-run Granger Causality Analysis

From the results of dynamic correlation, cointegration and ECM-based long-run Granger causality analysis between the S&P 500 and FTSE 100, S&P 500 and EURO STOXX 50, and FTSE 100 and EURO STOXX 50 over 1980–2015 in both common and local currencies terms, the following similarities are derived. As shown in Fig. 2 and Figs. 5–10, the dynamic correlation and cointegration analysis between all pairs of stock market indices becomes stronger and more deeply integrated with each other when they are associated with external or internal economic, financial and political shocks. However, the decreasing, weaker correlation and cointegration evolving over time have been found during the bull market or the recovery of the stock market after serious shocks. Specifically, identifying the similarities between dynamic correlation and ECM-based long-run Granger causality provides more interesting results not only for the interaction detection, but also for the directed causal relations.

The dynamic correlation analysis highlights the interactions between US and UK stock markets tend to increase significantly during: 1) the early 1980s recession of the US, the 198485 UK miners’ strike, the 1990 Gulf War, both associated with bidirectional long-run Granger causality running between US and UK stock markets; 2) the 1987 “Black Monday” stock market crash, the 2002 stock market downturn, the 2007 sub-prime mortgage crisis, the 2011 US debt-ceiling crisis, associated with long-run Granger causality running from the S&P 500 to FTSE 100; 3) the 199293 European currency crisis, before the 1997 Asian financial crisis, with long-run Granger causality running from FTSE 100 to S&P 500. In contrast, the significantly decreasing correlation between S&P 500 and FTSE 100 are observed during: 1) the 1982 economic recovery of the US and the UK, the 1994 Mexico peso crisis, accompanied with long-run Granger causality running from the US to the UK stock market; 2) the 199293 European currency crisis, the period of the US Dot-com bubble, the period of 2004–2006 US housing price bubble, with long-run
Granger causality running from the UK to the US stock market.

In terms of the correlation dynamics across the US and Eurozone stock markets tend to increase significantly during: 1) the bear market between post 2001 and 2003, the US recession from December 2007 to post 2008, the Lehman brother collapse in September 2008, the 2015-16 US stock market sell-off, associated with long-run Granger causality running from the S&P 500 to the EURO STOXX 50; while during 2) the 2000 dot-com bubble burst, the beginning of US housing bubble from 200405, the 2011 US debt-ceiling crisis, all associated with long-run Granger causality running from the EURO STOXX to the S&P 500. In contrast, the gradually decreasing correlation could be observed during: 1) the periods after the Euro was introduced and the 1999 Kosovo war, the beginning of 2007, both associated with significant magnitude of long-run Granger causality from the S&P 500 to the EURO STOXX 50; while long-run Granger causality from the EURO STOXX 50 to the S&P 500 during the second round of US QE policy implementation.

By observing the dynamic correlation and ECM-based long-run Granger causality of the FTSE 100 and EURO STOXX 50, all increasing correlation accompanied with significantly stronger long-run Granger causality in both direction during: 1) the bear market between post 2001 and 2003 with FTSE 100 long-run Granger causes EURO STOXX; 2) the 9/11 Attack, the 2001 US war in Afghanistan and the 2011 US debt-ceiling crisis with significantly long-run Granger causality running from the EURO STOXX 50 to the FTSE 100. On the contrary, the decreasing correlation associated with direction causal relations during the introduction of the Euro, the 1999 Kosovo war and the 200506 US housing price bubble, the US QE2, the EU QE during 20152016, both associated with long-run Granger causality running from the FTSE 100 to the EURO STOXX 50, respectively. However, during the implementation of QE in the US (QE 3&4), the EURO STOXX 50 significantly long-run Granger causes the FTSE 100 with decreasing correlation.

Finally, the following similarities and differences from dynamic correlation, cointegration and ECM-based long-run Granger causality analysis of each pair of developed stock markets of the US, UK and Eurozone can be summarized:

- During the periods of internal and external economic, financial and political episodes, the degree of dynamic correlation, cointegration and ECM-based long-run Granger causality between the pairs of stock market indices increased significantly in all cases. While during the bull market and recovery period of the stock market after shocks, the correlation decreased gradually associated with weaker integration and long-run Granger causality. In particular, there is stronger and more significant interactions, causal relations between the stock market indices when they are both measured in local currency terms.

- The dynamic correlation analysis ascertains the degree of co-movement between stock markets based on synchronous changes, which might miss long-run relationships occurring on a long time scale. Since the common force between two cointegrated stock market indices that are cannot deviate too far away from each other in the long term, the dynamic cointegration between pairs of stock markets is more persistent than the dynamic correlation associated with exogenous and endogenous shocks. Furthermore, the ECM test to examine whether returns of one market influence another based on the existed long-run cointegration, which could reflect the direction and strength of the long-run Granger causality between stock market indices easily.

18
4 Conclusion

In this paper, by combining the rolling-window technique with correlation, cointegration and ECM tests, the dynamic integration and causality between each pair of US, UK, and Eurozone stock markets are explored from January 1st, 1980 to December 29th, 2015 under the impact of external and internal economic, financial and political shocks. Specifically, we measure those time-varying symmetric and asymmetric interactions under the same currencies and under local currencies, to comprehensively analyze how the exchange rates fluctuation affects the integration and linkages between stock market indices over time. In addition, the similarity and difference between the integration and causality are studied.

The findings obtained indicate that the degree of short-term correlation, long-term cointegration and ECM-based long-term Granger causality between all pairs of stock market indices are both evolving over time, especially, stronger interactions and causality when measured in local currency terms than used in common currencies. The dynamic correlation analysis ascertains the degree of co-movement between US, UK and Eurozone stock markets based on stationary returns, and highlights the interactions between stock markets tend to increasing during external and internal economic, financial and political shocks over 1980–2015. However, the decreasing correlations were found during bull market and the recovery of stock market after shocks. Similarly, the existence of long-run cointegration between each pairwise stock markets are more significant during times of exogenous and endogenous economic, financial and political episodes, whereas the weaker cointegration varied over time have been found during the bull market or the recovery of the stock market after those “extreme events”. In particular, the stronger cointegration appears during times of domestic shocks than the external, and the strongest and most persistent cointegration exists between US, UK and Eurozone stock markets are during the 2007–09 global financial crisis.

Furthermore, the ECM-based long-run Granger causality which exacts from the existed cointegration relationships reveals the directed dynamic causal relation between pairwise stock markets of US, UK and Eurozone from 1980 to 2015. Specifically, we found that associated with increasing correlation evolved with time, the US stock market long-run Granger caused the UK and Eurozone markets during the economic, financial and political episodes happened in the US market, for example, during the 1987 “Black Monday” stock market crash, the 2002 stock market downturn, the 2007 sub-prime mortgage crisis and the Lehman Brother collapse in September 2008, etc. In contrast, the UK and Eurozone markets cause the US market especially during the 1992–93 European currency crisis, the 2000 dot-com bubble burst and the beginning of the US housing bubble from 2004–05, etc. In particular, there is significantly stronger long-run Granger causality from UK to Eurozone markets during the bear market between post 2001 and 2003, meanwhile, Eurozone stock markets lead UK market during the periods of the 9/11 Attack, the 2001 US war in Afghanistan and the 2011 US debt-ceiling crisis all accompanied with increasing correlation, respectively. On the other hand, with the decreasing correlation over time, the US market has remained dominant in leading the information transmission to UK and Eurozone markets during the 1982 economic recovery of US and UK, the 1994 Mexico peso crisis, the periods after the Euro was introduced, the 1999 Kosovo war and the beginning of 2007. While the unidirectional causality are found from UK, Eurozone markets to the US market during the 1992–93 European currency crisis, the period of the US Dot-com bubble, the period of 2004–2006 US housing price bubble and the US QE2
policy implementation. The obtained results further shown that during the introduction period of Euro, the 1999 Kosovo war, the 2005–06 US housing price bubble, the US QE2, the EU QE during 2015–2016, there is long-run Granger causality from UK to Eurozone markets, while the reverse causality could be observed during the implementation of QEs in the US (QE3 & QE4).

To conclude, in terms of policy implications, testing for cointegration and any changes in it over time is crucial since, if cointegration does not hold, it indicates that the markets are not linked and no Granger causality in the long run and therefore it is possible to gain from diversification. As for the dynamic correlation, lower correlation between pairs of stock markets will be beneficial to investors.

Acknowledgments

The authors would like to acknowledge the support for this work provided by the EPSRC and ESRC Centre for Doctoral Training on Quantification and Management of Risk & Uncertainty in Complex Systems & Environments (EP/L015927/1). We would like to thank participants at the 60th ISI World Statistics Congress, the 2nd Quantitative Finance and Risk Analysis (QFRA2016) symposium, and at the seminar talks in the University of Liverpool (UK), Shanghai and Chinese Academy of Sciences (China) and Monash University (Australia), for helpful comments. Particular thanks to Ai Han (Academy of Mathematics and Systems Science, Chinese Academy of Sciences, China) who read very carefully the last version of our paper and the comments she made. Any remaining errors are ours.
References

C. Alexander. Optimal hedging using cointegration. *Philosophical Transactions of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, 357 (1758):2039–2058, 1999.

C. Alexander. *Market models: A guide to financial data analysis*. John Wiley & Sons, 2001.

C. Alexander and R. Thillainathan. The asian connection. *Emerging Market Investor*, 2 (6):42–46, 1995.

J. V. Andrei, M. Micila, and M. Panait. The impact and determinants of the energy paradigm on economic growth in european union. *PloS one*, 12(3):e0173282, 2017.

B. Arshanapalli and J. Doukas. International stock market linkages: Evidence from the pre-and post-october 1987 period. *Journal of Banking & Finance*, 17(1):193–208, 1993.

M. Balcilar, C. Jooste, S. Hammoudeh, R. Gupta, and V. Babalos. Are there long-run diversification gains from the dow jones islamic finance index? *Applied Economics Letters*, 22(12):945–950, 2015.

M. Beine, A. Cosma, and R. Vermeulen. The dark side of global integration: Increasing tail dependence. *Journal of Banking & Finance*, 34(1):184–192, 2010.

Y. Benjamini and Y. Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the royal statistical society. Series B (Methodological)*, pages 289–300, 1995.

D. A. Bessler and J. Yang. The structure of interdependence in international stock markets. *Journal of International Money and Finance*, 22(2):261–287, 2003.

G. Bonanno, G. Caldarelli, F. Lillo, S. Micciché, N. Vandewalle, and R. N. Mantegna. Networks of equities in financial markets. *The European Physical Journal B*, 38(2):363–371, 2004.

G. Buccheri, S. Marmi, and R. N. Mantegna. Evolution of correlation structure of industrial indices of us equity markets. *Physical Review E*, 88(1):012806, 2013.

G. M. Chen, M. Firth, and O. M. Rui. Stock market linkages: evidence from latin america. *Journal of Banking & Finance*, 26(6):1113–1141, 2002.

D. Dickey, D. Jansen, and D. Thornton. A primer on cointegration with an application to money and income. *Federal Reserve Bank of St. Louis Review*, (Mar):58–78, 1991.

D. A. Dickey and W. A. Fuller. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, 74(366a):427–431, 1979.

W. Enders. *Applied Econometric Time Series*. John Wiley & Sons, 2010.

R. F. Engle and C. W. J. Granger. Co-integration and error correction: representation, estimation, and testing. *Econometrica*, 55(2):251–276, 1987.
R. F. Engle and C. W. J. Granger. Time-series econometrics: cointegration and autoregressive conditional heteroskedasticity. *Advanced information on the Bank of Sweden Prize in Economic Sciences in Memory of Alfred Nobel*, pages 1–30, 2003.

C. S. Eun and S. Shim. International transmission of stock market movements. *Journal of Financial and Quantitative Analysis*, 24(02):241–256, 1989.

B. W. Fawley and C. J. Neely. Four stories of quantitative easing. *Review*, 95, 2013.

Y. C. Gao, Y. Zeng, and S. M. Cai. Influence network in the chinese stock market. *Journal of Statistical Mechanics: Theory and Experiment*, 2015(3):P03017, 2015.

C. G. Gilmore, B. M. Lucey, and G. M. McManus. The dynamics of central european equity market comovements. *The Quarterly Review of Economics and Finance*, 48(3):605–622, 2008.

C. W. J. Granger. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica*, 37(3):424–438, 1969.

C. W. J. Granger. Some properties of time series data and their use in econometric model specification. *Journal of Econometrics*, 16(1):121 – 130, 1981.

C. W. J. Granger. Some recent development in a concept of causality. *Journal of econometrics*, 39(1-2):199–211, 1988.

C. W. J Granger, B. N Huangb, and C. W. Yang. A bivariate causality between stock prices and exchange rates: evidence from recent asianflu. *The Quarterly Review of Economics and Finance*, 40(3):337–354, 2000.

C. S. Hakkio and M. Rush. Market efficiency and cointegration: an application to the sterling and deutschemark exchange markets. *Journal of International Money and Finance*, 8(1):75 – 88, 1989.

J. E. Hilliard. The relationship between equity indices on world exchanges. *The Journal of Finance*, 34(1):103–114, 1979.

S. J. Hyde, D. P. Bredin, and N. Nguyen. Correlation dynamics between asia-pacific. *EU and US stock returns*, Munich Personal RePEc Archive, (9681), 2007.

G. Iori, R. N. Mantegna, L. Marotta, S. Micciché, J. Porter, and M. Tumminello. Networked relationships in the e-mid interbank market: A trading model with memory. *Journal of Economic Dynamics and Control*, 50:98 – 116, 2015.

J. Jaffe and R. Westerfield. The week-end effect in common stock returns: The international evidence. *The Journal of Finance*, 40(2):433–454, 1985.

S. Johansen. Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, 12(2-3):231–254, 1988.

S. Johansen. stimation and hypothesis testing of cointegration vectors in gaussian vector autoregressive models. *Econometrica*, 59(6):1551–1580, 1991.

S. Johansen. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford University Press, New York, USA, 1995.
G. B. Kadlec and D. M. Patterson. A transactions data analysis of nonsynchronous trading. *Review of Financial Studies*, 12(3):609–630, 1999.

A. Kanas. Linkages between the US and European equity markets: further evidence from cointegration tests. *Applied Financial Economics*, 8(6):607–614, 1998.

K. Kasa. Common stochastic trends in international stock markets. *Journal of Monetary Economics*, 29(1):95–124, 1992.

P. D. Koch and T. W. Koch. Evolution in dynamic linkages across daily national stock indexes. *Journal of International Money and Finance*, 10(2):231–251, 1991.

H. Lehkonen. Stock market integration and the global financial crisis. *Review of Finance*, pages 1–56, 2014.

F. Lillo, S. Micciché, M. Tumminello, J. Piilo, and R. N. Mantegna. How news affects the trading behaviour of different categories of investors in a financial market. *Quantitative Finance*, 15(2):213–229, 2015.

R. N. Mantegna. Hierarchical structure in financial markets. *The European Physical Journal B*, 11(1):193–197, 1999.

R. N. Mantegna and H. E. Stanley. *An Introduction to Econophysics: Correlations and Complexity in Finance*, 2000. Cambridge University Press, Cambridge, UK, 2000.

G. J. Miao. High frequency and dynamic pairs trading based on statistical arbitrage using a two-stage correlation and cointegration approach. *International Journal of Economics and Finance*, 6(3):96, 2014.

B. Moro and V. A. Beker. *Modern Financial Crises: Argentina, United States and Europe*. Springer, 2015.

N. Mylonidis and C. Kollias. Dynamic European stock market convergence: Evidence from rolling cointegration analysis in the first euro-decade. *Journal of Banking & Finance*, 34(9):2056–2064, 2010.

Olusegun A. S. Olawale, A. N. and A. Taofik. Statistically significant relationships between returns on Ftse 100, S&P 500 market indexes and macroeconomic variables with emphasis on unconventional monetary policy. *International Journal of Statistics and Applications*, 4(6):249–268, 2014.

D. B. Panton, V. P. Lessig, and O. M. Joy. Comovement of international equity markets: A taxonomic approach. *The Journal of Financial and Quantitative Analysis*, 11(3):415–432, 1976.

A. G. Pascual. Assessing European stock markets (co) integration. *Economics Letters*, 78(2):197–203, 2003.

K. Pearson. Note on regression and inheritance in the case of two parents. *Proceedings of the Royal Society of London*, 58:240–242, 1895.

K. Pukthuanthong and R. Roll. Global market integration: An alternative measure and its application. *Journal of Financial Economics*, 94(2):214–232, 2009.
C. M. Reinhart and K. S. Rogoff. *This time is different: eight centuries of financial folly.* Princeton University Press, 2009.

R. Roll. Industrial structure and the comparative behavior of international stock market indices. *The Journal of Finance,* 47(1):3–41, 1992.

H. Schöllhammer and O. Sand. The interdependence among the stock markets of major European countries and the United States: An empirical investigation of interrelationships among national stock price movements. *Management International Review,* pages 17–26, 1985.

G. Schwarz. Estimating the dimension of a model. *The Annals of Statistics,* 6(2):461–464, 1978.

R. J. Simes. An improved Bonferroni procedure for multiple tests of significance. *Biometrika,* pages 751–754, 1986.

D. M. Song, M. Tumminello, W. X. Zhou, and R. N. Mantegna. Evolution of worldwide stock markets, correlation structure, and correlation-based graphs. *Physical Review E,* 84(2):026108, 2011.

H. Y Toda and P. C. B Phillips. Vector autoregression and causality: a theoretical overview and simulation study. *Econometric Reviews,* 13(2):259–285, 1994.

M. Tumminello, F. Lillo, and R. N. Mantegna. Correlation, hierarchies, and networks in financial markets. *Journal of Economic Behavior and Organization,* 75(1):40 – 58, 2010.

M. Umutlu, L. Akdeniz, and A. Altay-Salih. The degree of financial liberalization and aggregated stock-return volatility in emerging markets. *Journal of Banking & Finance,* 34(3):509–521, 2010.

S. Voronkova. Equity market integration in Central European emerging markets: A cointegration analysis with shifting regimes. *International Review of Financial Analysis,* 13(5):633–647, 2004.

M Wahab and M. Lashgari. Price dynamics and error correction in stock index and stock index futures markets: A cointegration approach. *Journal of Futures Markets,* 13(7):711–742, 1993.

I. W. Yu, K. P. Fung, and C. S. Tam. Assessing financial market integration in Asia–equity markets. *Journal of Banking & Finance,* 34(12):2874–2885, 2010.
### Table 1: Name and dates of external and internal financial and economic shocks during 1980–2015.

| Period | Name of shock | Date |
|--------|---------------|------|
| 1      | Early 1980s recession in the UK | January 1st, 1980–March 31st, 1981 |
| 2      | Early 1980s recession in the US | July 1981–November 1982 |
| 3      | 1982 Latin American debt crisis | August 1982 |
| 4      | Economic recovery of US and UK | From December 1982 |
| 5      | 1984–85 UK miners’ strike | March 5th, 1984–May 3rd, 1985 |
| 6      | Beginning of US saving & loan crisis | March 5th, 1985 |
| 7      | 1985–87 US economic crisis after Paliza Accord | December 22nd, 1985–1987 |
| 8      | 1987 Lawson Boom in the UK | March 1987 |
| 9      | 1987 “Black Monday” stock market crash | October 17th, 1987 |
| 10     | 1989 mini-crash of stock market | October 13th, 1989 |
| 11     | 1990 Japanese asset bubble collapse | August 2nd, 1990–February 28th, 1991 |
| 12     | Early-1990s recession in US & UK | July 1990–March 1991, US (July 1990–September 1991, UK) |
| 13     | 1991 European Union established | December 31st, 1991 |
| 14     | 1992 “Black Wednesday” in UK | September 16th, 1992 |
| 15     | 1992–93 European currency crisis | January 1st, 1993 |
| 16     | 1994 Mexico peso crisis | December 20th, 1994 |
| 17     | 1995-96 US government shut-down | November 13th, 1995–January 6th, 1996 |
| 18     | 1997 Asian financial crisis | July 2nd, 1997 |
| 19     | 1997 Russian financial crisis | October 27th, 1997 |
| 20     | 1998 Russian financial crisis | August 17th, 1998 |
| 21     | 1999 Euro introduced | January 1st, 1999 |
| 22     | 1999 Kosovo War | March 24th, 1999 |
| 23     | 2000 bursting of dot-com bubble | March 10th, 2000 |
| 24     | 2001 Turkish economic crisis | February 19th, 2001 |
| 25     | Early-2000s recession in US | March 2001 |
| 26     | 9/11 Attacks | September 11th, 2001 |
| 27     | 2001 US war in Afghanistan | October 7th, 2001 |
| 28     | 2002 stock market downturn | October 9th, 2002 |
| 29     | 2003 US war in Iraq | March 20th, 2003 |
| 30     | Beginning of US housing bubble of 2004–06 | February 2004 |
| 31     | Collapse of US housing bubble in mid-2006 | June 2006 |
| 32     | Origin of 2007 sub-prime mortgage crisis | April 2nd, 2007 |
| 33     | US recession of Dec 2007–Jun 2009 | December 2007 |
| 34     | 2008 Lehman Brothers collapse | September 16th, 2008 |
| 35     | US QE1 implementation | November 25th, 2008–April 8th, 2010 |
| 36     | UK QE1 implementation | March 22nd, 2009–January 2010 |
| 37     | EU QE implementation | May 7th, 2009 |
| 38     | 2009 Dubai debt standstill | November 27th, 2009 |
| 39     | 2010 European sovereign debt crisis | April 27th, 2010 |
| 40     | US QE2 implementation | November 4th, 2010–June 30th, 2011 |
| 41     | 2011 US debt-ceiling crisis | July 31st, 2011 |
| 42     | UK QE2 implementation | October 6th, 2011–May 31st, 2012 |
| 43     | UK QE3 implementation | July 5th, 2012–November 30th, 2012 |
| 44     | US QE3 implementation | September 14th, 2012–September 17th, 2014 |
| 45     | US QE4 implementation | December 13th, 2012–September 17th, 2014 |
| 46     | 2013 US debt-ceiling crisis | January 1st, 2013 |
| 47     | 2014 Russian financial crisis | December 16th, 2014 |
| 48     | EU QE implementation | January 22nd, 2015–present |
| 49     | 2015–2016 US stock market selloff | August 15th, 2015 |

### Table 2: The three pairs of indices out of S&P 500, FTSE 100 and EURO STOXX 50, and the different currency terms used.

| Stock Market Indices | Common Currency | Common Currency | Domestic Currencies |
|----------------------|-----------------|----------------|--------------------|
| S&P 500 vs. FTSE 100 | USD/USD         | GBP/GBP        | USD/GBP (GBP/USD)  |
| S&P 500 vs. EURO STOXX 50 | USD/USD       | EUR/EUR        | USD/EUR (EUR/USD)  |
| FTSE 100 vs. EURO STOXX 50 | GBP/GBP       | EUR/EUR        | GBP/EUR (EUR/GBP)  |
### Table 3: Statistical Analysis of Dynamic Correlation Coefficient.

| Stock Market Indices | Strongest Coeff | Weakest Coeff | Average Coeff |
|----------------------|-----------------|---------------|---------------|
| **S&P 500 vs. FTSE 100** |                 |               |               |
| Measured in USD/USD  | 0.917           | 0.0014        | 0.544         |
| Measured in GBP/GBP  | 0.888           | 0.0003        | 0.545         |
| Measured in local currencies | 0.914 | 0.0020 | 0.586 |
| **S&P 500 vs. EURO STOXX 50** |                 |               |               |
| Measured in USD/USD  | 0.786           | 0.3340        | 0.596         |
| Measured in EUR/EUR  | 0.781           | 0.0215        | 0.515         |
| Measured in local currencies | 0.851 | 0.3260 | 0.597 |
| **FTSE 100 vs. EURO STOXX 50** |                 |               |               |
| Measured in GBP/GBP  | 0.838           | 0.3730        | 0.646         |
| Measured in EUR/EUR  | 0.843           | 0.2620        | 0.621         |
| Measured in local currencies | 0.822 | 0.4500 | 0.652 |

Table 4: Observed periods of cointegration and Granger causality (in long run) between the S&P 500 and FTSE 100 during 1980–2015.

| S&P 500 → FTSE 100 | USD/USD | GBP/GBP | GBP/USD |
|---------------------|---------|---------|---------|
| **At 1% significance level** |         |         |         |
| periods 1, 3–5, 8–10 | periods 1, 3, 4, 9 | periods 1, 3–5, 8, 9 |
| periods 13, 14, 16, 18–20 | periods 13–14, 16–20 | periods 13, 16, 18–20 |
| periods 23, 25–31, 33–38 | periods 23, 25–30, 33–38 | periods 23, 25–31, 33–43 |
| periods 41–43, 47, 50 | periods 42–44, 47, 48, 50 | periods 45, 46, 50 |
| **At 5% significance level** |         |         |         |
| periods 2, 6, 7 | periods 2, 6–8, 10–12 | periods 2, 6, 7–10–12 |
| periods 11, 17, 24, 32 | periods 17, 24, 31, 32 | periods 14, 17, 24, 32 |
| periods 39, 40, 44–46, 48, 49 | periods 39, 40, 44–46, 49 | periods 44, 48, 49 |
| **S&P 500 causes FTSE 100** |         |         |         |
| periods 1, 5, 7, 9, 11 | periods 1, 3–5, 11 | periods 1, 3–5, 11 |
| periods 15–17, 19–21, 24–25 | periods 15–16, 19–21, 24–25 | periods 15–16, 19–21, 24–25 |
| periods 30–31, 35, 40, 48–50 | periods 30–31, 35–38 | periods 30–31, 35–38 |
| **Notes:** To indicate that A cointegrates with B, we write B → A.
Table 5: The observed periods of cointegration between the S&P 500 and EURO STOXX 50 during 1998–2015.

| S&P 500 → EURO STOXX 50 | USD/USD | EUR/EUR | EUR/USD |
|--------------------------|---------|---------|---------|
| At 1% significance level | periods 22, 23, 27–39 | periods 22–24, 27–30 | periods 23–29, 31–39 |
|                         | periods 41–43 | periods 32–39, | periods 41–43, 45–48 |
|                         | periods 47, 50 | periods 41, 50 | periods 50 |
| At 5% significance level | periods 24–26, 45, 46 | periods 25, 26, 31, 40 | periods 30, 40, 44 |
|                         | periods 48, 49 | periods 42–46, 48, 49 | periods 49 |

| S&P 500 causes EURO STOXX 50 | periods 22–23, 27–34 | periods 22–23, 25 | periods 22–23, 25 |
|                             | periods 38–39, 41  | periods 27–34, 40–41 | periods 27–36, 38–39, 41 |
|                             | periods 47–50 | period 47–49 | periods 47–48 |
| (26 sub-periods)            | (65%)          | (65%)          | (73%)          |

| EURO STOXX 50 → S&P 500 | USD/USD | EUR/EUR | EUR/USD |
|--------------------------|---------|---------|---------|
| At 1% significance level | periods 23, 24, 27–31, 33 | periods 22–24, 27–30 | periods 23–39 |
|                         | periods 35–39, 42, 43 | periods 33, 35–39, 43 | periods 41, 43–47 |
|                         | periods 45–50 | periods 45, 46, 50 | periods 48–59 |
| At 5% significance level | periods 22, 25, 26, 32 | periods 25, 26, 31, 34 | periods 40, 42 |
|                         | periods 34, 40, 41 | periods 40, 41, 47–49 | periods 50% |

| EURO STOXX 50 causes S&P 500 | periods 24–25, 27–28, 31 | periods 24–25, 27–28, 31 | periods 24–28, 31 |
|                             | periods 35–36, 40, 42–43 | periods 35–36, 38–39 | periods 40, 42–43 |
|                             | periods 43–49 | periods 42–43, 45–47 | periods 45–47, 50 |
| (26 sub-periods)            | (58%)          | (54%)          | (42%)          |

Note that, to indicate that A cointegrates with B, we write B → A.

Table 6: The observed periods of cointegration between the FTSE 100 and EURO STOXX 50 during 1998–2015.

| FTSE 100 → EURO STOXX 50 | GBP/GBP | EUR/EUR | EUR/GBP |
|--------------------------|---------|---------|---------|
| At 1% significance level | periods 22, 23, 26–39 | periods 22, 23, 26–30 | periods 22, 23, 26–39 |
|                         | periods 41–43, 45–50 | periods 41–43, 45–50 | periods 41–46, 50 |
| At 5% significance level | period 40 | period 40 | periods 40, 48, 49 |

| FTSE 100 causes EURO STOXX 50 | periods 22–23, 29–31, 33 | periods 22–29, 30, 33–34 | periods 22–23, 29–31 |
|                             | periods 35–36, 39, 41 | periods 40–41 | periods 33–34, 36, 41 |
|                             | periods 48–49, 50 | periods 48–50 | periods 48–50 |
| (50%)                      | 38%               | (54%)          | (42%)          |

| EURO STOXX 50 → FTSE 100 | GBP/GBP | EUR/EUR | GBP/GBP |
|--------------------------|---------|---------|---------|
| At 1% significance level | periods 22, 23, 25–39 | periods 22, 23, 25–39 | periods 22, 23, 25–39 |
|                         | periods 41, 43–50 | periods 41, 43–50 | periods 41–45, 47–50 |
| At 5% significance level | periods 24, 40, 42 | periods 24, 40, 42 | periods 24, 40, 46 |

| EURO STOXX 50 causes FTSE 100 | periods 24, 26–28, 34 | periods 27–28, 36 | periods 24–28, 31 |
|                              | periods 40, 43 | periods 40, 43 | periods 43, 45–46 |
|                              | periods 45–46 | periods 45–46 | periods 48–49 |
| (58%)                      | 54%               | (46%)          | (46%)          |

Note that, to indicate that A cointegrates with B, we write B → A.
Table 7: Statistical Analysis of Dynamic Error Correction Coefficients of ECTs.

| Stock Market Indices       | Maximum Coef | Minimum Coef | Average Coef |
|----------------------------|--------------|--------------|--------------|
| **S&P 500 vs. FTSE 100**   |              |              |              |
| S&P 500 causes FTSE 100 (USD/USD) | 0.970        | 0.124        | 0.387        |
| FTSE 100 causes S&P 500 (USD/USD) | 0.856        | 0.120        | 0.366        |
| S&P 500 causes FTSE 100 (GBP/GBP) | 0.895        | 0.116        | 0.336        |
| FTSE 100 causes S&P 500 (GBP/GBP) | 0.917        | 0.113        | 0.349        |
| S&P 500 causes FTSE 100 (GBP/USD) | 0.926        | 0.136        | 0.429        |
| FTSE 100 causes S&P 500 (USD/GBP) | 1.284        | 0.141        | 0.377        |
| **S&P 500 vs. EURO STOXX 50** |              |              |              |
| S&P 500 causes EURO STOXX 50 (USD/USD) | 1.668        | 0.141        | 0.441        |
| EURO STOXX 50 causes S&P 500 (USD/USD) | 0.783        | 0.157        | 0.416        |
| S&P 500 causes EURO STOXX 50 (EUR/EUR) | 1.407        | 0.115        | 0.339        |
| EURO STOXX 50 causes S&P 500 (EUR/EUR) | 1.308        | 0.109        | 0.368        |
| S&P 500 causes EURO STOXX 50 (EUR/USD) | 1.332        | 0.191        | 0.504        |
| EURO STOXX 50 causes S&P 500 (USD/EUR) | 0.963        | 0.122        | 0.511        |
| **FTSE 100 vs. EURO STOXX 50** |              |              |              |
| FTSE 100 causes EURO STOXX 50 (GBP/GBP) | 1.225        | 0.143        | 0.498        |
| EURO STOXX 50 causes FTSE 100 (GBP/GBP) | 1.119        | 0.154        | 0.425        |
| FTSE 100 causes EURO STOXX 50 (EUR/EUR) | 1.154        | 0.177        | 0.479        |
| EURO STOXX 50 causes FTSE 100 (EUR/EUR) | 1.233        | 0.191        | 0.504        |
| FTSE 100 causes EURO STOXX 50 (EUR/GBP) | 0.930        | 0.091        | 0.553        |
| EURO STOXX 50 causes FTSE 100 (GBP/EUR) | 1.050        | 0.215        | 0.524        |
Fig. 1: (a)-(c) Time variations in weekly stock price indices and returns of S&P 500, FTSE 100 and EURO STOXX 50 based on local currency terms.
(a) Dynamic correlation between S&P 500 and FTSE 100 over 1980–2015

(b) Dynamic correlation between index S&P 500 and EURO STOXX 50 over 1998–2015

(c) Dynamic correlation between FTSE 100 and EURO STOXX 50 over 1998–2015

Fig. 2: Dynamic correlation between S&P 500, FTSE 100 and EURO STOXX 50 based on common and local currency terms (red shading represents implementation of QE).
Fig. 3: ADF $t$-statistics from dynamic unit root tests of the indices S&P 500, FTSE 100 and EURO STOXX 50, based on USD, GBP and EUR respectively, in log levels (red line indicates 5% statistical significance level).
Fig. 4: $t$-statistics from dynamic unit root tests of the indices S&P 500, FTSE 100 and EURO STOXX 50 based on USD, GBP and EUR respectively, in log differences (red line indicates 1% statistical significance level).
Fig. 5: Dynamic $p$-values after BH FDR controlling showing FTSE 100’s cointegration with S&P 500 in USD, GBP and local currency terms, GBP/USD (red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1980–2015; red shading represents implementation of QE policies).
Fig. 6: Dynamic p-values after BH FDR controlling showing S&P 500’s cointegration with FTSE 100 in USD, GBP and local currency terms, USD/GBP (red horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1980–2015; red shading represents implementation of QE policies).
Fig. 7: Dynamic $p$-values after BH FDR controlling showing EURO STOXX 50’s cointegration with S&P 500 in USD, EUR and local currency terms, EUR/USD (horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies).
Fig. 8: Dynamic p-values after BH FDR controlling showing S&P 500’s cointegration with EURO STOXX 50 in USD, EUR and local currency terms, EUR/USD (horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies).
Fig. 9: Dynamic $p$-values after BH FDR controlling showing EURO STOXX 50’s cointegration with FTSE 100 in GBP, EUR and local currency terms, GBP/EUR (horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies).
Fig. 10: Dynamic p-values after BH FDR controlling showing FTSE 100’s cointegration with EURO STOXX 50 in GBP, EUR and local currency terms, EUR/GBP (horizontal line denotes the false discovery rate with 0.05 for the multiple tests; gray vertical lines correspond to external and internal financial shocks during 1998–2015; red shading represents implementation of QE policies).
Fig. 11: The statistical significant and negative dynamic ECM-based long-run Granger causality of S&P 500 and FTSE 100 measured in common and local currency terms in 1980–2015. The blue bars show the S&P 500 causes FTSE 100, and the yellow bars show the FTSE 100 causes S&P 500, respectively. The red shading represents implementation of QE policies.
Fig. 12: The statistical significant and negative dynamic ECM-based long-run Granger causality of S&P 500 and EURO STOXX 50 measured in common and local currency terms in 1998–2015. The blue bars show the S&P 500 causes EURO STOXX 50, and the yellow bars show the EURO STOXX 50 causes S&P 500, respectively. The red shading represents implementation of QE policies.
Fig. 13: The statistical significant and negative dynamic ECM-based long-run Granger causality of FTSE 100 and EURO STOXX 50 measured in common and local currency terms in 1998–2015. The blue bars show the FTSE 100 causes EURO STOXX 50, and the yellow bars show the EURO STOXX 50 causes FTSE 100, respectively. The red shading represents implementation of QE.