Empirical Evidence of Associations and Similarities between the National Equity Markets Indexes and Crude Oil Prices in the International Market

Salles, Andre Assis de and Maria Eduarda, Silva and Paulo, Teles

Polytechnic School, Federal University of Rio de Janeiro, FEP, School of Economics and Management, University of Porto, FEP, School of Economics and Management, University of Porto

January 2022

EMPIRICAL EVIDENCE OF ASSOCIATIONS AND SIMILARITIES BETWEEN THE NATIONAL EQUITY MARKETS INDEXES AND CRUDE OIL PRICES IN THE INTERNATIONAL MARKET

Andre Assis de Salles
Polytechnic School, Federal University of Rio de Janeiro, Rio de Janeiro, Brazil
as@ufrj.br
https://orcid.org/0000-0001-5218-4006

Maria Eduarda Silva
FEP, School of Economics and Management, University of Porto, Porto, Portugal
mesilva@fep.up.pt
https://orcid.org/0000-0003-2972-2050

Paulo Teles
FEP, School of Economics and Management, University of Porto, Porto, Portugal
pteles@fep.up.pt
https://orcid.org/0000-0001-7969-1403

Abstract

The stock market is a major component of the financial sector of any economy and it is particularly affected by crude oil price. Moreover, the financialization of the oil market in the last three decades increased its association with the financial markets. The main purpose of this paper is to uncover similarities among the economy of selected countries based on the association between their national stock markets and crude oil price. This is achieved by time series clustering of the conditional correlations between the national stock market index returns and crude oil price returns estimated from bivariate GARCH models. The clusters do not lead to a clear classification concerning the countries stage of development, emerging and developed, or the geographical region which can be explained by crude oil market financialization.

Keywords: Crude Oil Prices, Stock Markets, GARCH models, Time Series Clustering.
JEL Code: C58 F21 G15 Q43

1. Introduction

The way expectations of economic and financial variables are generated is crucial for economic agents and particularly in financial markets. Among those variables, stock market performance is especially important, being an economic leading indicator. Furthermore, this market provides resources for investment and production financing. Consequently, knowledge of the stock market performance relevant factors is necessary to determine the behavior of the expectations in such market and, more generally, in global and domestic economies. The crude oil benchmark price change in the international market is one of those factors. In fact, oil is directly or indirectly present in every productive activity and consequently crude oil price movements are relevant for the expectations concerning productive activities' returns, equity returns and the stock market. Thus, the crude oil market is related to financial markets and, in particular, to the stock market. Furthermore, oil is a cost for importing countries and a revenue for producers, making it important for economic development. Crude oil price changes have a direct impact on domestic and foreign trade, on developed and emerging countries' financial markets, on investment and on productive activity financing. Growing economic and market integration that has occurred together with globalization has brought a stronger association between different types of markets, particularly the oil and stock markets. It is also important to mention the increasing creation and trading of indexed financial instruments or derivatives and of spot and futures commodity markets in the past decades, especially in the oil market, leading to the financialization of those markets and strengthening their association with the financial markets. Moreover, investors and portfolio managers can diversify their investments, intensifying the use of commodity markets and their derivatives.

Recent research has focused on inference concerning the data generating process of the crude oil or stock prices returns, their volatility and associations, with the goal of improving stock price expectations. A large part of that research studied the relationship between crude oil and equity prices. [1] tested the hypothesis of influence of crude oil price on stock prices in the US stock market and, unlike the results of other studies, they did not find evidence to support that hypothesis. [2] showed evidence of the influence of crude oil prices on the stock market of 18 countries with different impacts. In order to test whether oil price shocks cause any reaction on the Canadian, Japanese, UK and US stock markets and based on quarterly data, [3] showed the existence of a relationship between crude oil prices and the returns of those markets. [4] analyzed the influence of crude oil prices on sectors of the Australian stock market, in order to explain the returns of those sectors through an augmented market model or a two-factor market model derived from the diagonal model introduced in the finance literature by [5]. They rejected the hypothesis of influence of crude oil price in only 4 out of the 24 sectors studied. Based on a vector autoregressive model (VAR), [6] confirmed that the crude oil price return and volatility are important for economic activity. [6] suggested that crude oil price movements are relevant to explain economic activity but that those movements have little influence on oil prices. [7] investigated the interaction of crude oil prices with stock prices and some macroeconomic variables in Greece, showing that oil price changes have direct influence on economic activity. [8] showed that, among several macroeconomic factors, crude oil prices have a significant impact on the equity capital volatility in the technology sector of the US stock market. [9] obtained a close empirical relationship between crude oil and equity prices in some Gulf Cooperation Council member states. Based on daily data, [10] made a large study concerning the effects of crude oil prices on the oil industry in the USA with cointegration tests and GARCH models and suggested that the oil industry market, the crude oil market and the stock market offer opportunities for portfolio diversification. The results by [11] showed that crude oil price shocks were not significant for the index returns of equities traded in developed countries. [12] studied the relationship between crude oil and stock prices returns based on an asset pricing model. [13] analyzed the stock indices of 35 industrial sectors and their results showed a negative relationship between crude oil prices and stock market returns with the exceptions of the mining and oil and gas sectors. [14] studied conditional correlations and volatility spillovers between crude oil returns and stock market indices using multivariate GARCH models. The results indicate that, in fact, the crude oil and financial markets are dependent. Also, the results of Huang et al. (2011) showed a relationship between oil prices and stock market indices. Using cointegration and causality tests and VAR models [16], showed the existence of a causal relationship between oil prices and Iranian economic growth. [17] also tested oil prices and three Bombay stock exchange indices for cointegration and causality. The results indicate that stock market prices are not causal for oil prices but there is no evidence to reject cointegration between oil prices and the selected stock indices. Recently, [18] studied the effect of oil price change and volatility on the returns and volatility of certain sectors of the Australian stock market, using a GARCH models approach. The results indicate that, for the sectors of materials and energy, the relationship is positive but it is negative for the remaining sectors considered in the study. [19] results suggest that the positive correlation between daily returns of oil and stock markets is due not only to supply and demand shocks but also to the financialization of the oil market. Further, [20] argue that the financialization of commodity markets leads to a new class of financial assets to improve investment.

The main purpose of this paper is to uncover similarities among the economy of selected countries based on the association between their national stock markets and crude oil price. To this end, we use a two-stage approach. First, we estimate the time-varying conditional correlation between the national stock market index returns and crude oil price returns using bivariate GARCH models. Second, we search for similarities among these conditional correlations using appropriate time series clustering methods. The clusters thus obtained provide useful information for investors and portfolio managers concerning the optimal allocation of financial resources in the international market.

The paper is organized as follows. Section 2 presents methodological issues regarding bivariate GARCH models and time series clustering, Section 3 describes the data used in the study. The results obtained are analyzed in Section 4 and Section 5 finalizes the paper.

2. Methodology Approach

This section describes the statistical methodologies used. First, bivariate GARCH models are fitted to Brent crude oil price returns and national stock market index returns leading to implied conditional correlation series. Then, time series clustering techniques are used to cluster the conditional correlation series.

2.1. Multivariate Garch Models

Consider a stochastic vector process $\{Y_t\}$ of dimension $k \times 1$ and let I_{t-1} denote the σ-field generated by the past information up to time $t-1$. Then we write

$$\begin{aligned} Y_t &= \mu_t(\theta) + e_t \\ e_t &= H_t^{\frac{1}{2}}(\theta) Z_t \end{aligned} \tag{1}$$

where θ is a vector of parameters, $\mu_t(\theta)$ is the conditional mean vector, e_t is a $k \times 1$ vector of serially uncorrelated random variates with $\mathrm{E}(e_t) = 0$ and covariance matrix

$H_t(\theta)$, which is a $k \times k$ positive definite matrix, $\{Z_t\}$ is a $k \times 1$ random vector with $\mathrm{E}(Z_t) = 0$ and $\mathrm{Var}(Z_t) = I_k$, the identity matrix of order k. It is clear from the above that $\mathrm{Var}(Y_t|I_{t-1}) = H_t$, where for simplicity of notation θ is omitted. There are several specifications for H_t (see [21]) but in this work we consider the diagonal VECH(1,1) (D-VECH) proposed by [22] and defined by as follows:

$$Vech(H_t) = C + AVech(e_{t-1}e'_{t-1}) + BVech(H_{t-1}) \tag{2}$$

where $Vech(\cdot)$ denotes the operator that stacks the lower triangular portion of a $k \times k$ matrix as a $k(k+1)/2 \times 1$ vector. A and B are diagonal parameter matrices of order $k(k+1)/2$ and C is a $k(k+1)/2 \times 1$ parameter vector. It is easy to see that the conditional covariance satisfies the following equation $h_{ijt} = c_{ij} + \alpha_{ij}e_{it-1}e_{jt-1} + \beta_{ij}h_{ijt}$, $i,j = 1, \ldots\ldots, k$ where ω_{ij}, α_{ij} and β_{ij} are $3k(k+1)/2$ parameters. Thus, each element h_{ijt} of H_t depends only on its own lagged value and on the previous value of e_t. The diagonal VECH model can be written as follows:

$$H_t = C^o + A^o \odot e_{t-1}e'_{t-1} + B^o \odot H_{t-1} \tag{3}$$

where $\odot$ is the Hadamard product and A^o, B^o and C^o are symmetric $k \times k$ matrices. If the parameters in the matrices are allowed to vary without any restrictions, i.e. parameterized as indefinite matrices, then there is no guarantee that H_t will be positive definite. There are, however, several parameterizations for these matrices that, together with an unconditional positive definite variance matrix H_0, ensure the positive-definiteness of H_t [23]. The matrix diagonal model parametrizes the matrices C^o, A^o and B^o as $C^o = CC'$, $A^o = AA'$and $B^o = BB'$ so that the positive semi-definiteness is guaranteed in estimation without imposing any further restrictions. The vector-diagonal or rank one model considers the matrices A^o and B^o to be of rank one and therefore $A^o = aa'$ and $B^o = bb'$, where a and b are $k \times 1$ vectors. The scalar diagonal or two-parameter model considers a very strong restriction in which the matrices A^o and B^o are scalars, $A^o = \alpha$ and $B^o = \beta$. Additionally, the following restrictions may be imposed on the constant matrix C^o, given as

$$C^o = H_0(1_t 1'_t - A - B) \tag{4}$$

where 1_k is a $k \times 1$ vector of ones, leading to the so called variance targeting model. Given a bivariate time series $Y_1, \ldots\ldots, Y_T$, estimation of the parameters θ of the VECH models is accomplished by maximum likelihood (ML). This requires the construction of a likelihood function and consequently an assumption on the distribution for the *iid* innovation process Z_t. The most commonly employed distribution is the multivariate normal in which case the likelihood function is

$$L(\theta) = -\tfrac{1}{2}\textstyle\sum_{t=1}^{T} log|H_t| - \tfrac{1}{2}\sum_{t=1}^{T}(Y_t - \mu_t)' H_t^{-1}(Y_t - \mu_t) \tag{5}$$

It is, however, well known that most daily or weekly financial data present high kurtosis, rejecting the normality assumption. However, [24] show that a consistent estimator may still be obtained from maximizing (5), yielding a quasi-maximum likelihood estimator provided the conditional mean and the conditional variance are specified correctly. A natural alternative to the multivariate Gaussian distribution is the Student distribution, as in [25] and [26], the approach used.

2.2. Time Series Clustering

The fundamental issue in time series classification and clustering is the choice of a metric. There are several metrics for time series proposed in the literature which can be broadly classified as model based or feature based, in the time domain or in the frequency domain, see [27] for a review. We consider a feature based approach and an approach in the time domain. The first method, proposed by [28], is characteristic-based because it clusters global features extracted from each k time series using a hierarchical clustering algorithm. Seven characteristics of the correlation coefficient time series are considered, namely: trend, serial correlation, skewness, kurtosis and non-linearity, self-similarity (Hurst coefficient) and chaos (Lyapunov coefficient). These measures are normalized to the interval [0,1] to indicate the degree of presence of the feature. A measure near zero for a certain time series indicates near absence of the feature, while a measure near 1 indicates a strong presence. The set of feature measures extracted from each the time series forms the input vector for the hierarchical clustering algorithms directly without the need for further data pre-processing. The hierarchical clustering algorithm is a well-known clustering method which starts by considering the interval [0,1] to indicate the degree of presence of the feature. A measure near zero for a certain time series indicates near absence of the feature, while a measure near one indicates a strong presence. The set of feature measures extracted from each the time series forms the input vector for the hierarchical clustering algorithms directly without the need for further data pre-processing. The hierarchical clustering algorithm is a well-known clustering method which starts by considering each time series as a separate cluster, forming k clusters or groups. Subsequently, the closest two groups are linked to form $k-1$ clusters. This process continues until the last stage in which all the time series are in the same cluster. We use Ward's algorithm which is a minimum-variance algorithm (see [29]) implemented in [30].

The other approach for time series clustering considered here is based on defining the Mahalanobis distance between sample autocorrelation coefficient vectors as the similarity measure between two time series X, Y as proposed by [27]:

$$d_{ACFM}(X,Y) = \sqrt{(\hat{\rho}X - \hat{\rho}Y)^T \Omega (\hat{\rho}X - \hat{\rho}Y)} \tag{6}$$

where $\hat{\rho}_i$, $i = X, Y$ represents the vector of sample autocorrelation coefficients, $\hat{\rho}_i = (\hat{\rho}_{i,1}, \ldots\ldots, \hat{\rho}_{i,m})$ for some m such as $\hat{\rho}_{i,j} \approx 0$ for $j > m$, and Ω is the inverse covariance matrix of the sample autocorrelations which is given by Bartlett's formula (see [31]). Other time series similarity measures were tried in the data set under study and the results were almost coincident. Thus a distance matrix is defined and Ward's hierarchical clustering algorithm is used on that matrix.

In order to facilitate the interpretation of the clustering results, we use two well-known techniques: multidimensional scaling and the hierarchical clustering tree or dendrogram (see for example, [32]). The multidimensional scaling, also often referred to as principal coordinate analysis, creates a configuration of k points in a lower-dimensional map, usually of dimension two or three. Letting D be the observed $k \times k$ dissimilarity matrix and applying multidimensional scaling to D returns a $k \times s$ configuration matrix T, where the rows of T are the coordinate values of the k points in the s-dimensional representation for some $s < k$. The dimensionality that accurately reproduces D is given by the largest s eigenvalues of TT' . A scatter plot of the coordinate values provides a visual representation of the original distances. The dendrogram is a tree diagram which illustrates the arrangement of the clusters produced by hierarchical clustering. The height of each node in the plot is proportional to the value of the intergroup dissimilarity between its two daughters (the bottom nodes representing individual observations are all plotted at zero height).

3. Sample Used and Data Description

The data are the weekly close quotations of the representative aggregate stock market indices from 48 different countries and of the Brent crude oil price negotiated in the London Market. The stock market index primary data were compiled from DataStream and the Brent crude oil price from EIA (US Energy Information Administration). All data were collected in current US dollars. The sample spans from January 2nd, 2004 to October 3rd, 2014, a total of 562 observations. Return time series R_t are constructed from the weekly quotes (I_t) as $R_t = lnI_t - lnI_{t-1}$.

Table 1. Statistical Summary of Latin American Market Index – Developed Countries

Index	ID	*Mean*	*Median*	*Min*	*Max*	*Std D.*	*Skew*	*Kurt*	*JB test*	*ADF test*
Asia Pacific (dAP)										
Australia	**AU**	0.0011	0.0055	-0.3552	0.1324	0.0375	-2.0599	19.0328	6416.73	-5.10
Hong Kong	**HK**	0.0011	0.0043	-0.1766	0.1190	0.0310	-0.3308	6.2929	264.16	-23.95
New Zealand	**NZ**	0.0006	0.0034	-0.2370	0.1027	0.0288	-1.6749	13.6882	2937.84	-4.73
Singapore	**SG**	0.0016	0.0030	-0.1963	0.1855	0.0301	-0.6033	11.6258	1776.40	-14.36
Europe (dE)										
Austria	**AT**	0.0006	0.0046	-0.3634	0.1865	0.0437	-1.5749	13.6846	2905.60	-4.85
Belgium	**BE**	0.0006	0.0044	-0.2832	0.1025	0.0342	-1.6205	12.8687	2526.56	-4.51
Denmark	**DK**	0.0020	0.0056	-0.2459	0.1322	0.0348	-1.5207	11.3967	1867.58	-4.83
Finland	**FI**	0.0004	0.0045	-0.2018	0.1181	0.0374	-0.8892	6.3252	332.97	-4.45
Greece	**GR**	-0.0014	0.0022	-0.2576	0.1712	0.0472	-0.6346	5.5020	184.30	-14.59
Ireland	**IE**	0.0000	0.0039	-0.3511	0.1403	0.0394	-1.8756	16.2575	4445.27	-3.85
Netherlands	**NL**	0.0003	0.0042	-0.3096	0.1390	0.0352	-1.4825	15.1097	3639.76	-4.69
Norway	**NO**	0.0016	0.0075	-0.2887	0.2075	0.0450	-1.0261	9.6045	1120.03	-24.24
Portugal	**PT**	-0.0004	0.0035	-0.2278	0.1023	0.0341	-1.3025	8.7067	921.48	-23.06
Spain	**ES**	0.0005	0.0041	-0.2604	0.1253	0.0393	-1.1032	8.6115	851.36	-4.93
Sweden	**SE**	0.0013	0.0037	-0.2385	0.1615	0.0389	-0.7841	8.1500	678.64	-4.79
Switzerland	**CH**	0.0013	0.0038	-0.2433	0.1310	0.0278	-1.5452	16.5092	4497.17	-5.07
G7										
Canada	**CA**	0.0013	0.0046	-0.2663	0.1637	0.0340	-1.4282	13.5397	2792.30	-6.99
France	**FR**	0.0003	0.0038	-0.2726	0.1386	0.0359	-1.1956	10.6280	1496.41	-4.99
Germany	**DE**	0.0015	0.0064	-0.2656	0.1451	0.0366	-1.0995	10.1885	1323.28	-5.09
Japan	**JP**	0.0006	0.0020	-0.2198	0.0701	0.0275	-1.1213	10.1838	1326.23	-24.62
Italy	**IT**	-0.0005	0.0029	-0.2657	0.1306	0.0399	-1.1955	8.5778	862.40	-4.95
United Kingdom	**UK**	0.0005	0.0039	-0.2782	0.1628	0.0314	-1.5077	16.8927	4732.49	-4.32
United States	**US**	0.0010	0.0017	-0.2008	0.1136	0.0247	-0.9916	12.8390	2358.94	-5.29
Middle East (dME)										
Israel	**IL**	0.0019	0.0034	-0.1741	0.1483	0.0330	-0.7670	7.4796	525.01	-24.73

Table 1 and 2 presents statistical summary as well as the economic country classification in nine groups, according to [33] and the Morgan Stanley Capital International (MSCI), as follows: developed Asia Pacific (dAP), developed Europe (dE), G7, developed Middle East (dME), emerging Middle East (eME), emerging Africa (eA), emerging Asia Pacific (eAP), emerging Europe (eE), emerging Latin America (eLA). The descriptive statistics for the return time series show return means ranging between -0.0014 and 0.0018. Among the stock market indices, the lowest mean of returns occurs in Greece followed by Italy and Portugal while the largest occurs in Colombia followed by Egypt and Indonesia. While for emerging markets, particularly the BRICS, the means of returns are close to each other, ranging from 0.0012 to 0.0018, the same is not true for the developed markets, particularly the G7 countries. Note that, except for the Chinese market, the median is always greater than the mean indicating a negative skewness. The standard deviation of the returns ranges from 0.0258 to 0.0535, indicating high volatility. Among the stock market indices, the highest volatility occurs in Turkey followed by Brazil and Russia whereas the lowest occurs in the US followed by Japan and Switzerland. It must be emphasized that emerging markets present the highest volatility whereas the developed markets show the lowest. Except for China, all the skewness coefficients are negative and all the kurtosis coefficients indicate leptokurtic series. Thus, all the time series show a departure from the normal distribution, confirmed by the results of the Jarque-Bera test (JB) in Table 1. Moreover, the results of the Augmented Dickey-Fuller test (ADF) in Table 1 indicate stationarity. It is worth mentioning that all the p-value obtained in the JB and ADF tests is close to zero. Finally, the Ljung-Box test (LB) shows no serial correlation except for New Zealand.

Table 2. Statistical Summary of Return Time Series – Emerging Countries

Index	ID	*Mean*	*Median*	*Min*	*Max*	*Std D.*	*Skew*	*Kurt*	*JB test*	*ADF test*
Africa (eA)										
South Africa	**ZA**	0.0019	0.0034	-0.1741	0.1483	0.0330	-0.7670	7.4796	525.01	-24.73
Asia Pacific (eAP)										
China	**CN**	0.0013	0.0005	-0.1462	0.1369	0.0346	0.0366	4.9260	86.99	-3.44
India	**IN**	0.0018	0.0048	-0.1965	0.2162	0.0397	-0.4591	6.7278	345.16	-5.62
Indonesia	**ID**	0.0028	0.0052	-0.2774	0.1706	0.0398	-1.0880	9.2788	1034.04	-8.61
Malaysia	**MY**	0.0018	0.0027	-0.1008	0.0745	0.0219	-0.6612	5.6747	208.48	-14.86
Philippine	**PH**	0.0033	0.0052	-0.2136	0.1275	0.0335	-0.8923	7.5999	570.05	-24.77
Pakistan	**PK**	0.0024	0.0069	-0.2095	0.1082	0.0337	-1.4331	8.9622	1024.80	-9.60
South Korea	**KR**	0.0015	0.0061	-0.2703	0.2963	0.0423	-0.3551	11.2518	1606.31	-5.37
Taiwan	**TW**	0.0008	0.0032	-0.1235	0.0918	0.0311	-0.6283	4.4039	83.13	-15.78
Thailand	**TH**	0.0016	0.0044	-0.2888	0.1297	0.0358	-1.0384	10.8013	1526.13	-5.10
Europe (eE)										
Czech Republic	**CZ**	0.0010	0.0036	-0.3278	0.1894	0.0419	-1.2107	12.1165	2083.47	-5.17
Hungary	**HU**	0.0001	0.0046	-0.3744	0.2041	0.0494	-1.0438	10.6380	1468.15	-22.56
Poland	**PL**	0.0010	0.0042	-0.2634	0.2400	0.0465	-0.7758	7.7023	574.16	-22.95
Russia	**RU**	0.0012	0.0042	-0.2373	0.3419	0.0501	-0.3445	9.5654	1020.47	-5.20
Turkey	**TR**	0.0016	0.0052	-0.2852	0.2460	0.0535	-0.4009	5.8960	211.45	-15.23
Latin America (eLA)										
Argentina	**AR**	0.0023	0.0047	-0.3303	0.1713	0.0470	-1.1823	10.2172	1350.64	-15.51
Brazil	**BR**	0.0017	0.0051	-0.3306	0.2562	0.0513	-0.6684	9.4698	1022.01	-15.87
Chile	**CL**	0.0017	0.0034	-0.3326	0.1712	0.0348	-1.8496	19.7196	6866.49	-6.81
Colombia	**CO**	0.0037	0.0041	-0.2730	0.1242	0.0391	-1.4408	10.8516	1638.04	-10.73
Mexico	**MX**	0.0026	0.0049	-0.3020	0.2391	0.0405	-0.6989	13.4179	2587.22	-5.22
Peru	**PE**	0.0033	0.0035	-0.4161	0.1744	0.0461	-1.3281	17.3111	4961.10	-6.17
Middle East (eME)										
Arab Emirates	**UE**	0.0019	0.0022	-0.1849	0.1708	0.0323	-0.3220	8.4064	694.17	-6.56
Egypt	**EG**	0.0035	0.0061	-0.2606	0.1466	0.0440	-1.0015	8.1372	711.94	-6.87
Qatar	**QA**	0.0022	0.0025	-0.2290	0.1555	0.0384	-0.6383	8.7632	815.93	-22.93

Table 3. Statistical Summary of Return Time Series – World Index and Brent Crude Oil

Other Time Series	*Mean*	*Median*	*Min*	*Max*	*Std D.*	*Skew*	*Kurtosis*	*JB test*	*ADF test*
World Equity Index	0.0020	0.0042	-0.2534	0.2414	0.0456	-0.5211	6.4601	305.78	-11.95
Brent Crude Oil	0.0009	0.0036	-0.2240	0.1166	0.0258	-1.4747	15.3157	3755.46	-4.87

4. Empirical Results Obtained

In order to investigate the relationship between the Brent crude oil price returns and the selected national stock market index returns, bivariate Diagonal-VECH models are fitted considering a constant mean , $\mu_t = \mu$ and innovations distributed as Student-t with one degree of freedom, $Z_{i,t} \sim t(1), i = 1, 2$. For each bivariate model, the parametrization of the matrices C, A and B is chosen according to the Akaike (AIC) and the Schwartz (BIC) criteria, yet ensuring the semi-positive definiteness of matrix H_t. Since there is no statistically significant bivariate model for China (CN), Hong Kong (HK), Malaysia (MY), Pakistan (PK), Taiwan (TW) and United Arab Emirates (AE), the stock market index returns of these six countries are discarded.

The conditional correlations between Brent crude oil price returns and national stock market index returns implied by the estimated models for the remaining 42 countries are represented in Figure 1 and 2.

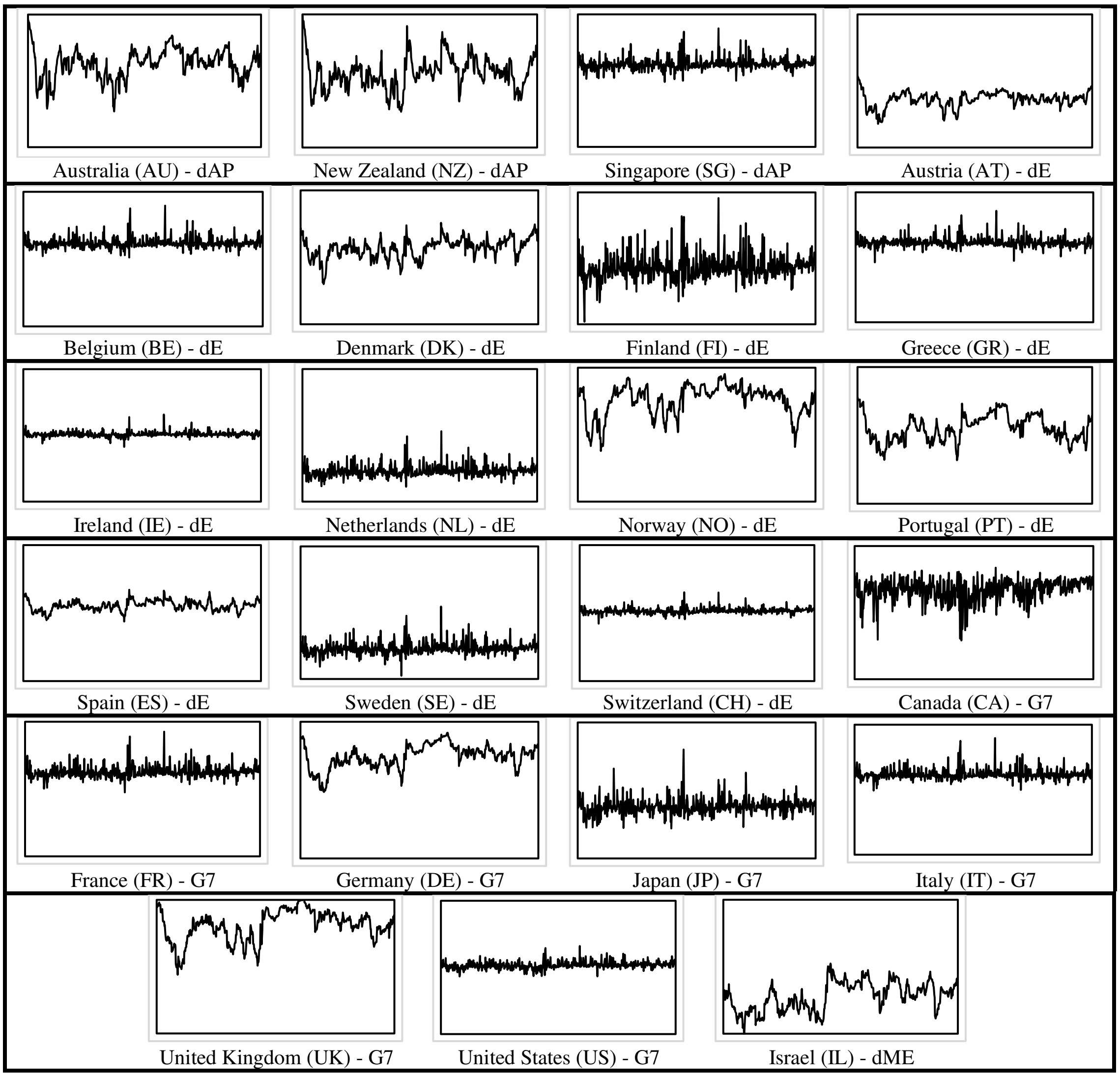

Figure 1. Equity Index and Crude Oil Returns Correlation Series Plots: Developed Countries

The plots show that the dynamic correlations between Brent price returns and national stock market returns present two main features: either trend or high variability with spikes. Furthermore, the features of the correlation coefficient time series differ even for countries that belong to a same economic group. For instance, among the G7 countries, Germany (DE) and United Kingdom (UK) series exhibit similar behavior with local trends in the mean, while the United States (US), Japan (JP), Italy (IT) and France (FR) are characterized by high variability and some spikes. Moreover, Canada (CA) exhibits a different behavior from all the other countries in the group with high positive correlation over time. Similar remarks may be made for the other groups, as shown in Figure 1 and 2. It is thus appropriate to cluster the correlation coefficient time series for further analysis.

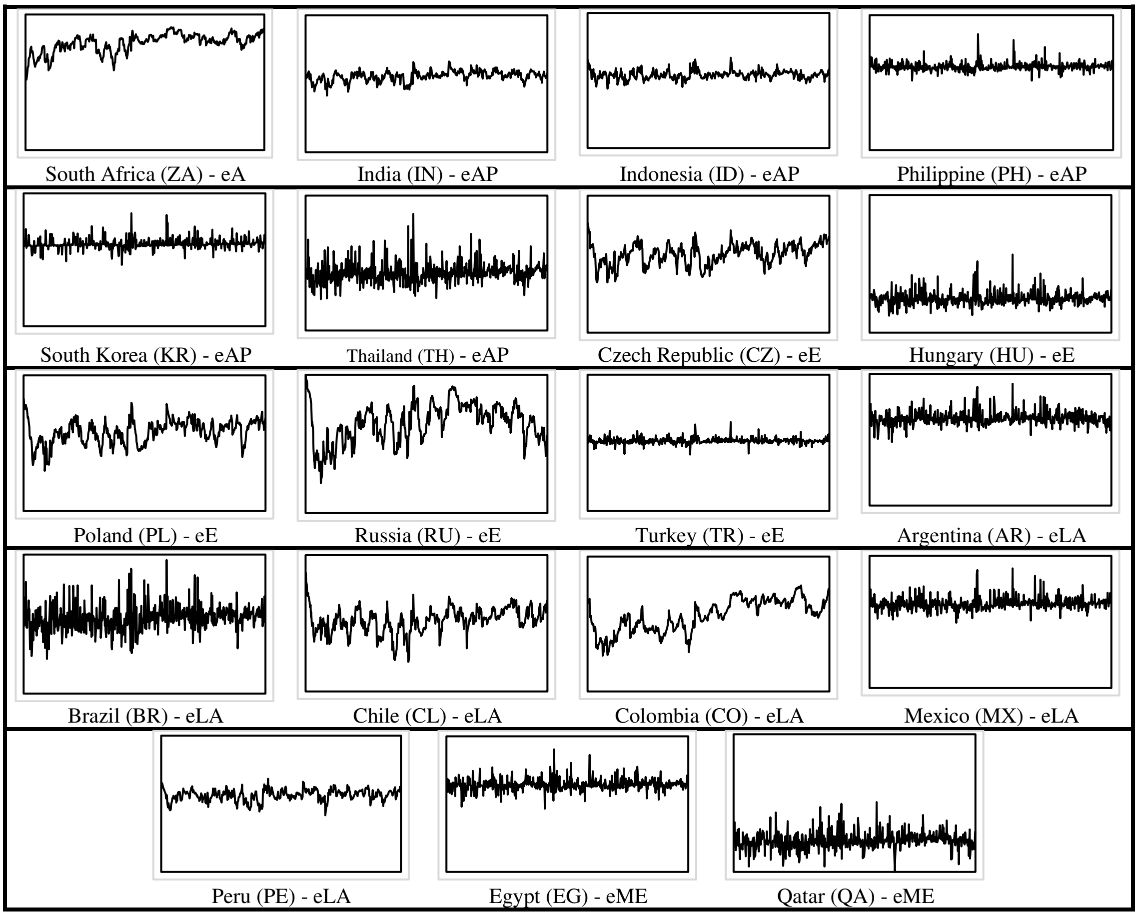

Figure 2. Equity Index and Crude Oil Returns Correlation Series Plots: Emerging Countries

To this purpose, the feature based approach described in Section 2 is used first. The multidimensional scaling of the corresponding dissimilarity matrix between the features extracted from the correlation time series results in a set of eigenvalues which indicate that a 2-dimensional representation of the distance matrix is appropriate. In fact, the first two eigenvalues account 95.01% of the sum of all the eigenvalues and the first one accounts for 89.13%. Accordingly, representing the countries in the scaling map of Figure 3, three main clusters are easily identified: a group with negative first coordinate $\boldsymbol{D_1}$ = {Australia (AU), Austria (AT), Chile (CL), Colombia (CO), Czech Republic (CZ), Germany (DE), Denmark (DK), Spain (ES), Israel (IL), India (IN), Norway (NO), New Zealand (NZ), Peru (PE), Poland (PL), Portugal (PT), Russia (RU), the United Kingdom (UK), South Africa (ZA)}; another one, with positive first coordinate $\boldsymbol{D_2}$ = {Argentina (AR), Belgium (BE), Brazil (BR), Canada (CA), Switzerland (CH), Egypt (EG), Finland (FI), France (FR), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), South Korea (KR), Mexico (MX), the Netherlands (NL), the Philippines (PH), Qatar (QA), Sweden (SE), Singapore (SG), Thailand (TH), Turkey (TR), the United States (US)}; and a country D_3 = {Indonesia (ID)}, with negative but close to zero first coordinate, which is almost equidistant of the other two groups. The first group, with negative first coordinate, shows smaller intra-group distances than the second group, with positive first dimension. In fact, the second group can be divided in four sub-groups stand out from the latter: $D_{2.1}$ = {Canada (CA)}; $D_{2.2}$ = {Brazil (BR), Qatar (QA)}; $D_{2.3}$ = {Argentina (AR), Switzerland (CH), Finland (FI), Egypt (EG), South Korea (KR), Thailand (TH), Turkey (TR), the United States (US)}; and $D_{2.4}$ = {Greece (GR), Hungary (HU), Mexico (MX), Sweden (SE), Japan (JP), Singapore (SG), France (FR), Ireland (IE)}. In the scaling map shown in Figure 2, clusters D1, D2 and D3 are indicated by a circle on a dotted line, a rectangular figure and a circle on a solid line, respectively.

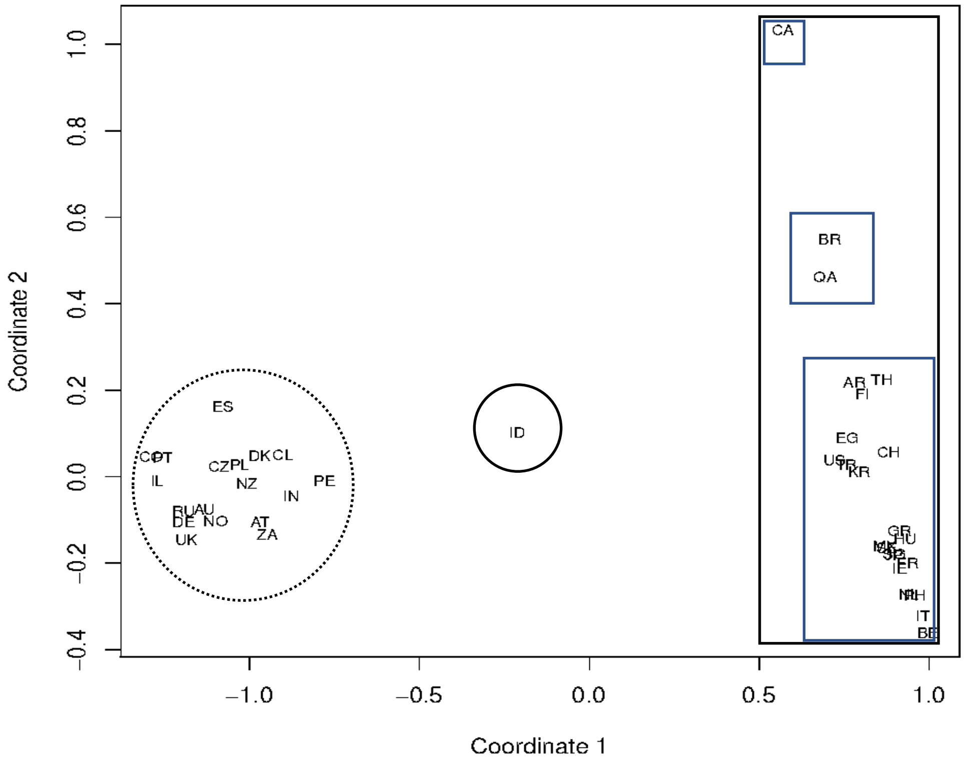

Figure 3. Multidimensional Scaling for Feature Based Distance

The dendrogram resulting from the hierarchical clustering displayed in Figure 4 indicates four reasonable clusters: C_{H1} = {Austria (AT), Colombia (CO), Germany (DE), Israel (IL), Norway (NO), Portugal (PT), Russia (RU), the United Kingdom (UK), South Africa (ZA)}; C_{H2} = {Australia (AU), Chile (CL), Czech Republic (CZ), Denmark (DK), Spain (ES), Indonesia (ID), India (IN), New Zealand (NZ), Peru (PE), Poland (PL)}; C_{H3} = {Belgium (BE), France (FR), Greece (GR), Hungary (HU), Ireland (IE), Italy (IT), Japan (JP), Mexico (MX), the Netherlands (NL), the Philippines (PH), Sweden (SE), Singapore (SG)}; and C_{H4} = {Argentina (AR), Brazil (BR), Canada (CA), Switzerland (CH), Egypt (EG), Finland (FI), South Korea (KR), Qatar (QA), Thailand (TH), Turkey (TR), the United States (US)}. Note that $C_{H1} \cup C_{H2} = D_1 \cup D_3$ and $C_{H3} \cup C_{H4} = D_2$. Thus both representations convey the same results. Using the Mahalanobis distance between sample autocorrelation coefficient vectors for clustering leads to the following three clusters: $C_{M1} = C_{H1}$; $C_{M2} = C_{H2}$, with the exception of Australia (AU); and $C_{M3} = C_{H3} \cup C_{H4}$. Since both approaches lead to similar results, only those yielded by the feature based clustering will be further analyzed.

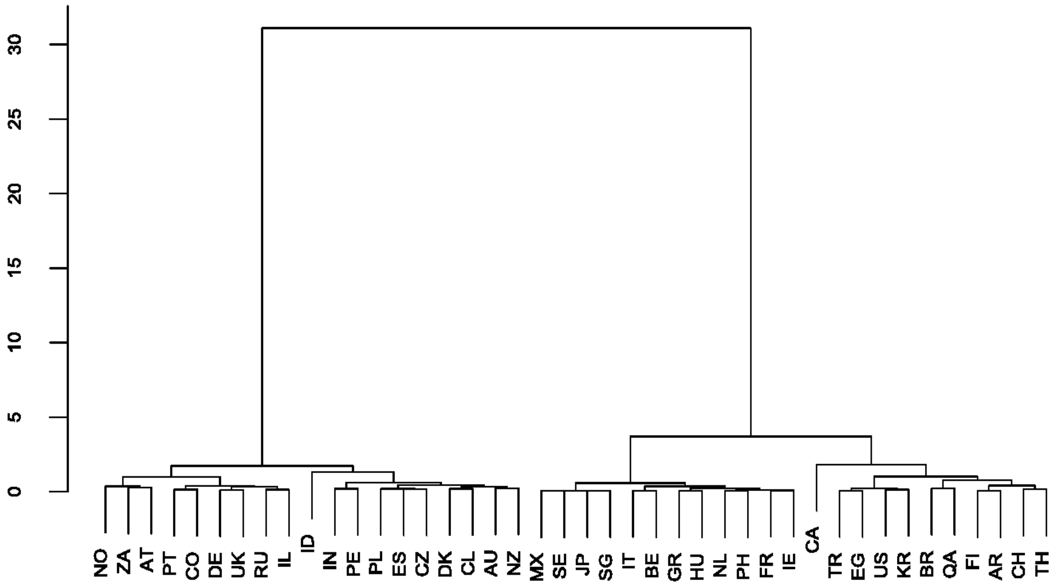

Figure 4. Dendrogram for Feature Based Clustering

Table 2. Summary of Features Measures for Each Cluster
-- Mean (Standard Deviation) –

Cluster / *Coefficient*	C_{H1}	C_{H2}	C_{H3}	C_{H4}
Trend	0.609 (0.086)	0.282 (0.112)	0.017 (0.014)	0.052 (0.048)
Autocorrelation	0.987 (0.010)	0.871 (0.126)	0.021 (0.007)	0.055 (0.080)
Non-Linear	0.035 (0.029)	0.064 (0.061)	0.037 (0.030)	0.266 (0.275)
Skewness	0.167 (0.012)	0.010 (0.044)	0.631 (0.084)	0.306 (0.117)
Kurtosis	0.160 (0.018)	0.227 (0.179)	1.000 (0.000)	0.990 (0.019)
Hurst	0.999 (0.000)	0.998 (0.001)	0.549 (0.019)	0.592 (0.054)
Lyapunov	0.982 (0.003)	0.989 (0.003)	0.993 (0.001)	0.994 (0.001)

Table 2 describes the mean and standard deviation of feature values for each cluster. Recall that the values of the features represent the degree of the presence of the feature, with values near one indicating the strong presence of the feature and values near zero its almost absence. Globally, cluster C_{H1} in Figure 5 is similar to cluster C_{H2} in Figure 6, as can be inferred from the dendrogram presents in Figure 4. These clusters are characterized by predominantly positive correlations, the presence of an overall increasing trend over time with local levels, leading to high values of the autocorrelation and of the Hurst coefficient. The autocorrelation values remain high even after removing the trend. The correlation coefficient time series in these clusters do not present either skewness or kurtosis. On the contrary, clusters C_{H3} and C_{H4} are similar in that the correlation series exhibit lower values, do not exhibit trend, are serially uncorrelated but show high kurtosis. However, $\boldsymbol{C_{H4}}$ exhibits the highest degree of non-linearity among the four groups. Most interesting is the fact that the Lyapunov coefficient is high for all clusters indicating lack of short-term forecast ability of the correlation coefficient between the Brent crude oil price returns and national stock market index returns.

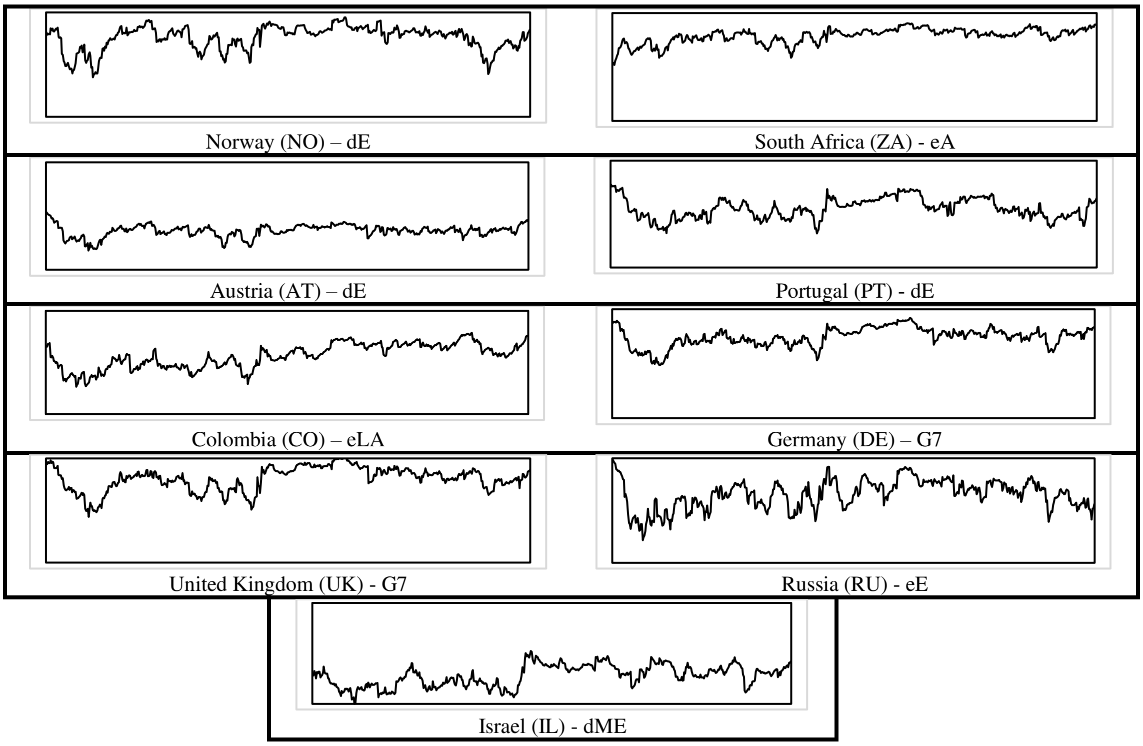

Figure 5. Equity Index and Crude Oil Returns Correlation Series Plots – Cluster C_{H1}

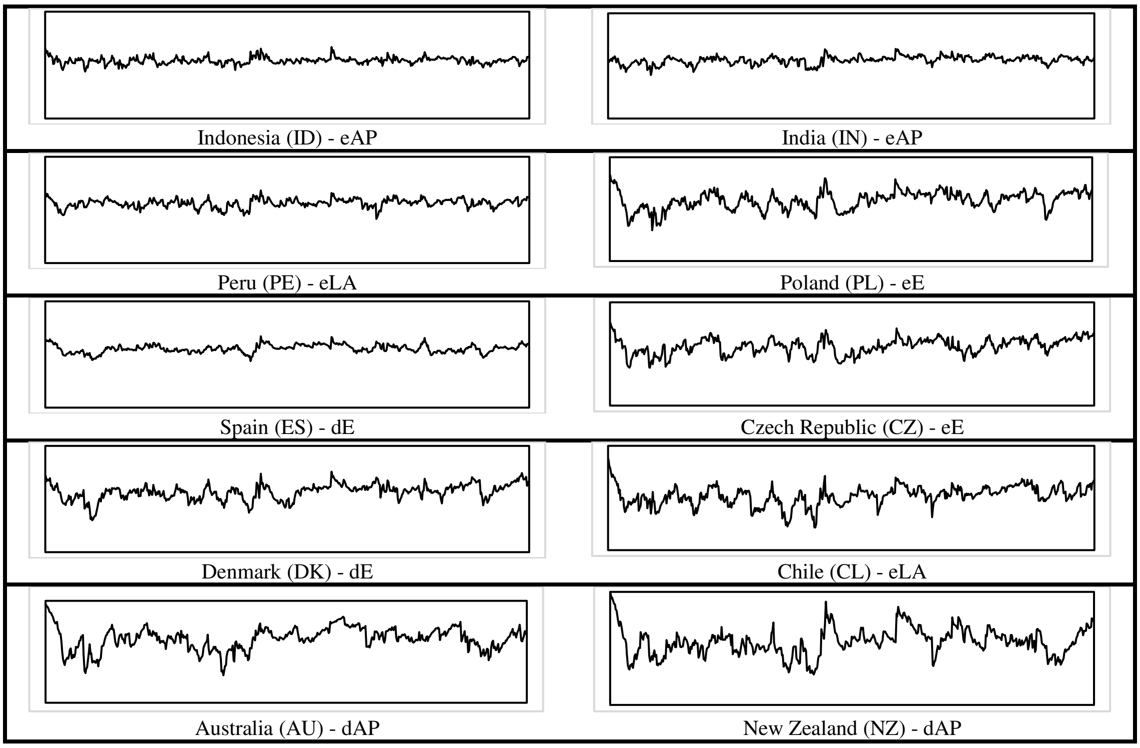

Figure 6. Equity Index and Crude Oil Returns Correlation Series Plots - Cluster C_{H2}

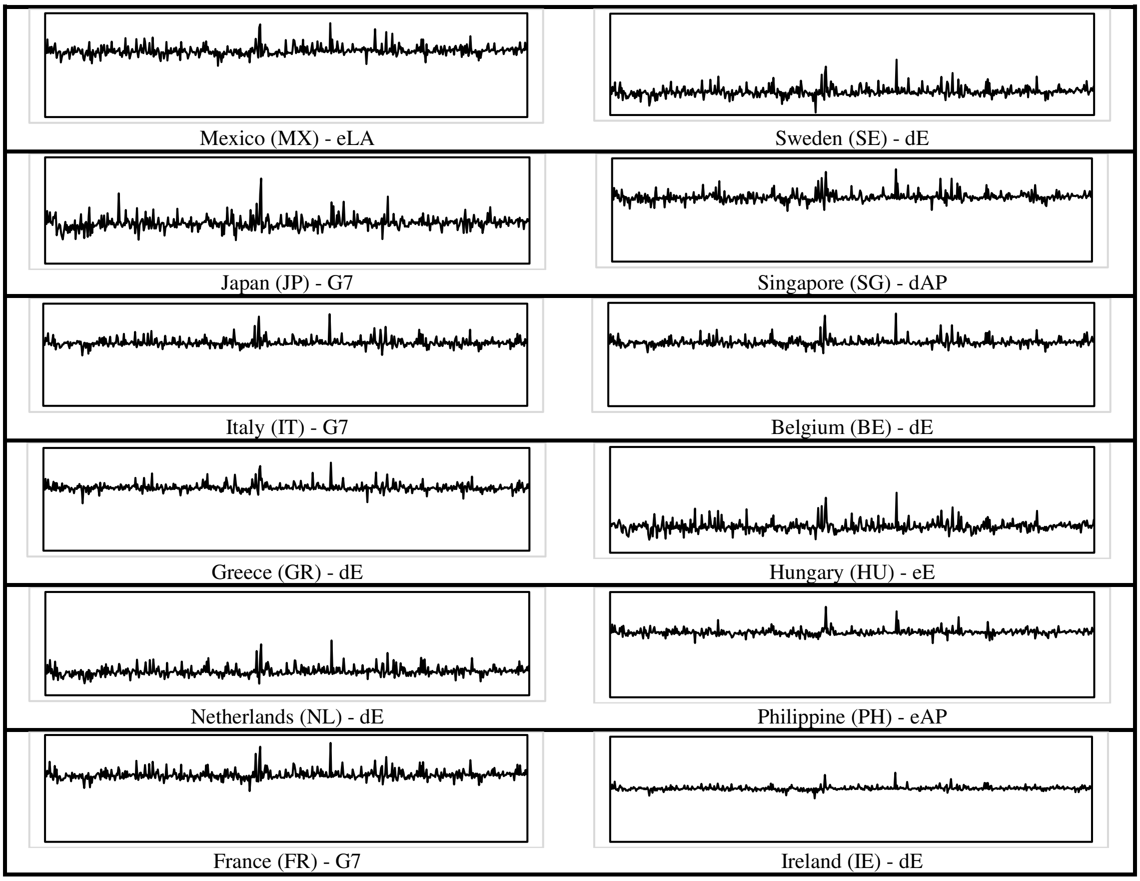

Figure 7. Equity Index between Crude Oil Returns Correlation Series Plots – Cluster C_{H3}

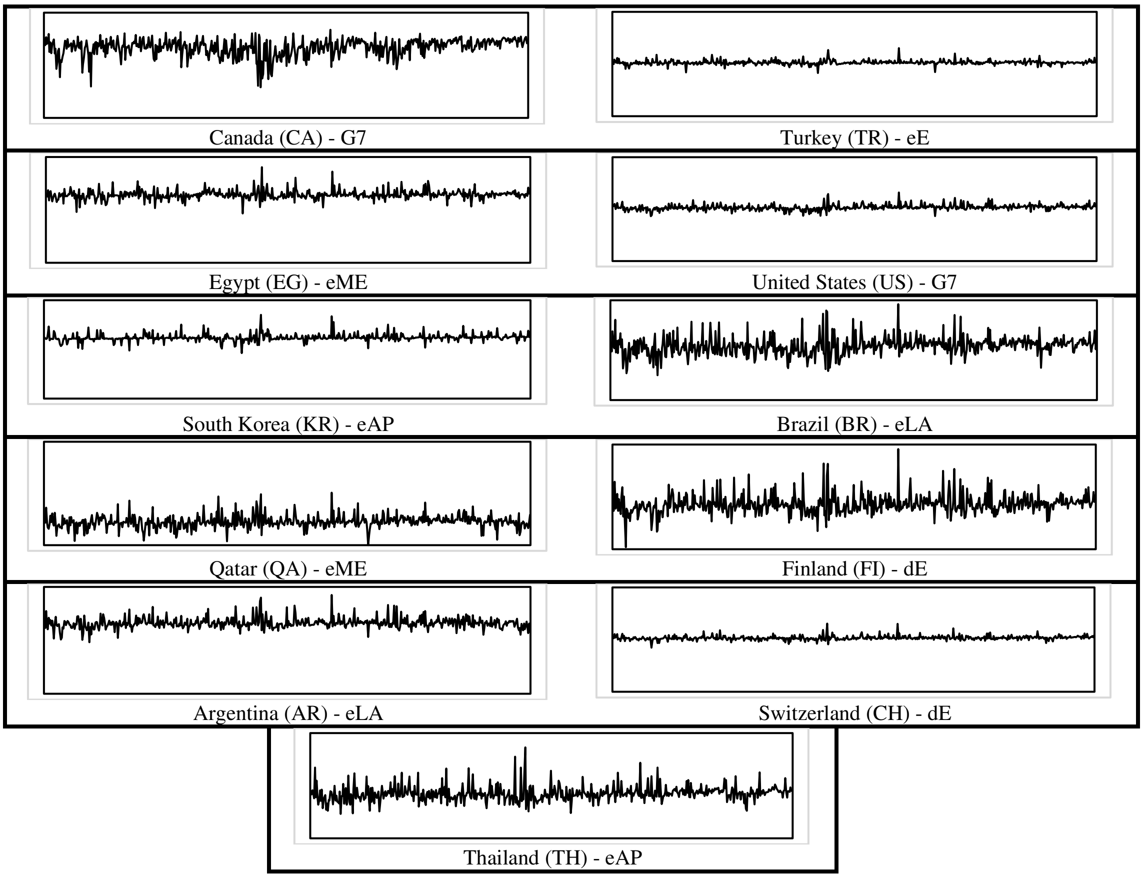

Figure 8. Equity Index between Crude Oil Returns Correlation Series Plots – Cluster C_{H4}

Table 4. Statistical Summary of Correlation Time Series - Cluster C_{H1} and Cluster C_{H2}

CH1	Mean	Std D.	Min	Max	CH2	Mean	Std D.	Min	Max
NO	0.507	0.139	0.054	0.743	**ID**	0.168	0.123	-0.243	0.676
ZA	0.377	0.138	-0.162	0.612	**IN**	0.219	0.152	-0.348	0.647
AT	0.323	0.112	-0.045	0.670	**PE**	0.254	0.162	-0.339	0.733
PT	0.262	0.114	-0.018	0.532	**PL**	0.300	0.104	-0.044	0.592
CO	0.274	0.142	-0.082	0.543	**ES**	0.221	0.149	-0.248	0.686
DE	0.292	0.173	-0.228	0.640	**CZ**	0.289	0.092	0.040	0.560
UK	0.411	0.230	-0.321	0.836	**DK**	0.281	0.088	-0.040	0.509
RU	0.385	0.168	-0.141	0.788	**CL**	0.224	0.109	-0.139	0.645
IL	0.158	0.214	-0.401	0.648	**AU**	0.353	0.133	-0.077	0.752
-	-	-	-	-	**NZ**	0.270	0.144	-0.077	0.784

Table 5. Statistical Summary of Correlation Time Series - Cluster C_{H3} and Cluster C_{H4}

CH3	Mean	Std D.	Min	Max	CH4	Mean	Std D.	Min	Max
MX	0.075	0.091	-0.214	0.609	**CA**	0.402	0.098	-0.051	0.605
SE	0.059	0.091	-0.351	0.693	**TR**	0.057	0.083	-0.345	0.610
JP	0.056	0.068	-0.135	0.561	**EG**	0.085	0.085	-0.268	0.608
SG	0.049	0.086	-0.220	0.589	**US**	0.067	0.106	-0.271	0.641
IT	0.036	0.079	-0.213	0.595	**KR**	0.040	0.075	-0.275	0.503
BE	0.037	0.075	-0.176	0.594	**BR**	0.250	0.109	-0.101	0.753
GR	0.029	0.073	-0.278	0.515	**QA**	0.053	0.121	-0.400	0.615
HU	0.096	0.094	-0.154	0.735	**FI**	0.115	0.110	-0.376	0.748
NL	0.061	0.086	-0.175	0.662	**AR**	0.122	0.099	-0.235	0.650
PH	0.036	0.059	-0.171	0.519	**CH**	0.064	0.082	-0.311	0.613
FR	0.053	0.086	-0.250	0.652	**TH**	0.111	0.087	-0.122	0.637
IE	0.033	0.075	-0.347	0.631	-	-	-	-	-

Group C_{H1} gathers mostly countries classified as developed, such as Israel (IL), or developed and European, namely Austria (AT), Germany (DE), Norway (NO), Portugal (PT), Russia (RU) and the United Kingdom (UK). Among the nine countries in this cluster, only Colombia (CO) and South Africa (ZA) are emerging countries. Cluster C_{H2} joins seven countries, out of the ten countries, that can be classified as emerging countries such as Chile (CL), Czech Republic (CZ), Indonesia (ID), India (IN), Peru (PE) and Poland (PL). The exceptions, or developed countries, in this cluster are Australia (AU), Denmark (DK), New Zealand (NZ) and Spain (ES). Among the twelve countries grouped in the C_{H3} cluster, nine can be classified as developed countries namely: Belgium (BE), France (FR), Greece (GR), Ireland (IE), Italy (IT), Japan (JP), the Netherlands (NL), Sweden (SE) and Singapore (SG). The remaining three countries, Mexico (MX), the Philippines (PH) and Hungary (HU) are emerging in Latin America, Asia and Europe respectively. Among the eleven countries of cluster C_{H4} only four can be classified as developed: Canada (CA), Switzerland (CH), United States (US) and Finland (FI). All the other countries in C_{H4} are classified as emerging economies.

Tables 4 and 5 present the time series statistical summary of correlations coefficient grouped in C_{H1}, C_{H2}, C_{H3} and C_{H4} clusters. These statistical summaries allow to observe the time series of the estimated correlation coefficients between the equity index returns of each countries and the returns of crude oil prices in the international market similarities in a more detailed or precise form.

Thus, this work shows that the correlation between Brent crude oil price returns and national stock market index returns changes over time and that Brent crude oil price volatility is reflected in the stock market through this correlation. However, it is impossible to classify an economy as developed or emerging based on these time varying correlations.

5. Final Comments

Energy price changes and, in particular, crude oil prices have a direct influence on economic activity. Determining this influence is valuable for national economic policymakers and all participants of national and global capital markets. The primary purpose of this paper was to analyze the dynamic correlation between Brent crude oil market returns and the domestic capital market returns.

To that purpose, bivariate GARCH models were first fitted to Brent crude oil price returns and national stock market index returns, leading to the estimation of implied dynamical correlations. Then, the correlation time series were clustered using two different, albeit related, time series distances. The clusters obtained by the two methodologies were essentially the same. They did not provide well defined clustering solutions concerning the country capital market rankings, the stage of development and the geographical region. Recent decades' greater integration of national capital markets may have contributed to the exceptions shown in the correlation time series clustering. It should be noted that those exceptions can also be caused by the financialization of the crude oil market, with its increasing indexed financial instruments or derivatives and their use in portfolio diversification.

It is worth mentioning that for six of the selected markets, namely China, Hong Kong, Malaysia, Pakistan, Taiwan and United Arab Emirates (UAE), it was impossible to estimate a statistically significant bivariate GARCH model. This difficulty can be explained by the characteristics concerning the crude oil market supply and demand shocks and the dissociation of these markets from the global financial markets.

Further studies on this topic should be carried out using other samples and methodological approaches to gather more information to improve resource allocation in the international market.

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