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SCHOOL OF SCIENCE & TECHNOLOGY
A thesis submitted for the degree of
Master of Science (MSc) in Energy Systems

DECEMBER 2013
THESSALONIKI-GREECE

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By Kilintari Sofia

Abstract

The present dissertation study investigates empirically the volatility spillover from oil prices to stock markets from a global perspective. The crude oil volatility will be identified through the newly published CBOE Crude Oil Volatility Index (OVX) while at the same time global stock markets will be examined through global stock indexes such as MSCI ACWI, BBC Global 30, Dow Jones Global Titans, FTSE Global100, Global Dow, S&P Global Net Return, S&P Global 1200. For the purpose of this study, we use daily time series data which have been retrieved from the Bloomberg database. The preliminary econometric analysis begins with unit root and stationarity tests in order to test the order of integration of variables and proceeds with cointegration tests. To examine the interrelationship between the variables of interest advance causality techniques were applied. Firstly, the traditional Granger causality test and Todo-Yamamoto causality test were implemented to reveal the linear causality. Secondly, frequency domain causality tests were applied to reveal the nonlinear interaction. More precisely, Breitung and Candelon (2006) model was used to explore the long and short run causality, as well as the Lemmens et al (2008) approach. The identification of the causal relationship is of paramount importance for a financial hedger, policy maker or market participant.
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1. Introduction

Policymakers are concerned when large price movements are taking place in the crude oil market. For example, the majority of the global, post-World War II, recessions were preceded by sharp increases in crude oil prices. Particularly, seven out of eight US recessions follow the above mentioned pattern according to a research conducted by Hamilton (1983). A straightforward explanation is that oil price increases lower future economic growth by raising the production cost, fact that also affects firms’ profits and consequently stock prices. Understanding the existing links between financial markets is of great importance for policy makers, financial hedgers, portfolio managers or other financial analysts. The study of volatility spill-over from one market to another is a crucial domain of this subject. Already a large literature exists on the volatility spill-over for a variety of markets such as the equity markets, the bond markets, and exchange rate markets.

Major increases in West Texas Intermediate crude oil prices appear to associated with significant geopolitical and economic events. Before 1986, the most significant events that affected crude oil prices were: a) the decline in US reserves (in 1969), b) the Libyan production cutbacks (in 1970) and c) OPEC embargo in 1973 and the war between Iran and Iraq in 1980. The latter produced an oil price shock and followed by a recession for the US economy. After 1986 the oil price dynamics and the influence in several economic parameters has changed. Figure 1 illustrates WTI spot prices for the period 1986- 29/08/2013. The first major increase since 1986 was produced by the invasion of Iraq in Kuwait in 1990. The global financial downturn in 2008 caused a large increase in prices which returned to average levels in 2009. The next spike appears in March 2011 produced by the war in Libya while investors, and not only, worried for a decrease in the supply of crude oil. There is a strand of literature examining the effect of oil prices changes in the stock markets by using either simply price series or by employing generalized autoregressive conditional heteroscedastic (GARCH) models to model crude oil price volatility. The results are not in a consensus, since it is a key element for resulted finding in each case the methodological approach adopted. An extensive presentation of numerous studies will be presented in the literature review.
Unlike a large number of publications which employ GARCH models to model crude oil price volatility, in this study an alternative implied volatility index will be used. The Chicago Board Options Exchange (CBOE), the largest U.S. options exchange first published stock volatility index (VIX). Implementing the methodology of the aforementioned index to options on the United States Oil Fund,\(^1\) Crude Oil Volatility Index (OVX) or the “Oil VIX” was introduced in 2007 and it was the first volatility index of a commodity. It is a measure of market’s expectation of 30-day volatility of crude oil prices. It is worth noting two key characteristics of the index. Firstly, OVX does not illustrate a specific trend as a reaction in oil price changes. For instance, VIX mainly illustrates an upward trend when stock prices decrease, unlike OVX when oil prices change. Secondly, major economic as well as political events are reflected in the variations of the volatility index. All the above demonstrate that the constructed index measures effectively the prevailing uncertainty in the market.

\(^1\) The United States Oil Fund is an exchange-traded security designed to track changes in crude oil prices. By holding near-term futures contracts and cash, the performance of the Fund is intended to reflect the spot price of West Texas Intermediate light, sweet crude oil, less USO expenses.
Figure 2 illustrates the Crude Oil Volatility Index while the four clearly observed spikes are triggered by major political events. More precisely, the first one illustrates the beginning of global economic downturn caused by the bankruptcy of Lehman Brothers in September 2008. The second represents investor’s worries of economic double dip in April 2010. The Libyan war causes another spike in March 2011 due to the potential shortage in the crude oil supply. Finally, the debt default risk of US and Europe, resulted in another significant change in the OVX index, change that took place in August 2011.

![OVX Index Chart](chart.png)

**Figure 2 OVX**

*Sources: Bloomberg and CBOE*

The question whether crude oil volatility index interacts with other commodity or financial markets has received relatively limited attention. Consequently, the contribution of this dissertation lays on the fact that we will try to investigate empirically the volatility spill-over from oil prices to global stock markets using a newly published measure of volatility, instead of constructing the volatility from standard GARCH type models. The crude oil volatility is quantified through the CBOE Crude Oil ETF Volatility Index (OVX) while at the same time global stock markets movements will be captured through global stock indexes such as BBC 30,
S&P Global 100, S&P Global 1200 etc. To examine the interrelationship between the variables of interest recently advanced causality techniques will be implemented.

The structure of dissertation study is as follows. Section 2 will provide an extensive literature review on the effect of oil prices towards the financial markets and more specifically on stock prices. The methodological approaches adopted in the literature will be discussed and the role of oil prices in affecting financial markets will be analyzed. Section 3 will present the methodological framework to be used. To begin with, three alternative unit-root tests will be implemented such as ADF, GLS-ADF, PP. The KPSS stationarity test will be also implemented. Three alternative cointegration tests will be implemented. In particular, the Engle and Granger, the Phillip and Ouliaris approach to cointegration and finally the Johansen approach to cointegration. The standard Linear Granger causality as well as the Toda-Yamamoto causality test will be conducted. Finally, two spectral causality tests will be applied, which are the Breitung and Candelon (2006) test and the Lemmens et al. (2008) test. Section 4 will present the aforementioned test results. Section 5 will provide the concluding remarks and a short summary of the findings will be presented.
2. Review of the Literature

It is an unquestionable fact that several researchers have tried to identify the effect of oil price on the economy as well as the stock prices. The oil price shock of 1973 was a key parameter for several researches to be conducted. Thus, there is a strand of literature regarding emerging and developed economies while alternative methodological frameworks are used. In this dissertation numerous publications will be presented in chronological order.

The main objective of several studies was the case of US. To begin with, Hamilton (1996) analyses the relationship between oil shocks and macroeconomic fluctuations. The methodological framework used is the same with the one presented by Hooker (1996) but in this study the net oil price is used as a measure instead of the nominal. The implementation of the Granger causality tests reveal significant connection only for the period 1948-1973 but not for the subsample after 1973. The results are consistent with the findings presented by Hamilton (1983) that for post-1973 period, the influence of an upward trend in oil prices to macro economy had been less significant compared to the same effect before 1973.

Jones and Kaul (1996) investigate the nexus between oil shocks and stock markets for the following countries: US, UK, Japan and Canada. The postwar period is under examination and initially is examined whether each stock market is rational or not. In the context of this study, the influence of oil shocks in cash flows and expected returns is tested. The empirical analysis consists of two steps, considering first the effect on cash flows and then the possible transitions of expected returns and cash flows caused by oil price variations. The findings clearly indicate the rationality only for US and Canada. In other words, the effect of oil shocks clearly results in changes in cash flows which explain the movements of stock prices. Hence, UK and Japan stock markets overreact with changes larger in magnitude and cannot be considered as rational. In general, stock market returns in the four countries are influenced negatively by oil price shock.
Sadorsky (1999) explores the relationship of oil price changes, stock market returns and economic activity for the case of US. In short, the methodology used is as follows: a generalized autoregressive conditional heteroskedastic (GARCH) model is constructed to reveal the correlation of oil shocks and stock market and VAR model is implemented to explore the relationship with regard to the variables examined. The results suggest that oil price fluctuations influence changes in stock returns. More precisely, there is evidence of unidirectional relationship, characterized by asymmetry. Oil price changes have a negative influence on stock returns and the same applies among stock returns and interest rates.

As it was mentioned before Hamilton (1996) published remarkable findings regarding oil shocks and macroeconomic fluctuations. Apart from this publication another interesting research was conducted by Hamilton in 2003, regarding oil prices and economy. The results reveal the nonlinear interaction between the examined series. More precisely, an upward trend of the oil prices impact the economy, while a downward trend do not. The oil price increases following a period of almost constant prices have a stronger impact compared to those that follow an equal decrease as a correction.

The majority of the studies investigate the effect of oil shocks in industrialized and developed countries but it is worth noting that only few, study the emerging financial markets. Maghyereh (2004) employs a generalized VAR model to reveal the relationship among oil shocks and emerging stock markets. The period covered is between 1998 until mid-2004. The 22 indices used for each emerging market are in comparison with Brent crude oil prices. Variance decomposition analysis and impulse response functions are utilized to explore the short term relationship. The key findings of the analysis suggest that oil price fluctuations have insignificant effect on the emerging stock markets examined. The weak transmission of oil market changes in stock markets is evident from the study. Overall, the oil prices are not a significant determinant of these economies.

Covering the period 1970-2003, Huang et al (2005) uses a multivariate threshold approach to study oil price volatility and the economic activity for Canada, US and Japan. These countries represent three different economies: net oil exporting, net oil importing and pure oil importing respectively. The MTVAR model is used in order to
provide results that vary with respect to the oil dependency of each country. The results demonstrate the existence of a threshold value and the impact on economy and stock returns is different for oil price changes above and below this value. For the first case - above threshold value- oil price changes have a stronger impact on stock returns compared to the effect of oil volatility. Although below this value the impact of volatility and changes is weak.

The economies of Gulf Cooperation Council (GCC) countries are considered as some of the fastest growing and characterized by significant dependence on oil, as major oil exporting countries, owning 47% of global oil reserves. Consequently, Hammoudeh and Choi (2005) study the relationship between GCC stock markets, MSCI, S&P 500 and WTI prices for the period 1994-2004. In addition, the Mexican market is included in comparison with the previous indices as another major oil exporting country in totally different region. The unobserved-component model with Markov-switching heteroskedasticity (US-MS) is used as presented by previous publications (Kim (1993), Kim and Kim (1996)). Using this model the decomposition of GCC stock returns in transitory and permanent parameters is presented and examined for low and high variance regimes. The existence of regime switching with regard to volatility for both parameters is proved. The results for the high regime are significant only for GCC countries and for the low, for all markets except Mexico’s. The Dynamic Conditional Correlation (DCC) multivariate GARCH model is also utilized to reveal the long run relationship between these markets. The results of DCC model indicate weak dynamic correlation among oil and each of GCC markets. Among the correlations examined the stronger is between Mexico and WTI.

Nadha and Faff (2007) explore the influence of oil shocks in stock markets for the period 1983 to 2005 by using WTI prices and 35 global indices-each one for different industry. A standard market model expanded with a factor concerning oil price is employed and the negative association between returns and oil price movements is confirmed like previous researchers. Oil &gas and mining sectors are excepted of the previous therefore positive association exists. Moreover, Wald tests are implemented after oil exposure estimates and the results are unexpected. Their findings indicate a symmetric impact of oil price volatility on equity markets, although, it is found to be asymmetric in several other publications.
Park and Ratti (2008) researched the linkage between oil shocks and stock returns. Linear and non-linear measures of oil price shocks are formed and included in multivariable VAR analysis for the case of US and 13 European countries. In addition, linear and scaled oil prices are categorized further and calculated in world-nominal Brent price deflated by U.S. PPI, and national-nominal Brent and exchange rate deflated by the Consumer Price Index of the country examined. Consequently, the significant effect of oil price changes in stock returns is confirmed for all countries, although the impact of world oil prices in stock returns is stronger than the impact of national oil prices. The asymmetric reaction of stock returns is investigated concerning the negative and positive changes in oil prices. There is evidence of the asymmetric effect only for oil exporting countries—US and Norway.

O’Neill et al (2008) examine the relationship between oil prices and stock returns during the period 2003-2006 for the following major OECD countries: US, UK, Canada, Australia and France. The economic environment of this period is characterized by an upward trend of world oil prices thus it is a matter of paramount importance the effect of these movements in stock returns. The data consists of the benchmark price of crude oil for each country and Dow Jones (for the case of US, Canada and Australia), FTSE 100, CAC 40. ARX model is implemented and the results are different between the countries. That is because countries as US, UK and France are oil consuming countries while the others are oil exporters. For the former group of countries, the upward trend of oil prices has a negative impact on stock returns as it was expected. For the latter group, a positive impact between the variables exists. In addition, the magnitude of the impact in oil consuming countries is higher in the US compared to the other.

There is an extremely limited amount of literature that uses Markov-switching EGARCH model (MS-EGARCH) to explore the relationship of oil volatility and stock markets. Aloui and Jammazi (2009) implement MS-EGARCH(1,1) model in their study, based on the one presented by Henry (2009). It is worth noting that both WTI and Brent prices are used in order to shed light in the interaction of crude oil prices with France, UK and Japan stock markets, thus two versions of MS-EGARCH are discussed. Their findings suggest the presence of regime shifting and the inclusion of two regimes: one with low mean and high volatility state-bear market and the other
with high mean and low volatility state-bull market. The former tends to characterize mainly Japan and the latter France and UK. The insistence of low mean and high variance is found to have a more significant effect in stock returns variation. In accordance with previous studies, it is again confirmed the significant reaction of stock returns in a positive change of oil prices, albeit there is a dependence from the type of regime.

Chiou and Lee (2009) examines the impact of WTI prices on S&P 500 returns. VAR cointegration test is implemented and suggests no cointegration. TAR and MTAR cointegration tests are implemented to explore for potential asymmetry. Thus, MTAR model, as the most suitable, rejects the null hypothesis of no cointegration and asymmetry. Unlike the previous authors Chiou and Lee use structural change test to reveal two structural breaks for oil spot and futures prices, which result in three time intervals. Expected, unexpected and negative unexpected changes are constructed and included in the ARJI model for the three time intervals. ARJI results conclude that unexpected asymmetric changes in oil prices have a negative influence on stock returns when oil price fluctuation is high.

Kilian (2008) presents a different approach of oil shocks. Based on this approach, Kilian and Park (2009) research the influence of oil shocks to US stock returns by classifying shocks as follows – demand and supply shocks. There is a negative association between demand shocks and returns albeit the connection with supply shocks is found to be weak. What is evident from the examination in the long-run, 22% of the fluctuations in stock returns is caused by oil demand and supply shocks.

Apergis and Miller (2009) examine the effect of structural oil shocks on stock market returns in a multi-country sample- G7 countries and Australia. Based on the methodology provided by Kilian (2008), their analysis consider the oil prices as endogenous and distinguish oil shocks as it was previously presented. Structural vector error correction (VER) or vector autoregressive model (VAC) is used to decompose oil price changes into three parameters. Next, these parameters are recovered and VER or VAC model is employed with four variables. The results indicate that the parameter affecting stock market returns is oil demand shocks, which are related to the idiosyncratic features of the market. The other two parameters- global aggregate demand shocks and oil supply shocks- do not have a significant
impact on stock market returns. In general, the effect of oil shocks is found to be insignificant because other key parameters such as interest rates are not included.

Papapetrou (2001) explores the interaction between oil, economy and stock markets for the case of Greece as a country significantly dependent by oil. In short, a multivariate VAR model is employed and results in a strong correlation between oil prices and stock market performance. Particularly positive oil shocks weaken stock market returns. Another research presented by Filis (2010) with regard to the interaction among oil prices, consumer price index, industrial production and stock market in Greece. The first part of the methodology framework consists of Johansen co-integration tests and VECM using data series in levels and suggest a long-run interaction between oil prices and consumer price index. In the short run, negative correlation exists between oil shocks and Greek stock market. The second part consists of VAR model using the cyclical components of the data series (derived after the implementation of Hodrick-Prescott and Baxter-King filters). Concerning the cyclical parameters, it is suggested the negative and strong impact of oil price to stock market. The results of VECM and VAR are in consensus although these cannot be compared because different types of data are used.

In contrast with the research presented by Chiou and Lee (2009) concerning the association of WTI prices and S&P 500 returns, Vo (2010) investigates the respective volatility association. The analysis is based on VAR analysis including stochastic volatility. Initially, VAR model with constant correlation multivariate stochastic volatility (CC-MSV) is used and then dynamic correlation model (DC-MSV). For the evaluation of the previous models the Bayesian MCMC method is employed and Value at Risk (VaR) analysis to evaluate further the forecasting ability of each method used. The findings confirm the interaction between the markets and it is stronger when markets become more volatile. Changes in each market can result in volatility changes on the other. Furthermore, the volatility in oil futures market has forecasting ability over the future volatility in the stock markets and vice versa. Another key element of their findings is that according to VaR analysis the CC-MSV method is the most precise compared to others such as GARCH (1,1) and DC-MSV.

Instead of using country or global market indexes as numerous researchers in the literature, Arouri et al (2011) uses European equity market indices to study the nexus
among oil and stock markets. The stock market indices consist of seven sector indices and one that represents the whole European stock market activity. They employ a bivariate VAR-GARCH model between each one of the aforementioned Indices and Brent Crude Oil Index. The results are presented with regard to oil shocks because the volatility spillover is proved to be insignificant. They conclude that oil shocks result in increased volatility to all sectors except for Automobile & Parts sector. For each sector the magnitude of the impact is different, hence the impact on Basic Materials sector is the most significant. The inverse effect exists only from Financials and Utilities sectors to Oil. The previous results are used to calculate the optimal weights and hedge ratios across sectors for creating an effective and diversified portfolio that contains oil stocks.

The interaction between oil shocks and stock markets is again investigated by H. -M. Zhu et al (2011) but instead of using time series data they adopt a panel data approach for 14 OECD and non OECD countries. Panel threshold co-integration tests are applied to reveal the long-run interaction and threshold autoregressive model (TAR) is implemented in parallel with “momentum” threshold autoregressive model (MTAR) in order to extract the best results concerning the potential asymmetry. MTAR model is suggested as the most suitable and the asymmetric long run association is confirmed for the whole panel. Hence the existence of asymmetric threshold co-integration is proved, Granger causality tests are employed. As a result, it is proved that oil shocks Granger-cause stock prices in the long-run and vice versa. The same applies between oil shocks and industrial production. Concerning the Granger cause in the short term, it is proved bidirectional for oil prices and stock prices only if the change in deviation is positive. The aforementioned effect is proved between oil prices and industrial production when the change is negative.

Elyasiani et al (2012) studies the impact of oil shocks in 10 sector returns in the US. In contrast with previous papers, it is the first study that implements FIGARCH model since it is proved to be the most suitable for a sectoral analysis compared with Fama-French, GARCH and IGARCH models. For each sector under examination considers an oil return threshold. Prior to the study of threshold effect and the employment of this unique model, the period of study is separated in three periods- two characterized by high volatility and one by low. As a result, oil returns have a significant effect on
industry sector returns. The magnitude of the effect is higher during the period characterized by high volatility and rising oil prices. If the oil prices were above the threshold played a more significant role compared to those below the threshold. Oil related and oil substitute industries, when oil prices illustrate an upward trend the stock returns are higher. For oil consuming sectors, the same trend will have a negative impact. Last but not least for Depository Institution the effect presents a more complicated association.

The linkage between oil shocks and output at industrial level is investigated by Jimenez-Rodriguez (2011) for the case of six OECD countries: US, UK, France, Italy, Germany and Spain. Multivariate and bivariate VAR models are employed and compared to understand the importance of transmission channels concerning the macroeconomic structure for the period 1975-1988. The impulse responses to oil shocks are presented for the industry sector of each country. It is worth stressing that responses from both models are similar for all countries except France and Spain. In other words in these countries the transmission mechanisms effects exist but destroy each other.

The presence of asymmetry in the oil shocks and US stock returns interaction is again tested by Alsalman (2011) for the period 1947-2009. Concerning the oil prices both real and nominal prices are used. Firstly, slope based tests are applied using real prices to check the nonlinearity of the effect. This method is considered inadequate and with no evidence of nonlinearity hence impulse response function based tests as introduced by Kilian and Park (2009) are implemented to search for the asymmetry. The tests are applied taking into consideration several key aspects such as real and nominal oil prices, small and large shocks, and two sub-periods: after 1973 and the whole sample period. The findings suggest that nominal oil prices demonstrate the asymmetry more clearly compared to real. The results are different between the 50 indexes which are examined. One of the key findings regarding the post 1973 sample suggest that only 23 of the indices demonstrate asymmetry and is caused by small oil price fluctuation.

For the case of China, which is one of the largest oil consuming countries Cong et al (2008) considers the reaction of stock returns to oil shocks or oil volatility. The framework consists of a multivariate VAR model and results in insignificant reaction
of all stock returns except from oil and manufacturing stocks. A more recent study considering developing countries is presented by Li et al. (2012). The interaction between WTI prices and Chinese stock market for the period 2001 to 2010 is under examination. The sector-level analysis consists of panel cointegration and Granger causality tests. It is evident that structural breaks exist in the oil and stock market correlation. According to the empirical findings in the long run, a positive correlation exists between oil price increases to stock prices. For the period 2005-2007 stock prices Granger cause oil prices and this long term relationship is unidirectional. Concerning the subsample after 2007 structural breaks the findings coincide with the arguments that the oil-stock market nexus has changed. More specifically, bidirectional causality is evident in the long term but no causality in the short term.

Another research with respect to the economies of Gulf Cooperation Council (GCC) was conducted by Awartani and Maghyereh (2012). They consider the volatility and return spillovers for the (GCC) stock markets and WTI prices. The analysis concerning the direction of the spillovers is based on the model proposed by Diebold and Yilmaz (2009,2012). The advantage is the use of indices that can reveal whether the relationship is bi-directional or unidirectional. Their findings confirm the spillover from oil markets to GCC markets and vice versa. In addition the effect is asymmetric, the former spillover is more significant than the latter. The previous results are proved again by implementing simple correlation analysis but they are insignificantly different for 2008 crisis when dynamic conditional correlation model is implemented.

Soucek and Todorova (2013) study the volatility transmission between crude oil futures and equity futures markets for the period 9:2002-9:2012. The unique about this study is the implementation of HAR model in a multivariate and orthogonalized version. WTI futures and FTSE 100, S&P 500, Nikkei 225 futures are under examination so as to represent UK, US and Japanese markets respectively. Firstly, the whole sample is investigated and then is divided in pre-crisis, crisis and post-crisis periods. The results for the whole period indicate that crude oil volatility is caused by equity markets. For the pre-crisis period, the Granger causality tests present no significant causality. For the second period, the aforementioned tests state UK and US markets Granger cause oil volatility in contrast with Japan markets that follow oil futures volatility. For the post-crisis period, oil and financial markets were
characterized by high volatility as in the previous period and the Granger causality tests conclude in similar findings. Overall, the linkage between the volatilities of futures markets increased significantly during the financial crisis as the implementation of DCC-GARCH model suggests.

M. -L. Liu et al (2013) investigate the interaction between crude oil volatility index (OVX) and other implied volatility indices, which characterize other markets such as stock, exchange and gold. The aim of the analysis is to examine the uncertainty transmission between those markets and consists of three parts. The first part consists of bounds testing procedure in order to identify the long-run relationships among the indices. Next, Granger causality test used to identify the short-run relationships. Last, GVDs (generalized forecast error variance decompositions) and GIRFs (generalized impulse response functions) are applied to identify the effect of uncertainty shocks in the aforementioned markets. The study concludes that there is no significant long-term relationship between the indices but the strong short-term relationship is proved. Moreover, changes in stock market volatility index (VIX) lead changes in all other indices and changes in OVX are strongly affected by changes in other markets. Concerning the uncertainty shocks, the influence on OVX is reported to be positive.

It is evident from the review of the literature that the research regarding Crude Oil Volatility Index is limited. The abovementioned study uses volatility indices to investigate the relationship between crude oil and stock markets. Based on this, instead of using stock market volatility index, global stock market indices are used.
3. Methodological Framework

3.1 Unit-root tests

This section will present the methodological framework that is intended to be used. Three alternative unit root tests will be implemented to reject or accept the null hypothesis of a unit root in the series. Augmented Dickey-Fuller, Generalized Least Squares ADF and Phillips and Perron Tests will be discussed in brief.

3.1.1 The Augmented Dickey-Fuller Test

The presentation of the ADF Test begins with the description of the standard Dickey-Fuller test. The following equation (1) describes an AR(1) process which consists of the basis of the aforementioned test

\[ y_t = \rho y_{t-1} + x_t' \delta + \varepsilon_t \quad (1) \]

where \( \rho \) and \( \delta \) represent parameters to be estimated, \( x_t \) are optional exogenous regressors which contain either a constant or a constant and trend and \( \varepsilon_t \) is white noise. The series is considered stationary in case that \( |\rho| < 1 \) and non-stationary in case that \( |\rho| \geq 1 \). If we subtract equation (1) with \( y_{t-1} \), the standard DF test is calculated:

\[ \Delta y_t = a y_{t-1} + x_t' \delta + \varepsilon_t \quad (2) \]

where \( \alpha = \rho - 1 \). The test examines the null hypothesis of \( H_0 : \alpha = 1 \) against the alternative of \( H_1 : \alpha < 1 \) and the evaluation is made with the use of conventional \( t \)-ratio for \( \alpha \):

\[ t_\alpha = \frac{\hat{\alpha}}{(se(\hat{\alpha}))} \quad (3) \]

where \( \hat{\alpha} \) is the calculated value of \( \alpha \), \( se(\hat{\alpha}) \) the coefficient standard error.
The standard Dickey-Fuller model can be used only in case of an AR(1) process, in any other case the model has to be modified. As a result, if time series follow an AR(\(p\)) process, where \(p\) the lagged difference term, the augmented Dickey and Fuller test is used to extract valid results. For higher-order correlation, the ADF test creates a parametric correction and \(p\) lagged difference terms of \(y\) are added on the right hand side of the regression and results in the following equation:

\[
\Delta y_t = ay_{t-1} + x_i'\delta + \beta_1 y_{t-1} + \beta_2 \Delta y_{t-2} + ... + \beta_p \Delta y_{t-p} + \nu_t
\] (4)

Then, Equation (4) is used to examine the null hypothesis of \(H_0: \alpha = 1\) against the alternative of \(H_1: \alpha < 1\) while using \(t\)-ratio as it was mentioned before in equation (3).

Regarding the implementation of the ADF test, two key issues arise. Firstly, there is an option of taking into account exogenous variables in the regression. The following alternatives are provided to include a constant or a constant and a linear trend or neither. The constant and linear trend is considered as the most suitable and general option.

Secondly, the optimal lag length which is the number of lagged difference terms to be included has to be determined. If the optimal lag length is zero, the simple DF test is carried out, while for values greater than zero the ADF test is carried out. The recommended number is the one that is adequate to eliminate in the residuals any serial correlation.

3.1.2 The Generalized Least Squares Augmented Dickey-Fuller test

According to the previous analysis, the inclusion of a constant or a constant and trend is possible for the ADF-test. For both cases, a modification of the previous model is presented by Elliot et al. (1996). The adjustment de-trends data before running the regression. The quasi-difference of \(y\) depending on \(\alpha\) value:
Now consider the OLS regression of the quasi-differenced data $d(y_t | \alpha)$ on the quasi-differenced $d(x_t | \alpha)$:

$$d(y_t | \alpha) = d(x_t | \alpha)\delta(\alpha) + \eta_t \quad (6)$$

Where $\delta(\alpha)$ represents OLS estimates of the regression and $x_t$ includes either a constant or a constant and trend.

Regarding the value of $\alpha$, Elliot et al propose $a = \bar{\alpha}$ where:

$$\bar{\alpha} = \begin{cases} 1 - 7/T & \text{if } x_t = \{1\} \\ 1 - 13.5/T & \text{if } x_t = \{1, t\} \end{cases} \quad (7)$$

The definition of the GLS de-trended data $y_t^d$:

$$y_t^d = y_t - x_t^d \delta(\bar{\alpha}) \quad (8)$$

The DF-GLS test considers the estimation of ADF test after substituting the GLS de-trended data $y_t^d$:

$$\Delta y_t^d = a y_{t-1}^d + \beta_1 \Delta y_{t-1}^d + \ldots + \beta_p \Delta y_{t-p}^d + \epsilon_t \quad (9)$$

The $t$-ratio for $\hat{a}$ is considered as in the ADF test.
3.1.3 The Phillips and Perron Test

Phillips and Perron (1988) introduce a non-parametric model of checking for serial correlation. The implementation of PP test consists of the estimation of ADF equation (1) and modification of $t$-ratio. The following statistic is the basis of the PP test:

$$
\overline{t}_a = t_a \left( \frac{\hat{\gamma}_0}{f_0} \right)^{1/2} - \frac{T(\hat{f}_0 - \gamma_0)(se(\hat{\alpha}))}{2f_0^{1/2}s} 
$$

(10)

where $t_a$ stands for $t$-ratio, $\hat{\alpha}$ for the estimate, $se(\hat{\alpha})$ for coefficient standard error, $s$ for the standard error of regression and $f_0$ for an estimator of residual spectrum. Furthermore, $\gamma_0$ represents a consistent of error variance in equation (1).

It is worth noting that two steps have to be conducted before completing the test. The first is to choose the inclusion of a constant or a constant and linear trend or none of the previous. The second is the choice of the most suitable method for the estimation of $f_0$.

3.2 Stationarity testing

3.2.1 The Kwiatkowski, Phillips, Schmidt, and Shin Test

The Kwiatkowski, Phillips, Schmidt, and Shin Test examines the null hypothesis under which $y_t$ series is assumed to be stationary. The residuals from OLS regression of $y_t$ on $x_t$ are the basis of the KPSS model:
Consider the following Lagrange Multiplier-LM equation:

\[
LM = \frac{\sum S(t)^2}{(T^2 f_0)} \quad (12)
\]

where \( f_0 \) represents the estimator of the residual spectrum at frequency zero and \( S(t) \) the following equation:

\[
S(t) = \sum_{r=1}^{i} \hat{u}_r \quad (13)
\]

The previous equation is based on:

\[
\hat{u}_i = y_i - x_i' \delta(0) \quad (14)
\]

where \( \delta \) in this equation is different compared to \( \delta \) used in GLS de-trending.

Moreover, the application of the KPSS test includes the specification of \( x_i \) and estimation method of \( f_0 \).
3.3 Cointegration Tests, VAR and VECM

3.3.1 The Engle and Granger Cointegration Test

The Engle and Granger approach to cointegration is a residual based test. In other words, it is a unit root test employed to the residuals derived from the evaluation of the following equation:

\[ y_t = X_t \tilde{\beta} + D_t \gamma_t + u_t \quad (15) \]

If there is no cointegration among the series, all the combinations of \((y_t, X_t)\) which are linear, are non-stationary. Consequently, the examination of the null hypothesis of no cointegration is consistent to unit root testing of the null hypothesis of nonstationarity. Accordingly, the null hypothesis of cointegration is related to the null of stationarity.

The parametric augmented Dickey-Fuller model is used for the Engle and Granger approach. Consider the estimation of \( p \)-lag augmented regression:

\[ \Delta \hat{u}_t = (\rho - 1)\hat{u}_{t-1} + \sum_{j=1}^{p} \delta_j \Delta \hat{u}_{t-j} + u_t \quad (16) \]

The amount of \( p \) lagged differences should follow an upward trend to infinity with the sample size \( T \) which is considered zero-lag. Also, the rate should be lower than \( T^{1/3} \).

Two different statistics of ADF approach are examined, one that uses \( t \)-statistic to examine the null of nonstationarity (\( \rho = 1 \)) and the other depending on \( \hat{\rho} - 1 \) that represents the normalized autocorrelation coefficient:

\[ \hat{\tau} = \frac{\hat{\rho} - 1}{se(\hat{\rho})} \]

\[ \hat{\xi} = \frac{T(\hat{\rho} - 1)}{1 - \sum_j \delta_j} \quad (17) \]
where \( se(\hat{\rho}) \) represents the OLS estimator of the standard error according to the estimated \( \hat{\rho} \).

\[
se(\hat{\rho}) = \hat{\delta}_n \left( \sum \hat{\mu}_{t+1} \right)^{-1/2} \quad (18)
\]

The asymptotic distributions of \( z \) and \( t \) statistics are considered non-standard. The previous statistics are determined by the specification of deterministic regressors, thus critical values are extracted by simulation results. Although, the deterministics are not included in the auxiliary regressions because these have been excluded from the residuals, the dependence on them exists. Furthermore, critical values of test statistics should consider the dependence of residuals on estimated coefficients.

3.3.2 The Phillips-Ouliaris Cointegration Test

The Phillips-Ouliaris approach, similarly with the Engle-Granger model, is a residual based. As it was mentioned before, the Engle-Granger test considers the augmented Dickey-Fuller approach. In contrast to this test, the Phillips-Ouliaris test considers the following unaugmented Dickey-Fuller regression for the estimation of \( \rho \):

\[
\Delta \hat{u}_t = (\rho - 1)\hat{u}_{t-1} + w_t \quad (19)
\]

The results are used to calculate estimates of \( w_u \) and \( \lambda_{u_u} \) of the residuals. \( w_u \) is the long-run variance and \( \lambda_{u_u} \) is the strict one-sided long-run variance.

The autocorrelation coefficient is:

\[
(\hat{\rho}^* - 1) = (\hat{\rho} - 1) - T \hat{\lambda}_{u_u} \left( \sum \hat{\mu}_{t+1}^2 \right)^{-1} \quad (20)
\]

The test statistics are:

\[
\hat{\tau} = \frac{\hat{\rho}^* - 1}{se(\hat{\rho}^*)} \quad (21)
\]

\[
\hat{\zeta} = T(\hat{\rho}^* - 1)
\]

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Where

\[ \text{se}\left(\hat{\rho}^*\right) = \hat{w}_w^{1/2} \left( \sum_{t} u_{tt-1}^2 \right)^{-1} \]  
(22)

Regarding the asymptotic distributions of \(z\) and \(t\) statistics the same applies as in the Engle-Granger model.

3.3.3 Johansen Cointegration Test

The Johansen approach to cointegration is a VAR-based test. The methodology proposed by Johansen (1991, 1995) begins with the consideration of a VAR:

\[ y_t = A_1 y_{t-1} + \ldots + A_p y_{t-p} + B x_t + \epsilon_t \]  
(23)

which is of order \(p\), \(y_t\) represents \(k\)-vector of non-stationary variables, \(x_t\) is \(d\)-vector of deterministic variables, \(\epsilon_t\) a vector of innovations. The VAR can be written again as follows:

\[ \Delta y_t = \Pi y_{t-1} + \sum_{j=1}^{p} \Gamma_j y_{t-j} + B x_t + \epsilon_t \]  
(24)

where:

\[ \Pi = \sum_{j=1}^{p} A_j - I \]  
(25)

\[ \Gamma_j = -\sum_{j=1+1}^{p} A_j \]  
(26)

The representation theorem of Granger claims that in case \(\Pi\) the coefficient matrix has decreased rank \(r < k\), then \(k \times r\) matrices \(\alpha\) and \(\beta\) exist. The matrices are with
rank $r$ so that $\Pi = \alpha \beta'$ and $\beta' y_t$ is I(0). The number of cointegrating relations is $r$ which is also characterized as the cointegration rank. The cointegrating vector is each column of $\beta$. $\Gamma$ is the coefficient matrix, $p$ is the lag length and $e_t$ denotes the residual matrix. The adjustment parameters in VEC model are the elements of $a$. The approach of Johansen is the estimation of $\Pi$ matrix using an unrestricted VAR and the examination if restrictions indicated by decreased rank of $\Pi$ can be rejected.

The number of cointegrating relations $r$ conditional on the assumption made about the trend can be determined by proceeding from $r = 0$ until $r = k - 1$ until we fail to reject. The trace statistic examines the null hypothesis $r$ cointegration relations contrary to $k$ relations. $k$ denotes the number of endogenous variables for $r = 0,1,\ldots,k-1$. $k$ cointegrating relations are according to the condition of no unit root for any of the series. Stationary VAR can be specified according to levels of all series. The statistic concerning the examination of null hypothesis of $r$ cointegration relations is examined as follows:

$$LR_r(r|k) = -T \sum_{i=r+1}^{k} \log(1 - \lambda_i) \quad (27)$$

where $\lambda_i$ represents the largest $i$-th eigenvalue of $\Pi$, the matrix of equation (27).

Concerning the maximum eigenvalue statistic, the null hypothesis of $r$ cointegration relations is tested against the option of $r+1$ relations. This test is calculated as follows:

$$LR_{\max}(r| r+1) = -T \log(1 - \lambda_{r+1}) = LR_r(r|k) - LR_r(r+1|k) \quad (28)$$

for $r = 0,1,\ldots,k-1$.

3.3.4 The Vector Auto Regression (VAR) and Vector Error Correction (VEC) Models

The Vector Autoregressive model (VAR) is a generalization of the univariate Autoregressive models (AR). It is one of the most commonly models used for the study of time series which can be either multivariate or bivariate. In order to test if an
independent variable has the ability to influence or forecast the dependent variable in the short run a VAR model can be used. A VAR model with \( n \) variables consists of \( n \) linear equations and the variables are treated as endogenous. Consider the following VAR model after estimating first the optimal lag length \( p \):

\[
y_{1,t} = a_{1,0} + a_{1,1} y_{1,t-1} + a_{1,2} y_{2,t-1} + \ldots + a_{1,n} y_{n,t-1} + a_{1,0} y_{1,t-p} + a_{1,2} y_{2,t-p} + \ldots + a_{1,n} y_{n,t-p} + e_{1,t}
\]

\[
y_{2,t} = a_{2,0} + a_{2,1} y_{1,t-1} + a_{2,2} y_{2,t-1} + \ldots + a_{2,n} y_{n,t-1} + a_{2,0} y_{1,t-p} + a_{2,2} y_{2,t-p} + \ldots + a_{2,n} y_{n,t-p} + e_{2,t}
\]

\[
\vdots
\]

\[
y_{n,t} = a_{n,0} + a_{n,1} y_{1,t-1} + a_{n,2} y_{2,t-1} + \ldots + a_{n,n} y_{n,t-1} + a_{n,0} y_{1,t-p} + a_{n,2} y_{2,t-p} + \ldots + a_{n,n} y_{n,t-p} + e_{n,t}
\]

(29)

The matrix \( A \) which is \([n \times (n \cdot p + 1)]\) contains all the coefficients to be estimated. The matrix of error terms is \( E_t \) and contains \( n \times 1 \) terms. Note that the series should be \( I(0) \) or stationary in order to implement this model. If series are not stationary the model should be modified. Before any modifications, cointegration tests should be implemented in time series. In case there is no cointegration, the series are differenced \( d \) times, where \( d \) is the order of integration. Then, VAR is based on the differenced form of the variables. On the contrary, if there is cointegration an error correction term is included in the model.

Consider the following equations which represent a bivariate VAR model:

\[
y_{1,t} = a_{1,0} + a_{1,1} y_{1,t-1} + a_{1,2} y_{2,t-1} \quad (30)
\]

\[
y_{2,t} = a_{2,0} + a_{2,1} y_{1,t-1} + a_{2,2} y_{2,t-1} \quad (31)
\]

The corresponding VECM model is as follows:
\[ \Delta y_{1,t} = a_1 (y_{1,t-1} - \beta y_{2,t-1}) + e_t \quad (32) \]
\[ \Delta y_{2,t} = a_2 (y_{1,t-1} - \beta y_{2,t-1}) + e_t \quad (33) \]

where the cointegrating model is \( y_{1,t} = \beta y_{2,t} \). The previous equation is included in VECM and limits the long run performance of the variables. In the long run the error correction term is equal to zero. Note that when the order of VAR is \( p \), the VECM model is considered of order \( p-1 \).
3.4 Causality Tests

3.4.1 Granger Causality

In order to test for linear Granger causality the bivariate model as introduced by Granger (1969) is used. Consider two stationary variables $X_t$ and $Y_t$, then the following equation is used to test the null of no causality.

$$
V_t = \Theta(L) V_t + \varepsilon_t = \begin{pmatrix}
\Theta_{11}(L) & \Theta_{12}(L) \\
\Theta_{21}(L) & \Theta_{22}(L)
\end{pmatrix} \begin{pmatrix}
X_t \\
Y_t
\end{pmatrix} + \begin{pmatrix}
\varepsilon_{1t} \\
\varepsilon_{2t}
\end{pmatrix} (34)
$$

where, $V_t = (X_t, Y_t)^T$ is a $2 \times 1$ vector of stationary variables, $\Theta(L)$ is a $2 \times 2$ matrix of lag polynomials and $\varepsilon_t$ is a $2 \times 1$ vector of error terms assuming the usual properties. The null hypothesis of no causality running from $Y_t$ to $X_t$ (or from $X_t$ to $Y_t$) is rejected if at least one coefficient of the lag polynomial $\Theta_{12}(L)$ (or $\Theta_{21}(L)$) is significantly different from zero in explaining current values of $X_t$ ($Y_t$).

The definition of Granger causality is as follows. In case that the present and future values of $X_t$ have the ability to forecast $Y_t$, it is considered that $X_t$ Granger causes $Y_t$. Thus, the causality running from $X_t$ to $Y_t$ is characterized unidirectional. In case that $X_t$ Granger causes $Y_t$ and vice versa, the causality is characterized as bidirectional or “feedback” causality. If there is no interaction between $X_t$ and $Y_t$, is considered as “neutrality”.

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3.4.2 Toda-Yamamoto Causality Test

Toda and Yamamoto (1995) presented a model similar with the Granger causality approach but without testing previously for unit root and cointegration. A description of the general model begins with the following:

\[ y_t = \beta_0 + \beta_1 t + \ldots + \beta_q t^q + \eta_t \]  \hspace{1cm} (35)

where \( \eta_t \) represents the following vector autoregressive procedure:

\[ \eta_t = J_{1} \eta_{t-1} + \ldots + J_{k} \eta_{t-k} + \epsilon_t \] \hspace{1cm} (36)

and assume \( k \) is known. Substituting the following equation:

\[ \eta_t = y_{t-1} - \beta_0 - \beta_1 t - \ldots - \beta_q t^q \] \hspace{1cm} (37)

into the previous equation (36) the result is:

\[ y_t = \gamma_0 + \gamma_1 t + \ldots + \gamma_q t^q + J_{1} y_{t-1} + \ldots + J_{k} y_{t-k} + \epsilon_t \] \hspace{1cm} (38)

Instead of testing cointegration or stationarity of \( y_t \), consider testing the hypothesis with the following restriction:

\[ H_0 : f(\phi) = 0 \] \hspace{1cm} (39)

on \( \phi = vec(\Phi) \) and \( \Phi = (J_1, \ldots, J_k) \) according to Equation (39).

The hypothesis is tested with the estimation of levels VAR:

\[ y_t = \hat{\gamma}_0 + \hat{\gamma}_1 t + \ldots + \hat{\gamma}_q t^q + \hat{J}_{1} y_{t-1} + \ldots + \hat{J}_{k} y_{t-k} + \ldots + \hat{J}_{p} y_{t-p} + \epsilon_t \] \hspace{1cm} (40)

where \( t = 1, \ldots, T \), \( p \geq k + d \), \( k \) is the true lag length and \( d \) the additional lags. The Wald statistic is constructed and Equation (40) is estimated in order to test the null hypothesis as presented previously in Equation (39). It is worth noting that, if the series under examination are cointegrated perhaps the test will be inefficient.
3.5 Frequency Domain Causality Tests

3.5.1 Breitung and Candelon (2006) test

Breitung and Candelon (2006) proposed a methodological framework for the examination of short-run and long-run causality. Initially, assume a two-dimensional vector $z_t = [x_t, y_t]'$ concerning time series and $t = 1, \ldots, T$. Consider $z_t$, represented by the finite-order VAR of the following model:

$$\Theta(L)z_t = \varepsilon_t \quad (41)$$

where $\Theta(L) = I - \Theta_1 L - \ldots - \Theta_p L^p$ is a $2 \times 2$ lag polynomial with $L^k Z_t = Z_{t-k}$. $\varepsilon_t$ is the error vector and represents white noise with $E(\varepsilon_t) = 0$, $E(\varepsilon_t \varepsilon'_t) = \Sigma$. In the previous Equation (41), the deterministic terms are ignored although when the model is applied a constant exists.

Consider the $G$ the triangular matrix which is the lower of Cholesky decomposition $G'G = \Sigma^{-1}$ so as $E(\eta_t \eta'_t) = I$, $\eta_t = G\varepsilon_t$. In case that the system is considered stationary, the MA description is:

$$z_t = \Phi(L)\varepsilon_t = \begin{bmatrix} \Phi_{11}(L) & \Phi_{12}(L) \\ \Phi_{21}(L) & \Phi_{22}(L) \end{bmatrix} \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} = \Psi(L)\eta_t = \begin{bmatrix} \Psi_{11}(L) & \Psi_{12}(L) \\ \Psi_{21}(L) & \Psi_{22}(L) \end{bmatrix} \begin{bmatrix} \eta_{1t} \\ \eta_{2t} \end{bmatrix} \quad (42)$$

where $\Phi(L) = \Theta(L)^{-1}$, $\Psi(L) = \Phi(L)G^{-1}$

Geweke (1982) and Hosoya (1991) propose as a measure of causality the following:

$$M_{y\rightarrow x}(\omega) = \log \left[ \frac{2\pi f_y(\omega)}{|\Psi_{11}(e^{-i\omega})|^2} \right] = \log \left[ 1 + \frac{|\Psi_{12}(e^{-i\omega})|^2}{|\Psi_{11}(e^{-i\omega})|^2} \right] \quad (43)$$

In case that $|\Psi_{12}(e^{-i\omega})| = 0$ then measure is zero and we state that $y$ does not cause $x$ at frequency $\omega$. 
The aforementioned null hypothesis of non-causality is described in the following equation:

\[ M_{y \rightarrow x}(\omega) = 0 \] (44)

Breitung and Candelon (2006) present a more simple model for causality testing. Taking into account:

\[ \Psi(L) = \Theta(L)^{-1}G^{-1} \]

\[ \Psi_{12}(L) = \frac{g^{22}\Theta_{12}(L)}{|\Theta(L)|} \] (45)

where \(|\Theta(L)|\) and \(g^{22}\) are the determinant of \(\Theta(L)\) and the lower diagonal element of \(G^{-1}\) respectively. The following equation corresponds to non-causality hypothesis:

\[ \left| \Theta_{12}(e^{-i\omega}) \right| = \left| \sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) - \sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) \right| = 0 \] (46)

where \(\theta_{12,k}\) is the corresponding element of \(\Theta_k\). Consequently, the following restrictions are necessary so as \(\left| \Theta_{12}(e^{-i\omega}) \right| = 0\)

\[ \sum_{k=1}^{p} \theta_{12,k} \cos(k\omega) = 0 \] (47)

\[ \sum_{k=1}^{p} \theta_{12,k} \sin(k\omega) = 0 \] (48)

Consider \(a_j = \theta_{11,j}\), \(\beta_j = \theta_{12,j}\) to extract the following VAR equation for \(x_r\):

\[ x_r = a_1x_{r-1} + \ldots + a_p x_{r-p} + \beta_1 y_{r-1} + \ldots + \beta_p y_{r-p} + \epsilon_r \] (49)

The hypothesis described in Equation (44) is equivalent with:

\[ R(\omega)\beta = 0 \] (50)
where $\beta = (\beta_1, \ldots, \beta_p)'$

\[
R(\omega) = \begin{bmatrix} \cos(\omega) & \cos(2\omega) & \cdots & \cos(p\omega) \\ \sin(\omega) & \sin(2\omega) & \cdots & \sin(p\omega) \end{bmatrix} (51)
\]

The restriction examines if Equation (50) can be characterized as ordinary $F$ statistic which is distributed as $F(2, T-2p)$ for $\omega$ with value $(0, \pi)$. The method can also be implemented in systems with higher dimensions.

3.5.2 Lemmens et al (2008) Test

Lemmens et al (2008) examine again the methodological framework presented by Pierce (1979). Regarding causality in the frequency domain, the measure proposed by Pierce is implemented on $u_t$ and $v_t$ which are the univariate innovations series. The series are obtained from $X_t$ and $Y_t$ which are formed as univariate Autoregressive Moving Average (ARMA) procedure:

\[
\Theta^x(L)X_t = C^x + \Phi^x(L)u_t
\]

\[
\Theta^y(L)Y_t = C^y + \Phi^y(L)v_t (52)
\]

Where $\Phi^x(L)$ and $\Phi^y(L)$, $\Theta^x(L)$ and $\Theta^y(L)$ are the moving average and autoregressive polynomials respectively. $C^x$ and $C^y$ are the potential deterministic parameters. Initially, the series are filtered with the aforementioned ARMA procedures and then the series $u_t$ and $v_t$ are derived. The innovation series are white-noise procedures with zero mean and potential correlation at particular lags.

Consider the following spectral density functions of $u_t$ and $v_t$:

\[
S_u(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_u(k)e^{-i\lambda k} (53)
\]

\[
S_v(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_v(k)e^{-i\lambda k} (54)
\]

Where

\[
\gamma_u(k) = Cov(u_t, u_{t-k}) (55)
\]

\[
\gamma_v(k) = Cov(v_t, v_{t-k}) (56)
\]
The autocovariances of $u_t$ and $v_t$ at lag $k$ are represented by the previous equations. Concerning the spectral representation, the decomposition of time series results in a sum of parameters which are uncorrelated, albeit each one is related to a frequency $\lambda$. To explore the interaction between two examined processes which are stochastic, consider a complex number between $u_t$ and $v_t$:

$$S_{uv}(\lambda) = C_{uv}(\lambda) + iQ_{uv}(\lambda) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{-i\lambda k} \quad (57)$$

where $S_{uv}(\lambda)$ is the cross-spectrum, $C_{uv}(\lambda)$ is the cospectrum and real part of the cross-spectrum, $Q_{uv}(\lambda)$ is the quadrature spectrum and imaginary part of $S_{uv}(\lambda)$. Consider the weighted covariance estimator and non-parametrical estimation of cross-spectrum:

$$\hat{S}_{uv}(\lambda) = \frac{1}{2\pi} \left\{ \sum_{k=-M}^{M} w_k \hat{\gamma}_{uv}(k) e^{-i\lambda k} \right\} \quad (58)$$

for $k = -M, \ldots, M$ where $M$ the determinant of maximum lag order.

The following equation represents the coefficient of coherence which is a measure of strength of linear relationship between the series:

$$h_{uv}(\lambda) = \frac{|S_{uv}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \quad (59)$$

Note that the coefficient does not examine the direction of the relationship.

The $R$-squared of a regression has similar meaning with the squared coefficient of coherence. Thus, Lemmens et al (2008) based on the findings of previous researchers regarding $R$-squared (Barksdale et al (1974), Woitek (2003)) proved that under the null hypothesis of $h_{uv}(\lambda) = 0$ the squared coefficient of coherence converges to $\chi_2^2$ as:

$$2(n-1)\hat{h}_{uv}^2(\lambda) \xrightarrow{d} \chi_2^2 \quad (60)$$
where frequency is \( \lambda \in (0, \pi) \), chi-squared distribution with two degrees of freedom is represented by \( \chi_2^2 \) and the convergence is denoted by \( \overset{d}{\rightarrow} \).

The null \( h_{w}(\lambda) > 0 \) is accepted in case that:

\[
\hat{h}_{w}(\lambda) > \sqrt{\frac{\chi_{2,1-a}^2}{2(n-1)}} \tag{61}
\]

where \( \chi_{2,1-a}^2 \) is \( 1-a \) quantile of \( \chi_2^2 \).

To examine the direction of the interaction under examination the cross-spectrum in Equation 6 is separated in the following three components: \( S_{u \leftrightarrow v}, S_{u \rightarrow v} \), and \( S_{v \rightarrow u} \).

\[
S_{u \rightarrow v}(\lambda) = \left[ S_{u \leftrightarrow v} + S_{u \rightarrow v} + S_{v \rightarrow u} \right] = \frac{1}{2\pi} \left[ \gamma_{uv}(0) + \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{\gamma\lambda k} + \sum_{k=1}^{\infty} \gamma_{uv}(k) e^{-\lambda k} \right] \tag{62}
\]

If \( \gamma_{uv}(k) = 0 \) with regard to all \( k < 0 \), then \( X \), does not Granger cause \( Y \). The second part of Equation (62) provides information of the ability of \( X \), to predict \( Y \),

\[
S_{u \rightarrow v}(\lambda) = \frac{1}{2\pi} \left[ \sum_{k=-\infty}^{\infty} \gamma_{uv}(k) e^{\gamma\lambda k} \right] \tag{63}
\]

The Granger coefficient of coherence with values from zero to one:

\[
h_{u \rightarrow v}(\lambda) = \frac{|S_{u \rightarrow v}(\lambda)|}{\sqrt{S_u(\lambda)S_v(\lambda)}} \tag{64}
\]

In case of no Granger Causality, \( h_{u \rightarrow v}(\lambda) = 0 \). A natural estimator for the Granger coefficient of coherence at frequency \( \lambda \):

\[
\hat{h}_{u \rightarrow v}(\lambda) = \frac{|\hat{S}_{u \rightarrow v}(\lambda)|}{\sqrt{\hat{S}_u(\lambda)\hat{S}_v(\lambda)}} \tag{65}
\]
Where \( \hat{S}_{u\rightarrow v}(\lambda) \) as shown in Equation (18) but with all weights \( w_k \) equal to zero, for all \( k \geq 0 \). The distribution of the estimator of Granger coefficient of coherence is obtained by the distribution of coefficient as shown in Equation 60. The squared estimated coefficient of coherence at \( \lambda \) is obtained under the null \( h_{u\rightarrow v}(\lambda) = 0 \)

\[
2(n'-1)\hat{h}_{u\rightarrow v}^2(\lambda) \xrightarrow{d} \chi^2_2 \quad (66)
\]

Where \( n' = T / (\sum_{k=-M}^{-1} w_k^2) \) and only \( w_k \) with negative indices is considered. The null hypothesis \( h_{u\rightarrow v}(\lambda) > 0 \) is accepted if:

\[
\hat{h}_{u\rightarrow v}(\lambda) > \sqrt{\frac{\chi^2_{2,1-\alpha}}{2(n'-1)}} \quad (67)
\]

Consequently, \( h_{u\rightarrow v}(\lambda) \) identifies the contribution only for frequency \( \lambda \) but not the total interaction.
4. Data Sources and Empirical Application

4.1 Data sources

In this study we use daily time series data which have been retrieved from the Blookomberg database. The CBOE Crude Oil Volatility Index (OVX) will be used to proxy the oil price volatility and some indicative global stock indexes are used to proxy the global stock market movements. The global indexes examined are the following: S&P Global Net Return, S&P Global 1200, Global Dow, Dow Jones Global Titans, FTSE Global 100, MSCI ACWI and finally the BBC Global 30. The interrelationship of each one of the stock indices with the OVX will be investigated. 1589 observations of the OVX are matched with the respective 1589 observations for each one of the global stock process indexes selected. The period of analysis extends from 05/10/2007 to 08/29/2013. The abovementioned indices will be presented in detail below.

The CBOE Crude Oil Volatility Index (OVX) measures the market’s expectation of 30-day volatility of crude oil prices using the VIX methodology to United States. Figure 3 illustrates the index during the period 05/10/2007-08/29/2013 and Figure 4 illustrates the growth rate of the index. Major political events as well as economic events cause changes in OVX.

![Figure 3 OVX Index](image1.png)

![Figure 4 OVX Index growth rate](image2.png)
The MSCI ACWI Index is a free float-adjusted market capitalization weighted index that is designed to measure the equity market performance of developed and emerging markets. It has been released with a base value of 100 as of December 31, 1987. Figures 5 and 6, show the level and the growth rate of the index respectively for the period under consideration.

![ACWI Index](image1)
![ACWI growth rate](image2)

**Figure 5 ACWI Index**  
**Figure 6 ACWI growth rate**

The BBC Global 30 Index (BBC) combines Europe, Asia and North America - the three power centers of the global economy - in a single index. This index is designed to capture the economic mood of the industrialized world: In all three regions the economy is divided into 10 different industries; from each industry is selected the largest listed company by stock market value. This gives 30 companies from a wide range of industries and countries, and makes the BBC Global 30 a useful tool to see where the world's most important companies and thus the global economy are heading. The index is calculated - in pound sterling - for the BBC by FTSE, who revise it only once every year, in June, based on strict rules. Graphical illustration of the BBC index as well as of its growth can be seen in Figures 7 and 8, right below.
The Dow Jones Global Titans Index (DJGT) is a capitalization-weighted index of the 50 largest multinational companies around the world. As was the case with the previous indexes Figures 9 and 10 illustrate the level movements and the logarithmic differences of the Dow Jones Global Titans Index.

The FTSE Global 100 Index (FTSE 100) is a free float market capitalization weighted index. FTSE Multinationals and Local Indices include constituents of the large and mid-capitalization universe where the developed market constituents are classified as either Multinational (>30% of sales outside their domestic market) or Local (>70% of sales within their domestic market). Base value is 1000 at 9/30/1999. Figure 11 illustrates the level of the index and Figure 12 illustrates the growth rate of the index.
The Global Dow Index (GDOM) is a 150-stock index whose components are selected by the editors of The Wall Street Journal. It tracks the share prices of blue-chip companies in every industry- and not just those that already have “made it” but also those that are poised for global leadership. Visual inspection of the level of the index and the growth rate of it can be traced in Figures 13 and 14, respectively.

The S&P Global Net Return Index (SP100) measures the performance of 100 multinational, blue chip companies of major importance in the global equity markets. It is calculated with WN rates. Figure 15 illustrates the index during the period 05/10/2007- 08/29/2013 and Figure 16 illustrates the growth rate of the index.
The S&P Global 1200 Index (SP1200) is a composite index, comprised of seven regional and country indices - S&P 500, S&P Europe 350, S&P/TOPIX 150 (Japan), S&P TSX 60 (Canada), S&P/ASX (Australia), S&P Asia 50 and S&P Latin America 40. The S&P Global 1200 is calculated in US dollars. The index is market-cap weighted, free float adjusted outside US and introduced in 1999.
4.2 Preliminary Econometric Analysis

4.2.1 Unit Root and Stationarity testing results

In order to examine the existence of a unit-root for the time series under consideration, the following unit-root tests were implemented: a) the Augmented Dickey-Fuller (ADF), b) the generalized least squares detrending Dickey-Fuller (GLS-ADF) and c) the Phillips and Perron (PP) test. The testing results, for every single series, are presented in Table 1, 2, 3 respectively. All tests have been executed both on the levels and the first logarithmic differences of time series with and without trend. The optimal lag-length, $k$ was selected based on Schwarz information criterion. It has to be noted that in Tables 1, 2, and the symbols *, ** and *** indicate rejection of the null hypothesis at the 10, 5 and 1% significance level.

According to Table 1, in case that the ADF test is applied in levels we fail to reject the null hypothesis for existence of a unit root, while OVX without trend is the only index excluded. In particular, for this index we reject the null at 10% significance level. The application of the ADF test provides the opposite results when it is applied into the first differences. More precisely, we reject the null hypothesis at 1% significance level for all indexes with and without trend. Overall, the ADF test suggests that all series are integrated of order I(1)

<table>
<thead>
<tr>
<th>Table 1 ADF unit root test results</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Variable</strong></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>ACWI</td>
</tr>
<tr>
<td>BBC</td>
</tr>
<tr>
<td>OVX</td>
</tr>
<tr>
<td>DJGT</td>
</tr>
<tr>
<td>FTSE100</td>
</tr>
<tr>
<td>GDOW</td>
</tr>
<tr>
<td>SP100</td>
</tr>
<tr>
<td>SP1200</td>
</tr>
</tbody>
</table>
Note: ADF stands for the Augmented Dickey-Fuller test. The selected lag length is \( k \). The lag length was selected based on the Schwarz information criterion with \( k_{\text{min}}=0 \) and \( k_{\text{max}}=23 \). The rejection of the null hypothesis for the existence of a unit root at the 1, 5 and 10% significance level is denoted by ***, ** and * respectively.

As it is shown in Table 2, the GLS-ADF test results are similar with the ADF test. The null hypothesis for existence of a unit root fails to be rejected when the test is applied into the levels while the null is rejected for the first differences both with and without trend. Note that, the application of GLS-ADF test in the OVX level series without including trend, results in rejection of the null hypothesis at 5% significance level. Overall, the GLS-ADF test results provide qualitative similar inference to that of the standard ADF test. Therefore, all series appear to be I(1).

### Table 2 GLS-DF unit root test results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>1st Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No trend</td>
<td>Trend</td>
</tr>
<tr>
<td></td>
<td>( t ) Stat.(( k ))</td>
<td>( t ) Stat.(( k ))</td>
</tr>
<tr>
<td>ACWI</td>
<td>-0.94(1)</td>
<td>-1.13(1)</td>
</tr>
<tr>
<td>BBC</td>
<td>1.32(0)</td>
<td>-2.47(0)</td>
</tr>
<tr>
<td>OVX</td>
<td>-2.04(1)**</td>
<td>-2.18(1)</td>
</tr>
<tr>
<td>DJGT</td>
<td>-0.70(0)</td>
<td>-0.89(0)</td>
</tr>
<tr>
<td>FTSE100</td>
<td>-1.13(0)</td>
<td>-1.15(0)</td>
</tr>
<tr>
<td>GDOH</td>
<td>-1.24(1)</td>
<td>-1.62(1)</td>
</tr>
<tr>
<td>SP100</td>
<td>-1.15(0)</td>
<td>-1.14(0)</td>
</tr>
<tr>
<td>SP1200</td>
<td>-0.90(1)</td>
<td>-1.04(1)</td>
</tr>
</tbody>
</table>

Note: GLS-DF stands for the generalized least squares detrending Dickey-Fuller test. The selected lag length is \( k \). The lag length was selected based on the Schwarz information criterion with \( k_{\text{min}}=0 \) and \( k_{\text{max}}=23 \). The rejection of the null hypothesis for the existence of a unit root at the 1, 5 and 10% significance level is denoted by ***, ** and * respectively.
Last but not least, the PP test results are similar with the two previous tests. In other words, in the levels we fail to reject the null hypothesis for existence of a unit root but in first differences we reject the null consistently at the 1% significance level. In case of the OVX in levels (with and without trend) we reject the null at 10% significance level. The PP test results provide identical inference to that of the ADF and GLS-ADF tests. The series are I(1).

### Table 3 PP unit root test results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>1st Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No trend</td>
<td>Trend</td>
</tr>
<tr>
<td></td>
<td>t Stat.</td>
<td>t Stat.</td>
</tr>
<tr>
<td>ACWI</td>
<td>-1.71</td>
<td>-1.67</td>
</tr>
<tr>
<td></td>
<td>-34.95***</td>
<td>-34.97***</td>
</tr>
<tr>
<td>BBC</td>
<td>-0.80</td>
<td>-2.62</td>
</tr>
<tr>
<td></td>
<td>-31.68***</td>
<td>-31.67***</td>
</tr>
<tr>
<td>OVX</td>
<td>-2.68*</td>
<td>-3.17*</td>
</tr>
<tr>
<td></td>
<td>-57.99***</td>
<td>-58.11***</td>
</tr>
<tr>
<td>DJGT</td>
<td>-1.74</td>
<td>-1.53</td>
</tr>
<tr>
<td></td>
<td>-39.22***</td>
<td>-39.31***</td>
</tr>
<tr>
<td>FTSE100</td>
<td>-1.49</td>
<td>-1.59</td>
</tr>
<tr>
<td></td>
<td>-37.83***</td>
<td>-37.86***</td>
</tr>
<tr>
<td>GDOW</td>
<td>-1.73</td>
<td>-1.57</td>
</tr>
<tr>
<td></td>
<td>-34.23***</td>
<td>-34.22***</td>
</tr>
<tr>
<td>SP100</td>
<td>-1.45</td>
<td>-1.67</td>
</tr>
<tr>
<td></td>
<td>-37.79***</td>
<td>-37.83***</td>
</tr>
<tr>
<td>SP1200</td>
<td>-1.67</td>
<td>-1.64</td>
</tr>
<tr>
<td></td>
<td>-36.69***</td>
<td>-36.73***</td>
</tr>
</tbody>
</table>

**Note:** PP stands for the Phillips-Perron test. The bandwidth was selected with respect to Newey-West method and the spectral estimation method used is the Bartlett Kennel. The rejection of the null hypothesis for the existence of a unit root at the 1, 5 and 10% significance level is denoted by ***, ** and * respectively.

In contrast with the previous tests, the KPSS test examines the null hypothesis of stationarity against the alternative of non-stationarity. According to Table 4, the application of the test in levels results in rejection of the null for all indexes. When the test is applied in first differences we fail to reject the null hypothesis. Thus, all series at first differences are stationary or in other words are integrated of order one, I(1).
Table 4 KPSS stationarity test results

<table>
<thead>
<tr>
<th>Variable</th>
<th>Level</th>
<th>1st Differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No trend</td>
<td>Trend</td>
</tr>
<tr>
<td></td>
<td>LM-Statistic</td>
<td>LM-Statistic</td>
</tr>
<tr>
<td>ACWI</td>
<td>0.65**</td>
<td>0.66***</td>
</tr>
<tr>
<td>BBC</td>
<td>3.83***</td>
<td>0.45***</td>
</tr>
<tr>
<td>OVX</td>
<td>1.24 ***</td>
<td>0.33***</td>
</tr>
<tr>
<td>DJGT</td>
<td>0.86***</td>
<td>0.83***</td>
</tr>
<tr>
<td>FTSE100</td>
<td>0.79***</td>
<td>0.73***</td>
</tr>
<tr>
<td>GDOV</td>
<td>0.89***</td>
<td>0.54***</td>
</tr>
<tr>
<td>SP100</td>
<td>0.84***</td>
<td>0.69***</td>
</tr>
<tr>
<td>SP1200</td>
<td>0.69**</td>
<td>0.70***</td>
</tr>
</tbody>
</table>

Note: KPSS stands for the Kwiatkowski et al (1992) stationarity test. The bandwidth was selected with respect to Newey-West method and the spectral estimation method used is the Bartlett Kennel. The rejection of the null hypothesis at the 1, 5 and 10% significance level is denoted by ***, ** and * respectively.

Overall, unit root and stationarity testing indicate that all the series of interest in the first differenced form are stationary or more simply I(1). Therefore, cointegration analysis is a necessary step in order to receive robust results in our causality testing that follows.
4.2.2 Cointegration Testing Results

The next step of the empirical analysis consists of implementing three alternative techniques to cointegration. Residual based cointegration tests such as the Engle and Granger (1987) and the Phillips and Ouliaris (1990) together with the Johansen cointegration test (1988,1990) are implemented to assess possible existence of a long-run equilibrium. Seven pairs are examined for cointegration, the Crude Oil Volatility Index (OVX) with each one of the seven global stock price indices.

Initially, the Engle and Granger cointegration test is implemented examining the null hypothesis of no cointegration between the series. Each pair of series is tested firstly considering the global index as the dependent variable and then the Crude Oil Volatility index (OVX). The lag specification is based on Schwarz information criterion. The results are presented in Table 5. Taking into consideration the \( p \)-value, the cointegration is evident for all the pairs of indices except from the GDOW-OVX.

**Table 5 The Engle and Granger Cointegration test**

<table>
<thead>
<tr>
<th>Dependent</th>
<th>( \tau )-statistic</th>
<th>Prob.</th>
<th>( z )-statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACWI</td>
<td>-2.912</td>
<td>0.133</td>
<td>-16.698</td>
<td>0.108</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.612</td>
<td>0.024</td>
<td>-26.196</td>
<td>0.015</td>
</tr>
<tr>
<td>BBC</td>
<td>-3.286</td>
<td>0.058</td>
<td>-23.016</td>
<td>0.030</td>
</tr>
<tr>
<td>OVX</td>
<td>-5.517</td>
<td>0.000</td>
<td>-58.665</td>
<td>0.000</td>
</tr>
<tr>
<td>DJGT</td>
<td>-2.497</td>
<td>0.281</td>
<td>-11.782</td>
<td>0.269</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.242</td>
<td>0.064</td>
<td>-21.141</td>
<td>0.044</td>
</tr>
<tr>
<td>FTSE100</td>
<td>-2.959</td>
<td>0.121</td>
<td>-17.681</td>
<td>0.089</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.692</td>
<td>0.019</td>
<td>-27.220</td>
<td>0.012</td>
</tr>
<tr>
<td>GDOW</td>
<td>-2.172</td>
<td>0.438</td>
<td>-9.324</td>
<td>0.405</td>
</tr>
<tr>
<td>OVX</td>
<td>-2.971</td>
<td>0.118</td>
<td>-17.769</td>
<td>0.087</td>
</tr>
<tr>
<td>SP100</td>
<td>-3.225</td>
<td>0.066</td>
<td>-21.183</td>
<td>0.044</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.911</td>
<td>0.010</td>
<td>-30.557</td>
<td>0.006</td>
</tr>
<tr>
<td>SP1200</td>
<td>-2.881</td>
<td>0.142</td>
<td>-16.329</td>
<td>0.116</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.585</td>
<td>0.026</td>
<td>-25.770</td>
<td>0.017</td>
</tr>
</tbody>
</table>
Secondly, the Phillips-Ouliaris cointegration test is implemented. The null hypothesis of no cointegration is assessed through the testing procedure. The results are presented in Table 6. The null hypothesis is rejected for all groups of indices except from GDOW-OVX as previously. The cointegration inference is almost identical to that of the Engle and Granger approach.

<table>
<thead>
<tr>
<th>Dependent</th>
<th>tau-statistic</th>
<th>Prob.</th>
<th>z-statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACWI</td>
<td>-2.951</td>
<td>0.123</td>
<td>-16.918</td>
<td>0.103</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.649</td>
<td>0.022</td>
<td>-26.231</td>
<td>0.015</td>
</tr>
<tr>
<td>BBC</td>
<td>-3.379</td>
<td>0.045</td>
<td>-23.606</td>
<td>0.026</td>
</tr>
<tr>
<td>OVX</td>
<td>-4.906</td>
<td>0.000</td>
<td>-45.862</td>
<td>0.000</td>
</tr>
<tr>
<td>DJGT</td>
<td>-2.465</td>
<td>0.295</td>
<td>-11.336</td>
<td>0.290</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.204</td>
<td>0.070</td>
<td>-20.332</td>
<td>0.052</td>
</tr>
<tr>
<td>FTSE100</td>
<td>-2.967</td>
<td>0.119</td>
<td>-17.513</td>
<td>0.092</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.725</td>
<td>0.017</td>
<td>-27.172</td>
<td>0.012</td>
</tr>
<tr>
<td>GDOV</td>
<td>-2.188</td>
<td>0.430</td>
<td>-9.403</td>
<td>0.400</td>
</tr>
<tr>
<td>OVX</td>
<td>-2.914</td>
<td>0.133</td>
<td>-16.923</td>
<td>0.103</td>
</tr>
<tr>
<td>SP100</td>
<td>-3.270</td>
<td>0.060</td>
<td>-21.373</td>
<td>0.042</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.992</td>
<td>0.008</td>
<td>-31.142</td>
<td>0.005</td>
</tr>
<tr>
<td>SP1200</td>
<td>-2.903</td>
<td>0.136</td>
<td>-16.359</td>
<td>0.115</td>
</tr>
<tr>
<td>OVX</td>
<td>-3.611</td>
<td>0.024</td>
<td>-25.644</td>
<td>0.017</td>
</tr>
</tbody>
</table>

The final cointegration test applied is the Johansen approach to cointegration. It is a VAR-based technique, thus, the test begins with the determination of the optimal lag-length based on the Schwartz information criterion. For all the groups of variables examined the optimal lag-length is 2. The results are presented in Table 7. It is evident that all series are cointegrated.
<table>
<thead>
<tr>
<th></th>
<th>Null</th>
<th>Eigen value</th>
<th>Trace Statistic</th>
<th>5% critical</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACWI</td>
<td>r = 0</td>
<td>0.013</td>
<td>24.992</td>
<td>15.495</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.003</td>
<td>4.196</td>
<td>3.841</td>
<td>0.041</td>
</tr>
<tr>
<td>BBC</td>
<td>r = 0</td>
<td>0.024</td>
<td>28.136</td>
<td>15.495</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.001</td>
<td>1.136</td>
<td>3.841</td>
<td>0.287</td>
</tr>
<tr>
<td>DJGT</td>
<td>r = 0</td>
<td>0.012</td>
<td>22.855</td>
<td>15.495</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.003</td>
<td>4.318</td>
<td>3.841</td>
<td>0.038</td>
</tr>
<tr>
<td>FTSE100</td>
<td>r = 0</td>
<td>0.013</td>
<td>24.932</td>
<td>15.495</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.002</td>
<td>3.781</td>
<td>3.841</td>
<td>0.052</td>
</tr>
<tr>
<td>GDOH</td>
<td>r = 0</td>
<td>0.009</td>
<td>20.092</td>
<td>15.495</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.003</td>
<td>5.237</td>
<td>3.841</td>
<td>0.022</td>
</tr>
<tr>
<td>SP100</td>
<td>r = 0</td>
<td>0.014</td>
<td>26.192</td>
<td>15.495</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.002</td>
<td>3.783</td>
<td>3.841</td>
<td>0.052</td>
</tr>
<tr>
<td>SP1200</td>
<td>r = 0</td>
<td>0.013</td>
<td>25.241</td>
<td>15.495</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>r ≤ 1</td>
<td>0.003</td>
<td>4.229</td>
<td>3.841</td>
<td>0.040</td>
</tr>
</tbody>
</table>
4.3 Linear Causality testing

The empirical application proceeds with the application of causality tests. Initially, linear causality is investigated with the implementation of the standard linear Granger causality test and the Toda-Yamamoto causality test.

The implementation of the standard Granger causality test begins with the estimation of a simple VAR model in order to determine the optimal lag length. Given the presence of cointegration the examination of causality should take place within VECM framework. As a result based on the VECM specification and the optimal lag length we examine if each of the global indices Granger cause the Crude Oil Volatility index and vice versa. The optimal lag-length is selected with respect to the Schwartz information criterion and for all cases is 2. Table 8 illustrates the results of the Granger causality test. Clearly, a unidirectional relationship exists running from global stock price indices to OVX and not vice versa.

<table>
<thead>
<tr>
<th>Independent</th>
<th>Dependent</th>
<th>chi-square</th>
<th>Probability</th>
<th>inference</th>
</tr>
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<tbody>
<tr>
<td>ACWI</td>
<td>OVX</td>
<td>17.558</td>
<td>0.000</td>
<td>ACWI→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>ACWI</td>
<td>0.196</td>
<td>0.658</td>
<td>No Causality</td>
</tr>
<tr>
<td>BBC</td>
<td>OVX</td>
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<td>0.003</td>
<td>BBC→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>BBC</td>
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<td>0.818</td>
<td>No Causality</td>
</tr>
<tr>
<td>DJGT</td>
<td>OVX</td>
<td>18.275</td>
<td>0.000</td>
<td>DJGT→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>DJGT</td>
<td>0.264</td>
<td>0.608</td>
<td>No Causality</td>
</tr>
<tr>
<td>FTSE100</td>
<td>OVX</td>
<td>18.179</td>
<td>0.000</td>
<td>FTSE100→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>FTSE100</td>
<td>0.210</td>
<td>0.647</td>
<td>No Causality</td>
</tr>
<tr>
<td>GDOw</td>
<td>OVX</td>
<td>15.467</td>
<td>0.000</td>
<td>GDOw→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>GDOw</td>
<td>0.132</td>
<td>0.716</td>
<td>No Causality</td>
</tr>
<tr>
<td>SP100</td>
<td>OVX</td>
<td>17.685</td>
<td>0.000</td>
<td>SP100→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>SP100</td>
<td>0.020</td>
<td>0.886</td>
<td>No Causality</td>
</tr>
<tr>
<td>SP1200</td>
<td>OVX</td>
<td>18.806</td>
<td>0.000</td>
<td>SP1200→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>SP1200</td>
<td>0.708</td>
<td>0.400</td>
<td>No Causality</td>
</tr>
</tbody>
</table>
The Toda-Yamamoto begins, once again, with the estimation of a standard VAR model. The idea is similar with the previous causality approach but the number of lags is the optimal which is further augmented by one. Since the optimal lag length is two for all cases, three lags are used. The Wald statistic is used to the significance of past values in explaining the current values of the dependent variable. Table 9 presents the results which are similar to the standard Granger causality test. The unidirectional relationship is again confirmed.

<table>
<thead>
<tr>
<th>Independent</th>
<th>Dependent</th>
<th>chi-square</th>
<th>Probability</th>
<th>Results</th>
</tr>
</thead>
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<tr>
<td>ACWI</td>
<td>OVX</td>
<td>19.591</td>
<td>0.000</td>
<td>ACWI→ OVX</td>
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<tr>
<td>OVX</td>
<td>ACWI</td>
<td>0.242</td>
<td>0.886</td>
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<tr>
<td>BBC</td>
<td>OVX</td>
<td>9.431</td>
<td>0.009</td>
<td>BBC→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>BBC</td>
<td>3.169</td>
<td>0.205</td>
<td>No Causality</td>
</tr>
<tr>
<td>DJGT</td>
<td>OVX</td>
<td>19.498</td>
<td>0.001</td>
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<tr>
<td>OVX</td>
<td>DJGT</td>
<td>1.386</td>
<td>0.500</td>
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<tr>
<td>FTSE100</td>
<td>OVX</td>
<td>20.332</td>
<td>0.000</td>
<td>FTSE100→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>FTSE100</td>
<td>1.578</td>
<td>0.454</td>
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<tr>
<td>GDOw</td>
<td>OVX</td>
<td>16.402</td>
<td>0.000</td>
<td>GDOw→ OVX</td>
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<tr>
<td>OVX</td>
<td>GDOw</td>
<td>0.096</td>
<td>0.953</td>
<td>No Causality</td>
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<tr>
<td>SP100</td>
<td>OVX</td>
<td>19.474</td>
<td>0.000</td>
<td>SP100→ OVX</td>
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<tr>
<td>OVX</td>
<td>SP100</td>
<td>0.828</td>
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</tr>
<tr>
<td>SP1200</td>
<td>OVX</td>
<td>20.297</td>
<td>0.000</td>
<td>SP1200→ OVX</td>
</tr>
<tr>
<td>OVX</td>
<td>SP1200</td>
<td>0.566</td>
<td>0.754</td>
<td>No Causality</td>
</tr>
</tbody>
</table>

### 4.4 Frequency Domain Causality Testing

The scope of this dissertation is to capture the linear as well as the nonlinear effect of the relationship between the examined variables. The key idea of nonlinear causal relationship is the possibility of different direction or significance of Granger
causality with regard to different frequencies. The examination of the causal relationship in different frequencies is contacted using the Breitung and Candelon (2006) test. An alternative approach to frequency domain causality testing is presented by Lemmens et al (2008). Both are implemented in the first logarithmic differences and then to the VECM residuals, given the existence of cointegration. This way we can identify with higher precision the nature of the existing causality. Causality for the pre-filtered series reveals nothing about the moments to which the causality is attributed. We may have causality in first-moment, second moment or higher order moments. Causality to the VECM filtered residuals is indication that the causality is attributed to the second or higher-order moments.

4.4.1 Causality testing in the first logarithmic differences (pre-filtered series)

The frequency domain causality testing begins with the Breitung and Candelon (2006) approach in the first logarithmic differences of the series. This test provides results regarding the long-run and short-run causality of the examined series. The causal relationship of each of the seven global stock price indices to OVX is tested and vice versa. The frequency $\omega$ takes values within the range $(0, \pi)$. Figure 17 to 30 illustrate the findings for both directions and all indices. The 5% critical value of the null hypothesis of no Granger causality in all cases is 5.99 and is denoted with a dotted horizontal line. A solid line above the critical threshold signifies significant Granger causality while below the critical threshold there is no significant causality.

Figures 19 and 20 illustrate the Breitung and Candelon causality results between ACWI and OVX, and vice versa, respectively. The findings suggest that ACWI Granger cause OVX in the short and in the medium-run while the reverse effect is the opposite. That is, there is long-run causality between OVX and ACWI but no any other sense of causality. The long-run causality is identified within the range of frequencies $(0,0.4)$. 

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Figure 19 ACWI cause OVX  

Figure 20 OVX cause ACWI

Figure 21 illustrates a causal relationship running from BBC to OVX for all frequencies while Figure 22 the reverse effect. In the reverse direction, only for the range of (0, 0.25), OVX does not Granger cause the BBC index while for the rest frequencies causality at the 5% significance level is established.

Figure 21 BBC cause OVX  

Figure 22 OVX cause BBC

According to Figures 23 and 24, DJGT Granger causes OVX while the opposite effect is not evident for the majority of the frequencies examined. Again the only exception is a narrow range of frequencies that support only long-run causality.
The same pattern appears for the causality inference between FTSE 100 and OVX. The stock index Granger causes crude oil volatility index (Figure 25) in the medium-run and the short-run while there is evidence of reverse causality only in the long-run (Figure 26).

The causality inference between GDOW and OVX is illustrated in Figures 27 and 28. More precisely, the null hypothesis of no Granger causality is rejected for causality running from GDOW to OVX, but not in the long-run, while the null is fails to be rejected for the entire range of frequencies when the examined direction id the reverse.
The findings for SP 100 and OVX are almost identical to the previous case. On the one hand, Figure 29 illustrates that the global stock price index Granger causes the crude oil volatility index. On the other hand, OVX does not Granger cause SP 100.

The last pair of indices reveal a similar trend with our previous findings. Concerning Granger causality running from SP1200 to OVX, the null hypothesis is rejected in the medium and short-run since the Statistic’s value is over the critical value (Figure 31), but this not the case for the long-run. The null hypothesis is fails to be rejected with respect to causality running from OVX to SP 1200 (Figure 32) for the majority of the frequencies but this inference does not hold for the long-run causality.
Overall, the Breitung and Candelon (2006) frequency domain causality test results in this section imply a similar causal inference. In particular, the findings suggest that all global stock price indexes Granger cause crude oil volatility index mainly in the short and medium run and the reverse effect is evident persistently in low frequencies, implying causality in the long-run. Consequently, OVX does Granger cause global stock prices indices in the long run (exception is the GDOW index where there is no causality and the BBC index where the causality is medium-run and short-run but not a long-run).

The frequency domain causality testing in the first logarithmic differences proceeds with the application of Lemmens et al (2008) approach. The null hypothesis of no Granger causality running from each of the seven global indices to OVX is tested and vice versa. The frequency $\omega$ takes values within the range $(0, \pi)$. Figure 31 to 42 illustrate the findings for both directions and all indices. The 5% critical value of the null hypothesis of no Granger causality is denoted with a dotted horizontal line and takes a different value in each case. The solid line indicates the Granger causality running from one index to another and each index is denoted below the corresponding figure.

As it is shown in Figure 33 and 34, the results indicate that ACWI Granger causes OVX for all frequencies and vice versa. The findings are similar for all groups of indices. In other words, the null hypothesis of no Granger causality running from each stock index to crude oil volatility index and vice versa is rejected in every case.
Figure 33 ACWI cause OVX

Figure 34 OVX cause ACWI

Figure 35 BBC cause OVX

Figure 36 OVX cause BBC

Figure 37 DJGT cause OVX

Figure 38 OVX cause DJGT
Figure 39 FTSE 100 cause OVX
Figure 40 FTSE 100 cause ACWI
Figure 41 GDOW cause OVX
Figure 42 OVX cause GDOW
Figure 43 SP100 cause OVX
Figure 44 OVX cause SP100
4.4.2 Causality testing in the residuals

The next step of causality testing is the implementation of the Breitung and Candelon (2006) approach in the residuals. The 5\% critical value of the null hypothesis of no Granger causality in all cases is 5.99 and is denoted with a dotted horizontal line. The solid line indicates the Granger causality running from one index to another and each index is denoted below the corresponding figure.

Firstly, the null hypothesis of no Granger causality is tested to examine the causality between ACWI and OVX. According to Figures 47 and 48, in both cases the null cannot be rejected at the 5\% level of significance.
The causality between BBC and OVX result in similar findings to the previous. To be more specific, Figure 49 indicates no causality running from BBC to OVX and Figure 50 for the opposite direction.

![Figure 49 BBC cause OVX](image1)

![Figure 50 OVX cause BBC](image2)

Regarding the Granger causality running from DJGT to OVX, the null hypothesis fails to be rejected at all frequencies (Figure 51). For the adverse effect, the null cannot be rejected for all frequencies excluding the following ranges: (0, 0.4) and (2.6, 3.14). As it is shown in Figure 52 there is causality only for very low or very high frequencies.

![Figure 51 DJGT cause OVX](image3)

![Figure 52 OVX cause DJGT](image4)

Figures 53 and 54 illustrate similar findings with the previous. The stock price index FTSE 100 does not Granger cause the volatility index at 5% level of
significance and vice versa excluding a small range of frequencies, (0, 0.2) as well as (2.8, 3.14).

Figure 53 FTSE 100 cause OVX  

Figure 54 OVX cause FTSE 100

Again, Figure 55 denotes no causality running from the global stock index to OVX. Figure 56 illustrates mixed results for the causality running from OVX to GDOW. The null fails to be rejected for all frequencies excluding those within the range (1.2, 2.0).

Figure 55 GDO cause OVX  

Figure 56 OVX cause GDOW

In the long-run as well as in the short run SP 100 does not cause the crude oil volatility index (see Figure 57). Additionally, as it is shown in Figure 58, when the opposite direction is examined, only for a small range of frequencies (0, 0.4) the null of no causality is rejected, verifying this way causality only in the long-run.
As it is presented in Figure 59, SP1200 does not Granger cause OVX at the 5% significance level. As it is shown in Figure 60, the same applies in case that causality running from OVX to SP100 is examined. In this case, for a narrow range of frequencies (2.8, 3.14) we reject the null (only a short-run causality is verified).

The major findings of the particular frequency domain causality test in the residuals are as follows. Firstly, neither of the stock indices Granger causes the crude volatility index both in the short and long-run. Secondly, OVX does not Granger cause in any systematic way the global stock price indices as it is obvious from the presented Figures.
In order to reveal nonlinear causality in the residuals, the analysis continues with the implementation of Lemmens et al (2008) approach. Clearly the results obtained from Figures 61-74 are as follows: There is lack of evidence regarding causality running from the stock indices to OVX as well as the reverse direction.

**Figure 61** ACWI cause OVX  
**Figure 62** OVX cause ACWI  
**Figure 63** BBC cause OVX  
**Figure 64** OVX cause BBC  
**Figure 65** DJGT cause OVX  
**Figure 66** OVX cause DJGT
Figure 67 FTSE 100 cause OVX

Figure 68 OVX cause FTSE 100

Figure 69 GDOw cause OVX

Figure 70 OVX cause GDOW

Figure 71 SP100 cause OVX

Figure 72 OVX cause SP100
**Figure 73** ACWI cause OVX

**Figure 74** OVX cause ACWI
5. Concluding Remarks

The present dissertation study investigates the interaction of the newly published Crude Oil Volatility Index OVX with seven global financial stock indices for the period 05/10/2007-08/29/2013. In more detail, the main purpose of the dissertation is to reveal the relationship between crude oil volatility and global stock markets. The methodological framework adopted consists of unit root and stationarity testing, in the second stage we continue by testing for cointegration land finally we investigate the possible existence of a linear as well as non-linear causality. The contribution to the literature can be identified as follows. First, the usage of the volatility index instead of using GARCH models to extract crude oil volatility and second the utilization of two frequency domain causality tests. More precisely, the non-linear causality framework defined by the Breitung and Candelon (2006) and Lemmens et al (2008) tests.

Table 10 Causality Testing Results

<table>
<thead>
<tr>
<th>Independent</th>
<th>Dependent</th>
<th>Linear Causality</th>
<th>Non linear Causality</th>
</tr>
</thead>
<tbody>
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<td>OVX</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>OVX</td>
<td>ACWI</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>BBC</td>
<td>OVX</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>OVX</td>
<td>BBC</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>DJGT</td>
<td>OVX</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>OVX</td>
<td>DJGT</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>FTSE100</td>
<td>OVX</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
<td>OVX</td>
<td>FTSE100</td>
<td>¥</td>
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</tr>
<tr>
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<tr>
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<td>GDOW</td>
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<td>OVX</td>
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</tr>
<tr>
<td>OVX</td>
<td>SP100</td>
<td>¥</td>
<td>¥</td>
</tr>
<tr>
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<td>OVX</td>
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</tr>
<tr>
<td>OVX</td>
<td>SP1200</td>
<td>¥</td>
<td>¥</td>
</tr>
</tbody>
</table>

Notes: TY and GC stand for Toda Yamamoto and Granger causality tests respectively. BC and L stand for Breitung and Candelon (2006) test as well as Lemmens et al (2008) test in the first differences, respectively. BC* and L* are the aforementioned tests in the residuals. ¥ denotes that the independent variable Granger causes the dependent. ¥ denotes that the independent variable does not Granger cause the dependent. ** denotes causality in the short and medium run. * denotes causality in the long run.
Initially, unit root and stationarity testing was implemented to conclude that all the series of interest are first difference stationary processes. Then cointegration analysis consists of three alternative tests which uniformly show the existence of a long-run equilibrium. The next step of the analysis is linear causality testing. The conventional Granger causality as well as the Toda-Yamamoto test, both were employed to reveal linear linkages. The methodological approach proceeds with the implementation of the Breitung and Candelon (2006) test and the Lemmens et al. (2008) test in the first differences of the series as well as in the VECM residuals. The results of the aforementioned causality tests, linear and non-linear, are not in a consensus.

Table 12 summarizes the results of all causality tests implemented in this study. The derived conclusions from the linear methodological framework suggest a unidirectional relationship. More precisely, each financial stock price index Granger causes OVX but the reverse direction is not confirmed. The results of the frequency domain causality tests are mixed. The implementation of Breitung and Candelon (2006) test in the first differences indicates that all the implemented global stock price indexes Granger cause crude oil volatility index mainly in the short and medium-run, while at the same time OVX does Granger cause global stock prices indices in the long-run (exception are BBC and GDOW). The implementation of the Lemmens et al. (2008) test, reveals bidirectional causality for all examined groups of series. Lastly, when both tests are employed in the VECM residuals, the null hypothesis of no causality is not rejected in every case.

To sum up, the implemented econometric analysis provides mixed results regarding the interaction between crude oil volatility and global stock markets for the relatively recent period 2007-2013. Thus, the identification of the causal relationship in different frequencies provides a better understanding and it can be regarded of a paramount importance for financial hedgers, policy makers or market participants.
6. References


