The Predictive Power of Oil and Commodity Prices for Equity Markets

Leila Dagher* **Ibrahim Jamali**** **Nasser Badra***

Abstract

Using a seven-variable Vector Autoregressive (VAR) model and a rolling window approach, this paper investigates causality between oil price changes and the aggregate stock market returns of France, Italy, Saudi Arabia and the United Arab Emirates. We provide strong empirical evidence that oil price changes cause aggregate stock returns for the two oil-exporting Arab countries starting in 2014. Since the post-2014 period is one of declining oil prices, our findings may suggest that causality depends on the prevailing oil price regime. Our findings also suggest that copper price changes are, to a lesser extent, useful predictors of the equity returns of Saudi Arabia and the United Arab Emirates.

Keywords: Oil Prices; Energy Finance; Stock Returns; Commodity Prices; Gold; Copper; Silver; Baltic Dry Index; Causality; Rolling Window; Vector Autoregression.

JEL Codes: C32, C58, G15, Q43

* Associate Professor, Department of Economics and Director of Institute of Financial Economics, American University of Beirut, P.O. Box 11-0236, Riad El-Solh, Beirut 1107 2020, Lebanon. Tel: +961-3-308891, Fax: +961-1-744461, Email: ld08@aub.edu.lb

** Associate Professor, Department of Finance, Accounting and Managerial Economics, Olayan School of Business, American University of Beirut, Beirut 1107 2020, P.O. Box 11-0236, Riad El-Solh Street, Lebanon, Email: ij08@aub.edu.lb. Fax: +961-1-750 214. Tel: +961-1-340 460 (ext. 3770).

1. Introduction

Understanding the relation between equity markets and oil price movements is a subject of intense academic scrutiny. Starting with the seminal papers of Kling (1985) and Jones and Kaul (1996), a sizeable literature has explored the linkages between the stock and oil markets.[1] A relatively newer strand of the literature examines the predictive ability of oil market information to stock returns. For example, Liu *et al.* (2015) find that including oil market variables yields better stock market return forecasts.

The goal of this study is to examine the predictive ability of oil and commodity (metals) price changes for the equity markets of four countries using causality tests. With the possible financialization of commodity markets, commodity and oil price changes might possess predictive ability for stock returns.[2] One of our contributions is that we straddle three separate strands of the literature on the interlinkages between equity and oil prices, between equity and commodity prices, as well as the literature on the relation between equity markets and exchange rates.

We employ a multivariate vector autoregressive (VAR) model to undertake the analysis. This choice is motivated by the cautionary notes echoed in a number of studies regarding bivariate VAR models especially in the context of Granger causality testing.[3] In fact, existing

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[1] An excellent review of the literature on interaction between oil price movements and stock returns is provided in Degiannakis, Filis and Arora (2017). In general, studies that examine the interdependence between oil and stock price movements employ multivariate time series models (Hammoudeh and Choi, 2006; Sadorsky, 1999 among others) while those examining the volatility transmission between equity and oil markets use multivariate generalized autoregressive conditional heteroskedasticity models (Arouri *et al.*, 2011; Guesmi and Fattoum, 2014 among others).

[2] The 'financialization debate' garnered significantly more academic attention following the testimony of Masters (2008) before Congress, in which he attributes the increase in commodity prices to the participation of long-only commodity index traders in commodity investing. Academics have largely been skeptical of the financialization view. For an excellent review of the literature, see Fattouh *et al.* (2013).

[3] For instance, Tang and Yao (2017) consider bivariate Granger causality studies as 'incomplete systems' due to the omission of important variables, while Phylaktis and Ravazzolo (2015) caution against the use of bivariate VARs to test for Granger causality. Our decision to employ a seven variable VAR stems, in part, from being mindful of the prior cautionary notes regarding bivariate studies.

research (Caporale and Pittis, 1997; Lütkepohl, 1983; Lütkepohl, 2006) demonstrates that the omission of an important variable may lead to invalid inferences about causality in a bivariate system.

Our VAR model comprises seven variables which are: market returns, Brent oil price changes, gold price changes, copper price changes, silver price changes, exchange rate changes and changes in the Baltic Dry Index. We conduct causality tests using a rolling window approach for two main reasons: (i) Causality may be time-varying and studies that treat the whole sample as one fixed period will not detect such time variation, and (ii) traditional causality tests are not valid in the presence of structural breaks within a sample period.[4] The analysis is conducted for France, Italy, Kingdom of Saudi Arabia, and the United Arab Emirates which are, respectively, two oil importers and exporters.

Our paper differs from existing studies by assessing the predictive power of oil price movements while accounting for the changes in the prices of other important commodities as well as changes in the exchange rate. As a by-product of our analysis, the predictive power of the exchange rate, copper, gold and silver price changes for equity returns can also be assessed.

We complement existing work (Broadstock and Filis, 2014; Kang and Ratti, 2013; Cuando and de Garcia, 2014) by providing evidence that oil and, to a lesser extent, copper price changes are useful predictors of the stock returns of the two oil exporters in the post-2014 period. The strong predictive ability of oil price changes in the post-2014 period is possibly related to the declining oil price regime prevailing over that period. Contrary to the latter contributions, we do not disentangle oil supply and demand shocks using the methodology of Kilian (2009) and Kilian and Park (2009) given that our primary concern is to examine the predictive ability of the oil price changes for equity returns at high frequencies. Our study also differs from the prior

[4] The rolling window approach is used by a number of studies. See, for example, Swanson (1998).

contributions by focusing squarely on two oil-importing and two oil-exporting countries to assess oil price changes' predictive ability for the equity markets of oil exporters and importers.

Our findings also suggest that copper price changes are, to a lesser extent, useful predictors of equity returns for Saudi Arabia and the United Arab Emirates. We argue that our results are of interest to local authorities in the studied countries but even more so to national and international investors, forecasters, and portfolio managers. For forecasters, our findings may imply that the use of oil price changes is essential when predicting the equity returns of oil exporters after 2014. Because oil (and copper) price changes are not ubiquitous predictors of the equity returns of the four countries, we view our findings as not consistent with the financialization view but rather indicative of oil's importance for the economies of the two oil exporters. Indeed, the financialization of commodity markets would suggest an important predictive role for oil in predicting equity returns for the four countries.

The rest of the paper proceeds as follows. Section 2 provides a review of the related literature. Section 3 discusses the data and variables used in our empirical analysis while Section 4 outlines our econometric methodology and tests. The empirical results are provided and discussed in Section 5 while section 6 offers some concluding remarks.

2. Literature Review

Under market efficiency, prices quickly impound all the available information. That is, in an efficient market, stock prices cannot be predicted using variables that are in investors' information set at time *t*. Conversely, evidence that a variable that is part of the information set at time *t* has predictive ability for stock returns implies either that markets are inefficient or that there is a time-varying risk premium. As noted earlier, causality tests are tests of predictive ability. Therefore, finding that a variable causes stock returns indicates inefficiency or the existence of a time-varying risk premium.

The consensus emerging from existing studies which examine Granger causality from oil price changes to stock returns is somewhat mixed. Using monthly data for the period 1973-1982, Kling (1985) finds causality running from the S&P500 to crude oil prices, but not in the opposite direction. In contrast to those findings, Jones and Kaul (1996) provide empirical evidence that oil price changes Granger-cause aggregate real stock returns in the United States, Japan, and Canada but not the United Kingdom. Using daily data for the period October 9, 1979 to March 16, 1990, Huang *et al.* (1996) do not detect causality running in any direction between crude oil prices and the S&P 500 index. However, they find evidence of Granger causality running from oil futures price changes to the returns of individual oil companies.

Another strand of literature that investigates causality between foreign exchange rates and stock market returns has also reached somewhat inconclusive results. Bahmani-Oskooee and Sohrabian (1992) find bidirectional causality between stock prices measured by the S&P 500 index and the effective exchange rate of the dollar for the period July 1973 to December 1988, while Ajayi *et al.* (1998) find unidirectional causality from stock returns to exchange rates for six developed countries (Canada, Germany, France, Italy, Japan, UK, and USA) using daily data April 1985 to August 1991. Using monthly data for the period 1993 to 1998, Hatemi and Irandoust's (2002) findings for Sweden agree with those of Ajayi *et al.* (1998) but the authors do not detect consistent causal relations between these two markets in the case of emerging economies. Smyth and Nandha (2003) find unidirectional causality that runs from exchange rates to stock prices for India and Sri Lanka but do not detect causality in either direction for Bangladesh and Pakistan.

Very few papers have combined the former two strands of the literature and even fewer have explored the predictive power of commodity prices for equity returns, after evidence of a higher correlation between equities and commodities emerged from the 'financialization' literature. Among these, is the paper by Basher *et al.* (2012), which investigates very thoroughly the relationship between oil prices, exchange rates, and stock prices using a structural VAR, impulse response analysis and variance decompositions. However, Basher *et al.*'s (2012) study does not include the price of non-energy commodities and the authors do not conduct any causality testing. Another paper by Choi and Hammoudeh (2010) uses a GARCH model to analyze volatility spillovers between WTI oil prices, Brent oil prices, gold, silver and copper prices as well as the US S&P 500 index. The authors estimate dynamic conditional correlation models with weekly data over the period January 2, 1990 to May 1, 2006 and their results point to increasing correlations among all the commodities since the 2003 Iraq war. They also find that the correlation between commodities and equities is decreasing over the same period. Choi and Hammoudeh (2010) do not, however, conduct any causality testing.

Even though it is widely known that causality results are sensitive to the sample period being studied, only a few attempts at investigating time-varying relationships in the causality between equity returns and commodities price or exchange rate changes have been made. In order to account for time-varying causality, one can split the sample into multiple sub-samples. However, this requires a priori knowledge of the dates at which the causality relationship changes, which could be difficult to obtain. An example is Tsai (2015) who divides his sample into pre-, post- and during a financial crisis, while another example is El Charif *et al.* (2005) who divide their sample into six periods. Umer *et al.* (2015) divide their sample into two periods, the tranquil and the crisis periods, and find the results to be divergent across the two subsamples.

Using a rolling window approach allows researchers to examine all possible subsamples and to avoid ad-hoc sample splitting. The rolling window approach may also shed light on the reasons underlying the divergence in the results reported in the literature. Time-varying causality tests using a fixed size rolling window have already been used by researchers to examine the output and economic growth relation in the US (Inglesi-Lotz *et al.*, 2014), money and real output (Swanson, 1998), money stock and disposable income (Hill, 2007), money and aggregate prices (Tang, 2010), economic growth and energy consumption (Balcilar *et al.*, 2010), economic growth and electricity consumption (Dlamini *et al.*, 2015), export and GDP (Balcilar and Ozdemir, 2013), house price index and GDP (Nyakabawo *et al.*, 2015), tourism receipts and GDP (Arslanturk *et al.*, 2011) and stock market returns of different markets (Smith *et al.*, 1993).

A single study in the literature we are interested in uses the rolling window approach. Smiech and Papiez (2013) use a three-year rolling window with weekly data to investigate the dynamics of causality between each pair of the following variables: oil prices, coal prices, German stock market index, and the exchange rate USD/EUR. However, the study is only concerned with the German stock market and the authors' modeling strategy differs significantly from ours.

3. Data and Variables

We collect data on the nearest Brent crude oil (OIL), gold (GLD), silver (SIL), and copper (CPR) futures, denominated in US Dollar (USD), from Datastream. Our data span the period May 31, 2005 to April 27, 2018 for a total of 3369 observations. We construct a continuous futures price series by rolling over from the nearest (or front) to the next-to-nearest (or second) contract on the first day of the expiration month.[5] Following existing studies (Fama and French, 1987; Gospodinov and Ng, 2013), we employ the nearest futures prices as a proxy for the spot (or cash) prices. The prior studies argue that the spot prices in commodity markets are not accurate and opt for using the nearest futures price instead of the spot price. Recent contributions to the literature (Baumeister and Kilian, 2017; Kilian, 2016) also indicate that, following the U.S. shale oil revolution, the price of Brent oil is a better proxy of the global price

[5] Existing studies commonly employ this rollover strategy. See, for example, Bessembinder (1992), de Roon *et al.* (2000), and Gorton and Rouwenhorst (2006).

of oil. Therefore, we employ Brent prices as the main proxy for the price of oil in our empirical analysis.

Our cross-section of countries comprises two oil exporting countries, the Kingdom of Saudi Arabia (KSA) and the United Arab Emirates as well as two oil importing countries which are France and Italy. The UAE and KSA have pegged exchange rates while the exchange rates of France and Italy are floating. We obtain data on the exchange rate (XR), expressed in units of the foreign currency per USD, for each of the countries included in our sample. The investible MSCI index, expressed in USD, is used as a measure of aggregate equity prices for each of the countries. Data on the MSCI index as well as the exchange rate for each of the countries are obtained from Datastream.

We control for global economic activity using the Baltic Dry Index (BDI).[6] The BDI, which is constructed and disseminated by the Baltic Dry Exchange, measures the cost of shipping major raw materials by sea (Dbouk and Jamali, 2018; Schinas *et al.* 2015). The use of the BDI as a measure of global economic activity stems from the insight, articulated in detail by Kilian (2009), that economic activity is possibly the most important determinant of transport services (Klovland, 2004). Kilian (2009) provides compelling arguments that an increase in freight rates is an indicator of strong cumulative global demand pressures.[7] The BDI, and freight rates in general, have also been widely used by practitioners to assess the degree of global demand pressures (Kilian, 2009). Bakshi *et al.* (2011) provide empirical evidence of the predictive ability of the BDI for global economic activity as well as for equity and commodity returns.

[6] Not controlling for global economic activity may lead to omitted variable bias. Lütkepohl (2005) demonstrates that the omission of an important variable leads to invalid inferences about the causality structure in a bivariate system.

[7] In fact, Kilian (2009) constructs a monthly measure of global economic activity whose underlying nominal data are identical to those used in constructing the BDI (Alquist *et al.*, 2013). Given that we require a daily measure of global economic activity, we cannot employ Kilian’s (2009) index and we rely instead on the BDI, which is available daily.

We test for a unit root in the levels of each of the series using the Augmented Dickey-Fuller (ADF) (1979), Phillips and Perron (PP) (1988) and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) (1992) test. The null hypothesis for the ADF and PP tests is that the series contains a unit root. The KPSS test, whose null is that the series is (trend-) stationary, is employed for confirmatory analysis. The ADF test is known to exhibit low power when the alternative is near unit root behavior (Elliot *et al.*, 1996). Therefore, we also employ the ADF test with GLS detrending of Elliot *et al.* (1996). The existing literature shows that the ADF-GLS test has good power properties against near unit root behavior.

[Insert Table 1 here]

The results, presented in Table 1, show that the null of a unit root in the level of each of the series cannot be rejected. Based on the unit root test results, we proceed with testing for a cointegrating relationship among the variables using the Johansen (1988) approach.[8] The trace and maximum eigenvalue tests both suggest the absence of cointegrating relationships between the variables and our results are consistent with those of Granger *et al.* (2000), Nieh and Lee (2001), Yang and Doong (2004), Aloui (2007), and Le and Chang (2015).

Based on the discussion above, our empirical analysis is conducted with log changes in the variables. Using log changes in the variables is also consistent with our goal of examining the *short-run* predictive power of crude oil price changes and other variables for stock returns using causality tests. In fact, log changes in the MSCI index and exchange rates are continuously compounded returns and several studies (Bessembinder, 1992; de Roon *et al*., 2000; Gorton and Rouwenhorst, 2006) refer to log changes in the nearest futures prices for oil, gold and copper as the returns on the futures contract.[9]

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[8] The results are available from the authors upon request.

[9] Some studies refer to changes in the nearest futures price simply as price changes. We prefer the former terminology when using commodity futures prices. However, we henceforth use the terms ‘price changes’ and ‘returns’ interchangeably.

The time series dynamics of the commodity and oil prices (in levels) are displayed in Figure 1. Figure 2 presents the time series dynamics of log changes in the prices of copper, gold, silver, oil and the Baltic Dry Index, while Figure 3 shows the continuously compounded returns on the investible MSCI index for KSA, UAE, France and Italy.

[Insert Figures 1, 2 and 3 here]

As can be seen in Figure 1, oil prices were on an upward trend over the period 2005 to 2008. The sharp increase in oil prices corresponded to a run-up in commodity prices during the same period. Oil prices exhibited a sharp decline since 2014 (that lasted until 2016). The time series dynamics in Figure 1 suggest the presence of different price regimes (especially in oil prices) which can potentially induce shifts in the dynamic relationships between the variables. To account for the possible presence of structural breaks or regime shifts, it is important to employ a rolling window approach when testing for causality.

Table 2 provides the descriptive statistics of the variables used in our empirical analysis.

[Insert Table 2 here]

The summary statistics show that the returns on the KSA, UAE and Italian MSCI investible indexes are, on average, negative while the return on the French MSCI is, on average, positive over our sample period. The average commodity price change for the four commodities is also positive over our sample period suggesting that investors who held a long position in one of the commodity futures contracts earned a positive risk premium over the sample period.[10] The descriptive statistics in Table 2 show very little persistence in the variables as evidenced by the low first-order autocorrelation coefficient. Commodity prices appear to be slightly more volatile than the equity index returns of the four countries that we consider, while exchange rate returns exhibit the lowest volatility. As widely documented in the literature, the equity index return distributions are leptokurtic as evidenced by a kurtosis coefficient that is much larger

[10] This positive risk premium induces investors to hold a long position in the futures contract.

than three. While gold and silver price changes appear to also have leptokurtic distributions, the other commodity price changes do not exhibit excess kurtosis.

The cross-correlations between the variables in levels, reported in Panel A of Table 3, show that that the highest correlation of 0.86 is between gold and silver prices. The cross-correlation between the variables in log changes are reported in Panel B of Table 3.

[Insert Table 3 here]

Similarly to the results with the levels of the variables, the largest cross-correlation in log changes of 0.81 is also between gold and silver.

4. Econometric Methodology

In an important contribution to the literature, Granger (1969) introduced a concept of causality which closely ties to the predictive power of one variable for another variable. Let y_{1t} and y_{2t} denote two time series.[11] The variable y_{2t} is said to Granger-cause y_{1t} when accounting for the information in y_{2t} lowers the Mean Square Prediction Error (MSPE) in y_{1t}.

More formally, let Ω_t denote the information set at time *t* and $y_{1,t+h,\Omega_t}$denote the optimal (i.e. lowest Mean Square Error) h-step prediction of y_{1t}. Let $\sigma^2_{y_1}(h/\Omega_t)$ denote the MSPE of the variable y_{1t}. Kilian and Lütkepohl (2017) note that the process y_{2t} is said to Granger-cause the process y_{1t} if:

$$\sigma^2_{y_1}(h/\Omega_t) < \sigma^2_{y_1}(h/\Omega_t\{y_{2s}|s \leq t\}),$$

where $\Omega_t\{y_{2s}|s \leq t\}$ denotes the information set excluding past and present information regarding the series y_{2t}. In other words, the process y_{2t} is said to Granger-cause the process y_{1t} if exploiting information on the past and contemporaneous values of y_{2t} lowers the prediction error of the process y_{1t} at some horizon h.

[11] Our exposition in this section follows Kilian and Lütkepohl (2017) and Lütkepohl (2006).

Tests of Granger causality are performed by placing restrictions on the coefficients of a Vector Autoregression (VAR). Denote by Y_t a vector of variables of interest. A VAR relates Y_t to p of its lags. A test of Granger causality amounts to zero restrictions on a subset of the coefficients of the VAR.

We follow the exposition in Lütkepohl and Kratzig (2004) to demonstrate testing for causality within the context of a trivariate VAR. A trivariate VAR(p) is given by:

$$\begin{bmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \alpha_{11,i} & \alpha_{12,i} & \alpha_{13,i} \\ \alpha_{21,i} & \alpha_{22,i} & \alpha_{23,i} \\ \alpha_{31,i} & \alpha_{32,i} & \alpha_{33,i} \end{bmatrix} \begin{bmatrix} y_{1,t-i} \\ y_{2,t-i} \\ y_{3,t-i} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{bmatrix}.$$

In the above VAR, $Y_t = (y_{1t} \quad y_{2t} \quad y_{3t})'$. As noted in Lütkepohl and Kratzig (2004), checking for causality of y_{2t} for y_{1t} by testing $H_0\colon \alpha_{12,i} = 0, i = 1, \ldots, p$ is equivalent to equality of the one-step forecasts $y_{1,t+1/\Omega_t} = y_{1,t+1/\Omega_t \backslash \{y_{2,s} | s \leq t\}}$. The latter restriction can be tested using a Wald (F-) test but is not strictly a test of Granger causality in the general sense first introduced in this section. If this restriction is rejected by the data then the variable y_{2t} causes y_{1t} in the sense that it possesses predictive power for the *one-step-ahead* forecast of y_{1t}.

In our empirical application, the horizon of interest is h = 1. We restrict the forecast horizon to one given that Dufour and Renault (1998) caution against using multivariate VAR models for testing for causality at multiple steps ahead. Our VAR contains seven variables and is given by $Y_t = \{\Delta Brent_t, \Delta MSCI_t, \Delta Gold_t, \Delta Silver_t, \Delta Copper_t, \Delta Exchange\ Rate_t, \Delta BDI\}'$. Despite the larger VAR model that we employ, testing for causality from Brent oil price changes to stock returns, for example, still amounts to testing zero restrictions on the lags of the oil price changes in the stock return equation of the VAR.

Having differenced the data, our sample consists of a total of 3368 observations. When testing for causality, we use a fixed rolling window of size 600, resulting in 2769 windows. That is, the first test of causality is conducted with a VAR estimated over the period June 1, 2005 to September 18, 2007. The window is then shifted by one observation and the next test of causality is conducted with a VAR estimated over the sample June 2, 2005 to September 19, 2007. The last causality test is performed using a VAR estimated over the period January 11, 2016 to April 27, 2018.

In every window, the lag length of the VAR is selected based on the Akaike Information Criterion (AIC) and the maximum lag length is selected using Schwert's (1989) criterion $p_{max} = 12 * (\frac{T}{100})^{0.25}$ where T is the window size.[12]

5. Results and Discussion

We start by estimating the VAR over the full sample for the four countries and testing for autocorrelation and heteroscedasticity in the residuals of the VAR. We also test for stability of the covariance matrix of the VAR. We employ the Hosking (1981) variant of the multivariate Q statistic to test for autocorrelation and test for the presence of conditional heteroscedasticity in the VAR's residuals using a multivariate test for Autoregressive Conditional Heteroskedasticity (ARCH). We assess the stability of the VAR's covariance matrix using the Nyblom (1989) test.

The results, reported in Panel A of Table 4, overwhelmingly reject the null hypotheses of no autocorrelation, homoscedasticity and covariance matrix stability.

[Insert Table 4 here]

In view of the evidence of autocorrelation and conditional heteroscedasticity in the VAR's residuals, we employ the Heteroscedasticity and Autocorrelation Consistent (HAC) standard errors of Newey and West (1987) for inference. The Nyblom (1989) stability test provides preliminary evidence of instability in the VARs. We proceed to a more thorough assessment of the stability of the VAR parameters. To test for parameter stability, we apply the Chow (1960) breakpoint test and the Quandt-Andrews (Quandt, 1960; Andrews, 1993) tests to the VAR

[12] In our case, T = 600 which implies that the maximum lag length is 19.

equation with stock returns as a dependent variable. The Chow test rejects the null of stability for multiple dates while the Quandt-Andrews breakpoint test, whose results are reported in Panel B of Table 4, detects the date associated with the highest likelihood of having a break. In addition to the latter tests, we employ the CUSUM of squares, reported in Figure 4, to test for instability. The CUSUM of squares test relies on the cumulative sum of the squared residuals to detect structural instability in the VAR's equation with stock returns as a dependent variable.

[Insert Figure 4 here]

Figure 4 clearly shows evidence of instability given that the CUSUM of squares test statistic lies outside of the 95% confidence interval. Overall, we find compelling evidence of structural breaks as well as parameter and covariance matrix instability which justifies the use of a rolling window estimation scheme. In fact, Rossi (2013) emphasizes the fact that causality tests are inconsistent in the presence of instabilities. Therefore, the use of a rolling window estimation scheme that accounts for instabilities is critical.

The results of the rolling window causality tests are displayed in Figures 5 to 10 while the results of the bi-directional causality tests are provided in Table 5. When interpreting the results, we combine information from the table and from the graphs. The numbers presented in Table 5 represent the number of windows out of a total of 2769 rolling windows in which a variable is found to cause the other. The *p*-value of the causality test as well as a horizontal line indicating the 5% level of significance are displayed in each of the figures. We view the information from the graphs and Table 5 as complementary and essential in interpreting the results.

[Insert Figures 5 to 10 here]

[Insert Table 5]

We begin by examining bidirectional causality from exchange rate returns to stock returns. Figure 5 shows no causality running from exchange rate changes to stock returns. However, Panel B of Table 3 provides evidence of causality running from stock returns to the exchange rate for France and Italy. Our results regarding the direction of causality are consistent with those of Ajayi *et al.* (1998) and Aloui (2007) who find unidirectional causality from stock to exchange rate returns for both France and Italy using daily data from 1985 to 1991 and from 1990 to 2005, respectively. One might conclude that the stock market has maintained its predictive ability for exchange rates that was present since the 1980s in the case of France and Italy.

We turn next to examining the causality between gold price changes and stock returns. Our results also show that there is sparse evidence of gold price changes causing stock returns for KSA, and similarly scant evidence of UAE and KSA stock market returns causing gold price changes. These results are consistent with those of Al Janabi *et al.* (2010) who do not find any significant causality between gold and stock returns in KSA and UAE for the period 2006 to 2008. Miyazaki and Hamori (2013) find a unidirectional causality from stock returns to gold prices for the US during the period 2000 to 2011.

The results in Figure 7 and Table 5 provide very weak evidence of silver price changes causing the stock index returns for KSA and UAE. Furthermore, there is no evidence of stock returns causing silver price changes.

These results are in line with our *ex ante* expectations. In fact, existing studies (Baur and Lucey, 2010; Baur and McDermott, 2010; Ciner *et al.*, 2013; Lucey and Li, 2015) provide empirical evidence that the precious metals, and in particular gold and silver, act as safe havens and hedges to equity markets. As such, it is unlikely for the precious metals' price changes to cause equity returns.

Figure 8 and Table 5 show that copper price changes cause the returns on the KSA and UAE returns but not the equity returns of Italy and France. With the exception of meager evidence for the UAE, we also find that stock returns do not cause copper price changes. These results have an intuitive explanation. Former Federal Reserve Chairman Bernanke (2016) notes that the price of industrial metals commodities act as a gauge of global economic activity and reflect investors' perceptions of global demand. Other important contributions (Pindyck and Rotemberg, 1990; Labys *et al.*, 1999; Lombardi *et al.*, 2012) also document a relation between global economic activity and metals prices.[13] Starting from the premise that copper prices are high-frequency indicators of global economic activity, our results which indicate that causality runs from copper prices to the returns on the UAE and KSA market highlights the latter two equity markets' sensitivity to global economic conditions. To our knowledge, no existing study has examined the causality between copper price changes and stock returns.

We turn next to assessing the predictive ability of the BDI. Figure 10 suggests that changes in the BDI cause the returns on the KSA market for a short period in 2011 and 2012. Changes in the BDI do not appear to cause the returns on the equity indexes of any of the other countries that we consider. This latter finding might be attributable to copper prices embedding similar information the BDI as a gauge of global economic activity. The returns on the four equity markets appear to cause the changes in the BDI, but the evidence is rather sparse.

Our strongest causality results are obtained when we examine the relation between oil price changes and stock returns. In fact, Figure 9 shows that oil price changes cause UAE and KSA's stock returns for extended periods of time and France's equity returns to a lesser extent. Panel A of Table 5 clearly shows that the most frequent occurrences of causality in our sample pertain to oil price changes causing stock returns. In contrast, Panel B of Table 3 shows no causality running from equity returns to oil price changes. Notably, the evidence in favor of causality running from oil price changes to equity returns coincides with a period of declining oil prices. While there could be other contributing factors, our findings show hardly any causality during

[13] Caldara *et al.* (2016) provide a lengthier discussion of the literature on the role of metals prices as indicators of global economic activity. The financial press also views copper prices as a leading indicator of global economic activity. See, for example, The Economist article: https://www.economist.com/blogs/buttonwood/2014/03/commodities-and-economy

the period when oil prices are on an increasing trend, while the causality is significant when the trend reverses. From the results, we can conclude that evidence of oil price changes causing equity returns is more pronounced and persistent for the oil-exporting countries relative to the oil-importing countries.

As a robustness check for our results, we examine the sensitivity to: (i) employing the West Texas Intermediate WTI prices instead of Brent prices, (ii) the length of the fixed window by experimenting with two alternative window sizes (300 and 900) and (iii) replacing the investible MSCI index with each country's main stock index. All robustness checks yield very similar results (available from the authors upon request).

6. Concluding Remarks

The aim of this paper is to investigate causality between oil price changes, commodity (metals) price changes, exchange rates, and equity returns. We examine causality within the framework of a multivariate VAR model that includes stock market returns, Brent oil price changes, gold price changes, copper price changes, silver price changes and exchange rate returns and control for global economic activity using the Baltic Dry Index. The empirical analysis is carried out at the daily frequency for Saudi Arabia, the United Arab Emirates, Italy and France which are, respectively, two oil-exporting and oil-importing countries.

Due to the expected time-varying nature of causality as well as evidence of parameter and covariance matrix instability, we employ a rolling window methodology for the period June 1, 2005 to April 27, 2018. Fortunately, this sample period includes all possible oil price trends (rising, declining, and stable).

We provide strong empirical evidence that oil price changes cause equity returns for Saudi Arabia and United Arab Emirates since 2014. Given that the post-2014 period is one of declining oil prices, our findings may suggest that causality depends on the prevailing oil price regime. Our findings also suggest that copper price changes are, to a lesser extent, useful predictors of the equity returns of Saudi Arabia and the United Arab Emirates.

Because oil (and copper) price changes are not pervasive predictors of the equity returns of the four countries, we view our findings as not consistent with the financialization view but rather indicative of oil's importance for the economies of the two oil exporters.

Acknowledgments

The authors would like to thank the participants in the 2nd International Conference of the Hellenic Association for Energy Economics, the WEAI 14th International Conference, seminar participants in UC Dublin as well as in the 2018 International Conference on Energy Finance in Beijing, China for numerous insightful comments and suggestions. We gratefully acknowledge support in funding conference travel from the Institute of Financial Economics at the American University of Beirut and from the American University of Beirut's University Research Board. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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FIGURE 1

Time series dynamics of oil, silver, copper and gold prices as well as the Baltic Dry Index. The sample period is May 31, 2005 to April 27, 2018.

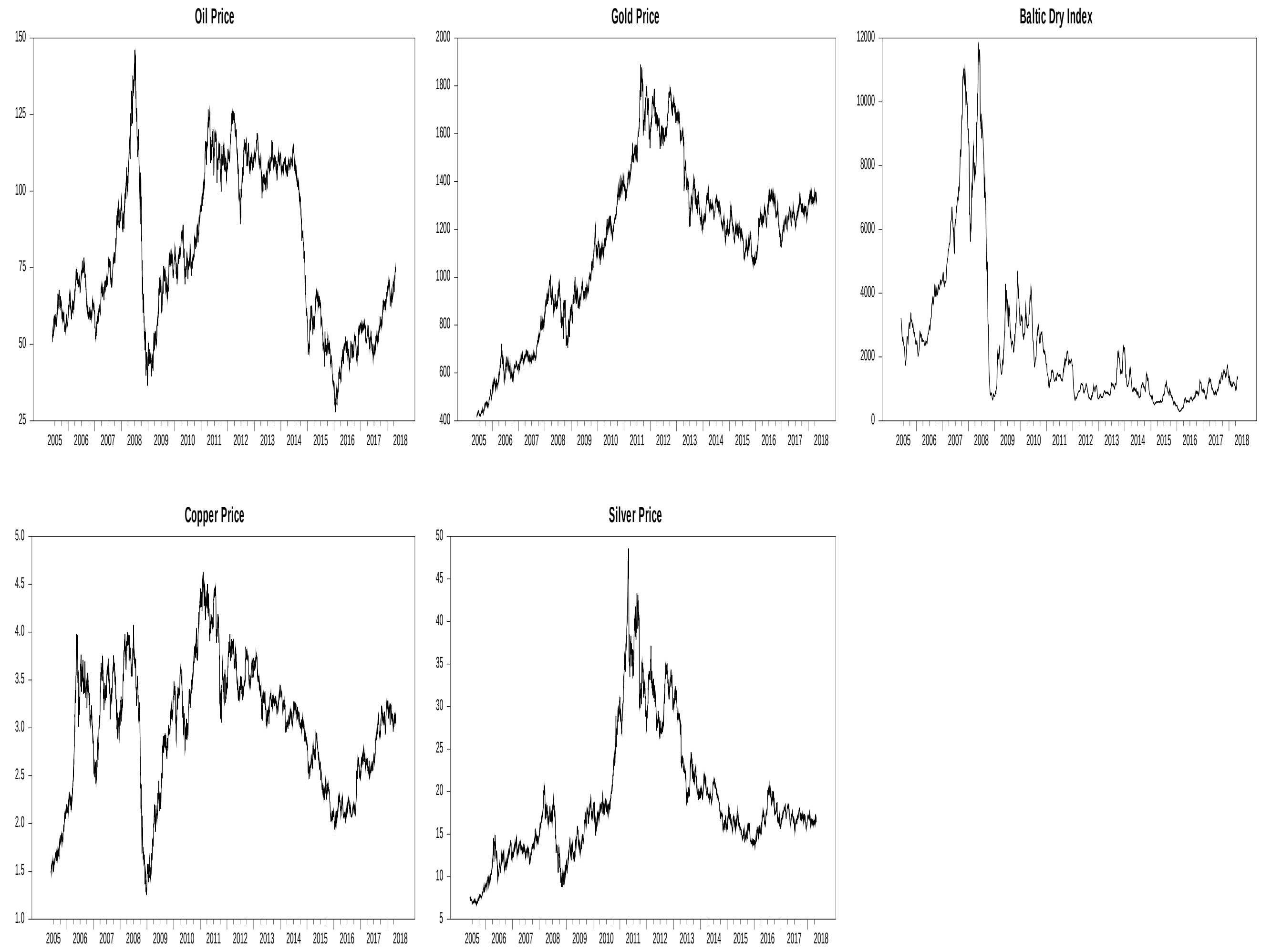


FIGURE 2

Time series dynamics of the changes in oil, silver, gold and copper prices as well as the Baltic Dry Index. The sample period is June 1, 2005 to April 27, 2018.

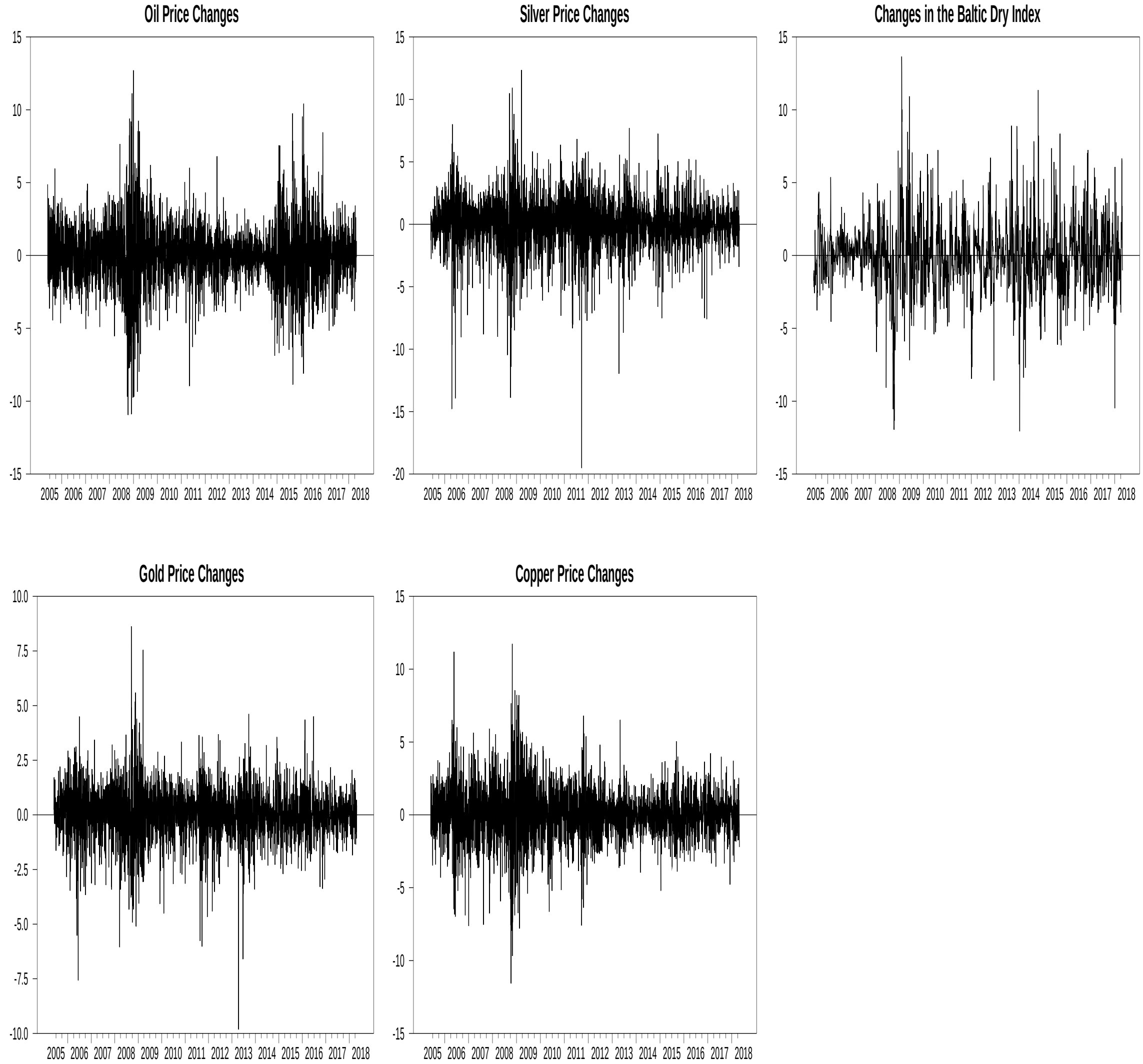


FIGURE 3

Time series dynamics of the MSCI returns for Saudi Arabia (KSA), United Arab Emirates (UAE), France and Italy. The sample period is June 1, 2005 to April 27, 2018.

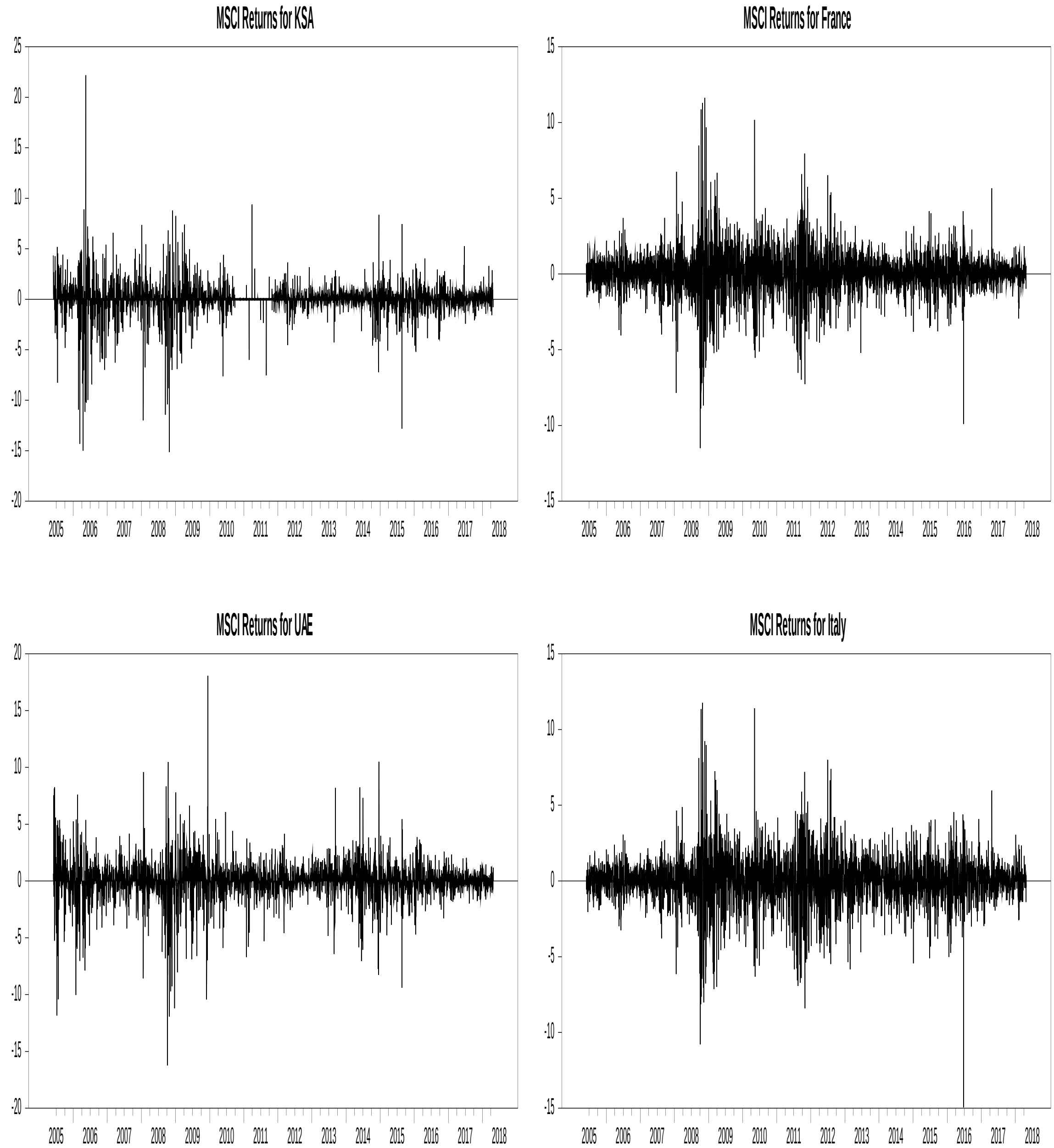


FIGURE 4

CUSUM of squares plots for the regressions where the stock market returns is the dependent variable.

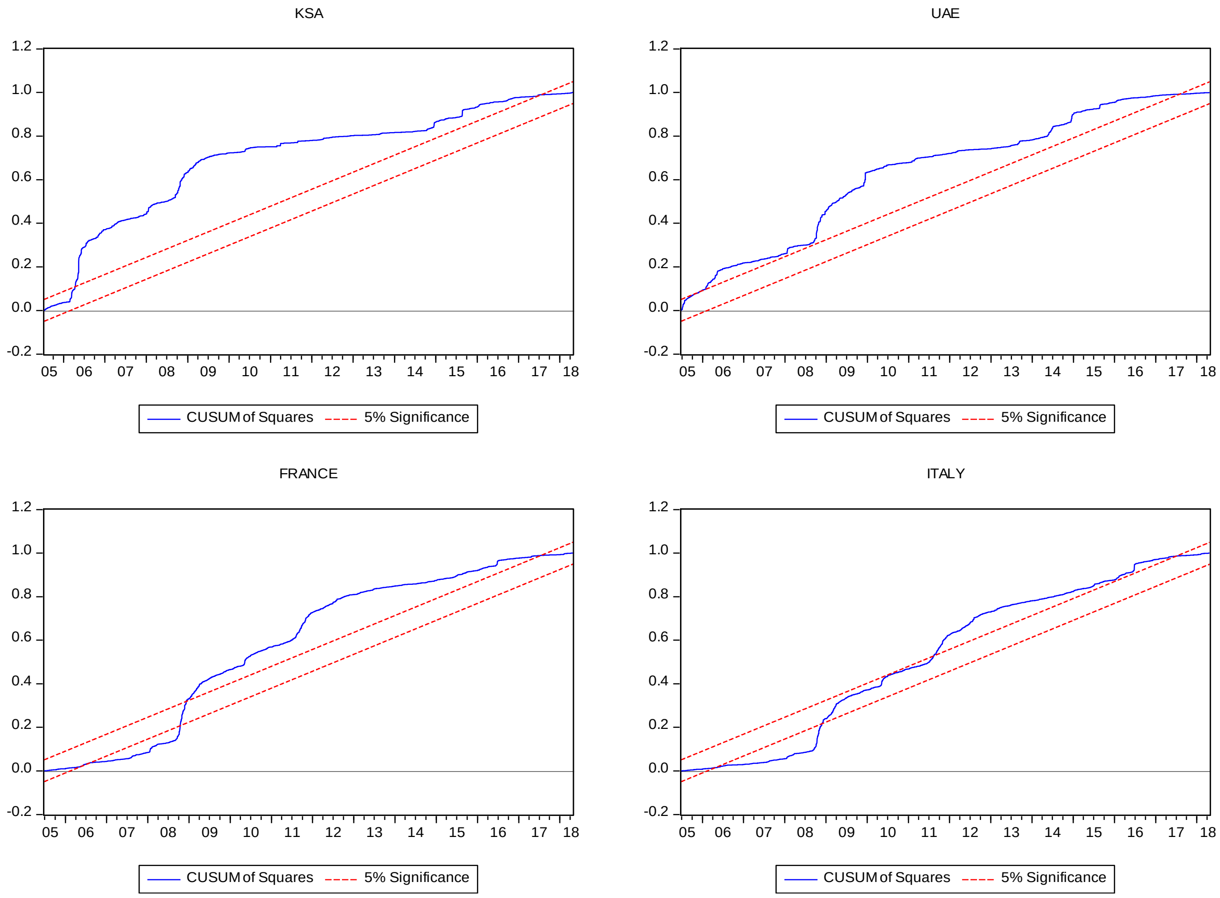
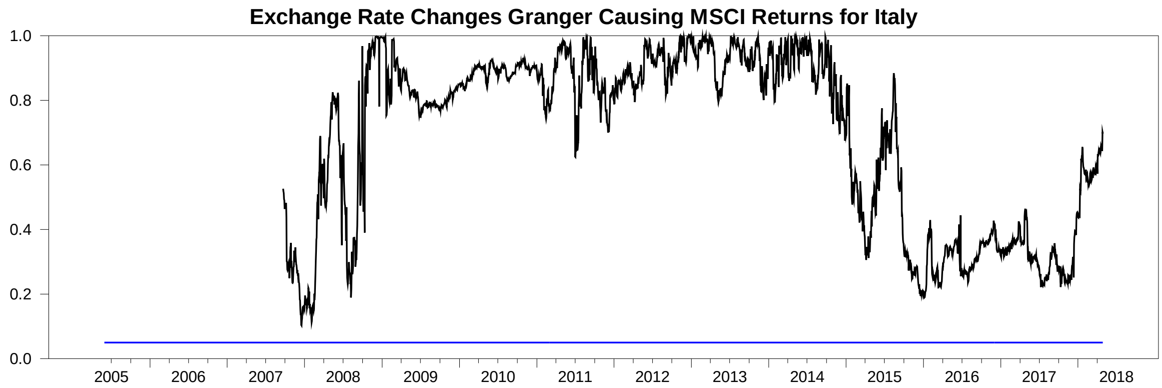


FIGURE 5

P-values of causality tests from exchange rate changes to stock returns. The null is one of no causality and the blue line indicates the 5% level of significance.



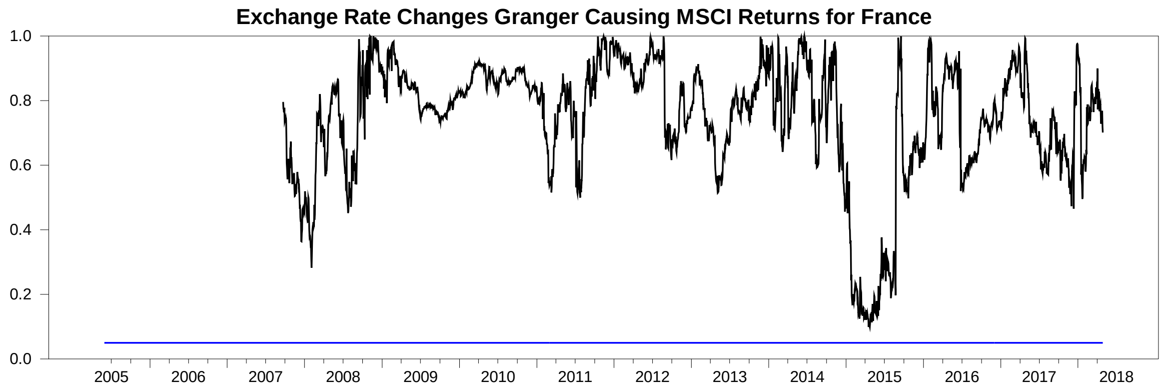


FIGURE 6

P-values of causality tests from gold price changes to stock returns. The null is one of no causality and the blue line indicate the 5% level of significance.

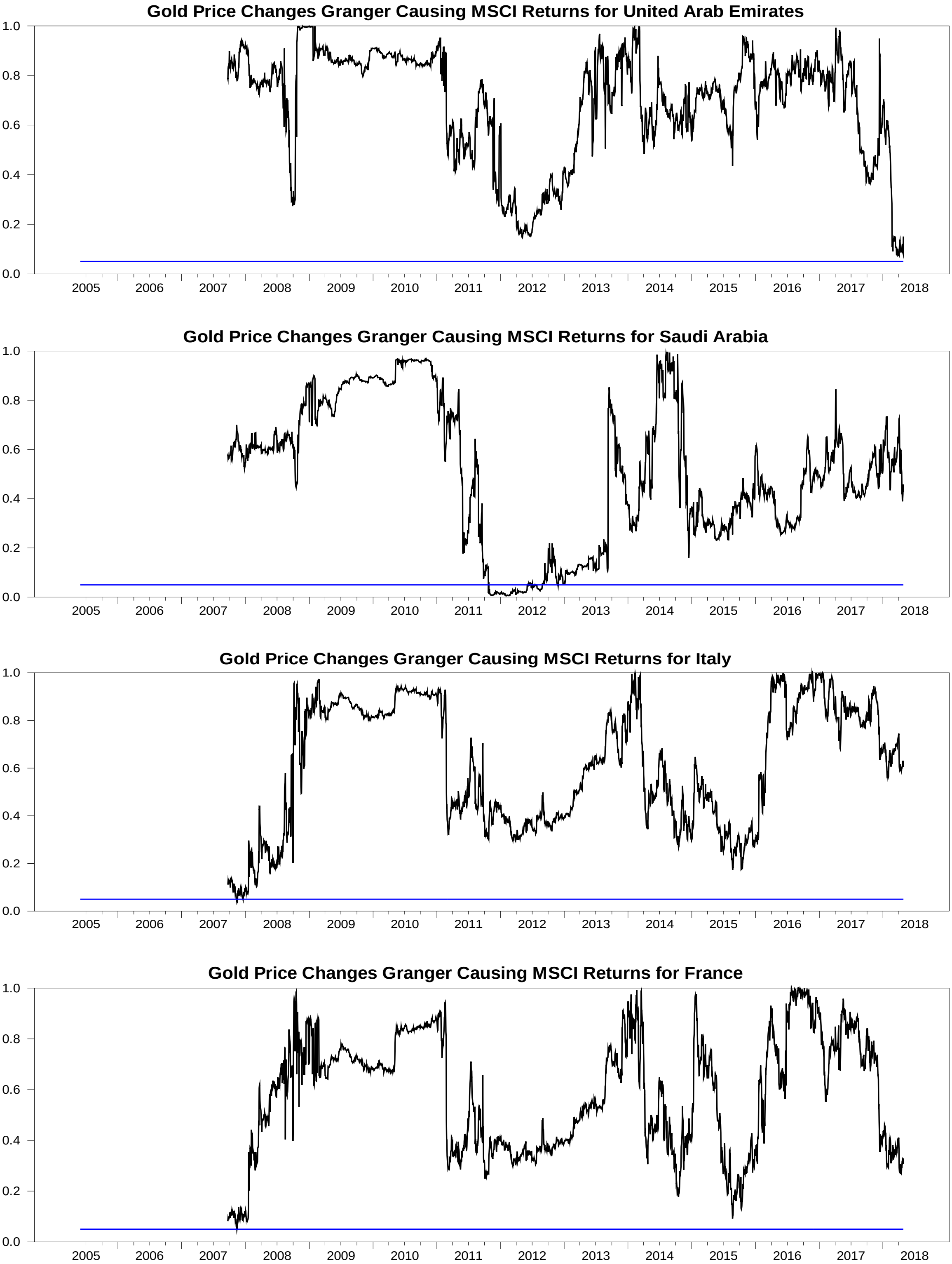


FIGURE 7

P-values of causality tests from silver price changes to stock returns. The null is one of no causality and the blue line indicate the 5% level of significance.

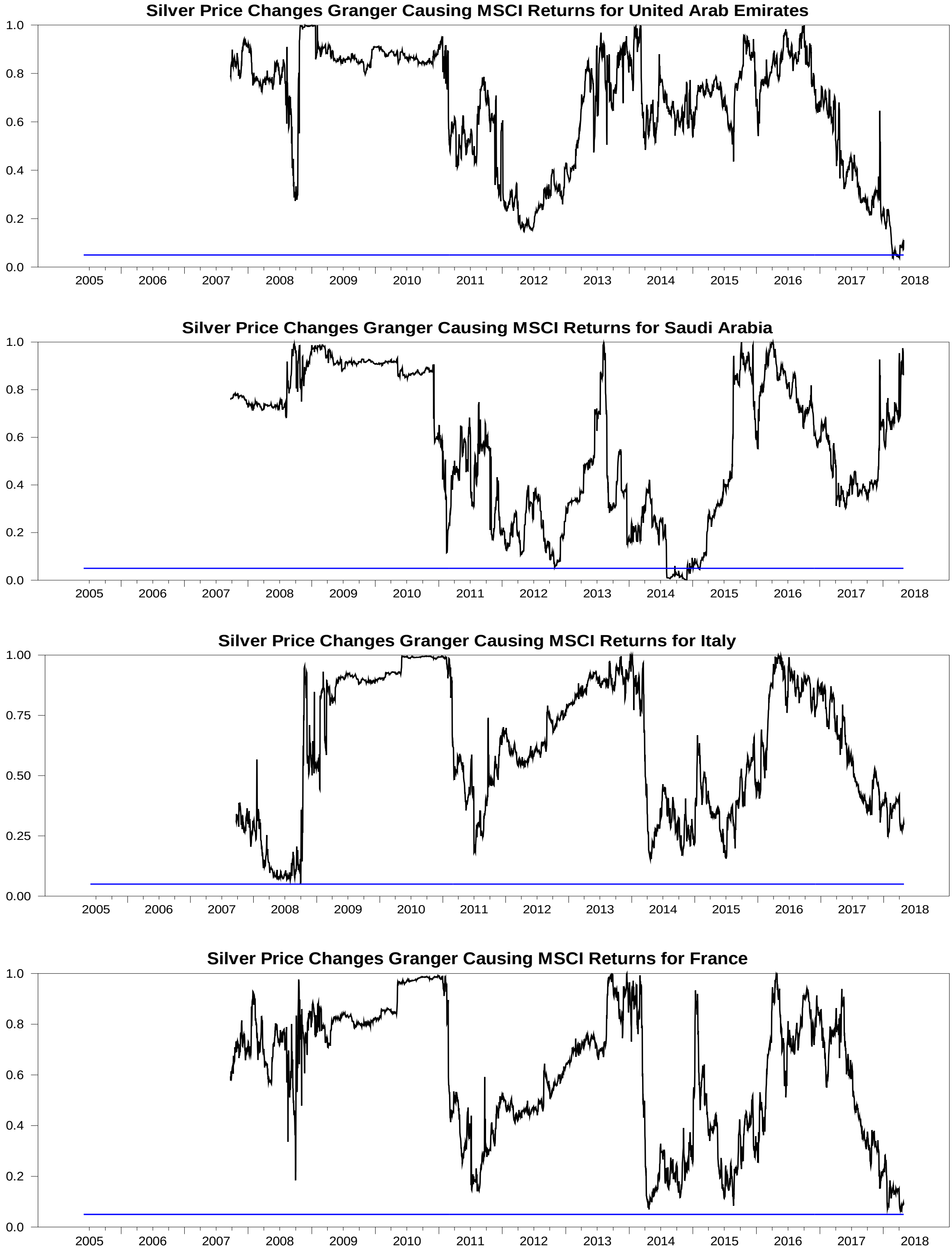


FIGURE 8

P-values of causality tests from copper price changes to stock returns. The null is one of no causality and the blue line indicate the 5% level of significance.

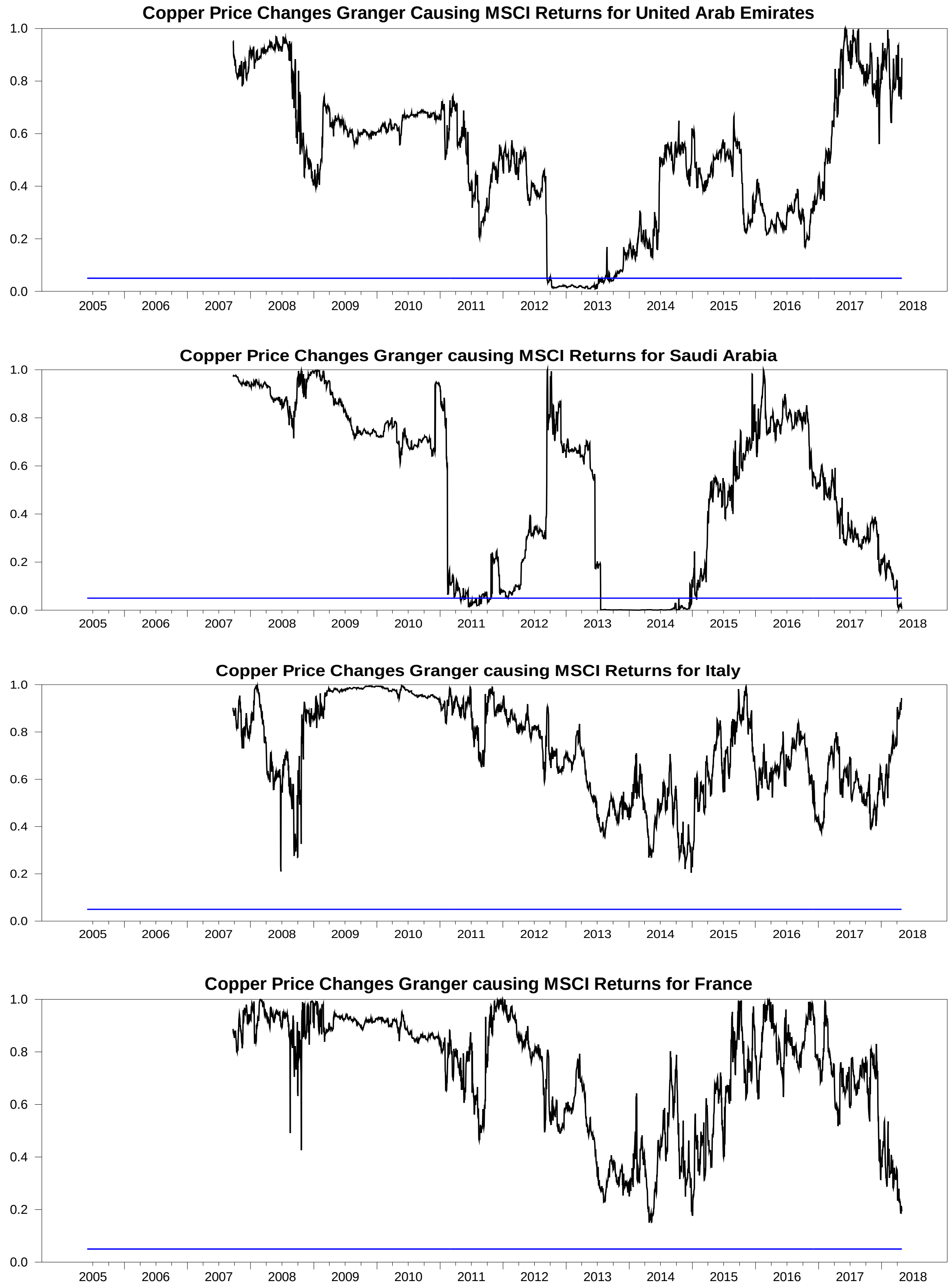


FIGURE 9

P-values of causality tests from oil price changes to stock returns. The null is one of no causality and the blue line indicate the 5% level of significance.

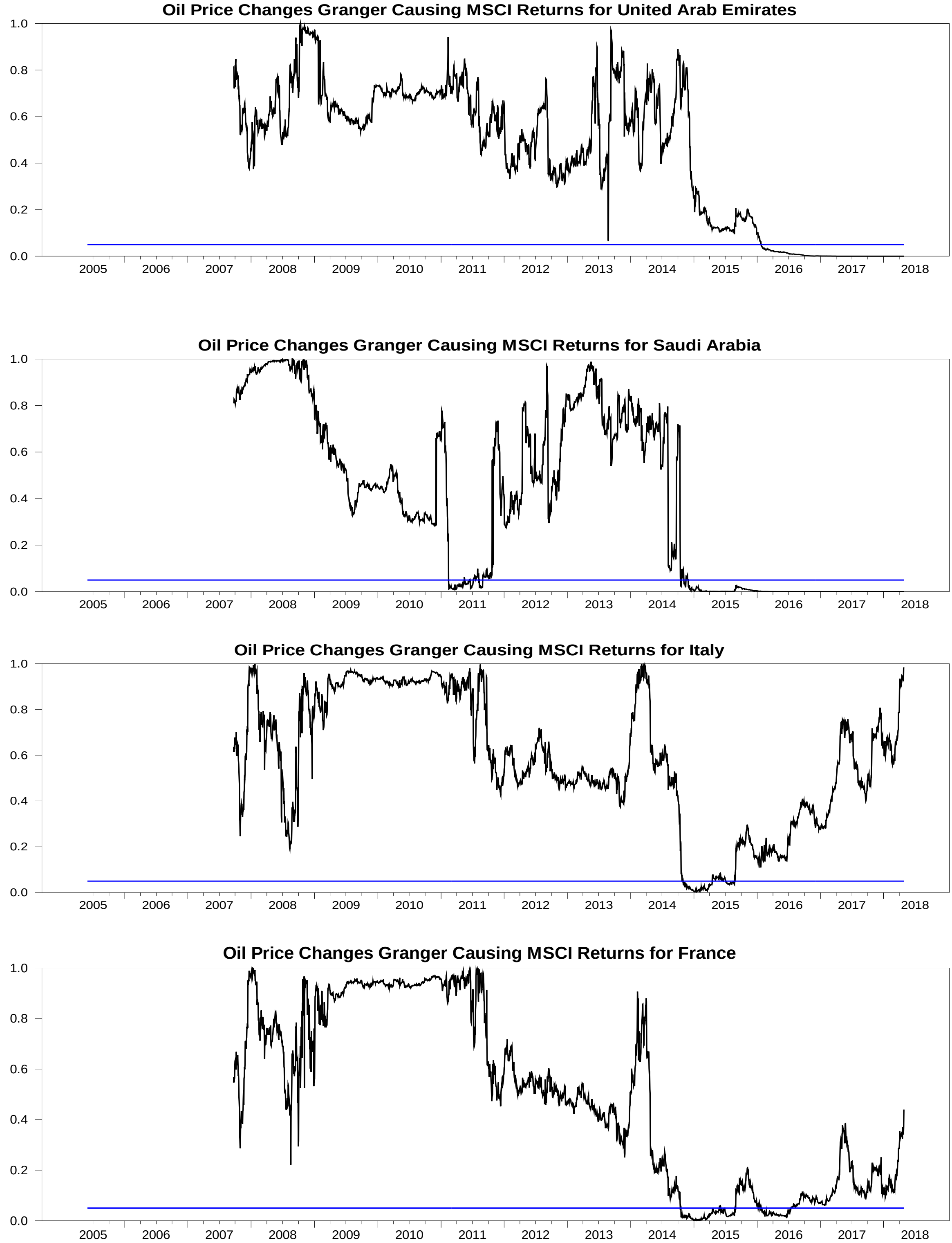


FIGURE 10

P-values of causality tests from changes in the Baltic Dry Index to stock returns. The null is one of no causality and the blue line indicate the 5% level of significance.

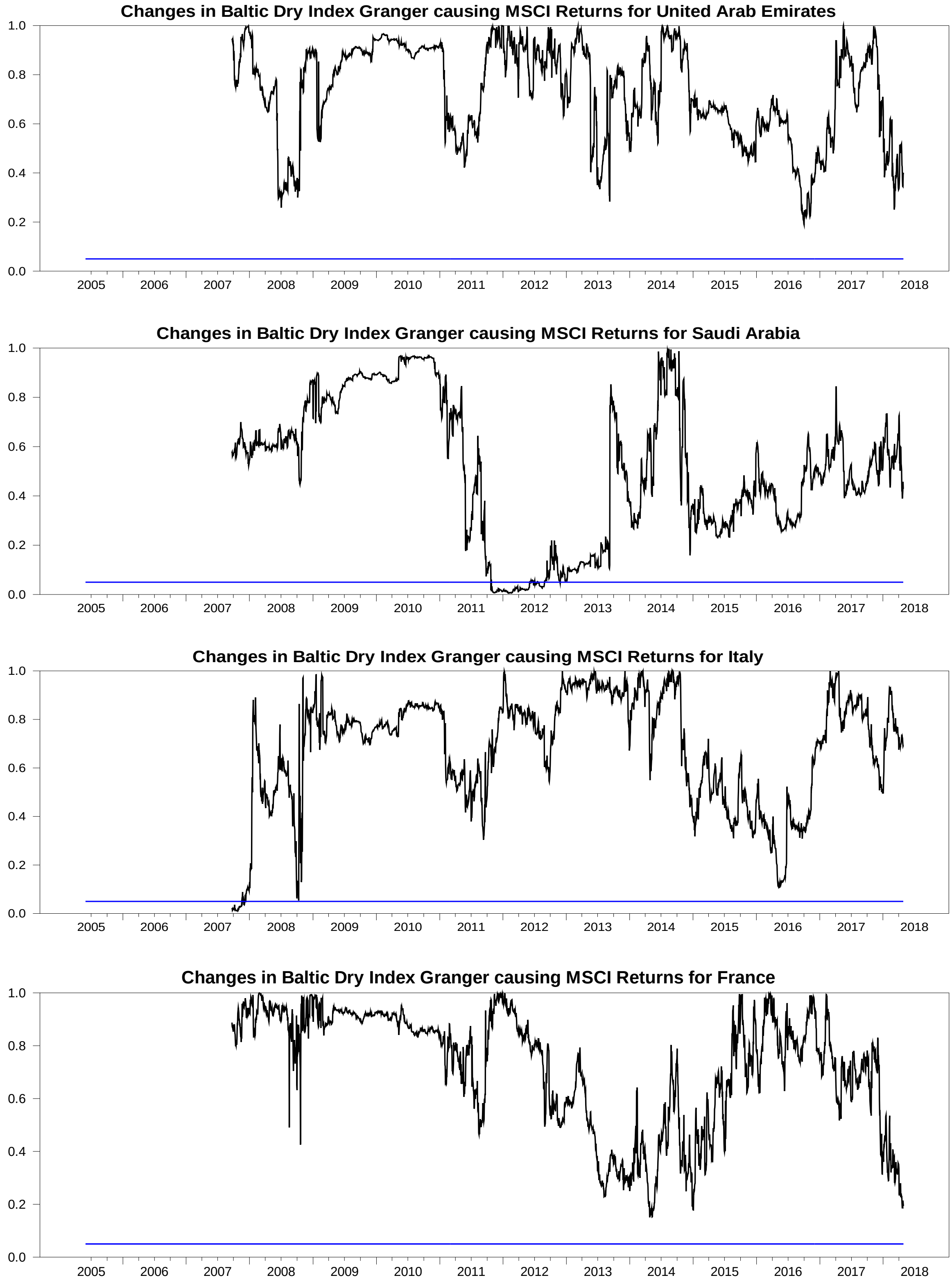


TABLE 1. Unit Root Tests

Panel A: Unit Root Tests for Variables in Log Levels				
	ADF	ADF-GLS	PP	KPSS
Commodities				
Brent oil (OIL)	-1.97	-1.37	-2.06	1.02***
Copper (CPR)	-2.89	-1.11	-2.92	0.59***
Gold (GLD)	-2.03	-0.65	-2.02	1.67***
Silver (SIL)	-2.02	-1.09	-2.00	1.36***
Baltic Dry Index (BDI)	-2.63	-2.51	-2.99	0.37***
Stock Market				
KSA	-1.81	-1.44	-1.95	0.86***
UAE	-1.50	-1.08	-1.52	1.32***
France	-2.37	-2.25	-2.37	0.64***
Italy	-1.82	-1.90	-1.71	0.83***
Exchange Rates				
EUR/USD (XR)	-2.42	-1.70	-2.44	0.87***
Panel B: Unit Root Tests for Variables in Log Changes				
	ADF	ADF-GLS	PP	KPSS
Commodities				
Brent oil (OIL)	-61.88***	-2.53	-61.87***	0.08
Copper (CPR)	-62.56***	-7.34***	-62.41***	0.08
Gold (GLD)	-58.03***	-57.89***	-58.05***	0.05
Silver (SIL)	-59.49***	-56.89***	-59.49***	0.04
Baltic Dry Index (BDI)	-23.62***	-17.80***	-21.57***	0.03
Stock Market				
KSA	-56.75***	-2.70	-56.84***	0.04
UAE	-37.20***	-35.34***	-53.65***	0.09
France	-59.13***	-56.61***	-59.22***	0.05
Italy	-58.45***	-57.84***	-58.53***	0.07
Exchange Rates				
EUR/USD (EX)	-57.67***	-5.26***	-57.67***	0.05

Notes: All unit root tests are performed with an intercept and a trend in the test equation. The optimal lag length is selected using the Bayesian Information Criterion (BIC). ADF refers to the Augmented Dickey and Fuller (1979) test. ADF-GLS refers to the ADF with GLS detrending of Elliott, Rothenberg and Stock (1996). PP is the Phillips and Perron (1988) test. KPSS is the Kwiatkowski, Phillips, Schmidt and Shin (1992) test. With the exception of the KPSS test whose null is trend stationarity, the null for all the tests is one of a unit root. *, **, *** denote, respectively, statistical significance at the 10%, 5% and 1% levels.

TABLE 2. Descriptive Statistics

	mean	std. dev.	skewness	kurtosis	AC(1)
Commodities					
Δln(OIL)	0.011	2.096	0.013	3.460	-0.063
Δln(CPR)	0.020	1.815	-0.092	3.911	-0.075
Δln(GLD)	0.034	1.178	-0.347	5.580	0.000
Δln(SIL)	0.023	2.097	-0.893	7.188	-0.024
Δln(BDI)	-0.025	2.226	0.078	3.545	0.757
Stock Market Returns					
KSA	-0.009	1.657	-0.988	25.104	0.023
UAE	-0.016	1.768	-0.584	12.659	0.086
France	0.012	1.568	-0.084	7.535	-0.019
Italy	-0.008	1.735	-0.254	6.323	-0.007
Exchange Rate Returns					
EUR/USD (XR)	-0.000	0.607	0.136	3.38	0.005

Notes: The table provides the summary statistics of the variables used in the empirical analysis. Std. Dev. refers to the standard deviation, while AC(1) denotes the first-order autocorrelation.

TABLE 3. Cross-Correlations among Variables

Panel A: Cross-Correlations in Levels										
	OIL	CPR	GLD	SIL	BDI	XR	KSA	UAE	FRANCE	ITALY
OIL	1.00									
CPR	0.41	1.00								
GLD	0.25	0.36	1.00							
SIL	0.32	0.46	0.81	1.00						
BDI	0.04	0.01	0.03	0.04	1.00					
XR	0.20	0.28	0.34	0.36	0.02	1.00				
KSA	0.06	0.06	-0.10	-0.00	0.01	0.01	1.00			
UAE	0.10	0.09	-0.00	0.06	0.05	0.06	0.40	1.00		
FRANCE	0.37	0.48	0.15	0.30	0.02	0.56	0.12	0.19	1.00	
ITALY	0.36	0.44	0.12	0.27	0.01	0.54	0.13	0.18	0.92	1.00

Panel B: Cross-Correlations in Log Changes										
	OIL	CPR	GLD	SIL	BDI	XR	KSA	UAE	FRANCE	ITALY
OIL	1.00									
CPR	0.41	1.00								
GLD	0.25	0.36	1.00							
SIL	0.32	0.46	0.81	1.00						
BDI	0.04	0.01	0.03	0.04	1.00					
XR	0.20	0.28	0.34	0.36	0.02	1.00				
KSA	0.06	0.06	-0.06	-0.01	0.01	0.01	1.00			
UAE	0.10	0.09	-0.01	0.06	0.05	0.06	0.40	1.00		
FRANCE	0.37	0.48	0.15	0.30	0.02	0.56	0.12	0.19	1.00	
ITALY	0.36	0.44	0.12	0.27	0.01	0.54	0.13	0.18	0.92	1.00

Notes: The table provides the cross-correlations between the variables used in VAR analysis in levels and log changes.

TABLE 4. VAR Diagnostic Tests

Panel A: Autocorrelation, Heteroskedasticity and Stability Tests				
	KSA	UAE	France	Italy
Multivariate *Q*	3004.13	3044.43	3045.45	3034.00
p-value	0.00	0.00	0.00	0.00
Multivariate ARCH	48655.06	44964.48	68620.47	64653.34
p-value	0.00	0.00	0.00	0.00
Nyblom Test for Covariance Matrix	37.13	35.29	36.73	39.82
p-value	0.00	0.00	0.00	0.00
Panel B: Quandt-Andrews Breakpoint Test				
	KSA	UAE	France	Italy
Max LR (F-statistic)	3.50	4.30	4.89	3.40
p-value	0.00	0.01	0.02	0.03
Dates	10/28/2008	10/7/2008	10/14/2008	10/14/2008

Notes: Panel A provides the Hosking (1981) variate of the multivariate *Q* statistics for serial correlation in the VAR's residuals. The table also provides multivariate tests for Autoregressive Conditional Heteroskedasticity (ARCH) in the VAR's residuals as well as the Nyblom (1989) test for stability of the estimated VAR's covariance matrix. Panel B provides the Quandt (1960) and Andrews (1993) breakpoint tests applied to the VAR's equation with stock returns as a dependent variable. The asymptotic *p*-values of the Quandt-Andrews test are computed using Hansen (1987)'s approach.

TABLE 5. Rolling Window Causality Test Results

	Oil	Gold	Silver	Copper	Exchange Rate	Baltic Dry Index
Panel A: Causality from Commodity Price Changes, Exchange Rates and Baltic Dry Index Changes to Stock Returns						
Italy	590	5	1	0	0	48
France	347	0	0	0	0	0
KSA	1013	203	99	474	-	203
UAE	590	0	14	259	-	0
Panel B: Causality from Stock Returns to Commodity Price Changes, Exchange Rates and Baltic Index Price Changes						
	Oil	Gold	Silver	Copper	Exchange Rate	Baltic Dry Index
Italy	0	0	0	0	489	252
France	0	8	0	0	1344	179
KSA	0	331	0	0	-	130
UAE	0	281	0	108	-	21

Notes: The table provides the number of significant causality tests (at the 5% level) in 2769 windows.