Movements in International Bond Markets: The Role of Oil Prices

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Abstract

In this paper, we analyze daily data-based price transmission and volatility spillovers between crude oil and the bond markets of major oil exporters and importers, accounting for structural shifts as a smooth process in causality and volatility spillover estimations. In general, we find that oil prices tend to predict bond prices in the majority of oil exporting countries and two large oil importers (India and China). The feedback from bonds to oil prices is weak and detected only for China and the USA. Oil volatility affects the bond market volatility of some major oil exporters (Kuwait, Norway, and Russia) and one importer (France). However, the most prominent volatility spillovers are from bonds to oil, except for Kuwait and Saudi Arabia. We reveal that taking structural shifts into account strengthens our findings and is particularly important for volatility spillover analysis.

Keywords: Bond and oil markets; price and volatility spillovers; major oil exporters and importers; structural changes

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1. Introduction

The existing international literature on the price, returns, and volatility relationship between oil and equity markets is extensive (for detailed reviews see, for example, Degiannakis, Filis, & Arora, 2018; Smyth & Narayan, 2018). In comparison, the literature examining the causal linkage between bond and oil markets is small (see, for example, in pressKang, Ratti, & Yoon, 2014; Bouri, Shahzad, Raza, & Roubaud, 2018, 2019a, 2019b, 2017, Lee, Lee, & Ning, 2017; Shahzad, Naifar, Hammoudeh, & Roubaud, 2017; Gormus, Nazlioglu, & Soytas, 2018; Balcilar et al. (in press)). Note that high oil prices increase inflation expectations and hence increase nominal bond yields, which in turn moves bond prices or returns in the opposite direction, with this channel being especially important for oil importers. For oil exporters, higher oil prices generate increased domestic income and can result in higher demand for investment in the financial asset market (including bonds), and hence produce higher asset prices or returns. Moreover, given the recent financialization of the commodity sector, the oil market is now also considered a profitable alternative investment in portfolio decisions (Bahloul, 2018), and hence portfolio reallocations are likely to see feedback from bond markets to the oil market in terms of prices, and bi-directional risk (volatility) spillovers (Tiwari, Cunado, Gupta, & Wohar, 2018). In other words, bond and oil markets are intertwined in terms of their first and second moment movements.

The general lack of attention to analyzing the relationship between oil and bond prices (barring the few studies mentioned above), and concentration on the oil-stock nexus, is quite baffling, given that stock and bond markets are of comparable size in the functioning of the global financial system. For instance, the US stock market capitalization in 2017 stood at about $30 trillion, but the corresponding value of the US bond market was $40.7 trillion (Securities Industry and Financial Markets Association (SIFMA), 2018). Outside the US, debt market capitalization exceeds equity market capitalization by a larger relative amount ($100.1 trillion to $85.3) than in US markets (SIFMA, 2018). Given that the bond market is often viewed as a safe haven (Habib & Stracca, 2015; Hager, 2017; Kopyl & Lee, 2016), in this paper we analyze the Granger causal relationships between the daily price returns and volatility of the bond and oil markets of major oil exporters (Canada, Kuwait, Mexico, Norway, Russia, Saudi Arabia, and Venezuela) and importers (China, France, Germany, India, Japan, the United Kingdom (UK), and the US), with these countries accounting for over 90 percent of the value of the global bond market (SIFMA, 2018). The presumption is that oil exporters are likely to see relatively stronger interactions between oil and bond markets than oil importers, given the importance of oil revenues as a source of income for the former group of economies. To achieve our objectives, from an econometric modelling perspective, we first employ the Toda and Yamamoto (1995) approach to Granger causality and the Hafner and Herwartz (2006) test of causality-in-variance. We then proceed with the Fourier-based version of the Toda and Yamamoto (1995) test of causality in prices developed by Nazlioglu, Gormus, and Soytas (2016), and the modified Hafner and Herwartz (2006) test of causality-in-variance with Fourier approximations (Li & Enders, 2018; Pascalau, Thomann, & Gregoriou, 2011) to account for structural shifts, incorporated as gradual processes, in the relationships involving the first and second moments of oil and bond market movements. This is very important, given that (high-frequency) data related to financial and commodity markets are subject to structural changes, and mounting evidence that an inability to model structural breaks results in incorrect inferences (Guidolin, Hyde, McMillan, & Ono, 2009). To the best of our knowledge, this is the first attempt to analyze price and volatility spillovers between the oil and bond markets of major oil exporters and importers based on testing procedures with structural shifts.

The remainder of the paper is organized as follows: Section 2 reviews the related literature, Section 3 outlines the methodologies for testing causality in prices and volatility, Section 4 presents the data and its properties as well as the empirical results, and Section 5 concludes and draws implications from our results.

2. Literature review

In this segment, we discuss the sparse literature associated with the relationship between the bond and oil markets, emphasizing the contribution of our work by contextualizing its position in this literature. In this regard, one of the earliest studies is that of Kang et al. (2014) who use a structural vector autoregressive model to investigate how the demand and supply shocks driving the global crude oil market affect the real bond returns of the US. They find that a positive oil market-specific demand shock is associated with significant decreases in real returns of an aggregate bond index for 8 months following the shock. Related to the US bond market, the recent study of Balcilar et al. (forthcoming) analyzes the role of oil market uncertainty, instead of oil prices or shocks per se, on the first and second moments of the bond premia of the US Treasury based on a higher order nonparametric causality-in-quantiles framework to account for misspecification due to uncaptured nonlinearity and structural breaks. The study finds that oil uncertainty not only predicts (increases) the US bond premia of various maturities but also its volatility, with the effect on the latter being stronger.

Recent studies by Bouri, de Boyrie, and Pavlova (2017, 2018, 2019a, 2019b), Lee et al. (2017), and Shahzad et al. (2017) go beyond the US bond market to concentrate on sovereign credit default swap (CDS) of both developed and developing countries. In this regard, Lee et al. (2017) reveal the impact of oil prices on sovereign credit default swap (CDS) spreads for large developed countries, while Shahzad et al. (2017) concentrate on the important role of oil volatility on CDS spreads of GCC and oil-exporting countries. Shahzad et al. (2017) and Bouri et al. (2017, 2018, 2019a) provide evidence of the impact of commodity and oil market uncertainty on the volatility of the sovereign risks of a large number of emerging and frontier countries, primarily using quantile-based approaches to identify the impact of oil market volatility on various phases of the CDS spreads. More recently, Bouri, Kachacha, and Roubaud (2019b) extends these works by simultaneously considering the role of both oil prices and volatility on the CDS spreads of MENA oil exporters and importers, using a quantile-based (cross-quantilogram) approach and rolling estimations. The authors show that the impact of oil returns and volatility changes occur in a very short time span (within one day) and the quantile-specific reactions of sovereign risk spreads are time-varying.

Finally, Gormus et al. (2018) deal with price transmission tests of the high-yield bond market, accounting for gradual structural shifts. These authors detect a significant impact from oil and ethanol prices to high-yield bonds. Furthermore, based on volatility tests, Gormus et al. (2018) find unidirectional volatility transmission from energy markets to the high-yield bond market.[2]

In summary, a few observations that stand out from the review above are that: (a) the oil market not only affects the first moment, but also the second moment of the bond market; and (b) both oil and bond markets are characterized by regime changes. Given these points, our paper adds to this small but burgeoning literature by analyzing, for the first time, price and volatility spillovers between the oil and bond markets of major oil exporters and importers based on tests of Granger causality with structural shifts. From a methodological perspective, our paper is related to the work of Gormus et al. (2018), but differs in the fact that we look at government bonds, i.e. safe havens, instead of high-yield bonds which are considered to behave more like stocks than bonds.

3. Econometric Methodology

3.1. Testing for causality with structural changes

In order to test for causal linkages, Granger (1969) define VAR(p) model as

$$y_t = \alpha + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \varepsilon_t \qquad (1)$$

where y_t consists of *m* endogenous variables, α is a vector of intercept terms, β are coefficient matrices and ε_t are white-noise residuals. Here, y_t consist of oil and bond prices, and hence the VAR(p) is based on a bivariate estimation. y_t are assumed not to have any structural shifts and the intercept terms α are constant over time. Ventosa-Santaularia and Vera-Valdés (2008) show that the null of non-causality can be rejected even though there is no causality when data generating process has structural shifts. Enders and Jones (2016) find out a similar finding by Monte Carlo simulations which indicate that ignoring structural breaks in a VAR model leads Granger causality test to be biased towards a false rejection of the true null hypothesis. Authors further reveal that unless breaks are properly modelled, Granger causality tests also tend to have an over-rejection of the non-causality null hypothesis. Thereby, inferences from a standard Granger causality analysis may be misleading when structural breaks are ignored or improperly taken into account. These findings not only indicate the importance of accounting for any structural shifts but also necessitate a careful treatment of how breaks are captured (Nazlioglu et al., 2016).

The traditional approach to modelling breaks is to use dummy variables in which shifts are assumed to be sharp (for example, Perron, 1989; Zivot & Andrews, 1992; Lee & Strazicich, 2003). A smooth transition approach is also used for controlling for breaks since structural changes are gradual in nature (inter alia, Leybourne at al., 1998; Kapetanios, Shin, & Snell, 2003). Both approaches require knowledge of the functional form, number, and date of breaks. The Fourier approximation, based on a variant of flexible Fourier form by Gallant (1981), is also used for capturing structural shifts (see, Becker, Enders, & Lee, 2006; Enders & Lee, 2012a, 2012b; Rodrigues & Taylor, 2012). This approximation does not require prior knowledge of the form, number, or date of breaks and captures structural shifts as a gradual/smooth process.

In a VAR specification, not only controlling for structural breaks but also determining the original source of structural breaks is difficult, because a break in one variable potentially causes shifts in other variables (Enders & Jones, 2016; Ng & Vogelsang, 2002). To overcome this difficulty and simplify the determination of the form of shifts as well as estimation of the number and dates of breaks in a VAR framework, Enders and Jones (2016), Nazlioglu et al. (2016, 2019) and Gormus et al. (2018) employ the Fourier approximation.

Enders and Jones (2016) augments VAR model with Fourier approximation and then impose restrictions for the Granger causality. It is well known that the Granger causality analysis necessitates testing for unit root and co-integration properties of the variables because Wald test not only has a non-standard distribution if the variables in VAR model are integrated or co-integrated, but also depends on nuisance parameters (Toda and Yamamoto, 1995; Dolado and Lütkepohl, 1996). The Toda and Yamamoto approach (TY) overcomes these problems by estimating VAR(p+d) model that employs the level form of variables with *d* (the maximum integration order of variables) additional lag(s). By extending the TY framework with gradual structural shifts using a Fourier approximation, Nazlioglu et al. (2016, 2019) and Gormus et al. (2018) propose a simple approach to take into account breaks (both abrupt and gradual) in Granger causality analysis and they call this process as the Fourier TY approach to causality.

In order to account for structural shifts, the Fourier TY procedure relaxes the assumption of that the intercept terms α are constant over time and define VAR*(p+d)* model as

$$y_t = \alpha(t) + \beta_1 y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{2}$$

where the intercept terms $\alpha(t)$ are the functions of time and denote any structural shifts in y_t. In order to capture structural shifts as a gradual process, the Fourier approximation is defined by:

$$\alpha(\mathrm{t}) \cong \alpha_0 + \sum_{k=1}^{n} \gamma_{1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} cos\left(\frac{2\pi kt}{T}\right) \tag{3}$$

where *n* is the number of frequencies, γ_{1k} and γ_{2k} measures the amplitude and displacement of the frequency, respectively. By substituting equation (3) in equation (2), VAR*(p+d)* model is re-written as

$$y_t = \alpha_0 + \sum_{k=1}^{n} \gamma_{1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} cos\left(\frac{2\pi kt}{T}\right) + \beta_1 y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \tag{4}$$

As discussed in Becker et al. (2006), a large value of *n* is most likely to be associated with stochastic parameter variation and decreases degrees of freedom and can also lead to the over-fitting problem. A single Fourier frequency, on the other hand, mimics a variety of breaks in deterministic components, hence one can also use a single frequency component. In the single frequency case, $\alpha(\mathrm{t})$ is defined as

$$\alpha(t) \cong \alpha_0 + \gamma_1 sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) \quad (5)$$

where k denotes the frequency for the approximation. By substituting equation (5) in equation (2), we obtain

$$y_t = \alpha_0 + \gamma_1 sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 cos\left(\frac{2\pi kt}{T}\right) + \beta_1 y_{t-1} + \cdots + \beta_{p+d} y_{t-(p+d)} + \varepsilon_t \quad (6)$$

The specification problem in both equations (4), (6) requires determining the number of Fourier frequency components and lag lengths (*p*). A common approach to determining the optimal number of lags in a causality analysis is to benefit from the Akaike or Schwarz information criterion. This approach can also be used for determining the number of the Fourier frequency and number of lag lengths, together. Specifically, we first determine the maximum number of the Fourier frequency and number of lags and pare down one-by-one up to one. Then we select the optimal frequency and lag combination which minimizes the information criterion

In the Toda-Yamamoto framework, the null hypothesis of Granger non-causality is based on zero restriction on first *p* parameters ($H_o: \beta_1 = \cdots = \beta_p = 0$) of the *mth* element of y_t. Wald statistic for testing the null hypothesis has an asymptotic χ^2 distribution with *p* degrees of freedom. The recent works in the Granger causality literature have also relied on bootstrap distribution in order to increase the power of test statistic in small samples as well as being robust to the unit root and co-integration properties of data (see Mantalos, 2000; Hatemi-J, 2002; Hacker and Hatemi-J, 2006; Balcilar et al., 2010). In addition to the asymptotic chi-square distribution, we use the bootstrap distribution of Wald statistic by employing residual sampling bootstrap approach originally proposed by Efron (1979)[3].

Gormus et al. (2018) and Nazlioglu, Gormus, and Soytas (2019) compare the size and power properties of the TY and the Fourier TY approaches based the asymptotic or bootstrap distributions. They question whether using cumulative frequencies or a single frequency matters in small samples for the Fourier TY method. In small samples, the bootstrap distribution seems to show more desirable size and power properties, the TY test is more likely to have good size than the Fourier TY test, and the Fourier TY test appears to be more powerful than the TY test. On the other hand, as the number of observations grows, while the difference between the asymptotic and bootstrap distribution disappears, the importance of considering structural shifts in causality analysis becomes obvious. In large samples, while the TY test has severe size distortion problems, the Fourier TY test seems to have good size properties.

3.2. Testing for volatility spillover with structural changes

We also conduct a volatility transmission analysis in order identify the existence and the direction of possible volatility interactions between the oil prices and bonds. Some of the more common volatility transmission tests (Cheung and Ng, 1996; Hong, 2001) utilize univariate GARCH[4] models and cross-correlation functions of the standard residuals. This approach not only necessitate a selection of lead and lag orders but also suffers from significant oversize in the data with leptokurtic volatility processes (Hafner and Herwartz, 2006). Hafner and Herwartz (2006) developed Lagrange multiplier (LM) based volatility transmission test which does not suffer from those issues and has an increasing power with larger sample size.

The LM test for volatility transmission is based on the estimation of GARCH (1,1) models for series *i* and *j*. Let consider the series *i* for simplicity, then the GARCH (1,1) specification is

$$y_{it} = x'_{it}c_i + \varepsilon_{it} \quad (7)$$

$$\sigma_{it}^2 = \omega_i + \alpha_i \varepsilon_{t-1}^2 + \beta_i \sigma_{it-1}^2 \quad (8)$$

where the mean equation in (7) is a function of exogenous variables with an error term, ε_{it} denotes the real-valued information. σ_{it}^2 is the so-called "conditional variance" that is the one-period ahead forecast variance based on past information. $\omega_i > 0$, $\alpha_i, \beta_i \geq 0$ in order to ensure non-negativity of the conditional variance. In addition, $\alpha_i + \beta_i < 1$ to ensure that the variance is finite which means that the process is stable. All things for the series *i* are hold for the series *j*.

After the estimation of the GARCH (1,1) models for the series *i* and *j*, Hafner and Herwartz (2006) define that

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2(1 + z'_{jt}\pi)}, \qquad z_{jt} = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2\right)' \quad (9)$$

where ξ_{it} is the standardized residuals the series *i*. ε_{jt}^2 and σ_{jt}^2 are respectively the squared disturbance term and the volatility for the series *j*. The null hypothesis $H_0: \pi = 0$ of no-volatility transmission is tested against the alternative hypothesis $H_0: \pi \neq 0$ of volatility transmission. The log-likelihood function of ε_{it} (Gaussian) is used to achieve $x_{it} = (\xi_{it}^2 - 1)/2$ where x_{it} are the derivatives of the likelihood function. The LM statistic is:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1)\, z'_{jt}\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}(\xi_{it}^2 - 1) z_{jt}\right) \quad (10)$$

where

$$V(\theta_i) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt}\, z'_{jt} - \sum_{t=1}^{T} z_{jt}\, x'_{it}\left(\sum_{t=1}^{T} x_{it}\, x'_{it}\right)^{-1}\sum_{t=1}^{T} x_{it}\, z'_{jt}\right), \qquad \kappa = \frac{1}{T}\sum_{t=1}^{T}(\xi_{it}^{2} - 1)^{2}.$$

The asymptotic distribution of the volatility spillover test defined in (10) is depend on the number of misspecification indicators in z_{jt} and hence λ_{LM} has an asymptotic chi-square distribution with two degrees of freedom.

In equation (8), it is assumed that the conditional variance does not have any structural changes and hence it is only affected from the constant term ω_i, the ARCH term α_i, and the GARCH term β_i. Nonetheless, an increasing literature on the volatility modelling clearly indicates that the process of the long-run volatility can also be affected from structural changes (see among others, Diebold and Inoue, 2001; Mikosh and Starica, 2004; Starica and Granger, 2005). If the volatility process has structural changes, then the conventional GARCH(1,1) model may not be sufficient to modelling the long-run volatility which is assumed to be constant over time. In more recent studies, Teterin et al. (2016), Li and Enders (2018) and Pascalau et al. (2011), it has shown that structural changes in the conditional variance can be well approximated by a Fourier approximation which does not require a prior information regarding the numbers, dates and form of the variance of shifts. Moreover, a Fourier approximation may be more suitable for financial data since quite a few breaks may occur in a long financial series that often times little is known about structural changes (Li and Enders, 2018).

Pascalau et al. (2011) and Li and Enders (2018) extends the conventional GARCH model in order to account for the variance breaks. Specifically, the equation (8) is re-defined to include breaks in intercept of conditional variance:

$$\sigma_{it}^{2} = \omega_i(t) + \alpha_i \varepsilon_{t-1}^{2} + \beta_i \sigma_{it-1}^{2} \tag{11}$$

where $\omega_i(t)$ now depends on time and hence relax the assumption that the conditional variance is constant over time. To capture any shifts in volatility, $\omega_i(t)$ is approximated by a Fourier approximation and the conditional variance equation for the series *i* is given by

$$\sigma_{it}^2 = \omega_{0i} + \sum_{k=1}^{n} \omega_{1i,k} sin\left(\frac{2\pi k_i t}{T}\right) + \sum_{k=1}^{n} \omega_{2i,k} cos\left(\frac{2\pi k_i t}{T}\right) + \alpha_i \varepsilon_{t-1}^2 + \beta_i \sigma_{it-1}^2. \qquad (12)$$

Since our interest is to test for the volatility spillover, the test statistic in equation (10) can be obtained based on the conditional variance equation in (12) and other things in the estimations are being same. Note that we call the volatility spillover test based on equation in (12) as $F\lambda_{LM}$ (Fourier λ_{LM}). Since augmenting the conditional variance equation with a Fourier approximation does not lead to a change in the number of misspecification indicators in z_{jt}, $F\lambda_{LM}$ also has an asymptotic chi-square distribution with two degrees of freedom.

The equation (12) requires determining the number of Fourier frequency components. As discussed in Pascalau et al. (2011), one can benefit from Akaike or Schwarz information criterion. We first set he number of Fourier frequency to n^{max} and then we select the optima frequency number which minimizes information criterion.

4. Data and Empirical Results

Our data set is at the daily frequency. It consists of bond prices of the major oil exporters (Canada, Kuwait, Mexico, Norway, Russia, Saudi Arabia, and Venezuela) and importers (China, France, Germany, India, Japan, the UK, and the US) and the price of oil. Note that, as far as oil exports are concerned, the rankings are as follows: Saudi Arabia comes 1st, followed by Russia, Canada is in the 5th position, while Kuwait, Venezuela, Norway, and Mexico are in 7th, 12th, 13th and 14th positions respectively (Central Intelligence Agency (CIA) World Fact Book, 2019). As far as the oil importers are concerned: China, US, India, and Japan are ranked 1st, 2nd, 3rd, and 4th respectively, with Germany, the UK and France in the 6th, 10th, and 12th, positions (CIA World Fact Book, 2019). Note, even though the US is the 4th largest oil exporter, it is a net importer, and hence is listed in the group of oil importers. It must be realized that we consider the largest possible oil exporters and importers which simultaneously have well-functioning government bond markets. Hence, even though in some instances there are other major oil exporters and importers, we leave them out of the sample due to the lack of relatively long-span bond market data required to derive reliable econometric inferences. But, as indicated, these oil exporters and importers account for over 90 percent of the value of the global bond market (SIFMA, 2018), and hence are a good representation of the world bond market, simultaneously accounting for the role these economies play in the oil market. For the bond prices of the chosen countries, we generally use the 10-year Government Bond Index derived from the Datastream database of Thomson Reuters. But, where this is unavailable, as in the case of Kuwait, Russia, Saudi Arabia and Venezuela, we use the comparable government bond index for these countries.

As far as oil price is concerned, we use the daily price of Brent Crude, which serves as a benchmark price for purchases of oil worldwide, and is used to price two thirds of the world’s internationally traded crude oil supplies. The data is derived from the FRED database of the Federal Reserve Bank of St. Louis. The data of both oil and bond indices are in US dollars to avoid the impact of exchange rate movements on our analysis. The data is plotted in Figure A1 and summarized in Table A1 in the Appendix to the paper. The coverage of the data samples varies across countries (as detailed in Table A1), with

Kuwait having the shortest sample (03/14/2017–03/11/2019), and Canada, Germany, the UK and the US the longest samples (05/20/1987–03/11/2019). Besides the non-normality of the oil and bond prices, it is important to observe that these variables go through multiple regime changes in a consistent manner over the data sample considered, thus motivating our decision to analyze price and volatility spillovers based on models that incorporate structural breaks.

The TY approach to Granger causality requires determination of the integration degree of the variables in order to determine the maximum integration number (d) of the unit root. To this end, we first employ the conventional augmented Dickey Fuller (ADF) test of Dickey and Fuller (1979), then conduct the ADF test with one structural break (ZA-ADF) developed by Zivot and Andrews (1992) and the ADF with a Fourier approximation (F-ADF) developed by Enders and Lee (2012b) in order to account for structural breaks in the unit root analysis.[5] The results of the unit root tests are reported in Table 1. For the level of oil prices, none of the tests can reject the null hypothesis of the unit root. For the first difference of oil prices, the unit root tests strongly support the evidence for stationarity. Similar findings are made for the bond series. These findings clearly imply that the maximum integration of the variables (d) is equal to 1 in the estimated VAR(p + d) models.

Table 1: Results from unit root tests for oil and bond prices

	Level					First Difference					
	ADF	ZA-ADF		F-ADF		ADF		ZA-ADF		F-ADF	
Oil prices (BRENT)	-1.519	-3.879		-3.009		-87.126	***	-87.232	***	-87.132	***
Bond prices											
US	-1.513	-4.822	**	-2.578		-88.548	***	-88.568	***	-88.548	***
Germany	-0.784	-3.896		-2.353		-89.611	***	-89.642	***	-89.616	***
UK	-1.187	-4.388		-2.572		-89.510	***	-89.527	***	-89.508	***
France	-0.404	-3.363		0.061		-76.782	***	-76.839	***	-76.860	***
Japan	0.602	-3.565		1.156		-77.334	***	-77.415	***	-77.377	***
China	-1.546	-3.133		-2.051		-17.341	***	-32.026	***	-17.424	***
Canada	-0.468	-4.045		-1.18		-87.124	***	-87.143	***	-87.123	***
India	-2.249	-3.602		-2.421		-52.726	***	-52.784	***	-52.75	***
Mexico	-1.37	-3.33		-2.329		-44.883	***	-44.922	***	-44.922	***
Norway	-0.107	-4.957	**	-1.192		-43.730	***	-43.774	***	-43.751	***
Russia	-1.287	-4.175		-4.146	**	-64.366	***	-64.370	***	-64.397	***
Venezuela	-0.982	-3.23		-1.546		-58.978	***	-59.050	***	-59.032	***
Kuwait	-1.016	-3.045		-2.642		-17.310	***	-27.015	***	-17.706	***
Saudi Arabia	-1.785	-4.306		-1.757		-13.391	***	-17.165	***	-13.443	***

Notes: ADF: Augmented Dickey and Fuller (1979) unit root test ZA-ADF: Zivot and Andrews (1992) ADF unit root test with a break. F-ADF: Enders and Lee (2012b) ADF unit root test with Fourier approximation. ADF test includes a constant term. ZA-ADF and F-ADF tests include a structural shift in the constant term. The optimal lag(s) were determined by Schwarz information criterion for augmented ADF and ZA-ADF tests by setting maximum number of lags to 12. The optimal frequency and lags were determined by Schwarz information criterion for F-ADF by setting maximum number of lags to 12 and of Fourier frequency to 3. ADF critical values are -3.433 (1%), -2.862 (5%), -2.567 (10%). ZA-ADF critical values are -5.34 (1%), -4.80 (5%), -4.58 (10%). The critical values for F-ADF test with one frequency are -4.31 (1%), -3.75 (5%), -3.45 (10%). ** and *** indicate statistical significance at 5 and 1 percent, respectively.

The results from the Granger causality analysis are presented in Table 2[1]. The results from the TY test in panel A of Table 2, at a first glance, indicate that the null hypothesis of no-Granger causality from oil prices to bond cannot be rejected in relatively most of the countries. In five cases - namely China, Canada, India, Mexico and Venezuela (Russia)- on the other hand, the null hypothesis of no-causality is rejected, implying an information transmission from oil prices to bond prices. The evidence on causality provides a predictive power from oil prices to bond prices in these five countries, with Russia also included in the list if we consider the 10% significance level.

[1] Note that maximum k/n and p are respectively set to 3 and 7, then optimal Frequency and lags are determined by minimizing Akaike information criterion.

Table 2: Results from causality tests

	Panel A: No-shift				Panel B: Smooth shifts									
	TY				FTY with single frequency (k)					FTY with cumulative frequency (n)				
Oil ≠>Bond	*p*	Wald	p-val[a]	p-val[b]	*p*	*k*	Wald	p-val[a]	p-val[b]	*p*	*n*	Wald	p-val[a]	p-val[b]
US	1	0.015	0.901	0.897	2	1	2.168	0.338	0.330	2	2	2.149	0.341	0.352
Germany	1	2.082	0.149	0.178	2	1	4.142	0.126	0.124	2	3	4.122	0.127	0.105
UK	1	2.230	0.135	0.129	2	1	3.419	0.181	0.177	2	2	3.423	0.181	0.195
France	1	1.809	0.179	0.170	2	1	1.685	0.431	0.391	2	2	1.670	0.434	0.419
Japan	1	0.800	0.371	0.366	2	1	3.295	0.193	0.183	2	2	3.297	0.192	0.207
China	5	12.843	0.025	0.026	6	2	13.858	0.031	0.040	6	3	13.300	0.039	0.047
Canada	2	8.354	0.015	0.014	3	1	9.067	0.028	0.024	3	2	8.962	0.030	0.030
India	2	9.167	0.010	0.008	3	3	12.336	0.006	0.010	3	3	12.494	0.006	0.006
Mexico	1	5.343	0.021	0.022	2	1	6.608	0.037	0.036	2	3	6.379	0.041	0.048
Norway	4	5.479	0.242	0.255	5	1	10.571	0.061	0.054	5	2	10.372	0.065	0.051
Russia	2	4.569	0.102	0.101	1	1	4.247	0.039	0.034	1	3	4.651	0.031	0.032
Venezuela	7	66.588	0.000	0.000	7	2	67.197	0.000	0.000	7	3	65.013	0.000	0.000
Kuwait	4	6.188	0.186	0.188	5	1	5.729	0.334	0.322	5	3	5.650	0.342	0.341
Saudi Arabia	5	5.634	0.343	0.343	6	1	8.895	0.180	0.191	6	2	9.327	0.156	0.183
Bond ≠>Oil	*p*	Wald	p-val[a]	p-val[b]	*p*	*k*	Wald	p-val[a]	p-val[b]	*p*	*n*	Wald	p-val[a]	p-val[b]
US	1	7.423	0.006	0.006	2	1	8.252	0.016	0.009	2	2	8.217	0.016	0.019
Germany	1	0.512	0.474	0.472	2	1	1.790	0.409	0.406	2	3	1.848	0.397	0.393
UK	1	0.734	0.392	0.375	2	1	2.520	0.284	0.260	2	2	2.518	0.284	0.291
France	1	0.064	0.801	0.780	2	1	0.118	0.943	0.938	2	2	0.125	0.939	0.955
Japan	1	2.275	0.131	0.138	2	1	2.062	0.357	0.363	2	2	2.053	0.358	0.370
China	5	20.988	0.001	0.002	6	1	22.905	0.001	0.001	6	3	22.541	0.001	0.002
Canada	2	2.553	0.279	0.244	3	1	4.910	0.178	0.209	3	2	4.869	0.182	0.161
India	2	2.471	0.291	0.295	3	3	5.829	0.120	0.103	3	3	6.284	0.100	0.101
Mexico	1	0.020	0.886	0.897	2	1	0.157	0.924	0.939	2	3	0.189	0.910	0.900
Norway	4	7.010	0.135	0.122	5	1	8.638	0.124	0.131	5	2	8.653	0.124	0.125
Russia	2	1.680	0.432	0.419	1	1	0.510	0.475	0.469	1	3	0.644	0.422	0.440
Venezuela	7	8.501	0.291	0.289	7	2	8.488	0.292	0.285	7	3	8.661	0.278	0.280
Kuwait	4	9.002	0.061	0.069	5	1	8.536	0.129	0.121	5	3	8.566	0.128	0.114
Saudi Arabia	5	3.157	0.676	0.677	6	1	3.458	0.749	0.741	6	2	3.330	0.766	0.769

Notes: ≠> signifies the null hypothesis of no-Granger causality. TY: conventional TY approach which does not account for structural breaks, FTY(k): Fourier TY approach with single frequency which is based on equation (6), and FTY(n): Fourier TY approach with cumulative frequencies is based on equation (4). Maximum *k*/*n* and *p* are respectively set to 3 and 7, then optimal *k*/*n* and *p* are determined by Akaike information criterion. p-val[a] is the p-value based on the asymptotic chi-square distribution with p degrees of freedom. p-val[b] is the p-value based on the bootstrap distribution with 1,000 replications. VAR(p+d) models are estimated with d equal to 1. Bivariate VAR models include oil prices and bond prices.

As discussed, the results of the TY test do not take into consideration the role of possible structural shifts in the series. It is well known that both oil and bond prices have different trends and volatility dynamics after the 2007–2008 financial crisis and the European sovereign debt crisis starting in 2010, which are included in the samples of the majority of countries. In order to take into account the role of such structural shifts, it is normally required to know the date, number, and form of shifts which is a challenge for researchers in practice. As previously discussed, the Fourier approximation does not require any assumptions or a priori knowledge regarding the date, number, or form of shifts. This approach is able to accommodate structural shifts of any form and number in addition to having the advantages of the Toda-Yamamoto procedure. The results of the Fourier TY causality analysis in panel B of Table 2 are, in general, similar to those of the TY approach with a few exceptions. Specifically, the Fourier TY method provides evidence of the existence of a Granger causal linkage from oil to bond prices in Norway and Russia (at the conventional level of significance, i.e. 5%), whereas the TY approach does not show that causal linkage.

With respect to causality from bond to oil prices, the null hypothesis of no-Granger causality based on the TY test is rejected for China and the US, and weakly (at the 10% level) for Kuwait. When we account for the structural shifts in the estimations, while the causal linkage in the case of China and the US still holds, it disappears in the case of Kuwait, with marginal evidence appearing for India. This finding can be interpreted as that the causal linkages between oil prices and bond prices in China and the US are robust to structural shifts and thereby are stronger.

Combining the results from the TY and Fourier TY analyses in Table 2, we see that there is no feedback relationship between oil and bond prices in all cases except China. There is a unidirectional information flow from oil prices to bond prices in the oil exporting countries, with the exception of Kuwait and Saudi Arabia, which could be due to the relatively nascent government bond market in these two economies. Causality from oil to bond prices also holds true for the two largest oil importers, China and India. Last but not least, there is only one-way causal flow from bond prices to oil prices in the case of the US. Thus, for the US, the portfolio allocation channel is at work, with causality running from the bond to the oil market, which is not surprising given that US Government Treasury securities dominate the global bond market, while for China, with bidirectional causality, both inflation expectations and portfolio allocation channels operate. The observed lack of impact from oil prices to the bond market in the US could be due to the fact that the two opposite impacts from the inflation expectations and the revenue effects nullify each other, given that the US is not only a major importer of oil but it also exports oil, especially in its refined form.[6]

When we consider information transmission between markets, in addition to causality in levels (mean-spillover), there is also a risk transfer dimension which is referred to as causality in variance (volatility-spillover). The first dimension can be thought of as a gradual adjustment which is due to long-run portfolio diversification. On the other hand, hedging strategies require knowledge on volatility spillovers that may be more relevant in the short run, as risk perceptions may change rapidly (Nazlioglu et al., 2016). The nature of risk spillover between oil and bond prices are examined next using the volatility spillover tests.

The volatility spillover LM test by Hafner and Herwartz (2006) is relatively simple to implement because it is based on estimating a GARCH(1,1) specification. The results from the volatility spillover analysis are reported in Table 3. Note that λ_{LM} is the volatility spillover test based on the variance equation (8) which does not account for structural breaks and $F\lambda_{LM}$ is the volatility spillover Fourier LM test based on the variance equation (12) which accounts for structural breaks in the conditional variance of the oil and bond returns.

Table 3: Results from volatility spillover tests

	Oil ≠> Bond					Bond ≠> Oil				
	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value
US	0.542	0.763	1	0.558	0.756	7.118	0.028	3	7.254	0.026
Germany	0.824	0.662	3	0.607	0.738	5.999	0.050	3	5.926	0.051
UK	1.196	0.550	3	1.029	0.597	5.588	0.061	3	5.728	0.057
France	12.203	0.002	2	11.509	0.003	12.541	0.001	3	13.073	0.001
Japan	0.236	0.888	3	2.101	0.349	11.892	0.002	3	15.846	0.000
China	1.633	0.442	2	3.072	0.215	10.423	0.005	3	14.446	0.000
Canada	0.364	0.834	3	0.540	0.762	5.954	0.051	3	6.224	0.044
India	2.097	0.350	2	3.047	0.217	4.041	0.133	3	9.364	0.009
Mexico	1.558	0.459	3	0.866	0.648	4.149	0.126	3	4.887	0.086
Norway	2.636	0.267	3	5.569	0.061	11.987	0.004	3	11.938	0.002
Russia	7.436	0.024	3	8.709	0.012	9.984	0.007	3	12.736	0.001
Venezuela	3.526	0.171	2	3.633	0.162	19.066	0.000	3	17.152	0.000
Kuwait	6.616	0.037	2	10.429	0.005	2.371	0.306	1	2.389	0.302
Saudi Arabia	8.935	0.011	3	4.424	0.119	6.822	0.033	3	2.823	0.243

Notes: ≠> signifies the null hypothesis of no-volatility spillover. λ_{LM}: Volatility spillover LM test which does not account for structural breaks is based on the variance equation (8). $F\lambda_{LM}$: Volatility spillover Fourier LM test is based on the variance equation (12). Maximum number of Fourier frequency n are set to 3 and then optimal n is determined by Akaike information criterion. The mean equation is based AR(1) model for the return of bond and oil prices.

The λ_{LM} test indicates test the null hypothesis of no volatility spillover from oil prices to bond prices is rejected in the case of France, Russia, Kuwait and Saudi Arabia. The $F\lambda_{LM}$ test supports the same finding in France, Russia, and Kuwait but it leads to a change in findings for Norway and Saudi Arabia in which taking into account structural shifts results in different inferences. $F\lambda_{LM}$ supports the evidence on the (weak, at 10% level of significance) volatility/risk spillover from oil to bond markets in Norway. In Saudi Arabia, it appears that the risk spillover from oil prices to bond prices disappears when the structural shifts are considered the volatility process.

In relation to the risk transmission from bond to oil prices, the λ_{LM} test shows that the null hypothesis of no volatility spillover cannot be rejected in three cases – India, Mexico, and Kuwait. When we pay attention to smooth shifts in the volatility process, the $F\lambda_{LM}$ test provides the evidence of a volatility spillover for all cases (with the UK and Mexico at the 10% level of significance) but only Kuwait and Saudi Arabia. These findings hence imply that while there is a limited evidence on the risk spillover from oil to bond markets, the direction of spillover among these markets appears to be run from bond to oil markets. Again the lack of risk spillover in Kuwait and Saudi Arabia from the bonds to oil is possibly due to their pre-mature government debt market. In sum, there is stronger evidence of volatility spillover from the bonds to the oil market, rather than the other way around, highlighting the important role now oil plays in portfolios, following the financialization process.

5. Conclusion

The international literature on the causal relationship between first and second moment movements of oil and bond markets is limited to only few studies. Given the importance of both these markets for investors and policymakers (as well as academics), this is quite baffling, and in this paper, we make an attempt to address this limitation. We analyze daily data-based price transmission and volatility spillovers between crude oil and bond markets of major oil exporters and importers, by accounting for structural breaks - a historically important feature characterizing both oil and government bond prices.

In general, we find that, especially when structural shifts are accounted for, oil prices tend to predict bond prices in majority of oil exporting countries, barring Kuwait and Saudi Arabia, for which the government debt market is still underdeveloped. Similar impact is also observed for two major oil importers of India and China. The feedback from bond to oil prices is weak, but is detected for the US and China, highlighting the importance of crude oil in portfolio decisions of investors in these two countries. In case of volatility spillovers, while oil volatility affects the bond market volatility of some major oil exporters (Kuwait, Norway and Russia), and an importer (France), it is in fact volatility-based causality from the bond to oil that is more prominent, with the exceptions of Kuwait and Saudi Arabia. Again as with the case of price transmission, accounting for structural breaks, strengthens our findings.

Our results have important implications for academics, investors and policymakers. First of all, as far as academic researchers are concerned, we show that to derive appropriate statistical inferences when analyzing causal relationships between the first- and second- moments of oil and bond market, it is of paramount importance that structural changes are incorporated into the modelling frameworks; otherwise, statistically weak results would be derived. Second, from the perspective of bond investors, they can improve investment strategies by exploiting the predicting role of the oil prices for the bond prices of US and China. At the same time, investors aiming to include bonds in a portfolio comprising oil (commodities), should be careful of risk spillovers from the bond market as well. In other words, while government bond can indeed be considered a safe haven, especially in the USA, Japan, and Germany, it can also transfer its risk to the oil market. Finally, evidence that oil prices tend to move long-term government bonds, could be an indication, using the idea of the yield curve, that many oil exporting countries and major oil importers (e.g., China and India), in fact are taking into account oil prices in their interest rate setting behavior. But monetary authorities should simultaneously be mindful of the fact that frequent interest rate changes to respond to the oil prices, could lead to a volatile bond market, which in turn will be transmitted to the volatility of the oil market, and affect economic activity in a negative manner. This issue is also relevant to global investors who often see a safe haven role in some of government bonds, which might affect their investment and asset allocation decisions.

Realizing the importance of associating oil price movements to different structural shocks (like, oil-specific supply, demand and inventory shocks, and demand shock due to changes in global economic activity) (see, among others, Kilian, 2009; Kilian and Murphy, 2014), it would be interesting to analyze the impact of those various oil shocks, rather than aggregate oil price, to international bond market movements.

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Notes

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[2] In the context of investment bonds, Wan and Kao (2015) find that positive shocks in oil prices decrease the spreads between AAA and BAA rated bonds.

[3] In order to save space, we omit the details of the bootstrap procedure here and refer the interested reader to Hatemi-J (2002) and Balcilar et al. (2010).

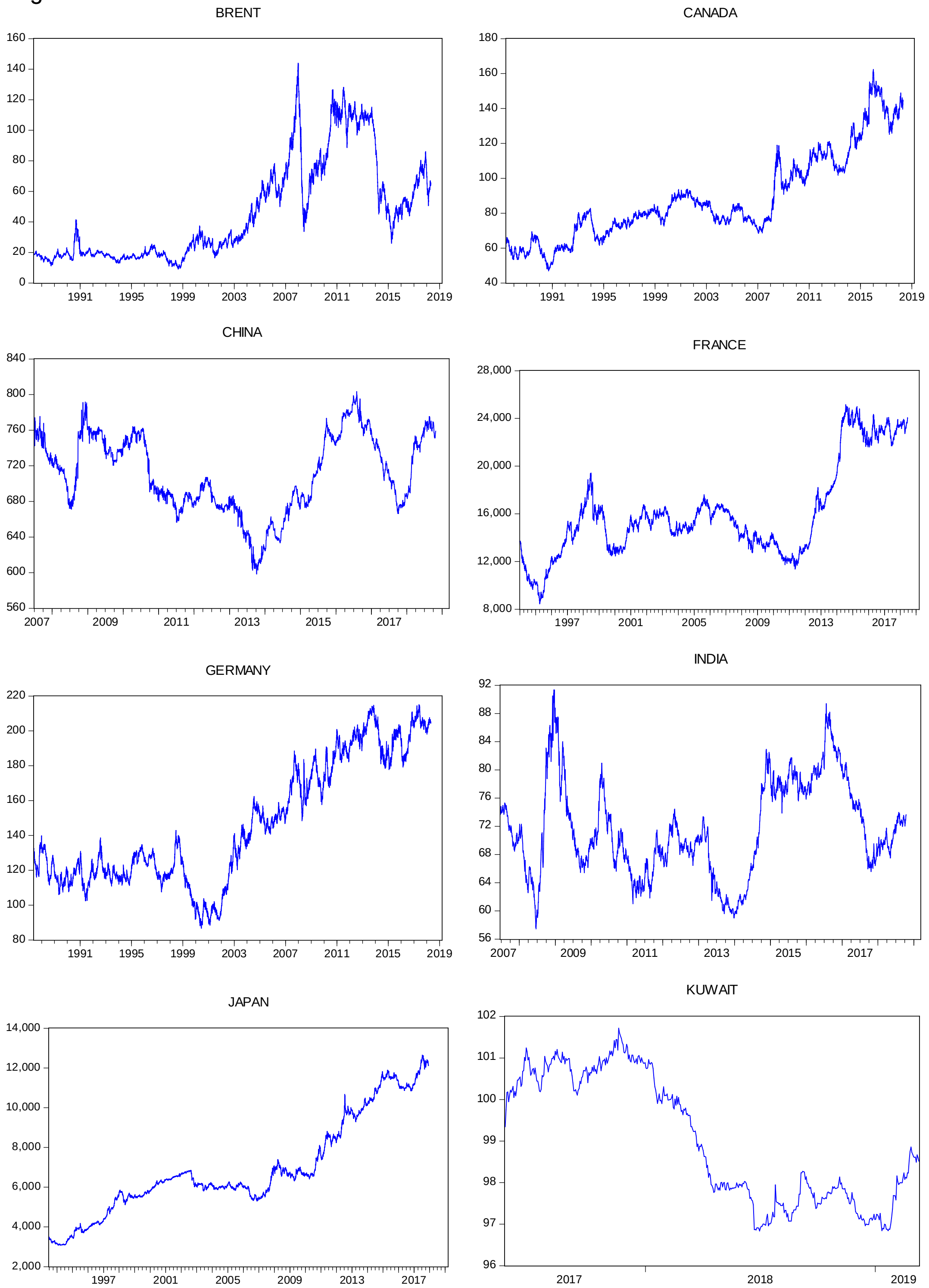
[4] We refer the interested reader to Engle (1982), Bollerslev (1986), and Bollerslev, Chou, and Korner (1992) for discussion and details of ARCH and GARCH models.

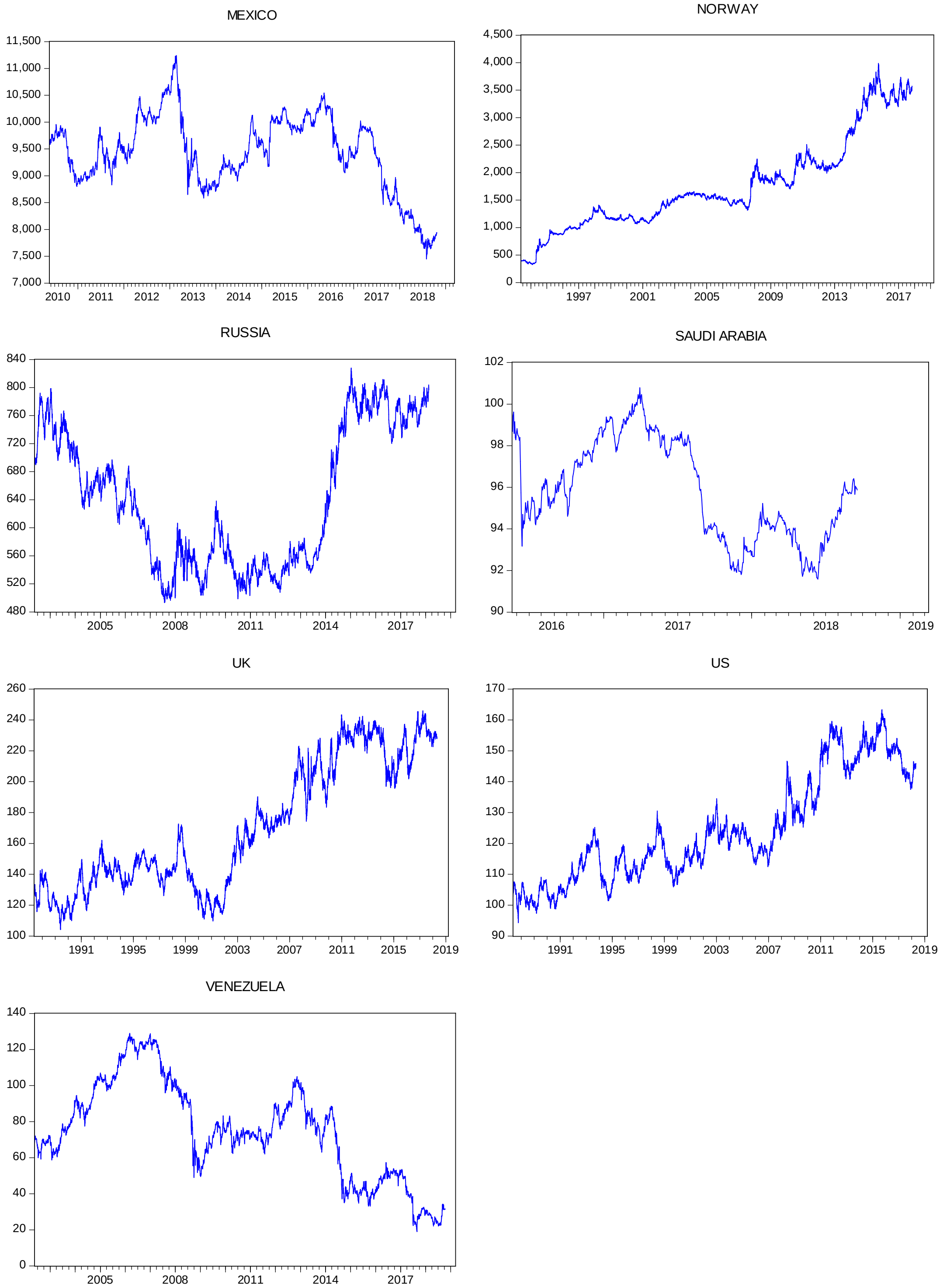
[5] In order to save space, we omit the details of the unit root tests. The interested reader is referred to the articles cited. For ZA-ADF and F-ADF tests, we use tspdlib library in GAUSS written by Saban Nazlioglu.

[6] Our result contradicts the findings of Kang et al. (2014), but these authors analyze the role of structural oil shocks on the bond market of the US, instead of actual oil price movements. We discuss the importance of identifying oil shocks in greater detail in the conclusion of the paper.

APPENDIX:

Figure A1. Data Plots




MEXICO
11,500
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8,500
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7,500
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2010 2011 2012 2013 2014 2015 2016 2017 2018
NORWAY
4,500
4,000
3,500
3,000
2,500
2,000
1,500
1,000
500
0
1997 2001 2005 2009 2013 2017
RUSSIA
840
800
760
720
680
640
600
560
520
480
2005 2008 2011 2014 2017
SAUDI ARABIA
102
100
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96
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92
90
2016 2017 2018 2019
UK
260
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140
120
100
1991 1995 1999 2003 2007 2011 2015 2019
US
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110
100
90
1991 1995 1999 2003 2007 2011 2015 2019
VENEZUELA
140
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20
0
2005 2008 2011 2014 2017

Table A1. Summary Statistics:

	Mean	Median	Maximum	Minimum	S.D.	Skewness	Kurtosis	Jarque-Bera	*p*-value	*N*	Date
BRENT	45,9921	30,38	143,95	9,1	32,8856	0,91186	2,59509	1173,93	0,00	8073	5/20/1987 to 3/11/2019
CANADA	88,3672	80,5195	162,386	46,9591	25,2494	0,84517	2,94991	961,944	0,00	8073	5/20/1987 to 3/11/2019
CHINA	711,278	709,72	803,344	598,367	43,5397	-0,21344	2,21344	98,5779	0,00	2954	6/29/2007 to 3/11/2019
FRANCE	16036,5	15224	25154,7	8446,67	3863,81	0,80461	2,82538	696,826	0,00	6383	12/31/1993 to 3/11/2019
GERMANY	146,431	133,951	215,05	86,7491	35,3401	0,37569	1,76554	702,511	0,00	8073	5/20/1987 to 3/11/2019
INDIA	71,6228	70,5032	91,3475	57,4396	6,70089	0,33891	2,49738	87,6423	0,00	2954	6/29/2007 to 3/11/2019
JAPAN	6970,66	6266,92	12646,6	3083,21	2445,85	0,6404	2,48306	507,364	0,00	6383	12/31/1993 to 3/11/2019
KUWAIT	98,9997	98,7382	101,717	96,836	1,48299	0,15955	1,48185	50,8398	0,00	507	3/14/2017 to 3/11/2019
MEXICO	9427,68	9462,1	11240	7449,88	701,309	-0,43597	3,0073	69,6655	0,00	2199	6/30/2010 to 3/11/2019
NORWAY	1758,79	1550,77	3986,76	327,449	835,244	0,79448	2,91478	673,419	0,00	6383	12/31/1993 to 3/11/2019
RUSSIA	641,213	629,159	827,822	493,272	97,3604	0,23007	1,54875	396,837	0,00	4109	12/31/2002 to 3/11/2019
SAUDI ARABIA	95,8092	95,6529	100,786	91,5862	2,38372	0,09996	1,77491	38,9699	0,00	607	10/20/2016 to 3/11/2019
UK	170,44	159,255	245,953	104,178	40,7971	0,32659	1,64884	757,616	0,00	8073	5/20/1987 to 3/11/2019
US	124,392	119,913	163,328	94,306	17,0044	0,53442	2,1027	655,113	0,00	8073	5/20/1987 to 3/11/2019
VENEZUELA	74,7479	74,417	129	18,992	26,9059	0,00147	2,28894	90,1895	0,00	4281	4/26/2002 to 3/11/2019

Notes: S.D. is standard deviation; *p*-value corresponds to the null hypothesis of normality for the Jarque-Bera test; *N* is number of observations.