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Price and Volatility Linkages between International REITs and Oil Markets[#]

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Abstract

This study analyzes price and volatility transmissions between nineteen real estate investment trusts (REITs) markets and the oil market. The REITs data represents a variety of countries at different stages of their development and the expanded analytical approach includes accounting for structural shifts as gradual processes – as opposed to strictly abrupt processes typically assumed in literature. Oil prices are found to primarily predict REITs prices in mature REITs markets, but the feedback from REITs to oil prices is weak. From the perspective of volatility, strong evidence of bidirectional transmission in majority of the markets is observed. This study further demonstrates the importance of accounting for gradual (smooth) structural shifts for price transmission analysis.

Keywords: REITs and oil markets; price and volatility spillovers; structural changes

JEL Codes: C32, Q02, R33

1. Introduction

An increasing number of studies outline the importance of real estate as part of a well-balanced investment portfolio (Hoesli et al., 2004; MacKinnon and Al Zaman, 2009; Hoesli and Reka, 2013; Bouri et al., 2018). However, the high unit value and the illiquid nature of these assets make them impractical for most investors. Real Estate Investment Trusts (REITs) address a significant portion of that issue via being securitized and exchange traded. Hence, it is not surprising that the market for these securities has grown substantially during the past decades, with a total market capitalization of US $ 1.7 trillion

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(Global REITs Market, EY Global Real Estate Report, 2018). Although the United States (US) continues to be the leader in the REITs markets (with a market capitalization of US $ 1.15 trillion), the number of countries now offering REITs as an investment vehicle has almost doubled in the last 10 years (37 countries). Since it is accessible to all investors irrespective of the portfolio size, the ability of the REITs sector to attract increased investment capital is expected. However, just like any other security, as the financial integration goes up, the importance of cross-market interactions also become increasingly significant for the investors. Furthermore, the real estate market having played a significant role during the most recent global financial crisis, and the REIT market being a good proxy for the overall real estate sector (Akinsomi et al., 2016), policy makers also have a vested interest in understanding the drivers of these markets (Gupta and Marfatia, 2018; Gupta et al., 2019).

In literature, studies have primarily analyzed the role of monetary policy and macroeconomic news shocks in affecting the REITs markets (see for example, Bredin et al. (2007, 2011), Xu and Yang (2011), Claus et al. (2014), Kroencke et al. (2016), Marfatia et al., (2017), Nyakabawo et al., (2018)). However, the variety of possible outside shock factors which interact with these markets are going up. For example, commodity markets – especially energy markets - are increasingly financialized and become less of a diversification option for investors (for example Henderson et al. 2014; Adams and Gluck 2015). In return, if an investor ignores any possible price or volatility interactions between REITs and those markets, the resulting portfolio would be inefficient. REITs shares trade like common stocks, and there is a significant amount of literature that strongly suggest an interaction between international equity markets and energy markets – oil in particular (see for example, Degiannakis et al., (2018), and Smyth and Narayan

(2018) for detailed reviews). However, the interactions between the REITs markets and the energy markets have been less explored. Some of the few studies that exist include Huang and Lee (2009) and Nazlioglu et al., (2016), which showed significant impact of oil price on the first- and second-moments of US REITs, and also indicated of possible feedbacks. These two studies highlight the interactions between the increasingly financialized oil markets (Bahloul et al., 2018) and financial markets – including REITs. In other words, movements in these markets are expected to affect each other – both in price and volatility - due to portfolio allocations of investors (Tiwari et al., 2018).

While there are a few studies in literature that analyze US REITs in light of energy markets (as mentioned above), we could not identify any studies that look at international REITs. This study attempts to extend that limited literature to an international dimension (involving 19 countries). In this regard, we analyze multiple REITs markets at different stages of development, and corresponds to the mature (US), the established (Australia, Belgium, Canada, France, Germany, Hong Kong, Japan, The Netherlands, New Zealand, Singapore and the UK), and the emerging (Ireland, Italy, Malaysia, Mexico, South Africa, Spain and Turkey) categories. Furthermore, there has been limitations in literature from an econometric perspective as well. With studies that include (high-frequency) data related to financial and commodity markets, appropriately accounting for structural shifts is of crucial importance. Typically, researchers make certain assumptions about structural shifts which include the abrupt nature, timing and the size of these shifts. The problem is that a significant portion of structural shifts are gradual in nature and are very difficult to observe visually. The inability to correctly model structural breaks would result in incorrect inferences (Kim et al., 2007; Salisu and Fasanya, 2013; Gil-Alana et al., 2016). Recognizing the challenges of analyzing data for multiple countries – which could include structural shifts (abrupt or gradual) that might be unique to each country - we expand on the already existing literature through employing some of the recently developed econometric models which are shown to be comparatively more accurate and less susceptible to data-driven bias. These models include the Fourier-based version of the Toda and Yamamoto (1995) test of price transmission (as developed by Nazlioglu et al., (2016)), and the modified Hafner and Herwartz (2006) test of volatility transmission with Fourier approximations (Pascalau et al., (2011) and Li and Enders (2018)). In addition to recognizing and accounting for abrupt structural shifts, both these models account for gradual (smooth) structural shifts in relation to movements in the first- and second moments of oil and REITs markets.

The remainder of the paper is organized as follows: Section 2 discusses the methodologies utilized in the study. Section 3 presents the data and its properties and the results. Finally, Section 4 discuss the implications of our results and concludes the paper.

2. Econometric Methodology

2.1. Testing for price transmission with structural changes

In order to test for price transmission, we start with the basic "causality" model developed by Granger (1969). Granger 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 k endogenous variables, α is a vector of intercept terms, β are coefficient matrices and ε_t are white-noise residuals. Here, y_t consists of oil prices and international REITs.

y_t are assumed not to have any structural shifts and the intercept terms α are constant over time. The null of non-transmission can be rejected even though there is no transmission when data generating process has structural shifts (Ventosa-Santaularia and Vera-Valdés, 2008). Monte Carlo simulations carried out by Enders and Jones (2016) 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. Furthermore, 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 (Enders and Jones, 2016). These findings not only indicate the importance of accounting for any structural shifts but also necessitate a careful treatment of how breaks are captured.

The traditional approach for modelling breaks is to use dummy variables in which shifts are assumed to be abrupt (for example, Perron, 1989; Zivot and Adrews, 1992; Lee and Strazicich, 2003). However, a significant portion of structural changes are gradual in nature. In order to partly remedy this issue, smooth transition approach was developed (inter alia, Leybourne at al., 1998; Kapetanios et al., 2003). The core problem with both of these approaches is that they require the knowledge on break dates, as well as the number and functional forms of the breaks. To deal with these problems, Fourier approximation which is based on a variant of Flexible Fourier Form by Gallant (1981) is proposed for capturing structural shifts (see, Becker et al., 2006; Enders and Lee, 2012a and 2012b; Rodrigues and Taylor, 2012). The Fourier approximation does not require a prior knowledge on the number, dates, and form of breaks and captures structural shifts as a gradual/smooth process by using a small number of low-frequency components.

In a VAR specification, controlling for structural breaks and determining the original source of breaks is difficult because a break in one variable potentially causes shifts in other variables (Ng and Vogelsang, 2002; Enders and Jones, 2016). To overcome this difficulty and to further 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 Fourier approximation in recent papers.

Enders and Jones (2016) augments VAR(p) model with Fourier approximation and then impose restrictions for the Granger's model. 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 by using level form of variables where d is the maximum integration order of variables. 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 price transmission analysis and they call this process as the Fourier TY approach to price transmission.

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 with an unknown date, number and form of breaks, the Fourier approximation is defined by:

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

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 – which can 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, α(t) is defined as

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

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

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

In the Toda-Yamamoto framework, the null hypothesis of Granger non-causality is based on zero restriction on first p parameters ($H_o\colon \beta_1 = \cdots = \beta_p = 0$) of the Kth element of y_t. Wald statistic 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 Mantolos, 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)[1]. It is worthwhile to emphasize that the asymptotic and bootstrap distributions show similar results.

In order to establish the robustness of the approaches, Gormus et al. (2018) and Nazlioglu et al. (2019) conduct simulation analyses in order to compare the size and power properties of the Fourier TY approach with those of the TY test. The Monte Carlo simulations show that as the number of observations grows, while the difference between asymptotic and bootstrap distribution disappears, the importance of considering the structural shifts in causality analysis becomes more obvious. In large samples, the TY test has severe size distortion problems, but the Fourier TY test seems to have correct size.

The specification problem in both equation (4) and (6) requires determining the number of Fourier frequency components and lag lengths (p). A common approach to determine the optimal number of lags in a causality analysis is to benefit from Akaike or Schwarz information criterion. This approach also can be used for determining the number of Fourier frequency and lag lengths, together. Specifically, we first set he number of Fourier frequency to k^{max} and number of lags to p^{max} and pare down one-by-one up

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

to $k = 1$ and $p = 1$. Then we select the optimal k and p combination which minimizes information criterion.

2.2. *Testing for volatility transmission with structural changes*

We also conduct a volatility transmission analysis in order identify the existence and the direction of possible volatility interactions between the REITs and oil markets. Some of the more common volatility transmission tests (Cheung and Ng, 1996; Hong, 2001) utilize univariate GARCH[2] models and cross-correlation functions of the standard residuals. This approach suffers from significant oversizing effects especially in the scenarios with leptokurtic volatility processes and necessitate a selection of lead and lag orders (Hafner and Herwartz, 2006). To combat this issue, Hafner and Herwartz (HH) (2006) developed Lagrange multiplier (LM) based volatility transmission approach which does not suffer from those issues and has an increasing power with larger sample size. Especially when international markets are analyzed, the HH approach provides more accurate results compared to the Cheung and Ng (1996) and Hong (2001) methods (Gormus, 2016).

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

$$y_{it} = x_{it}' c_i + \varepsilon_{it} \tag{7}$$

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

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" - which is the one-period ahead forecast variance based on past information. $\omega_i > 0, \alpha_i, \beta_i \geq 0$ is

[2] We do not detail the ARCH and GARCH processes in order to save space. Interested readers can refer to Engle (1982), Bollerslev (1986), and Bollerslev et al. (1992) for explanations of these models.

established in order to ensure non-negativity of the conditional variance. In addition, $\alpha_i + \beta_i < 1$ is established to ensure that the variance is finite - which means that the process is stable. Everything we assume for the series i hold for the series j as well.

After the estimation of the GARCH (1,1) models for the series i and j, HH define:

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

where ξ_{it} is the standardized residuals of the series i. ε_{jt}^2 and σ_{jt}^2 are the squared disturbance term and the volatility for the series j respectively. The null hypothesis $H_0\colon \pi = 0$ of no-volatility transmission is tested against the alternative hypothesis $H_0\colon \pi \neq 0$ 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:

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

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 transmission test defined (10) is depended 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 be also affected from the structural changes (see among others, Starica and Granger, 2005; Diebold and Inoue, 2013, Mikosh and Starica, 2004). 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 Pascalou et al. (2017) it is shown that the 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 the form of the variance of shift. Moreover, a Fourier approximation may be more suitable for financial data since several breaks may occur in a long financial series where it might be difficult to identify (Li and Enders, 2017).

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

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

where $\omega_i(t)$ now depend on T 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

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

Since our aim is to test for the volatility transmission, the test statistic in equation (9) can be obtained based on the conditional variance equation in (12) and where other estimations are kept unchanged. Note that we label the volatility transmission 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 Pascalou et al. (2011), one can benefit from Akaike or Schwarz information criterion. We first set he number of Fourier frequency to k^{max} and then we select the optima frequency number which minimizes information criterion.

3. Data and Empirical Results

Our analysis utilizes daily observations of REITs indices of nineteen countries (Australia, Belgium, Canada, France, Germany, Hong Kong, Ireland, Italy, Japan, Malaysia, Mexico, The Netherlands, New Zealand, Singapore, South Africa, Spain, Turkey, the UK, and the US), and the oil price. The REITs data is sourced from the DataStream database of Thomson Reuters, with the real estate data corresponding to the S&P REITs indices for each country. As for the oil prices, we use the daily price of Brent Crude as it 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. To avoid the impact of exchange rate fluctuations, both the REITs and oil price data are in US dollar terms. A graphically plotted version of the data can be seen in Figure A1 and summarized in Table A1 in the Appendix section. Expectedly the time span of REITs data varies across countries (as detailed in Table A1), with Ireland having the shortest sample (12/24/2013-03/11/2019), and the US covering the longest period (07/31/1989-09/13/2018). Besides the econometric “non-normality” of the oil and REITs prices, what is important to observe is that these variables have gone through multiple regime changes in a consistent manner over the sample of data considered. This fact further supports our decision of analyzing price and volatility transmissions using models that incorporate a variety of structural breaks.

In order to proceed with The TY approach to Granger-type price transmission analysis, one needs to determine the maximum integration number *(d)* of unit root of the variables. To accomplish this, we conduct the augmented Dickey & Fuller (ADF) test of Dickey and Fuller (1979), 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)[3]. Table 1 reports the results from these unit root tests. While the unit root tests cannot reject the null hypothesis of unit root for the level of oil prices at the 1 percent level of significance, they strongly support the evidence on stationarity for the first difference of the oil prices. Similar findings are also observed for the REITs series. Accordingly, the maximum integration of the variables (d) is equal to 1 to estimate VAR(p + d) models.

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

	Level						First Difference					
	ADF		ZA-ADF		F-ADF		ADF		ZA-ADF		F-ADF	
Oil prices	-1.453		-3.670		-3.571	*	-83.330	***	-83.365	***	-83.329	***
REITs												
Canada	-1.448		-2.865		-1.814		-33.362	***	-33.595	***	-33.476	***
Australia	-1.869		-4.804	*	-2.612		-32.705	***	-33.079	***	-32.788	***
France	-3.173	**	-3.401		-3.255		-59.935	***	-60.062	***	-59.972	***
Germany	-2.694	*	-3.478		-2.963		-21.061	***	-21.561	***	-21.133	***
Hong Kong	-0.142		-3.499		-0.334		-63.480	***	-63.540	***	-63.506	***
Japan	-2.219		-3.773		-2.255		-64.470	***	-64.475	***	-48.180	***
Netherlands	-1.644		-3.501		-2.726		-66.947	***	-67.014	***	-66.974	***
New Zealand	-1.369		-3.684		-1.925		-73.770	***	-73.848	***	-73.840	***

[3] In order to save space, we omit the details of unit root tests. An interested reader is referred to the cited articles. For ZA-ADF and F-ADF tests, we use tspdlib library in GAUSS, which is written by the first author of this paper.

Singapore	-2.935	**	-3.185		-3.252		-41.817	***	-62.700	***	-41.901	***
UK	-2.754	*	-4.140		-2.682		-51.799	***	-52.222	***	-51.870	***
USA	-0.981		-4.155		-1.011		-100.335	***	-100.419	***	-100.368	***
Belgium	-1.740		-3.727		-2.664		-72.562	***	-72.585	***	-72.596	***
Ireland	-3.049		-4.922	**	-3.645	*	-38.391	***	-38.498	***	-38.425	***
Italy	-3.554	***	-4.869	**	-3.695	*	-27.533	***	-27.607	***	-27.645	***
Malaysia	-1.928		-3.321		-2.534		-59.969	***	-60.051	***	-60.016	***
Mexico	-0.876		-4.480		-2.075		-32.951	***	-33.123	***	-32.989	***
South Africa	-3.191	**	-4.049		-3.523	*	-52.376	***	-52.480	***	-52.376	***
Spain	-1.634		-4.749	*	-2.260		-45.450	***	-45.539	***	-45.464	***
Turkey	-0.963		-3.477		-1.653		-53.090	***	-53.272	***	-53.110	***

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 5. The optimal frequency and lags were determined by Schwarz information criterion for F-ADF by setting maximum number of lags to 5 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 10, 5 and 1 percent, respectively.

Table 2 reports the results of the price transmission analysis. In order to determine the optimal lags in the TY test and the optimal Fourier frequency and lags in the Fourier TY approach, we use information criterion by setting the maximum number of frequency (k/n) to 3 and the maximum number of lags (p) to 5. The optimal frequency and lags are determined by minimizing Akaike information criterion.

The results from the TY test (see panel A of Table 2) show that the null hypothesis of no-price transmission from oil prices to REITs is rejected in nine countries (Australia, Hong Kong, Japan, New Zealand, Singapore, UK, Ireland, Italy, and Malaysia) with at least at the 10 percent significance level according to the bootstrap distribution.[4] This results imply that there is an information transmission, and hence a predictive power from oil prices to REITs in these countries. The TY test is not able to take into account the role of possible structural shifts in a VAR model. It is a well-known fact that the oil prices are characterized by a different trend and volatility dynamics after the 2007/2008

[4] Note that the asymptotic distribution does not support price transmission for the UK.

financial crisis. In order take into account the role of such structural shifts, one needs to know the date, number, and form of shifts which is challenge in practice for an applied research. A Fourier approximation is able to efficiently solve this problem because it does not require the knowledge of the date, number, and functional form of any break. The results from the Fourier TY causality analysis in panel B of Table 2 are in general similar to those of the TY approach with a few important exceptions. Specifically, the Fourier TY method does not provide evidence on the existence of a price transmission from oil prices to REITs in Australia and UK where the traditional TY approach showed there was.

As regards to a price transmission from REITs to oil prices, the TY test indicates that the null hypothesis of no-transmission is rejected for five countries (namely, Canada, Germany, Japan, USA, and Spain). When the structural shifts are taken into account in the estimations, even though the transmission results hold for Canada, Germany, USA, and Spain, it disappears in the case of Japan. The Fourier TY approach further shows a transmission from REITs to oil prices for Mexico where the traditional TY method does not.

In essence, the price transmission between REITs and oil markets is primarily concentrated in established markets,[5] though some evidence is detected for emerging REITs markets such as Ireland, Italy, Malaysia and Spain.

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 ≠>REITs	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]
Canada	5	1.812	0.874	0.872	5	3	1.882	0.865	0.880	5	3	1.854	0.869	0.846

[5] Unlike Nazlioglu et al., (2016), we could not detect bi-directional price transmission between oil and REITs for the USA. But realizing that Nazlioglu et al., (2016) had used the West Texas Intermediate (WTI) oil price instead of the Brent crude. We hence re-conduct the causality test using WTI oil prices, and just as in Nazlioglu et al., (2016), are able to detect bi-directional spillovers between the oil and real estate markets. Complete details of these results have been presented in Table A2 in the Appendix of the paper.

Australia	5	9.368	0.095	0.099	4	2	6.995	0.136	0.154	4	3	6.864	0.143	0.145
France	1	0.901	0.342	0.322	1	2	0.890	0.346	0.339	1	3	0.885	0.347	0.301
Germany	5	6.507	0.260	0.237	5	1	6.504	0.260	0.266	5	3	6.490	0.261	0.261
Hong Kong	1	14.384	0.000	0.000	2	1	15.736	0.000	0.000	2	2	15.065	0.001	0.000
Japan	5	35.669	0.000	0.000	3	2	34.690	0.000	0.000	3	3	34.908	0.000	0.000
Netherlands	1	0.338	0.561	0.555	2	1	0.868	0.648	0.644	2	2	0.961	0.618	0.644
New Zealand	1	3.423	0.064	0.055	2	2	5.478	0.065	0.063	2	2	5.369	0.068	0.086
Singapore	2	18.744	0.000	0.000	3	2	19.660	0.000	0.000	3	2	18.745	0.000	0.000
UK	1	2.654	0.103	0.096	2	1	3.115	0.211	0.218	2	2	3.001	0.223	0.216
USA	1	1.548	0.213	0.199	2	1	3.073	0.215	0.204	2	2	3.078	0.215	0.234
Belgium	1	0.071	0.790	0.792	2	2	0.165	0.921	0.926	2	3	0.169	0.919	0.932
Ireland	2	7.300	0.026	0.027	2	2	8.229	0.016	0.020	2	2	7.560	0.023	0.028
Italy	4	12.557	0.014	0.021	5	1	12.402	0.030	0.036	5	3	12.014	0.035	0.039
Malaysia	2	43.878	0.000	0.000	3	1	44.681	0.000	0.000	3	2	43.305	0.000	0.000
Mexico	4	5.068	0.280	0.265	2	1	0.672	0.714	0.730	2	2	0.641	0.726	0.737
South Africa	1	2.106	0.147	0.152	2	1	2.152	0.341	0.348	2	2	2.351	0.309	0.314
Spain	2	2.531	0.282	0.261	3	1	2.567	0.463	0.456	3	3	1.919	0.589	0.582
Turkey	1	0.717	0.397	0.405	2	1	2.699	0.259	0.236	2	2	2.677	0.262	0.274
REITs ≠>Oil														
Canada	5	24.385	0.000	0.000	5	3	24.025	0.000	0.002	5	3	24.395	0.000	0.000
Australia	5	4.452	0.486	0.486	4	2	3.157	0.532	0.526	4	3	2.914	0.572	0.578
France	1	0.005	0.945	0.953	1	2	0.002	0.961	0.970	1	3	0.000	0.983	0.988
Germany	5	13.807	0.017	0.023	5	1	14.579	0.012	0.017	5	3	15.188	0.010	0.013
Hong Kong	1	1.573	0.210	0.214	2	1	1.885	0.390	0.392	2	2	1.824	0.402	0.381
Japan	5	26.263	0.000	0.000	3	2	1.260	0.739	0.743	3	3	1.346	0.718	0.715
Netherlands	1	0.030	0.861	0.860	2	1	0.327	0.849	0.850	2	2	0.396	0.820	0.833
New Zealand	1	0.971	0.324	0.319	2	2	1.409	0.494	0.485	2	2	1.413	0.493	0.488
Singapore	2	3.238	0.198	0.183	3	2	4.919	0.178	0.181	3	2	4.860	0.182	0.190
UK	1	0.198	0.656	0.669	2	1	0.772	0.680	0.679	2	2	0.873	0.646	0.651
USA	1	30.433	0.000	0.000	2	1	31.628	0.000	0.000	2	2	31.682	0.000	0.000
Belgium	1	1.558	0.212	0.213	2	2	4.403	0.111	0.119	2	3	4.370	0.112	0.111
Ireland	2	0.965	0.617	0.609	2	2	0.903	0.637	0.619	2	2	0.945	0.624	0.625
Italy	4	4.552	0.336	0.354	5	1	4.397	0.494	0.481	5	3	4.205	0.520	0.542
Malaysia	2	0.068	0.967	0.967	3	1	0.535	0.911	0.923	3	2	0.279	0.964	0.968
Mexico	4	6.354	0.174	0.157	2	1	5.668	0.059	0.052	2	2	5.580	0.061	0.073
South Africa	1	2.224	0.136	0.131	2	1	2.617	0.270	0.260	2	2	2.296	0.317	0.297
Spain	2	7.465	0.024	0.026	3	1	8.499	0.037	0.046	3	3	7.929	0.047	0.056
Turkey	1	1.221	0.269	0.265	2	1	1.422	0.491	0.493	2	2	1.422	0.491	0.484

Notes: ≠> signifies the null hypothesis of no-transmission. TY: traditional 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 5, 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 REITs variable.

When we consider information transmission between markets, in addition to analyzing the data at level (mean price transmission), we also look at the risk transfer dimension (volatility transmission). Due to the econometric nature of the price transmission analysis, the identified interactions can be interpreted as a long-run phenomenon. However, volatility transmission analysis is a short-term model. This analysis is especially important because not only hedging strategies require knowledge on volatility spillovers between asset classes, identification of risk interactions is even more relevant in the short-run since risk perceptions can change rapidly (Nazlioglu et al., 2016).

The results from the volatility transmission LM test by Hafner and Herwartz (2006) are reported in Table 3. Note that λ_{LM} is the volatility transmission test based on the variance equation (8) which does not account for structural breaks, and $F\lambda_{LM}$ is the volatility transmission Fourier LM test based on the variance equation (12) which accounts for structural breaks in the conditional variance of the REITs and oil returns.

The λ_{LM} test indicates test the null hypothesis of no volatility transmission from oil prices to REITs is rejected in thirteen cases (at least at the 10 percent level of significance), but cannot be rejected for six cases (New Zealand, Ireland, Italy, Malaysia, Mexico, and Spain). These results are also supported by the $F\lambda_{LM}$, except for the case of Malaysia, for which significant volatility transmission from the oil to REITs is evidenced. In relation to the volatility transmission from REITs to oil prices, the λ_{LM} test shows that the null hypothesis of no transmission cannot be rejected only for three cases – UK, Ireland, and Malaysia. In other words, volatility in REITs market impacts risk in oil in sixteen countries (at least at the 10 percent level of significance). This evidence continues to hold even if we control for smooth shifts in the volatility process, since the $F\lambda_{LM}$ test reaches to the same conclusions. These findings therefore imply that there is a strong evidence of risk transmission between oil and REITs markets, and the interactions appear to work in both directions, as also detected by Nazlioglu et al., (2016) for the case of the USA. In other words, there exists a risk transmission feedback between oil markets and a significant portion of the international REITs we tested.

As we interpret the results of both price and volatility transmission tests together, we observe a stronger evidence of risk transmission between the REITs and oil markets (irrespective of the level of evolution of the real estate sector) compared to price interactions.

Table 3: Results from volatility spillover tests

	Oil ≠> REITs					REITs ≠> Oil				
	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value	λ_{LM}	p-value	n	$F\lambda_{LM}$	p-value
Canada	14.469	0.000	3	16.254	0.000	15.891	0.000	3	20.477	0.000
Australia	12.791	0.000	3	13.110	0.000	13.495	0.000	3	16.247	0.000
France	18.658	0.000	2	21.067	0.000	6.411	0.040	1	6.959	0.030
Germany	4.795	0.090	1	5.673	0.058	8.656	0.013	3	18.483	0.000
Hong Kong	13.019	0.001	1	13.107	0.001	14.571	0.000	2	16.862	0.000
Japan	10.425	0.005	3	12.454	0.001	11.788	0.002	3	14.328	0.000
Netherlands	14.324	0.000	3	14.361	0.000	8.290	0.015	3	10.233	0.005
New Zealand	2.369	0.305	3	1.506	0.470	15.817	0.000	3	15.118	0.000
Singapore	8.678	0.013	2	14.577	0.006	12.603	0.001	1	15.686	0.000
UK	4.660	0.097	3	5.611	0.060	3.085	0.213	3	3.798	0.149
USA	9.807	0.007	1	13.997	0.000	6.820	0.033	3	10.372	0.005
Belgium	10.492	0.005	3	13.902	0.000	13.222	0.001	3	15.410	0.000
Ireland	2.676	0.262	1	2.137	0.343	1.673	0.433	3	2.930	0.231
Italy	1.065	0.587	1	3.739	0.154	9.912	0.007	3	14.082	0.000
Malaysia	1.366	0.504	3	11.667	0.002	4.146	0.125	3	3.441	0.178
Mexico	1.646	0.438	3	1.860	0.394	10.091	0.006	3	10.316	0.005
South Africa	12.329	0.002	3	16.224	0.000	5.994	0.064	3	5.526	0.063
Spain	0.240	0.886	3	3.194	0.202	6.982	0.030	3	4.164	0.099
Turkey	11.412	0.003	3	7.453	0.024	7.064	0.029	3	7.949	0.018

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 REITs and oil prices.

4. Discussion and Conclusion

The rapid growth of REITs in recent years has made it an important portfolio option. Furthermore, the role of the real estate sector in driving the recent financial crisis is also well-accepted. Just like any other investment vehicle, as the REITs market grows in size and impact, it becomes important for investors and policy makers to understand the outside drivers that impact the dynamics of that asset group. As commodity markets become more financialized (Henderson et al. 2014; Adams and Gluck 2015), they tend to further interact with other financial markets - changing their portfolio and economic implications. Although energy markets are one piece of the overall commodity markets, numerous studies have suggested their strong impact – oil in particular – over the financial markets. Given these studies' findings and the growing impact of the REITs markets, it is important to evaluate the price and volatility sensitivity of REITs to fluctuations in the oil market.

In this paper, we evaluate nineteen international REITs markets which are at different stages of development. Furthermore, we try to verify the robustness of any suggested interaction with newly developed econometric techniques which minimize possible data and researcher-based biases. In the process, we aim to add to the limited literature which only concentrate on US REITs.

The results of our study suggest strong evidence of bidirectional volatility transmission between the REITs markets and the oil market, irrespective of the REIT market's state of evolution. In comparison, price-level transmissions are weak and primarily restricted to established and matured markets. For both the volatility and price transmission studies, accounting for gradual structural shifts suggested different results with some countries while confirmed the results with others.

These findings have important implications for academics, investors and policymakers. As far as academic researchers are concerned, we show that to derive appropriate statistical inferences when analyzing interactions between REITs and oil markets, it is of paramount importance that gradual structural changes are incorporated into the modelling frameworks. The lack of this statistical control could easily yield incorrect inferences - particularly for the first-moment. From the perspective of REITs investors, understanding the interactions between these markets can improve both short and long-term portfolio strategies – especially in the established markets as our results suggest. In particular, volatility transmission results show decreasing diversification capacity of oil markets with portfolios containing REITs. Finally, the negative implications of a shock to either of the markets is likely to be prolonged due to the bi-directional feedback effect, and in turn, this could have long-term economical outcomes (Nguyen-Thanh, 2018; van Eyden et al., 2019). Hence, policymakers need to give increased attention to the interaction between these markets as even short-term shocks can be detrimental for the economy in the long-run as history has shown.

While our study suggests interesting interactions between these markets, the specific shock drivers are not analyzed. For example, literature suggests shocks to different components of the oil market, such as supply, demand and geographical drivers, can have different impacts (Kilian, 2009; Kilian and Murphy, 2014). It would be interesting to analyze the impact of those various oil shocks, rather than aggregate oil price, on international REITs markets as part of future research.

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APPENDIX:

Table A1. Summary Statistics

Country	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	*p*-value	Obs.
Australia	147.3570	138.2050	324.1300	49.1500	47.7130	1.3799	4.9134	2386.183	0.0000	5078 (11/09/1998-13/09/2018)
Belgium	124.0825	123.9450	195.3400	64.0700	26.7265	0.0426	2.8271	7.859	0.0197	5078 (11/9/1998 - 13/09/2018)
Brent	47.8614	33.5800	143.9500	9.1000	33.2263	0.8423	2.4584	964.188	0.0000	7390 (31/07/1989-13/09/2018)
Canada	225.9882	246.7300	380.6900	88.5800	82.7368	-0.1702	1.6704	398.568	0.0000	5078 (11/9/1998-13/09/2018)
France	278.0702	300.0100	424.1400	99.9100	71.0661	-0.7449	2.6221	373.320	0.0000	3793 (30/09/2003-13/09/2018
Germany	72.4603	73.9300	118.6200	17.5200	14.3852	-1.0132	5.2027	1027.156	0.0000	2752 (23/10/2007-13/09/2018)
Hong Kong	205.4961	172.9900	442.5000	74.6500	93.8902	0.6859	2.3087	354.000	0.0000	3600 (30/06/2004-13/09/2018)
Ireland	87.0077	87.5450	103.9400	66.6000	6.7290	-0.4323	2.8905	38.095	0.0000	1204 (24/12/2013-13/09/2018)
Italy	50.2774	48.4500	104.9300	25.8700	12.9934	1.1803	5.3852	1220.434	0.0000	2601 (2/6/2008-13/09/2018)
Japan	174.1351	182.7650	289.9300	78.3000	41.1975	-0.2521	2.7495	56.869	0.0000	4306 (28/09/2001-13/09/2018)
Malaysia	120.6988	121.6300	178.0600	80.0200	18.2406	0.4565	3.3674	120.930	0.0000	2997

										(31/10/2006- 13/09/2018)
Mexico	110.3083	106.0500	172.5000	65.0200	27.6386	0.2084	1.7544	109.196	0.0000	1519 (25/09/2012- 13/09/2018)
Netherlands	144.0335	133.8500	298.4000	71.6000	50.5057	0.8496	3.1611	616.320	0.0000	5078 (11/09/1998- 13/09/2018)
New Zealand	140.0638	149.3700	223.1300	62.5300	37.9731	-0.3360	2.0657	280.213	0.0000	5078 (11/09/1998- 13/09/2018)
South Africa	114.1545	114.2600	158.7600	53.0900	17.2292	-0.3881	3.0728	85.587	0.0000	3379 (09/05/2005- 13/09/2018)
Singapore	269.0508	287.0800	401.6100	100.0000	71.2530	-0.6768	2.5952	320.983	0.0000	3859 (30/06/2003- 13/09/2018)
Spain	117.4411	119.1300	157.3200	90.1900	12.3405	0.5396	4.2022	252.950	0.0000	2326 (06/07/2009- 13/09/2018)
Turkey	43.7584	40.9600	102.6200	7.7400	17.9339	0.5863	2.7430	190.319	0.0000	3170 (28/02/2006- 13/09/2018)
United Kingdom	42.4712	38.3800	108.4600	13.9300	16.5967	1.7991	6.4709	3056.644	0.0000	2935 (31/01/2007- 13/09/2018)
United States	181.8762	150.0300	349.0300	74.2300	76.0220	0.4916	1.7850	752.216	0.0000	7390 (31/07/1989- 13/09/2018)

Table A2: Results from causality analysis for USA with WTI prices

	WTI ≠> REITs			REITs ≠>WTI		
	TY	FTY(k)	FTY(n)	TY	FTY(k)	FTY(n)
Wald statistic	15.993	10.602	10.574	9.901	8.997	9.019
p-value[a]	0.007	0.031	0.032	0.078	0.061	0.061
p-value[b]	0.009	0.019	0.027	0.082	0.067	0.062
Frequency	-	1	2	-	1	2
Lags (p)	5	4	4	5	4	4

Notes: See Table 2.

Figure A1. Data Plot