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Tracing the Genesis of Contagion in the Oil-Finance Nexus

Abstract

A new procedure to trace the sources of contagion in the oil-finance nexus is proposed. We do this by consolidating veteran rules derived from the empirical oil literature to filter oil supply, global demand, and oil demand shocks into discrete typical and extreme conditions. We show how these identified conditions can then be used to determine the stable and extreme sub-samples for comparing market relationships in the construction of contagion tests. Our original approach is useful for systemic risk assessment in countries vulnerable to oil market shocks. We illustrate the procedure using the dynamic relationships between the international crude oil market and the financial markets of a small oil-exporter.

JEL-Codes: C320, E370, Q430.

Keywords: contagion, correlation, exchange rate, oil, stock market.

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1. Introduction

Closely linked markets are more vulnerable as negative shocks are able to propagate and proliferate more relative to weakly associated markets (Kritzman et al., 2011). Meaningful market linkages can be either intermittent or consistent. Contagion characterises a marked increase in cross-market linkages after a shock to one country, whereas interdependence refers to a maintained co-movement under pre- and post-shock conditions (Forbes and Rigobon, 2002). A concept pertinent to countries whose financial and macroeconomic fate are tied to hard commodity prices is *energy* contagion, which refers to the deepening of energy-finance linkages under crisis periods in energy markets (Mahadeo et al., 2019). In this paper, we provide a novel approach for tracing the potential sources of oil market shocks for contagion testing, as there is convincing empirical evidence suggesting that different types of oil market shocks have different consequences for financial markets (see for example, Kilian and Park (2009); Filis et al. (2011); Broadstock and Filis (2014); Güntner (2014); Kang et al. (2015b); Basher et al. (2018)). Our original procedure makes the following important contributions to the oil-finance literature.

First, we propose a new rule-based specification to classify oil market shocks into discrete typical and extreme shock episodes. The motivation for our censoring measure comes from combining two concepts in the empirical oil literature. One is that only the most profound oil price movements over the preceding year are consequential to the economy (Hamilton, 1996). Another is that only oil price deviations outside a normal band are considered pertinent (Akram, 2004). We then apply these rules to structural oil supply, global demand, and oil-specific demand innovations estimated from a Kilian (2009) type of international oil market structural vector autoregression (SVAR). Second, we show these typical and extreme conditions can be used to design oil market contagion tests to trace the genesis of contagion. Such tests compare how correlations in the oil-finance nexus might change during periods of typical and extreme oil supply, global demand, and oil demand shocks.

In a seminal paper, Filis et al. (2011) use a dynamic conditional correlation (DCC) model and examine how the oil-stock market correlations for oil-exporting and importing countries change during momentous episodes in the crude oil market collated from Kilian (2009) and Hamilton (2009a,b). Moreover, Broadstock and Filis (2014) are the first to explicitly estimate the time-varying relationship between the various structural oil market shocks suggested in Kilian (2009) and stock market returns. The economic significance of the oil-stock market relationship is well-established in the energy-finance literature. For instance, the oil-stock market association explains the impact oil price changes have on investment and is a high frequency data proxy for the oil-macroeconomy connection. In the case of oil-exporting economies, the empirical evidence suggests that the sign and magnitude of responses to oil market shocks are country-specific (Basher et al., 2018).

We build on the work of Filis et al. (2011) and estimate a DCC model to acquire the time varying oil-stock market relationship, and augment the model to include the oil-exchange rate and the exchange rate-stock market relationships. The importance of the oil-exchange rate relationship is also well-known. In particular, the oil-exchange rate linkage has implications for the international competitiveness of an oil-exporter via the wealth effects (see, *inter* *alia*, Bjørnland (2009); Basher et al. (2016)) and Dutch disease (see Corden (1984, 2012)) channels. Both such channels detail the mechanisms by which oil price increases lead to exchange rate appreciations for oil-exporters, making their exports (imports) more expensive (cheaper). Our modification to the model put forward in Filis et al. (2011) is important because little is still known about the dynamic relationship between oil prices, exchange rates, and emerging market stock prices (Basher et al., 2012).

Another contribution of our work is that we are the first to explicitly consider how the exchange rate-stock market relationship evolves under alternative global crude oil market conditions. The trade flow-oriented model characterises the influence exchange rates can have on the stock market, while the portfolio balance approach establishes that stock prices affect exchange rates (see Chkili and Nguyen (2014) and references therein), and the correlation between these two variables can be either positive or negative (Tang and Yao, 2018).

We also extend the idea to qualitatively tie correlations to oil market episodes in the literature, suggested in Filis et al. (2011), by using our discrete typical and extreme oil market conditions to test for oil market contagion. Additionally, our new procedure is complemented by comparing whether financial relationships change under booming and slumping oil price phases, as testing the economic effects of crude oil price increases and decreases is a long-standing practice in the applied literature (see for example, Mork (1989) and Hamilton (1996, 2003)). For this purpose, we follow Mahadeo et al. (2019) and decompose crude oil prices into bull and bear states using a semi-parametric rule-based algorithm.

The relative influence of oil market shocks are based on the degree of importance of oil to national economy (Wang et al., 2013). Our new procedure is illustrated using the dynamic relationships between the international crude oil market and financial variables in Trinidad and Tobago. The main advantage of focusing on Trinidad and Tobago is that this is a small petroleum intensive economy, which makes it an appropriate study site to examine how the connections between oil and financial markets change in light of developments in international oil market. Over the period of 1995 to 2016 the petroleum sector in Trinidad and Tobago contributed, on average, to 36% of GDP[1]. Empirical evidence suggests that small open economies are more vulnerable to oil price changes compared to larger ones (Abeysinghe, 2001), and small resource-rich economies have a documented legacy of underachievement relative to both their larger counterparts and small resource-poor countries (see Auty (2017) and references therein).

Our key results convey that both the inverse crude oil-real effective exchange rate and the real effective exchange rate-stock market relationships increase during periods of extreme global demand shocks. Further, the inverse crude oil-real effective exchange rate relationship increases under episodes of oil demand shocks. Yet, such results appear to be associated with the Global Financial Crisis[2] (GFC) spillover effects. We also find that slumping oil markets,

[1]Calculated using data obtained from the Central Bank of Trinidad and Tobago available at https://www.central-bank.org.tt/statistics/data-centre/output-gdp-2000 and retrieved in October 2019.

[2]The National Bureau of Economic Research defines the timespan of the Great Recession in the US from December 2007 to June 2009. See www.nber.org/cycles. We use this dating for coverage of the main adverse events associated with GFC crisis in international markets, which incorporates the infamous collapse of Lehman Brothers in September 2008.

as indicated by bearish oil price phases, are a source of contagion in the exchange rate-stock market relationship and this result is robust to the GFC. Although we find statistically significant differences in the oil-stock returns correlation during bearish oil market phases, which are robust to the GFC, this inherently weak relationship only provides marginal support for oil market contagion. In totality, our findings for Trinidad and Tobago are consistent with those documented in Mahadeo et al. (2019).

The rest of this paper is organised as follows: Section 2 details the methodology and data we utilise; an application of our procedure to the international crude oil market and the financial markets of a small petroleum economy is presented in Section 3; and we conclude in Section 4.

2. Methods and data

Our empirical procedures can be outlined in two steps. In step one, we estimate global oil market shocks with a recursive SVAR model and, using rule-based specifications, we classify these shocks into relatively typical and extreme episodes. We also decompose crude oil prices into bull and bear market phases. For step 2, we estimate a DCC model to acquire the dynamic financial correlations, and compare these relationships under these typical/extreme and bull/bear oil market conditions. The period under investigation is February 1996 to August 2017[3], and the description, sources, and transformations of the data required for a particular step are elaborated therein. Our data is monthly primarily because the approach for identifying the structural oil market shocks is based on delay restrictions which are only economically plausible at this frequency (see Kilian (2009)).

There are a number of reasons why the contemporaneous nature of the time-varying correlations are appropriate for our analysis. First, contagion tends to appear and vanish quickly unlike interdependence and cointegrating relationships which are maintained over a much longer horizon (Reboredo et al., 2014). Second, stock prices absorb all available information relatively instantaneously including developments in international oil markets (Bjørnland, 2009), particularly in oil dependent economies (Wang et al., 2013). Third, crude oil is mainly indexed in US dollars (Kayalar et al., 2017), implying that this commodity is likely to be affected by movements in this currency (Zhang et al., 2008). At the same time, currency markets are one of the most liquid class of financial assets and the Trinidad and Tobago dollar is anchored to the US dollar. As such, the oil-exchange rate relationship is expected to promptly adjust to reflect the changes in this common factor.

2.1. Identifying discrete oil market conditions

Below, we detail two rule-based approaches to identify discrete oil market conditions.

[3]To facilitate this sample period we require monthly frequency data from January 1994 to August 2017, as we allow for a two year convergence period in the DCC model and the international oil market SVAR requires a 24 month lag period. The January 1994 start for empirical work is determined by the switch to a dirty floating exchange rate from a fixed exchange rate regime in Trinidad and Tobago, which occurred in April 1993.

2.1.1. Discrete typical and extreme oil market shock conditions from a global oil market SVAR model

We derive oil supply, global demand, and oil-specific demand shocks from an international oil market SVAR model postulated in Kilian (2009). The data is monthly from January 1994 to August 2017 on the growth rate in global oil production, which we proxy with the percent change in world petroleum production[4]; a Kilian (2019) correction of the global index of real economic activity introduced in Kilian (2009)[5]; and real oil price returns calculated from the European Brent crude oil spot prices deflated using the US CPI[6]. Eq. (1) gives the Kilian (2009) SVAR representation.

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \varepsilon_t \tag{1}$$

where ε_t is a vector of serially and mutually uncorrelated structural errors; and A_0^{-1} is recursively identified so the reduced-form errors e_t are linear combinations of the structural errors of the form $e_t = A_0^{-1}\varepsilon_t$, as described in Equation (2). Consistent with the empirical literature, we use a lag length of 24 months to remove residual autocorrelation and account for the possibility of delays in adjusting to shocks in the international oil market (see Kilian and Park (2009), as well as Kang et al. (2015a) and references therein).

$$e_t \equiv \begin{pmatrix} e_t^{\Delta global\ oil\ production} \\ e_t^{global\ real\ activity} \\ e_t^{real\ oil\ price} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil-specific\ demand\ shock} \end{pmatrix} \tag{2}$$

The identification strategy of the SVAR assumes a vertical short-run oil supply curve. This indicates that demand innovations in the oil market are contemporaneously restricted from affecting oil supply, as implied by the zeros imposed in the a_{12} and a_{13} positions of the A_0^{-1} matrix in Eq. (2). Kilian (2009) argues that such a specification is reasonable as the cost associated with adjusting oil production disincentives oil-producers to adjust to high frequency demand shocks. Further, aggregate demand shocks are innovations to global real activity unexplained by oil supply shocks. Another zero restriction is imposed in the position of a_{23} to delay real oil prices from affecting the aggregate demand within the same month. Lastly, oil demand shocks are the unexplained innovations to the real price of oil after oil supply and aggregate demand shocks have been accounted for.

Subsequently, to classify each of the structural oil market shocks into typical and extreme disturbances, we propose a new discrete rule-based specification which consolidates two veteran measures for identifying extreme oil prices:

[4]The data are available from the US Energy Information Administration at www.eia.gov/beta/international/data/browser and accessed in September 2018.

[5]It is important to note that Hamilton (2018) points out a data transformation error in the index of nominal freight rates underlying the Kilian (2009) global real economic activity measure, where the log operator is performed twice. Kilian (2019) acknowledges this coding error and corrects the global business cycle index. We use this updated data, which are available at https://sites.google.com/site/lkilian2019/research/data-sets and accessed in September 2018.

[6]These data are available from the Federal Reserve Economic Data (FRED) at fred.stlouisfed.org/, accessed in May 2018. Like Broadstock and Filis (2014), we use the Brent benchmark instead of the West Texas Intermediate (WTI) to represent the global price of oil. The latter has been traded at a discounted price since 2011 due to the the US shale boom (Kilian, 2016).

outlier oil prices outside a normal range and net oil price increases over the preceding year. Regarding the former measure, the idea that oil prices are important if found to be atypically high or low stems from the work of Akram (2004), who constructs extrema bands based on a normal range of oil prices with lower and upper bounds of USD 14 to USD 20, respectively, where values within the band are forced to zero and values outside the band are retained. Akram (2004) and Bjørnland (2009) use this oil price band to investigate the asymmetric effects extreme oil price changes have on the Norwegian exchange rate and stock market, respectively. However, this range is an artefact of oil price behaviour during the 1990s and much has changed since this period with unprecedented oil booms and busts characterising the 21st century energy markets. Therefore, we augment this approach by using the standard deviation value of the three structural oil market shocks to determine the maximum and minimum values of the band.

On the other hand, the net oil price increases measure is proposed by Hamilton (1996) as an extension of the positive and negative oil price transformation suggested in Mork (1989), in an effort to preserve the empirical importance of oil prices in the US macroeconomy. The net oil price increases measure compares the current growth rate in the price of oil with the rate over the preceding year and censors the current observation if it does not exceed the values observed over that period. It is straightforward to extend this approach beyond oil prices to consider net increases from all oil market shocks. We also invert this approach to also allow for net oil market shock decreases, which are also expected to have influential implications if, for instance, a small energy-exporting economy is being considered as is the case here.

We combine these rules to filter the oil market shocks into discrete typical and extreme oil market conditions defined in Equation (3).

$$shock_{i,t}^{dummy} = \begin{cases} 1, & \text{if } |\varepsilon_{i,t}| > \sigma; \\ & \text{if } \varepsilon_{i,t} > \max(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}); \\ & \text{if } \varepsilon_{i,t} < \min(0, \varepsilon_{i,t-1}, \varepsilon_{i,t-2}, ..., \varepsilon_{i,t-12}); \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

where i represents the oil supply, global demand, or oil demand shocks derived from the oil market SVAR model. In the first rule, σ is the standard deviation of the structural shocks, which is equal to 0.849 across all structural oil market shocks. Any value outside this standard deviation band is characterised as an extreme shock. The second and third rules correspondingly detects the presence of net oil price positive increases and negative decreases over the previous 12 months. To acquire the extreme positive and negative oil market shocks, from the rule-based specification described by Eq. (3), involves a further filtering of all periods identified as 1 into episodes where $\varepsilon_{i,t} > 0$ and $\varepsilon_{i,t} < 0$, respectively. Considering both symmetric or asymmetric movements in the crude oil market are especially useful, given that the conclusions in applied studies tend to vary depending on which has been used (Degiannakis et al., 2018).

2.1.2. Bull and bear oil market phases

As much of the literature has been devoted to debating and testing the asymmetric effects of oil prices (see, *inter alia*, Kilian and Vigfusson (2011a,b)), we use the semi-parametric rule-based algorithm suggested in Pagan and Sossounov (2003) to proxy oil price booms and slumps with bull and bear crude oil market phases, respectively. Therefore, we are able to test whether an environment where oil prices are increasing influence the relationships between oil and financial variables differently when compared to a period of decreasing oil prices. Phases are determined based on maxima and minima in real crude oil prices by applying rules. A peak (trough) is based on whether the oil price in month t is above (below) other months within the interval $t - \tau_{window}$ and $t + \tau_{window}$. Furthermore, the turning points which trigger a switch between phases are restricted with a minimum duration rule, τ_{censor}, to prevent extrema values towards the end of the interval from distorting the identification of market states. We set $\tau_{window} = 8$ months and $\tau_{censor} = 6$ months, which are feasible combinations given in Pagan and Sossounov (2003)[7]. Thus, we acquire an oil price dummy variable where bear (bull) phases are coded as 1 (0).

2.2. Oil-finance dynamic correlations

We specify a DCC model to obtain the three pairs of time varying correlations between oil, exchange rate, and stock returns. The DCC model uses data on real oil prices; an exchange rate indicator for Trinidad and Tobago, for which we use the real effective exchange rate (REER)[8]; and real stock prices, which are represented by the Trinidad and Tobago Stock Exchange (TTSE) Composite Stock Price Index (CSPI) adjusted for inflation using the RPI[9]. These three variables are expressed as returns[10]. The DCC estimation consists of a two-step process. Step 1 involves the estimation of both the autoregressive (AR) components and the combination of univariate generalised autoregressive conditional heteroskedastic (GARCH) processes for all three returns. Step 2 uses the residuals from the first stage to estimate the three pairs of conditional correlations between these three variables.

In step 1, we aim to optimally estimate each individual return series. We find no meaningful lead-lag relationships between oil, exchange rate, and stock returns. Furthermore, the Schwarz Bayesian Information Criterion (SBIC) suggests an optimal lag length of one month in each case. As such, the mean equation for each return series (r_t) takes the form of a simple AR(1) process specified in Eq. (4).

$$r_t = a_0 + a_1 r_{t-1} + \epsilon_t \tag{4}$$

[7]Mahadeo et al. (2019) finds that the bear and bull oil price phases identified with the Pagan and Sossounov (2003) method yields a 97% similarity using the Lunde and Timmermann (2004) approach on the same data set.

[8]REER data are sourced from the International Monetary Fund (IMF) International Financial Statistics and retrieved via Thomson Reuters Eikon, accessed in May 2018. A rise (fall) in this index implies currency appreciation (depreciation).

[9]These data are calculated using data from the Central Bank of Trinidad and Tobago (CBTT), available at www.central-bank.org.tt/statistics/data-centre and accessed in May 2018.

[10]Returns are calculated as the first difference in the natural logarithm for each series, times 100.

where a_0 is a constant and a_1 is the coefficient of the AR(1) term r_{t-1}. To estimate the conditional variances, we commence with the parsimonious GARCH(1,1) process given by Eq. (5) for each series:

$$h_t = \omega_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{5}$$

where ω_0 is the intercept of the variance, ϵ_t are ARCH innovations with a conditional distribution that has a time dependent variance h_t, and h_{t-1} are lags of the conditional variance. Further, ϵ_t follows the Student's t-distribution and the solver used is a non-linear optimisation with augmented Lagrange method. The GARCH(1,1) models for all returns are stable in variance as the condition $\alpha + \beta < 1$ is met (see Table 2). Additionally, the Ljung-Box and ARCH Lagrange multiplier (LM) tests indicate no concerns regarding autocorrelation and ARCH effects, respectively, in the residuals of the GARCH(1,1) specification for all three returns. Moreover, Engle and Ng (1993) sign bias tests provide no substantive evidence of asymmetric responses to positive and negative news in the three financial returns[11]. Hence, the parsimonious univariate GARCH(1,1) process is an optimal representation of the conditional variance for each return series.

Step 2 of the DCC model follows Engle (2002). The k x k conditional covariance matrix of returns, H_t, is decomposed as:

$$H_t = D_t P_t D_t \tag{6}$$

where D_t are the standard deviation diagonal matrices derived from the GARCH(1,1) models suggested in Eq. (5) and P_t is the correlation evolution of the (possible) time varying correlation matrix which takes the form:

$$P_t = diag\Big(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}) Q_t diag(q_{1,t}^{-1/2}, q_{2,t}^{-1/2}, q_{3,t}^{-1/2}\Big) \tag{7}$$

where Q_t defined in Eq. (8) is a symmetric positive definite matrix whose elements follow the GARCH(1,1) specified in Eq. (5):

$$Q_t = S(1 - \lambda_1 - \lambda_2) + \lambda_1 \frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \left(\frac{\epsilon_{t-1}}{\sqrt{h_{t-1}}} \right)' + \lambda_2 Q_{t-1} \tag{8}$$

where S is the unconditional correlations matrix, and the adjustment parameters λ_1 and λ_2 are time invariant non-negative scalar coefficients related to the exponential smoothing process that is used to construct the dynamic

[11]We find no statistically significant asymmetric responses to positive and negative news for exchange rates and stock returns. However, in the case of oil returns, the asymmetric volatility tests show that the individual sign bias tests convey no asymmetric volatility in the standardised residuals, but the joint effects test is statistically significant. Therefore, we consider asymmetric GARCH variants for this particular series to accommodate for this artefact. For instance, an EGARCH(1,1) for oil returns, which we find to be the most suitable alternative GARCH specification for this series, shows that the leverage effects term is not significant. Further, the differences in dynamic correlations estimated from a model where oil returns follows either a GARCH(1,1) or an EGARCH(1,1) specification is negligible. As such, we revert to the parsimonious GARCH(1,1) model for oil returns. The results from this alternative specification can be made available upon request.

conditional correlations. The constraint $\lambda_1 + \lambda_2 < 1$ indicates that the process is stationary. Finally, the time-varying correlations are estimated by:

$$\rho_{i,j,t} = q_{i,j,t} / \sqrt{q_{i,i,t} q_{j,j,t}} \tag{9}$$

Hence, with the discrete oil market conditions identified with the rule-based specifications and the time varying correlations obtained from the DCC model, it becomes straightforward to perform oil contagion tests. We use two-sample t-tests to compare the equality of means for the three pairs of market correlations under the calm versus extreme structural oil market shocks, and bullish versus bearish oil market phases.

3. Application to the international crude oil market and a small oil exporter

3.1. Discrete calm and crisis oil market conditions

Looking at Figure 1 (A), (B), and (C), oil market shocks in the blue and red horizontal regions illustrate the extreme positive and negative disturbances, respectively, detected by the standard deviation band specifications. Additionally, the vertical blue and red lines show extreme positive and negative oil market shocks, correspondingly, which reside within this band but are identified by the Hamilton net oil price increases and decreases rules. With reference to Figure 1 (A) and (C), extreme oil supply and oil-specific demand shocks, respectively, are seen to occur intermittently over the entire sample. On the other hand, when compared to the latter half of the 1990s, extreme global demand shocks in Figure 1 (B) appear to increase in frequency from the 2000s and especially so in the GFC and post-GFC eras. We also note that the Hamilton rules, illustrated by the vertical lines in Figure 1 (A) to (C), are able to detect extreme oil market shocks over the preceding year, which are not detected by the standard deviation rule. Such extreme shocks tend to happen in the latter half of the sample for oil supply shocks, the first half of the sample for global demand shocks, and generally in the middle part of the sample for oil-specific demand shocks.

Bearish Brent crude oil price behaviour is shown by grey vertical panels in Figure 1 (D). The slumps identified coincide with international crises such as the Asian financial crisis (1997), the internet bubble burst and the 9/11 terrorist attacks (2001) in the US, and the GFC (2008). Additionally, Baumeister and Kilian (2016b,a) find that the stark oil decline between June 2014 and January 2015 can be explained partly due to a negative oil demand shock from a slowdown in the global economy, and positive oil supply shocks coming from the US shale boom and other major oil producers.

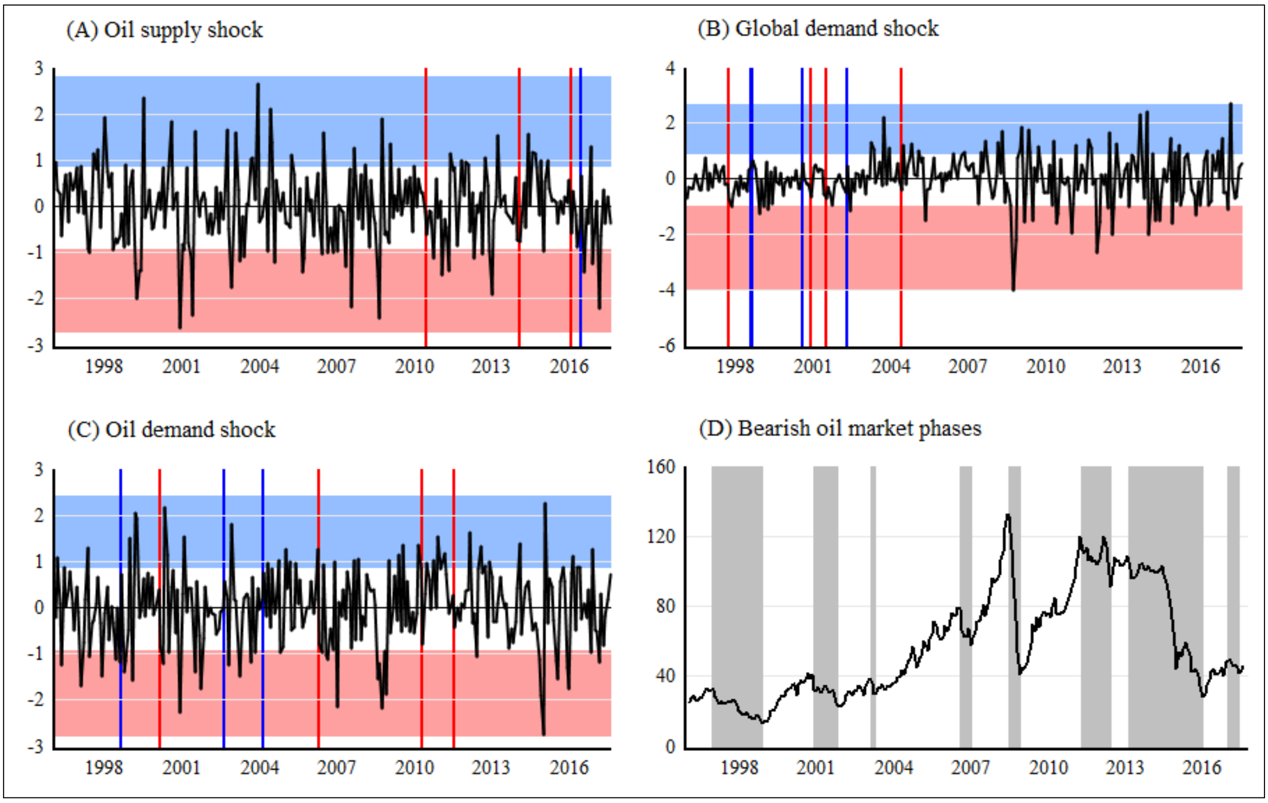

Figure 1: Graphs (A) to (C) show structural oil market shocks where extreme positive (negative) disturbances are either classified as shocks which are greater (less) than the standard deviation band of +0.849 (-0.849) and are highlighted by the blue (red) horizontal regions, or the vertical blue (red) bars which reside within the standard deviation band but are detected by the net oil market shock increase (decrease) specification; while graph (D) illustrates crude oil prices with bearish phases given by the grey vertical panels.

3.2. Performance of returns under alternative oil market conditions

Table 1 shows simple summary statistics which captures the behaviour of returns under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, for the full and GFC-censored samples. The relatively calm oil market condition is that time period in the international oil market where no extreme structural shock is identified by our non-linear rule-based specification. As anticipated, average oil returns are negative (positive) and volatility is higher (lower) under extreme (calm) structural oil market shocks and bearish (bullish) oil market phases. Moreover, the highest volatility in the crude oil market occurs during oil-specific demand shocks. As we might expect, oil returns are negative under extreme positive oil supply shocks and positive under extreme positive oil demand shocks. The mean exchange rate appreciations are higher (lower) during extreme (relatively calm) oil market shocks and bearish (bullish) oil market phases. Additionally, the periods of highest exchange rate volatility is exhibited under global demand shocks. There are two particularly surprising observations for this small oil exporter. First, the highest exchange rate appreciations occur during episodes of extreme negative oil demand shocks and bearish oil market phases. Second, the only periods of exchange rate depreciations are during extreme positive oil demand shocks. Both artefacts contradicts the Dutch disease and positive wealth effects propositions, at least from a contemporaneous perspective. Average stock returns behaviour appears to be particularly sensitive to the GFC, as noted by the marked differences in the mean, volatility, and range of returns obtained between the full and GFC-censored samples.

Table 1: Descriptive statistics of returns under calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, for the full and GFC-censored samples.

Sample	Oil Market Condition	Obs.	Returns											
			Oil				REER				Stock			
			Mean	SD	Min	Max	Mean	SD	Min	Max	Mean	SD	Min	Max
	Structural shocks													
	Relatively calm	91	1.63	5.29	-10.89	14.17	0.13	0.82	-2.15	2.14	0.68	3.36	-7.24	13.27
	Extreme oil supply	83	-1.15	10.36	-28.68	18.37	0.36	1.14	-2.63	5.71	-0.01	3.31	-16.63	7.80
	Positive	40	-2.26	9.27	-28.68	17.33	0.51	1.22	-1.30	5.71	0.38	3.95	-16.63	7.80
	Negative	43	-0.13	11.29	-28.47	18.37	0.23	1.06	-2.63	2.92	-0.37	2.58	-7.34	7.24
Full	Extreme global demand	81	-1.33	10.65	-28.68	19.12	0.33	1.31	-1.84	5.71	-0.12	3.55	-16.63	9.06
	Positive	42	0.83	9.27	-28.47	19.12	0.25	1.12	-1.72	3.50	0.43	2.77	-5.31	8.51
	Negative	39	-3.65	11.64	-28.68	17.77	0.43	1.50	-1.84	5.71	-0.72	4.19	-16.63	9.06
	Extreme oil demand	91	-1.46	13.02	-28.68	20.20	0.32	1.17	-2.63	5.71	-0.23	3.46	-16.63	8.51
	Positive	45	9.46	5.60	-1.90	20.20	-0.15	0.96	-2.63	1.70	-0.03	2.47	-5.31	7.35
	Negative	46	-12.14	8.51	-28.68	3.90	0.77	1.19	-1.09	5.71	-0.42	4.23	-16.63	8.51
	Oil market phases													
	Bull	163	3.83	6.81	-21.16	20.20	0.02	0.98	-2.63	3.80	0.59	3.03	-7.24	12.19
	Bear	109	-4.69	9.23	-28.68	19.66	0.53	1.01	-1.79	5.71	0.45	3.97	-16.63	13.27
	Structural shocks													
	Relatively calm	87	1.65	5.38	-10.89	14.17	0.13	0.82	-2.15	2.14	0.74	3.40	-7.24	13.27
	Extreme oil supply	77	-0.53	9.94	-28.47	18.37	0.25	0.93	-2.63	2.88	0.29	2.51	-4.16	7.80
	Positive	37	-1.74	8.51	-23.74	17.33	0.36	0.90	-1.30	2.88	0.88	2.92	-3.79	7.80
	Negative	40	0.59	11.10	-28.47	18.37	0.14	0.96	-2.63	1.78	-0.26	1.95	-4.16	5.35
GFC-censored	Extreme global demand	70	-1.56	9.55	-28.47	17.77	0.23	1.14	-1.84	3.80	0.28	2.92	-7.72	9.06
	Positive	36	-0.67	8.83	-28.47	11.61	0.32	1.08	-1.48	3.50	0.40	2.82	-5.31	8.51
	Negative	34	-2.50	10.30	-23.74	17.77	0.13	1.20	-1.84	3.80	0.16	3.07	-7.72	9.06
	Extreme oil demand	84	-0.50	12.09	-28.47	20.20	0.21	0.97	-2.63	3.50	0.22	2.83	-7.72	8.51
	Positive	43	9.30	5.52	-1.90	20.20	-0.11	0.96	-2.63	1.70	-0.03	2.52	-5.31	7.35
	Negative	41	-10.78	7.72	-28.47	3.90	0.53	0.86	-1.09	3.50	0.48	3.14	-7.72	8.51
	Oil market phases													
	Bull	150	3.59	6.86	-21.16	20.20	0.01	0.97	-2.63	3.80	0.59	3.05	-7.24	12.19
	Bear	103	-3.83	8.41	-28.47	19.66	0.42	0.84	-1.79	2.88	0.86	3.49	-7.72	13.27

3.3. Energy-finance time varying correlations under alternative oil market conditions

The DCC parameters are shown in Table 2, while the evolution of the dynamic oil-REER, oil-stock market, and REER-stock market relationships over the sample period are graphed in Figure 2[12]. Further, these time varying correlations are illustrated under extreme positive (blue filters) and negative (red filters) oil supply (A), global demand (B), and oil demand (C) shocks, as well as under bearish (grey filters) oil market phases (D). The oil-REER and REER-stock market time-varying correlations are negative and moderate across the two decade sample period. However, the oil-stock market association is typically weak with distinct punctuated phases where the correlation strengthens. The negative oil-stock market relationship prior to 1999 is reversed thereafter to a positive association, which is in line with the inferences of Miller and Ratti (2009) who examine a selection of OECD countries. They argue that the positive association is likely due to the existence of stock and oil market bubbles which have characterised 21st century financial markets. Indeed, we observe that there are two distinct periods where the time-varying oil-stock market correlation increase in the 2000s, which coincide with the dot-com and sub-prime bubbles and crashes. As expected, all three pairs of dynamic correlations exhibit financial contagion effects during the GFC as all relationships deepen in this period. The GFC is hallmarked by global demand and oil demand shocks, and is a bearish phase in oil markets.

Table 3 conveys the average financial correlations during relatively calm and extreme structural oil market shocks, and during bullish and bearish oil market phases, in the full sample and a GFC-censored sample for robustness analysis. The relatively calm period in the crude oil market forms the sample which is used as basis for comparing each of the extreme structural shock periods.

First, we observe a moderate and inverse oil-REER interdependence. This relationship suggests that oil price increases (decreases) are associated with exchange rate depreciations (appreciations), and is inconsistent with the Dutch disease conjecture and the positive wealth effect spillovers expected for an oil-exporter which implies the opposite outcome. Mahadeo et al. (2019) also find evidence for such a contradiction and explain this is likely due to the peg of the Trinidad and Tobago dollar to the US dollar. In the full sample, we find statistically significant results that the oil-REER relationship marginally deepens during extreme global demand and oil demand shocks. However, such evidence of oil market contagion in the oil-REER correlation is primarily associated with the GFC period.

Looking at the oil-stock market correlation, this association is generally weak. Therefore, we find no evidence of either interdependence or contagion. We also observe that oil-stock returns correlation in bullish oil market phases becomes weaker under bearish conditions. These results can be linked to the relatively underdeveloped stock market of Trinidad and Tobago, and the fact that there is only one energy security listed on the stock exchange, which subdues the spillover effects from the international oil market. The minimal effect of the oil market on the stock market is consistent with evidence from other oil-exporters such as the Gulf Cooperation Council countries (Al Janabi et al., 2010), Mexico (Basher et al., 2018), and Trinidad and Tobago (Mahadeo et al., 2019).

[12]The DCC model coefficients and dynamic correlations are estimated with the rmgarch package in R (see Ghalanos (2019)).

Table 2: DCC parameter estimates

	Coefficient	Std. error	t value	Prob.
a_0^{Oil}	0.0069	0.0059	1.1642	0.2443
a_1^{Oil}	0.1330	0.0653	2.0378	0.0416
ω_0^{Oil}	0.0006	0.0005	1.2529	0.2103
α_1^{Oil}	0.1820	0.0610	2.9837	0.0028
β_1^{Oil}	0.7485	0.0933	8.0193	0.0000
a_0^{REER}	0.1371	0.0743	1.8468	0.0648
a_1^{REER}	0.3118	0.0599	5.2042	0.0000
ω_0^{REER}	0.0238	0.0186	1.2773	0.2015
α_1^{REER}	0.0811	0.0464	1.7500	0.0801
β_1^{REER}	0.8915	0.0536	16.6226	0.0000
a_0^{Stock}	0.0916	0.2809	0.3263	0.7442
a_1^{Stock}	0.4002	0.0775	5.1628	0.0000
ω_0^{Stock}	0.0206	0.3232	0.0637	0.9492
α_1^{Stock}	0.0532	0.1371	0.3880	0.6980
β_1^{Stock}	0.9434	0.1497	6.3033	0.0000
λ_1	0.0238	0.0158	1.5033	0.1328
λ_2	0.9096	0.0650	14.0043	0.0000

Turning to the REER-stock market association, the inverse interdependence suggests that an exchange rate appreciation (depreciation) is correlated with a downturn (uptick) in stock returns. It can be useful to consider this result in tandem with the aforementioned oil-REER relationship. Although the oil-stock returns relationship is weak, it is possible for crude oil to have indirect spillovers for the stock market performance through the exchange rate channel. We also find that the REER-stock returns relationship becomes somewhat stronger under the global demand shocks, but this finding is sensitive to the GFC. While we do detect evidence for oil market contagion in the REER-stock market relationship during bearish oil market phases, which is robust to the GFC, the deepening of this correlation under such episodes is marginal.

Table 3 shows weak evidence for oil market contagion channels in the financial markets of Trinidad and Tobago. Generally, the variations in correlations under conditions of extreme positive and negative oil market shocks or bearish and bullish oil market phases is subtle. No significant changes in correlations are noted during the calm period versus periods of extreme oil supply shocks, across any of the dynamic relationships. Hence, this result converges with Basher et al. (2016) who find limited evidence that oil supply shocks affect exchange rates and with Filis et al. (2011)

who find that supply-side oil price shocks do not influence the oil-stock market relationship. In fact, many studies are alluding to the notion that the role of oil supply shocks on the real and financial sectors is no longer consequential (see Broadstock and Filis (2014) and references therein.). Our results also align with Antonakakis et al. (2017), who find that global demand innovations are the main source of shocks to stock market during economic turbulence. Shocks associated with the GFC appear to drive contagion more than oil shocks in this small open petroleum economy.

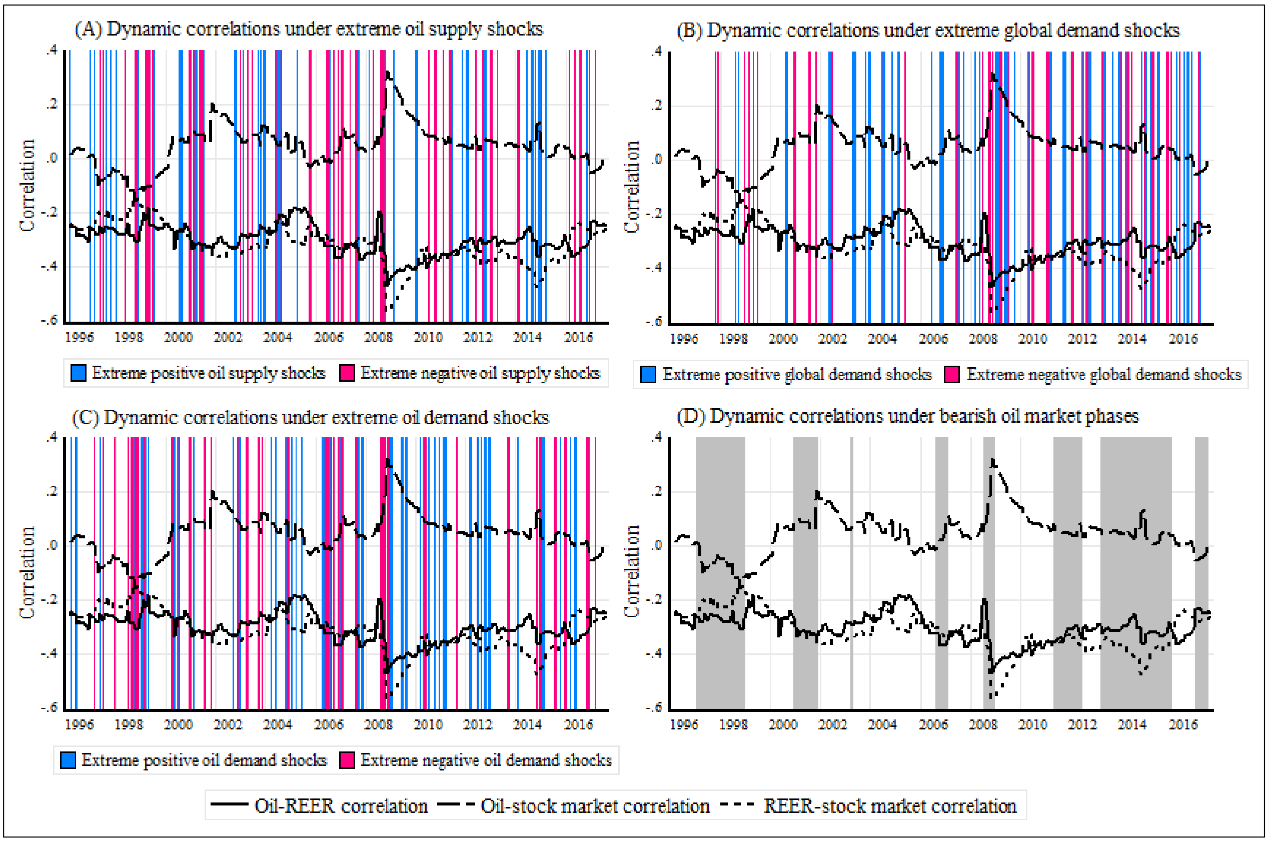

Figure 2: Time varying financial correlations under extreme positive and negative oil supply shocks (A), global demand shocks (B), oil demand shocks (C), and bearish oil market phases (D).

4. Conclusion

We put forward a new approach to trace the sources of contagion in three pairs of financial market relationships, i.e. the crude oil-exchange rate, crude oil-stock returns, and exchange rate-stock returns correlations. The sources of international crude oil market contagion are determined using two rule-based specifications: a novel specification which combines established non-linear oil market rules to identify between relatively calm and extreme structural oil market shocks, as well as the Pagan and Sossounov (2003) rule-based algorithm to identify bull and bear oil market phases. We obtain the time-varying financial market relationships with a dynamic conditional correlations model.

Then, we compare the correlations under calm versus extreme, and bullish versus bearish oil market conditions. The methodology we outline in this paper is useful for financial stability analysis in economies susceptible to disturbances from the international crude oil market.

Our empirical analyses are carried out on the financial markets of a small petroleum intensive economy of Trinidad and Tobago, from February 1996 to August 2017. Overall, although there is a moderate interdependence in the oil-exchange rate and exchange rate-stock returns linkages in Trinidad and Tobago, our evidence suggests that the risk of oil market contagion for the financial markets of this small energy economy is low. In particular, we find that contagion is transmitted in the oil-exchange rate correlation during global demand and oil demand shocks, and in the exchange rates-stock market linkage under global demand shocks. Yet, our robustness sample shows that these contagion channels are largely due to the Great Recession. Furthermore, periods of oil supply shocks appear inconsequential to the three energy-finance relationships examined in our study. We also find that the oil-stock market relationship is generally weak, which indicates that the spillover risk from the international crude oil market to the Trinidad and Tobago stock exchange is minimal.

Table 3: Average financial correlations under relatively calm and extreme oil market shocks, as well as under bull and bear oil market phases, in both the full and GFC-censored samples. Significant results from two sample *t*-tests for comparing the equality of means for correlations between calm/bullish and extreme/bearish oil market conditions are noted as $***$, $**$, and $*$ for the 1%, 5%, and 10% levels of significance, respectively, based on the Student's *t* distribution.

	Average financial market correlations							
	Full sample				GFC-censored sample			
Oil market conditions	Obs.	Oil-REER	Oil-stock	REER-stock	Obs.	Oil-REER	Oil-stock	REER-stock
Structural shocks								
Relatively calm	91	-0.29	0.04	-0.31	87	-0.29	0.04	-0.31
Extreme oil supply	83	-0.30	0.03	-0.31	77	-0.30	0.03	-0.31
Positive	40	-0.30	0.04	-0.32	37	-0.29	0.04	-0.31
Negative	43	-0.30	0.02	-0.30	40	-0.30	0.02	-0.30
Extreme global demand	81	-0.32^{***}	0.06	-0.34^{***}	70	-0.31^{*}	0.04	-0.33^{*}
Positive	42	-0.32^{***}	0.06	-0.35^{***}	36	-0.31^{*}	0.03	-0.33
Negative	39	-0.31^{*}	0.06	-0.34^{*}	34	-0.31	0.04	-0.33
Extreme oil demand	91	-0.31^{**}	0.04	-0.32	84	-0.30	0.03	-0.31
Positive	45	-0.31^{*}	0.04	-0.32	43	-0.31	0.03	-0.31
Negative	46	-0.31	0.04	-0.32	41	-0.30	0.02	-0.31
Oil market phases								
Bull	154	-0.30	0.06	-0.31	141	-0.30	0.05	-0.31
Bear	105	-0.31	-0.02^{***}	-0.33	99	-0.30	0.02^{***}	-0.32

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