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Dynamic relations between oil and stock markets: Volatility spillovers, networks and causality

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Abstract

We study the relation between oil and stock market returns for a set of seven countries that are important participants in commodity markets. Total and directional spillover indicators are computed using forecast error variance decomposition from vector autoregressions, and their dynamic nature is explored. We find that, on average, oil markets are net volatility receptors while the stock markets of Norway and the US are the main volatility trasmitters. However, transmission intensities and net positions present considerable time variation, being substantially different in moments of financial distress with respect to normal times. Furthermore, we perform dynamic Granger causality tests on recursive windows to explore the validity of the exogeneity assumption of oil market shocks frequently made in the literature. Our results show the existence of bidirectional causality relations, being stronger from stock to oil markets. The results of this study provide empirical evidence suggesting the validity of the oil markets financialization hypothesis, and have important implications for global investors and policymakers.

JEL Classification*:*G01; G12; C22.

Keywords*: Time-varying causality; Oil price; Stock market returns; Emerging market economies.*

Relaciones dinámicas entre petróleo y mercados accionarios: transmisión de volatilidad, redes y causalidad

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Resumen

Se estudia la relación entre los retornos de los mercados petroleros y los mercados accionarios de siete países que son participantes importantes de los mercados de bienes básicos. Se computan indicadores totales y direccionales de transmisión de volatilidad usando métodos de descomposición de la varianza del error de pronóstico de vectores auto-regresivos y se explora su dinámica. Se encuentra que, en promedio, los mercados de petróleo son receptores netos de volatilidad mientras que los mercados accionarios de Noruega y de los Estados Unidos son los principales transmisores de la misma. Sin embargo, las intensidades de transmisión y las posiciones netas exhiben importante variación temporal, siendo sustancialmente diferentes en momentos de tensión financiera frente a momentos de tranquilidad en los mercados. Adicionalmente, se realizan pruebas de causalidad en sentido de Granger dinámicas en ventanas recursivas para probar la validez de los supuestos de exogeneidad de los choques a los mercados petroleros que se hacen de forma frecuente en la literatura. Los resultados muestran que existen relaciones de causalidad bidireccionales, que son más fuertes de los mercados accionarios hacia el petróleo que viceversa. Los resultados de este estudio proveen evidencia empírica que sugiere la validez de la hipótesis de financiarización de los mercados de petróleo y tienen implicaciones importantes para los inversionistas globales y para los hacedores de política.

JEL Classification:G01; G12; C22.

Keywords: *Causalidad variable en el tiempo; Precios del petróleo; Retornos de mercados accionarios; Economías emergentes.*

1 Introduction

In this paper we study the relation between oil and stock market returns for a set of seven countries that are important participants in oil markets. Volatility of oil and financial markets has important effects on macroeconomic stability, specially for countries that are important producers and consumers of crude oil and its derivatives. Therefore, studying the linkages between these markets and understanding their changing behavior over time can derive important implications for global investors and for policy makers of countries that are affected by their price volatility (see, for example, Filis et al., 2010; Diaz et al., 2016; and Boldanov et al., 2016). While most related studies assume the exogeneity of oil prices, recent papers have shown that commodity prices are affected by the behavior of traditional financial markets. Their results have been considered evidence of the financialization hypothesis (see, for instance, Lee et al., 2012; Turhan et al., 2014; Ding et al., 2016; Basak et al. (2016); and, Zhang, 2017).

Our contributions to the literature are two-folded. First, we examine the dynamic multivariate relation between oil and stock market returns, measuring connectedness. We compute total and directional indicators using forecast error variance decomposition from vector autoregressions following Gamba-Santamaria et al. (2017). They extend the method developed by Diebold and Yilmaz (2012, 2014) by computing spillover indexes directly from the series of asset returns and recognizing the time-variant nature of the covariance matrix using a multivariate GARCH model. And, second, we study causality between oil and stock market returns dynamically, performing Granger causality tests on rolling windows.

Our results on connectedness show that spillovers vary importantly over time and occur mainly from stock to oil markets. Specifically, while oil shocks may affect single markets, we find that their effect on the stock markets of major oil consumer and producer countries as a whole are minor. The magnitude of their effect is large only during periods of high volatility consistent with the findings of Bedoui et al. (2018). On the contrary, shocks originating in global stock markets have significant effects on oil markets. This result supports the financialization hypothesis of commodity markets.

Regarding individual markets, an interesting result is that Norway's stock market is the main sillover transmitter in our sample, presenting larger transmisson values than those registered by the US, the UK, and Canada. This result follows from the high participation of oil and gas producing companies that are listed in the former. India and China are the main spillover receivers, showing that while emerging markets have gained importance, their influence in global financial markets is still limited.

Dynamic Granger causality tests show evidence of bidirectional causality between stock and oil market returns in all cases in line with the findings of Maghyereh et al. (2016). However, causality is detected for longer periods of time from stock to oil markets. As in the case of volatility spillovers, causality is stronger in times of financial distress.

Our results have important implications both for investors and policy makers. For the former, the fact that spillovers between oil and stock markets vary over time, indicates that portfolio diversification strategies must be time-varying as well. Additionally, the evidence indicates that oil markets are affected by stock market developments, and hence should not be assumed exogenous. Shocks affecting equity markets must be considered when predicting the future behavior of oil prices. Furthermore, policy makers in oil-dependent economies must consider the strong interactions between oil and stock markets when designing policies for minimizing the negative effects of oil price shocks, specially during moments of financial turbulence.

2 Methodology

Consider the following VAR(p) model

$$Y_t = \Phi_0 + \sum_{l=1}^{p} \Phi_l Y_{t-l} + \epsilon_t \tag{1}$$

where Y_t is a vector of size N, containing all stock market and oil returns at time t, and $\epsilon_t|t-1 \sim F\left(0, H_t\right)$ where F is the multivariate conditional probability distribution of errors. H_t is the time-varying conditional covariance matrix of errors. The VMA(∞) version is given by

$$Y_t = \Phi_0^* + \sum_{p=0}^{\infty} \Theta_p \epsilon_{t-p} \tag{2}$$

and the h-periods ahead forecast error is

$$e_{t+h}|t = \Theta_0\epsilon_{t+h} + \Theta_1\epsilon_{t+h-1} + \cdots + \Theta_{h-1}\epsilon_{t+1} \tag{3}$$

whose covariance matrix is given by

$$\Sigma^e_{t+h}|t = \Theta_0 H_{t+h}\Theta_0^{'} + \Theta_1 H_{t+h-1}\Theta_1^{'} + \cdots + \Theta_{h-1}H_{t+1}\Theta_{h-1}^{'}. \tag{4}$$

Each element of the diagonal of $\sigma^e_{t+h}|t$ is a summation that includes terms of past covariance matrices of the error term ϵ_t, given by H_{t+i} for all $i = 1, 2, ..., h$. It is important to notice that following Gamba-Santamaria et al. (2017, 2018), we model H_t in a time-varying framework using a DCC-GARCH model given by

$$H_t = D_t R_t D_t \tag{5}$$

where D_t is a diagonal matrix of time-varying standard deviations of each element in ϵ_t and R_t is the time-varying correlation matrix. In this methodology, squared elements of the diagonal of matrix D_t are modelled as univariate GARCH processes

$$h^2_{ijt} = \omega_i + \sum_{l=1}^{P_i}\alpha_{il}\epsilon^2_{i,t-l} + \sum_{l=1}^{Q_i}\beta_{il}h^2_{i,t-l}. \tag{6}$$

The correlation matrix can be decomposed in the following way:

$$R_t = Q_t^{*-1}Q_t Q_t^{*-1} \tag{7}$$

where Q_t^* is a diagonal matrix whose diagonal is the square root of the diagonal of Q_t and Q_t is the covariance matrix with the following representation:

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right)\bar{Q} + \sum_{m=1}^{M} a_m(\epsilon_{t-m}\epsilon_{t-m}^{'}) + \sum_{n=1}^{N} b_n Q_{t-n} \tag{8}$$

where $\bar{Q}$ is the unconditional expected value of Q_t. Additionally, variance decomposition $\Psi_{ij,t}(h)$ are defined in a way they contain the proportion of the h-step ahead forecast error variance of i coming from j at time t

$$\Psi_{ij,t}(h) = \frac{\sum_{k=0}^{h-1} \frac{(d_i' \Theta_k \Sigma_{t+k}^e | t d_j)^2}{\sqrt{d_j' \Sigma_{t+k}^e | t d_j}}}{\sum_{k=0}^{h-1} (d_i' \Theta_k \Sigma_{t+k}^e | t \Theta_k' d_i)} \tag{9}$$

where d_i and d_j are extraction vectors, i.e. zero vectors that are one in the i^{th} and j^{th} positions. It is important to note that we have extended the framework of Diebold and Yilmaz (2012) allowing for a time-varying covariance matrix, H_t. These indexed have to be normalized to obtain a variance share interpretation:

$$\tilde{\Psi}_{ij,t}(h) = \frac{\Psi_{ij,t}(h)}{\sum_{j=1}^{N} \Psi_{ij,t}(h)} \tag{10}$$

We compute different connectedness indexes, as in Diebold and Yilmaz (2009, 2012) and go one step further and compute dynamic Granger causality tests between pairs of market returns. We follow the method of Clements et al. (2017) who develop a test for detecting changes in causal relationships based on a recursive rolling window estimations.[1] The test has three advantages over others, the main being that the VAR model accounts for potential endogeneity issues overlooked by the traditional framework. Specially relevant, it accounts for endogeneity issues between cross-sectional return dispersion and market volatility. Additionally, the test involves a rolling window algorithm that enables endogenous dating of the change points in the predictive relationship. Hence, if causality is detected, its sign (positive or negative) is identified, as well as its intensity. Finally, the testing framework considers potential heteroskedasticity in the data, reducing the chance of flawed inference.

3 Data description

We use weekly data and examine the volatility of returns of the stock market indexes of seven countries: the US (S&P 500), Canada (S&P TSX), Russia (MICEX), Norway (OSEAX), India (SENSEX), China (SHCOMP), and the UK (FTSE100). We also collect weekly information on the BRENT's returns. The data, collected from Bloomberg, spans the period July 2002 - April 2018. Oil and stock market

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[1] For details in the test of causality employed in this study, please refer to Clements et al. (2016).

returns are computed taking first differences of the indexes' natural logarithms, and are depicted in Figures 1a to 1h. Volatility clusters can be eye-inspected, with higher differences in weekly returns observed around the Lehman Brother's episode of September 2008 and around the European sovereign bond crisis of 2012.

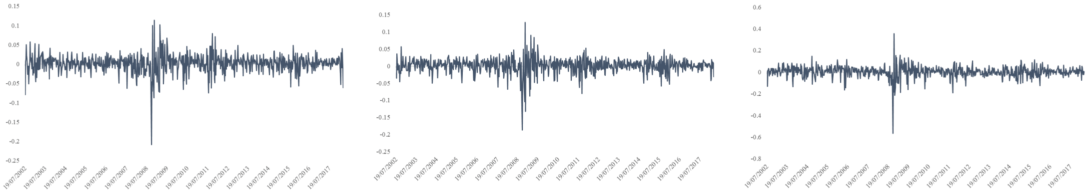
Descriptive statistics are presented in Table 1. Results from ADF tests (not shown in the table) indicate that returns are covariance-stationary. Notice that means are positive in all cases and distributions are left-skewed indicating that negative returns are more frequently obserevd than positive returns. Fat tails are evident from the fact that Kurtosis are much higher than those expected under a normal distribution.

Table 1: Descriptive statistics of returns

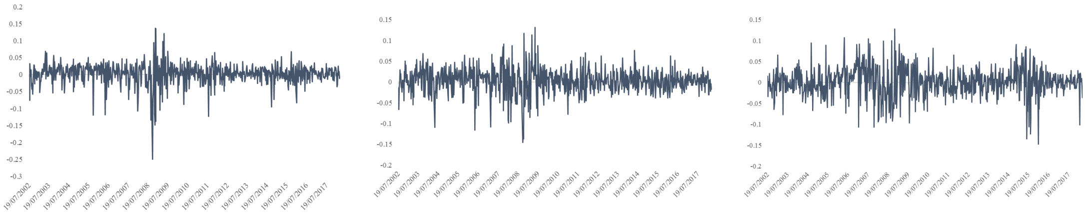
Index	**Mean**	**Std. Dev**	**Skewness**	**Kurtosis**
S&P 500	0.0013	0.0231	−1.0286	10.640
S&P TSX	0.0010	0.0221	−1.2930	10.972
MICEX	0.0018	0.0522	−1.6576	21.134
OSEAX	0.0023	0.0302	−1.5032	10.154
SENSEX	0.0029	0.0302	−0.4678	3.010
SHCOMP	0.0008	0.0341	−0.2192	1.683
FTSE100	0.0007	0.0236	−0.4269	5.419
BRENT	0.0013	0.0470	−0.7423	3.988

Figure 1: Weekly Returns

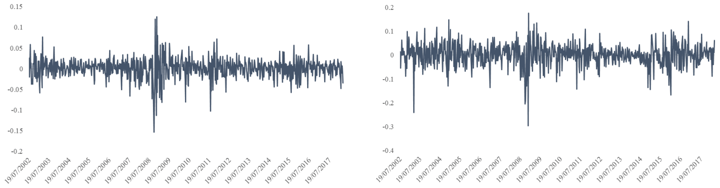
(a) US (S&P 500) (b) Canada (S&P TSX) (c) Russia (MICEX)



(d) Norway (OSEAX) (e) India (SENSEX) (f) China (SHCOMP)



(g) UK (FTSE100) (h) Oil (Brent)



4 Results

Table 2: Connectedness (%)

Index	US	CAN	RUS	NOR	IND	CHI	UK	Brent	From
US	4.6620	2.5260	1.2461	1.8374	1.0075	0.7234	2.5742	0.2802	10.1949
CAN	2.4477	4.5512	1.1891	2.4560	1.1282	0.6348	2.3982	0.6056	10.8596
RUS	1.2444	1.1914	4.4982	1.6510	0.8544	0.5693	1.3025	1.0307	7.8438
NOR	1.8832	2.3593	1.5736	4.2951	0.9125	0.3590	2.2577	1.0140	10.3594
IND	1.2589	1.2209	0.9071	1.0845	4.3129	0.4043	1.4349	0.1336	6.4442
CHI	0.8966	0.7888	0.6117	0.5067	0.5116	4.5062	0.7105	0.1892	4.2151
UK	2.5196	2.3647	1.2848	2.3074	1.3323	0.5517	4.4622	0.3060	10.6665
Brent	0.2699	0.6362	1.0368	1.0643	0.1406	0.1950	0.2948	4.4911	3.6376
To	10.5203	11.0873	7.8494	10.9072	5.8871	3.4376	10.9729	3.5594	63.1366

Table 2 presents conectedness results between oil and stock market returns.[2] The entry (i,j) in the table shows the gross volatiliy spillover transmitted from mar-

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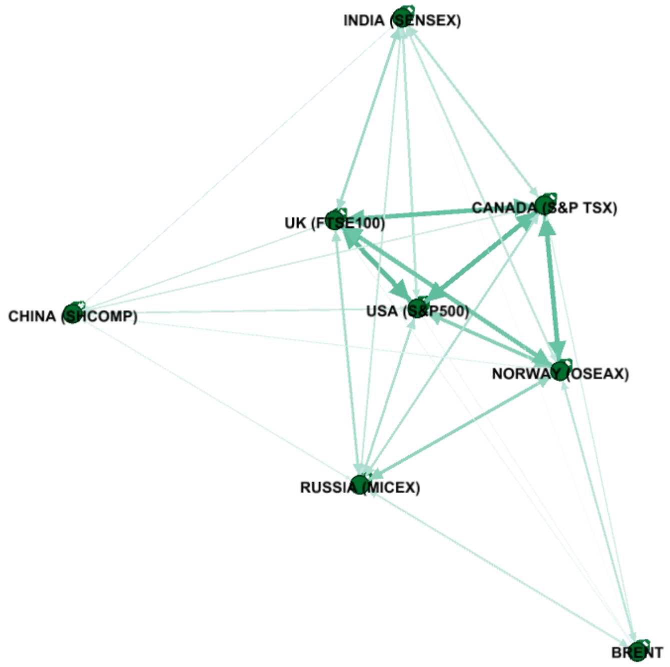
[2] Ljung-Box test for DCC-GARCH errors are reported in the Appendix.

ket j to market i. For example, entry (1,2) indicates that the Canadian stock market transmits a 2.52% gross spillover to the US stock market on average for the sample period. The summation of the entries of column j represents the total spillover produced by market j to all other markets (excluding itself). The summation of the entries of row i corresponds to the total gross spillover received by market i from the other markets. The total system's spillover corresponds to the sum of all columns' (or rows') summations. For the eight markets included in our sample, total volatility spillovers are of 63.14%.

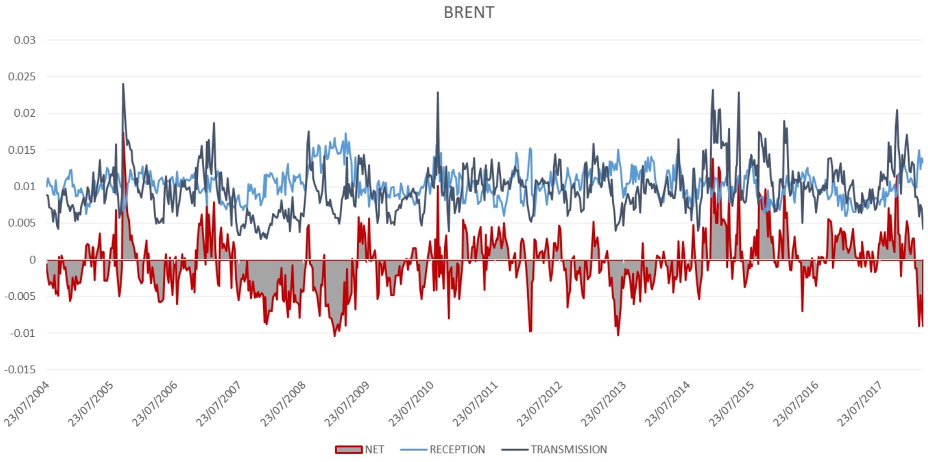
Figure 2: Net spillovers network



Net positions are calculated by substracting each market's total gross reception from its total gross transmission to other markets. Three net receivers (China, India and the BRENT) and five net transmitters (Norway, the US, Russia, Canada, and the UK) are identified. Importantly, for our set of markets, which includes stock markets of countries that are major participants in ol markets, the BRENT is a net volatilicty receptor. This result goes in line with those of previous papers that have found similar results using different samples of countries (e.g., Gomez-Gonzalez and Hirs-Garzon, 2017). The most important transmitter is Norway's stock market. Its transmission to the BRENT is high. Given the high participation of oil and gas producing firms in this market, this result supports the oil market financializacion hypothesis.

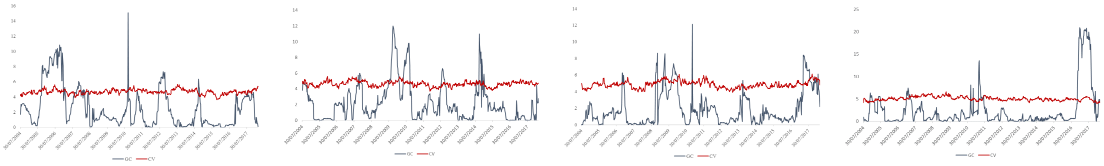
Figure 2 presents graphically the interaction between the eight markets included in this study using network analysis. The placement of nodes in the network is determined by the Force Atlas2 algorithm developed by Jacomy et al. (2014). This algorithm encounters a steady-state balance between forces of transmission and reception. Color intensity represents the degree of connectedness between the corresponding markets. Darker color segments correspond to more connected markets. Notice that the stock markets of the US, the UK, Canada and Norway are strongly connected, while those of India, China and Russia have negligible effects in total interaction. Importantly, the BRENT is connected to the network through Norway and Russia, two of the most important oil producers in the world.

Figure 3: Reception, transmission and net position

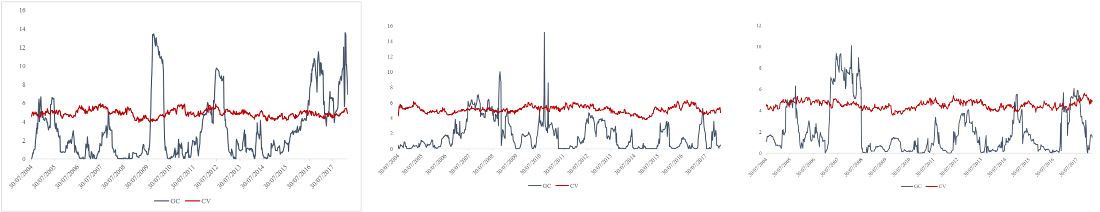


As in other studies, transmission and reception intensities are not constant over time. In fact, they exhibit large time variation. Figure 3 shows gross and net transmission positions of the BRENT, with respect to the group of seven stock markets in our sample. While its average net position is negative (net receiver), the BRENT has been a net volatility transmitter at some points in time. Of special relevance, while during the US Subprime Financial Crisis the BRENT was a large net spillover receiver, since 2014 it started to transmit spillovers changing its net position to a net transmiter. This result shows that volatility production and reception between financial and commodity markets exhibits interesting dynamics, and poses the question whether causality presents time variation as well.

Figure 4: Dynamic Causality Tests from Stock Markets to Oil



(a) US to Brent (b) Canada to Brent (c) Russia to Brent (d) Norway to Brent

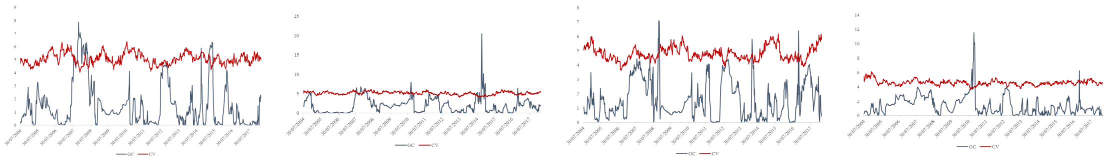


(e) India to Brent (f) China to Brent (g) UK to Brent

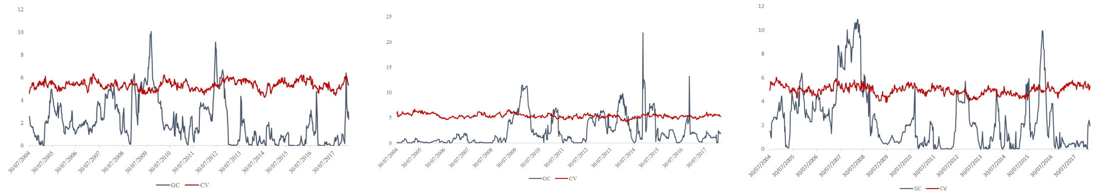
We perform dynamic Granger causality tets from stock markets to the BRENT and viceversa. Tests from stock to oil markets reveal several interesting features. First, similar to the behavior of spillovers, causality test results present considerable variation over time. For instance, while evidence of Granger causality is encounterd in all cases, causality is identified only for short periods of time. Many of these episodes occur during the recent global financial crisis. Others are registered during times of the European sovereign bond crisis of 2012. In this sense, our results agree with those of previous studies showing that volatility spillovers and causality are stronger during period of financial distress. Interestingly, we report evidence of Granger causality from the stock markets of Norway and India to the BRENT in the last part of our sample. This result indicates that stock markets that are generally not considered as major participants in global financial markets recently explain an important share of volatility transmission to oil and other markets. Notice that the last part of our sample period is characterized by strong oil price downturn.

Dynamic Granger causality tests from the BRENT to stock markets show also interesting results (see Figure 5). Considerable time variation is detected. Evidence of causality is found mainly during periods of financial turbulence as well. How-

Figure 5: Dynamic Causality Tests from Oil to Stock Markets



(a) Brent to US (b) Brent to Canada (c) Brent to Russia (d) Brent to Norway



(e) Brent to India (f) Brent to China (g) Brent to UK

ever, periods in which causality is identified are shorter than those in which stock markets Granger-cause the BRENT. This means that while there is evidence of bidirectional causality, the main causal relation flows from stock markets to the BRENT.

5 Conclusions

The study of volatility spillovers between financial markets has gained interest in recent years. The large variations in commodity prices and the financialization of commodity markets has provoqued their inclusion in financial spillover studies and the reconsideration of the exogeneity assumption that has been traditionally imposed to commodity price shocks in the literature. Our paper contributes by using a sample of stock markets from major oil market participant countries and the BRENT. We study the dynamic linkages between these markets focusing in connectedness and in the transmission of volatility spillovers. We compute total and directional indicators using forecast error variance decomposition from vector autoregressions, and study their time variation. Additionally, we use recently developed dynamic Granger causality tests to check the validity of the oil market financialization hypothesis that proposes that the behavior of these markets largely depends on the developments of financial markets.

We find three relevant results. First, conectedness and volatility spillovers between oil and stock markets are time-varying. Specifically, they are stronger during episodes of high market volatility. Second, the BRENT has on average a net reception position, while the stock markets of Norway and the US have the strongest transmission positions. However, net positions also exhibit time variation. For instance, the BRENT is a large spillover receiver during times of financial distress (e.g., the Subprime Financial Crisis and the European bond crisis) and a spillover transmitter in moments of oil price downturns (the last part of our sample period). The important position of Norway as a volatility transmitter suggests this country's financial markets should be included more often in related studies. Finally, results of dynamic Granger causality tests show evidence of bidirectional causality between oil and stock market returns. However, the effect from stock markets to oil returns seems to be more stable and of longer duration.

Our results provide additional empirical evidence suggesting the validity of the oil markets financialization hypothesis, and have important implications for global investors and policymakers. With respect to investors, the fact that volaytility spillovers (and causality) between oil and stock markets presents considerable time variation suggests that portfolio diversification strategies must be time-varying as well. Regarding policy makers, those in oil-dependent economies must consider the strong interactions between oil and stock markets when designing policies for minimizing the negative effects of oil price shocks, specially during moments of financial volatility.

Appendix

Table 3: Ljung-Box Test on the DCC-GARCH Errors (pvalues)

Lag	**US**	**CAN**	**RUS**	**NOR**	**IND**	**CHI**	**UK**	**Brent**	**Multivariate test**
					Standardized errors				
5	0.95	0.72	0.56	0.69	0.43	0.42	0.12	0.79	0.98
10	0.99	0.91	0.79	0.33	0.75	0.27	0.11	0.41	0.96
15	0.99	0.77	0.58	0.37	0.51	0.17	0.35	0.71	0.93
20	0.97	0.77	0.69	0.66	0.30	0.62	0.43	0.25	0.89
25	0.98	0.55	0.74	0.86	0.30	0.12	0.54	0.30	0.89
30	0.99	0.71	0.34	0.86	0.24	0.13	0.76	0.43	0.76
					Squared Standardized errors				
5	0.96	0.75	0.94	0.94	0.94	0.08	0.30	0.94	0.08
10	0.99	0.77	0.60	0.33	0.85	0.12	0.78	0.77	0.09
15	0.99	0.77	0.88	0.44	0.82	0.38	0.92	0.92	0.53
20	1.00	0.79	0.90	0.76	0.89	0.46	0.81	0.96	0.87
25	1.00	0.83	0.96	0.59	0.84	0.60	0.78	0.96	0.98
30	1.00	0.92	0.99	0.55	0.70	0.77	0.55	0.97	0.98

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