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Dynamic Connectedness and Causality between Oil prices and Exchange Rates[1]

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[1] *Disclaimer:* The views expressed in the paper are those of the authors and do not represent those of the Banco de la Republica or its Board of Directors.

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Abstract

We study connectedness and causality between oil prices and exchange rates dynamically. Using data on the WTI and exchange rate returns for six countries in which oil production is a major production activity, we show that oil prices are net receptors of spillovers from excahnge rate markets. Connectedness exhibits important time variation and presents a positive trend during our sample period. We find evidence of bidirectional causality between oil prices and exchange rates, which presents also considerable time-variation. Causality is identified for longer periods of time from oil prices to exchange rates. However, we also find evidence of reverse causality, mainly in the period after the Subprime Financial Crisis. Our results provide evidence supporting the hypothesis of the financialization of oil markets.

JEL Classification:G01; G12; C22.

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

1 Introduction

In this paper we study the relationship between oil prices and exchange rates for a set of six countries that are important producers in oil markets, and which present different levels of maturity (i.e. emerging and developed). Our contributions to the literature are two-folded. First, we examine the dynamic multivariate relation between oil prices and exchange rate returns, and measure connectedness from a global perspective in foreign exchange markets. We compute total and directional connectedness indicators using forecast error variance decomposition from vector autoregressions, following the method developed by Diebold and Yilmaz (2012, 2014). And, second, we study bidirectional causal relations between oil prices and exchange rate returns dynamically, using rolling windows, which allows for endogenously determining changes in causality over the time.

The relation between oil prices and exchange rates has recently regained interest in both academic and policy circles. Part of this renewed interest has been motivated by the surge of sharp movements in their prices occurring during and in the aftermath of the Global Financial Crisis. As the literature has shown, volatility of oil and financial markets has significant effects on macroeconomic stability, especially for countries that are producers and consumers of crude oil and its derivatives. Especially relevant, exchange rate and oil price volatility are closely connected in countries in which oil production represents an important share of total output. This has lead to the term "commodity currencies" introduced by Chen and Rogoff (2003). Understanding the dynamic linkages between oil and stock prices is therefore important both for investors and policy makers.

While the vast majority of studies assume exogeneity of oil prices and directly test their effect on exchange rates, a new strand of the literature has come to challenge this traditional view. Particularly, studies on the financialization of commodity markets point out that an increasing participation of institutional investors such as hedge funds and pension funds in these markets has led to a higher responsiveness of prices to investors' preferences and behavior. Indeed, the exposure to a variety of instruments including futures, options and exchange-traded funds, have made commodities an additional asset class, and therefore the behavior of other financial assets likely affect their performance (see, for instance, Irwin and Sanders, 2012; Tang and Xiong, 2012; Mensi et al., 2013; Cheng and Xiong, 2014; Kilian and Murphy, 2014; Turhan et al., 2014; Du and He, 2015; Cheng et al., 2015; De Nicola et al, 2016; and Zhang, 2017).

The aforementioned literature has focused on examining the interplay between stock and commodity prices, while mainly overlooking the expected relationship between foreign exchange and commodity prices. Nevertheless, the capital outflows-from and inflows-to the commodity markets are mediate by FX markets, to the extent that traditional portfolios in stocks and bonds are generally denominated in USD dollars. That is, by construction, currencies denominated in USD-dollars should have an effect on commodity prices, due to the continuously rebalancing of international portfolios in the hands of institutional investors. And as a consequence, exchange rates have predictive power on commodity prices (Chen et al., 2010). In this playing field, causality becomes a first order issue when modeling the relation between oil prices and exchange rate markets. Some recent studies that have considered this double causality between commodity prices and exchange rates include Akram (2009), Lizardo and Mollick (2010), and Brahmasrene (2014), Beckmann and Czudaj (2013) and finally Lof and Nyberg (2017). Our study belongs to this strand of the literature. Unlike them, we examine the dependence between oil prices and exchange rates from a multivariate perspective, and we also estimate causality in a dynamic fashion, which allows us to specifically date periods in which exchange rates have impacted oil markets, and viceversa.

Our results show that oil prices and exchange rate returns are importantly interrelated, as the value of the total connectedness indicator is high when compared to those of similar studies. Therefore, spillovers within these markets are frequently observed. One important aspect is that oil markets do not affect exchange rates as importantly as it is frequently assumed. In fact, our findings show that oil markets are net receivers of shocks during the vast majority of the sample period, providing evidence in favor of the oil financialization hypothesis.

Important to note, three countries are net transmitters of spillovers in our system, namely Australia, Canada and Mexico. However, while Australia has a net transmitter position most of the time, the positions of Canada and Mexico exhibit important variation over the time. Meanwhile, Brazil, Colombia and Norway are by general rule, net receivers of shocks, maintaining this position for almost the entire sample period.

Global connectedness exhibits a positive trend between January 2001 and June 2016, with a brief interruption between August 2012 and October 2014. This result indicates that oil and foreign exchange markets have become increasingly more integrated from the beginning of the 2000s onwards. Gomez-Gonzalez and Hirs-Garzon (2017) show a similar behavior between oil and stock markets in oil-dependent economies. Regarding causality, several results deserve to be highlighted. First, we find evidence on bidirectional causality between oil and exchange rate returns. Second, causal relations exhibit considerable time-variation and last only for short periods of time. Third, although causality relations run in both directions, they are more frequently encountered from oil prices to exchange rates than viceversa.

The remainder of the paper is organized as follows. Section 2 presents a brief review of the related literature. The third section is methodological. Section 4 describes the data used in our empirical analysis. Section 5 presents our main findings and the last section concludes.

2 Literature review

The seminal papers studying the relation between oil prices and exchange rates are Golub (1983) and Krugman (1983). Both assume exogenous oil prices and model the effect of oil price increases on exchange rates. The former focuses on the wealth transfer effects associated with oil price rises and their implications for portfolio equilibrium. The exchange rate adjusts in order to clear asset markets. The latter presents three models, each of them emphasizing on different channels through which exchange rates are affected by oil price shocks.

Based on these models, empirical papers have studied this relation using different econometric techniques, and considering different countries and sample periods.

Both real and nominal exchange rates have been considered in these studies. The evidence of the intensity of the relation between oil prices and exchange rates as well as on causality is mixed.

Amano and Van Norden (1998) study the effect of oil price shocks on the US real effective exchange rate over the post-Bretton Woods period. They find that oil prices are the dominant source of persistent real exchange rate shocks.

Chen and Rogoff (2003) study the behavior of real exchange rates in three commodity-dependent economies, namely Australia, Canada and New Zealand, and find that the world prices of commodity exports (in real US dollars) strongly influence the real exchange rates of Australia and New Zealand. In a similar study, for a set of 58 commodity-export countries between 1980 and 2002, Cashin et al. (2004) find that there is a long-run relationship between each country's real exchange rate and real commodity prices for about one-third of the countries in the sample. They also find that the long-run real exchange rate of these 'commodity-currencies' is time-varying as it responds to movements in the real price of commodity exports.

Bénassy-Quére et al. (2007) study cointegration and causality between the real price of oil and the real price of the dollar over the 1974–2004 period. Their empirical results suggest that causality runs from oil prices to the dollar, and oil price rises lead exchange rate appreciations. Zhang et al. (2008), using also a cointegration framework, show that there is a significant long-term equilibrium relationship between oil prices and the real US exchange rate. Regarding causality, they find that the US dollar exchange rate influences the international crude oil market in the long-run. In contrast, its short-term influence is small.

Akram (2009) finds that devaluations of the US dollar lead to higher commodity prices, for the period 1990 - 2007. Chen et al. (2010) show that "commodity currency" exchange rates have strong predictive power of global commodity prices, both in- and out-of-sample. Importantly, they find that the reverse causality is less significant. Lizardo and Mollick (2010), including oil prices to the monetary model of exchange rates, show that the opposite relation of causality exists as oil prices significantly explain movements in the U.S. dollar (USD) exchange rate against major currencies from the 1970s to 2008.

Reboredo (2012) studies the comovements between exchange rates and oil prices using copulas and correlations. According to his findings, the dependence between oil prices and exchange rates is weak, although it exhibits considerable time-variation. Particularly, it rose importantly in the aftermath of the Global Financial Crisis. He also finds that there is no extreme market dependence between them. Aloui et al. (2013) carry out a similar study, but include dynamics using a copula-GARCH approach. They find evidence of significant and asymmetric dependence for almost all the oil-exchange rate pairs considered, and provide evidence that the rise in the price of oil is associated with the depreciation of the US dollar.

Reboredo and Rivera-Castro (2013) studies the relationship between oil prices and US dollar exchange rates using wavelet multi-resolution analysis. Their main finding is that the relation between oil prices and nominal exchange rates changed in the aftermath of the Subprime Financial Crisis. Specifically, while oil prices and exchange rates did not exhibit dependence in the pre-crisis period, there is evidence of contagion and negative dependence after the onset of the crisis.

Turhan et al. (2014) studies dynamic correlations between oil prices and exchange rates of G20 countries. They provide evidence of time-variation of these correlations, which are significantly higher during moments of market turbulence. Brahmasrene et al. (2014) show that exchange rates Granger-cause crude oil prices in the short run while reverse causality is encountered in the long-run. Beckmann and Czudaj (2013) find that causality mainly runs from exchange rates to oil prices. Jammazi et al. (2015) find evidence of a nonlinear pass-through from exchange rates to crude oil prices. Their findings also suggest that oil prices respond asymmetrically to exchange rate movements in the short and long run.

Basher et al. (2016), using a Markov switching framework, find that the influence of oil supply shocks on exchange rates is rather limited. de Truchis and Keddad (2016), using fractional cointegration and dynamic copula-based models, show that little evidence of co-persistence appears between the volatilities of oil prices and nominal exchange rates for various countries. Aloui and Aissa (2016) apply a vine copula approach to investigate the dynamic relationship between energy, stock and currency markets. Their findings suggest that the relation between the WTI crude

oil, the Dow Jones Industrial average stock index and the trade weighted US dollar index returns is significant and symmetric. However, they show that important time-variation in this relation occurs.
Finally, Lof and Nyberg (2017) use noncausal autoregressions to test the commodity currency hypothesis. They find evidence suggesting that while exchange rates do not predict commodity prices, the reverse causality is strong. Their results are consistent with the hypothesis of financialization of commodity markets.

3 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 foreign exchange market 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 conditional covariance matrix of errors.
Our first step consists in computing different connectedness measures for the markets included in our sample. We follow Diebold and Yilmaz (2012, 2014), who develop a method for computing market connectedness in a general setup, flexible enough as to allow the calculation of pairwise and general connectedness indicators. These measures are based upon variance decompositions of vector autoregressions. Generalized variance decompositions following Pesaran and Shin (1998) are used, so results are invariant to the ordering of variables in the VAR model.
Regarding pairwise directional connectedness, market $j's$ contribution to market $i's$ H-step-ahead generalized forecast error variance[1] $\psi_{ij}^{g}(H)$ is calculated by

[1] In our empirical analysis we focus on a ten-day horizon, but our results are qualitatively identical for different horizons, from 5 to 10.

$$\psi_{ij}^{g}(H)=\frac{\sigma_{jj}^{-1}\sum\limits_{h=0}^{H-1}\left(e_i^{'}A_h\sum e_j\right)^2}{\sum\limits_{h=0}^{H-1}\left(e_i^{'}A_h\sum A_h^{'}e_i\right)} \quad , \quad H=1,2,... \tag{2}$$

where $\sum$ stands for the covariance matrix of error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th}equation, A_h is h^{th}-step moving average coefficient matrix and e_i is a extraction vector, i.e. a vector in which the i^{th} position is a one and the rest of entries are all zero.

In order to get well-defined percentages, i.e. numbers between 0 and 1, $\psi_{ij}^{g}(H)$ can be normalized in the following way:

$$\overset{-g}{\psi}_{ij}(H)=\frac{\psi_{ij}^{g}(H)}{\sum\limits_{j=1}^{N}\psi_{ij}^{g}(H)} \tag{3}$$

where $\sum\limits_{j=1}^{N}\psi_{ij}^{g}(H)=1$ and $\sum\limits_{i,j=1}^{N}\psi_{ij}^{g}(H)=N$ by construction. $\overset{-g}{\psi}_{ij}(H)$ is the indicator of pairwise connectedness from market j to market i. Directional connectedness is being measured by $\overset{-g}{\psi}_{ij}(H)$. Hence, we do not assume symmetry, i.e. $\overset{-g}{\psi}_{ij}(H)\neq\overset{-g}{\psi}_{ji}(H)$,for $i\neq j$. In words, the effect of market j on market i is not identical to the effect of market i on market j.

After computing pairwise connectedness measures for every possible pair of markets, different indicators of systemic connectedness can be computed. Three important systemic measures arise. First, a measure of connectedness from others to market i can be computed as $\sum\limits_{j\neq i}\overset{-g}{\psi}_{ij}(H)$. Second, a measure of connectedness from market i to the other markets, given by $\sum\limits_{j\neq i}\overset{-g}{\psi}_{ji}(H)$. The net position of market i is calculated as the difference of these two gross positions with respect to the rest of the system. And, finally, the total connectedness index of the system can be computed as

$$\frac{1}{N}\sum_{i,i\neq j}\overset{-g}{\psi}_{ij}(H) \tag{4}$$

This measure of total connectedness is simply the average of all total directional connectedness measures whether they are "to" or "from".

After computing the different connectedness measures, we go one step forward and compute dynamic Granger causality tests between pairs of market returns. We follow the method of Hurn et al. (2016) who develop a test for detecting changes in causal relationships based on a recursive rolling window.[2] The test has three advantages over others. The principal is 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 the potential heteroskedasticity of the data, reducing the chance of flawed inference.

4 Data description

In this study we test for the connectedness and causality between oil prices and the exchange rates of six oil-producing economies, namely Australia, Brazil, Canada, Colombia, Mexico and Norway. When selecting our sample we have considered oil exporting economies with free-float exchange rate during the sample period. Our data set consists of daily closing prices of the WTI and the exchange rate of each of these six countries with respect to the US dollar[3]. We use the first difference of the corresponding natural logarithms for computing returns. All data were collected from Bloomberg. Our sample spans the period comprised between January 4th, 2001 and July 29th, 2016, allowing us to assess the effect of the recent international financial crisis on the dynamic interactions between oil prices and exchange rates.

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

[3] Following the related literature, we compute the exchange rate as the number of US dollars per unit of domestic currency.

Table 1 presents descriptive statistics of our data. Notice that the WTI returns and those of the six exchange rates included in our sample are stationary, according to ADF unit root tests. All means but two (WTI and Canada) are negative and skewness is negative as well in most cases. This fact indicates that average returns are mostly encountered in the negative domain and negative returns are more frequent than positive returns in these markets. Kurtosis is higher than 3 for all returns, and results from Jarque-Bera tests (not reported in the table) indicate that the normal distribution is not adequate for our data as usually happens when financial markets are studied.

Table 1. Descriptive statatistics on the WTI and real exchange rate returns

	Mean	Std. Dev	Skewness	Kurtosis	ADF test
Norway	-0.0011	0.721	-0.15	5.43	-66,9***
Australia	-0.0024	0.843	0.34	12.00	-68,9***
Canada	0.0019	0.541	-0.11	5.83	-68,6***
Mexico	-0.0134	0.599	-0.61	14.02	-68,9***
Brazil	-0.0114	1.023	-0.05	9.41	-50,3***
Colombia	-0.0098	0.705	0.09	12.17	-61,5***
WTI	0.0136	2.148	-0.11	7.26	-68,1***

Note: *** denotes 1% level of significance. Lag selection in ADF test based on Bayesian Information Criteria (BIC). Mean returns and their standard deviations are multiplied by 100 in this table.

Figure 1 depicts the behavior of returns over time. Notice that in all cases returns were substantially lower and presented higher variance around the Lehman Brothers' failure in September 2008. Table 2 shows unconditional Pearson's correlation coefficients between pairs of returns. Interestingly, as most correlations are positive, Australian exchange rate returns present negative correlations with those of the other six markets. This fact illustrates that the Australian exchange rate serves as a hedge to the other assets included in our sample on average. Although these preliminary results appear to be intuitive and appealing, it is important to remember that unconditional correlations in this context present the serious limitation of being time-invariant.

Table 2: Correlation coefficients

	Norway	Australia	Canada	Mexico	Brazil	Colombia	WTI
Norway	1						
Australia	-0.58	1					
Canada	0.52	-0.64	1				
Mexico	0.34	-0.44	0.47	1			
Brazil	0.29	-0.38	0.36	0.50	1		
Colombia	0.26	-0.31	0.30	0.31	0.34	1	
WTI	0.31	-0.30	0.34	0.23	0.20	0.26	1

Figure 1: Market returns

5 Results

Table 3 presents results on connectedness for the full sample. The total connectedness in our system amounts to 46.9%. This indicates that the foreign exchange markets and the WTI market, analyzed herein are highly interconnected. The $ij-th$ entry of the table shows the contribution of the $j-th$ return to the explanation of the $i-th$ return. For instance, entry $(3,1)$ of the table shows a value of 12.20%. This value corresponds to the spillover from the Norwegian exchange rate to the Canadian exchange rate. The last entry in each column, labeled "To", presents results of total connectedness from the return corresponding to that column to the other markets. For instance, Norway presents a transmission of 49.69% to the other markets included in our sample. The column labeled "From" shows results of connectedness from the other markets to the market in the row. For instance, Norway receives a transmission of 50.11% from the other markets.

The last column of the table, labeled NDC (net directional connectedness), shows the net position of each index return in terms of global connectedness. A positive (negative) sign indicates a net positive (negative) contribution of the corresponding index return to total connectedness. The net contribution of return i is calculated as the difference between the total spillover given by return i and the total spillover it receives from the rest of returns in the sample. For instance, Norway has a net average reception of 0.41% from the other markets in our sample. Our results show that, on average during the sample period, Australia, Canada and Mexico are the main contributors to connectedness, as they exhibit the highest (positive) net positions. Meanwhile, Colombia, Brazil, Norway and the WTI are on average net receptors of connectedness from the system.

Table 3: Connectedness (full sample)

	Norway	Australia	Canada	Mexico	Brazil	Colombia	WTI	From	NDC
Norway	N/A	17.24%	13.81%	6.08%	4.62%	3.52%	4.83%	50.11%	-0.41%
Australia	15.05%	N/A	17.88%	8.90%	6.51%	4.27%	3.91%	56.53%	10.00%
Canada	12.20%	18.15%	N/A	9.97%	5.95%	4.34%	5.37%	55.98%	9.73%
Mexico	6.13%	10.25%	11.51%	N/A	13.20%	5.63%	2.91%	49.64%	2.48%
Brazil	5.03%	8.27%	7.52%	14.55%	N/A	6.87%	2.23%	44.47%	-2.67%
Colombia	4.71%	6.60%	6.71%	8.62%	8.75%	N/A	4.07%	39.47%	-10.30%
WTI	6.57%	6.01%	8.27%	3.99%	2.78%	4.52%	N/A	32.15%	-8.82%
To	49.69%	66.53%	65.71%	52.12%	41.80%	29.16%	23.33%	**46.00%**	

Table 3 shows that oil prices receive more than what they contribute to global connectedness, and hence their net position is negative (-8.82%). This finding provides evidence supporting the oil financialization hypothesis. Figure 2 graphically exhibits our results on total connectedness for each point in time. Note that this index varies considerably over time, ranging from a minimun value of 10.8% in February 12, 2001 to a maximum of 70.0% in July 19, 2010. Notice that while this systemic index decreased between August 2012 and October 2014, after that month it returned to its increasing trend.

Figure 2: Rolling-windows estimation of total connectedness

Figure 3 depicts the gross and net contributions of the WTI to and from the rest of the system. Clearly, most of the time it has been a net spillover receptor. Exceptions are few and short-lasting. Following the behavior of the systemic index, in the last two years of the sample the WTI has gained importance in both gross positions, but its net position has remeined relatively unchanged.

Figure 3: Contribution to, reception from, and net position. WTI

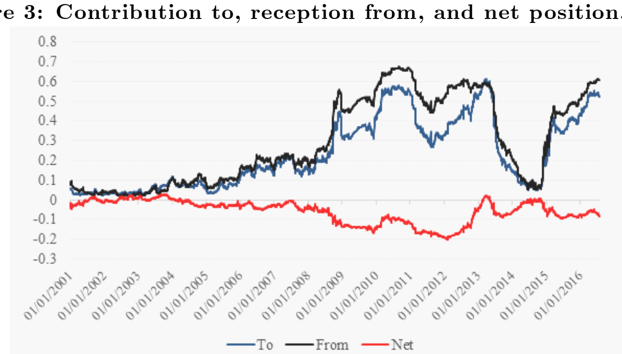
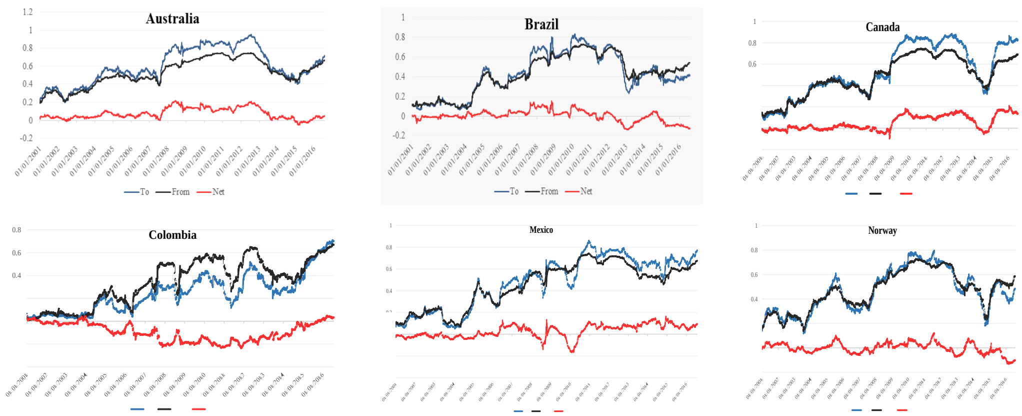


Figure 4 shows gross transmission, gross reception and the resulting net position for the six exchange rates included in our sample. Some interesting features are worthy of mentioning. The only country that is systematically a net transmitter is Australia. The other countries present negative and positive positions over the sample period. Brazil, Canada and Mexico are net transmitters most of the time. However, while Canada and Mexico presents a large net transmitter position from

2010 on, Brazil presents small positions when they are positive. Norway holds a net position close to zero during the whole sample period, and it changes from positive to negative almost randomly. Finally, Colombia exhibits a large negative position most of the time, as expected, given its relative size compared to the other markets in the sample.

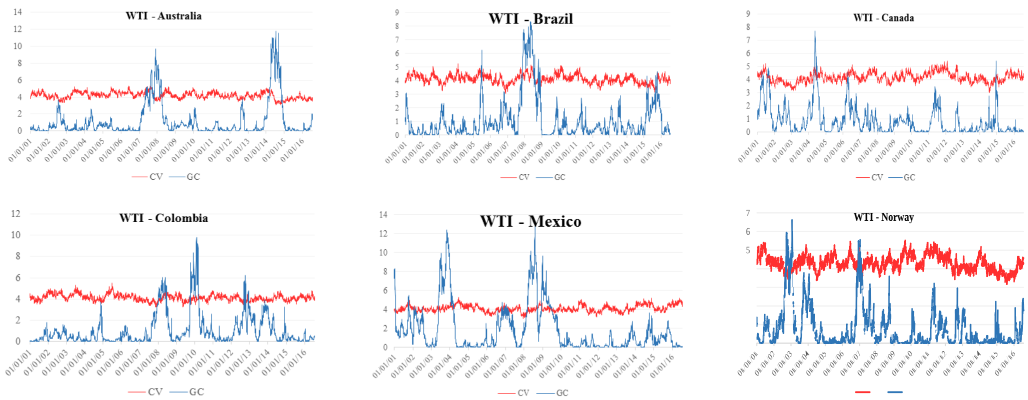
Figure 4: Contribution to, reception from, and net position. Exchange rates



So far we have reported results on interconnectedness between markets. However, an interesting question deals with causality. Considering the hypothesis of the financialization of oil, it is worthy to study the potential bidirectional causality between oil prices and exchange rates. This issue is specially relevant considering the fact that the existing empirical evidence is unconclusive (see the literature review section). Below we report our main findings using the time-varying Granger causality test described in the methodological section of this paper.

We report results in two stages. First we show our findings regarding causality from oil prices to each of the six exchange rates. In each case we perform our tests in a multivariate framework in which all included variables are allowed to be endogenous. Figure 5 depicts these results. In each panel the graph denoted "CV" shows the critical value of the test at the 95% significance level. The graph denoted "GC" shows the value of the test statistic. Granger causality from oil prices to the corresponding stock market is detected whenever GC lies above CV at a point in time, i.e. when the value of the test statistic is larger than the critical value at the 95% significance level.

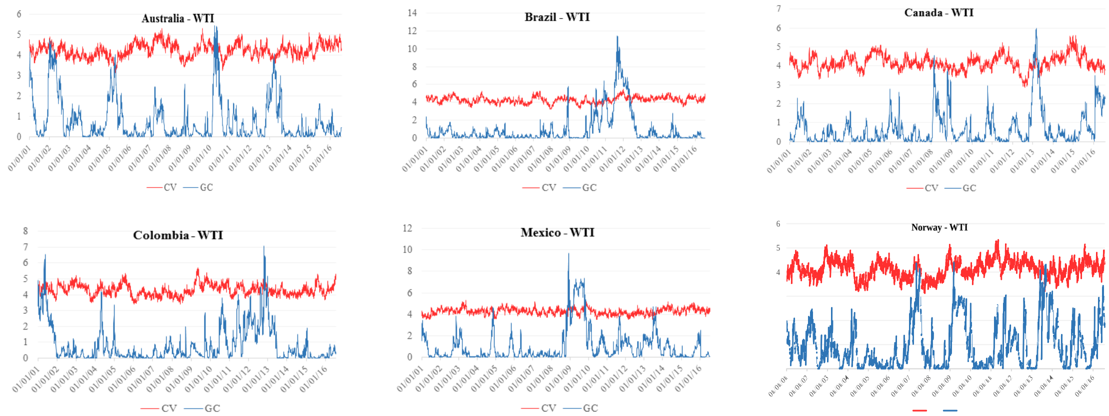
Figure 5: Time-varying Granger causality test results. Causality running from oil prices to exchange rates



Important to note, in all cases the WTI Granger-causes the respective exchange rate in at least one month. Note that the largest periods for which causality in this direction is detected are around the Subprime Financial Crisis.

Figure 6 shows results regarding reverse causality, i.e. from exchange rate returns to crude petroleum prices. Note that, according to our test results, all markets Granger-cause the price of oil at some moment of time, supporting the hypothesis of oil financialization. Episodes of causality are shorter in this direction than in the opposite one, and most occur after the Subprime Financial Crisis. Mexico is an important exception, in the sense that causality from its exchange rate returns to the returns of oil are encountered during this crisis. The lowest test statistic values are reported for Norway, country for which causality is barely identified in very short periods of time.

Figure 6: Time-varying Granger causality test results. Causality running from exchange rates to oil prices



6 Conclusions

In this paper we study the relation between oil prices and exchange rate returns for a set of six countries, including important oil producers. While many related studies consider oil prices exogenous and focus on their effects on exchange rates, we allow them to be endogeous in our system. Using the method developed by Diebold and Yilmaz (2012, 2014), we study interconnectedness between oil and exchange rate markets, and characterize the dynamics of transmission and reception between them. Furthermore, we test for Granger causality between markets dynamically, endogenously identifying periods for which oil prices have responded to innovations in foreign exchange markets.

Our results on connectiveness show that transmission occurs mainly from exchange rates to crude petroleum prices. Connectedness is time-varying, and presents a positive time-trend that was shortly interupted from August 2010 to October 2014. Australia, Canada and Mexico are the main transmitters of spillovers.

We find evidence of bidirectional causal relations between oil prices and exchange rates in all cases. Causality is endogenously identified in our paper using a rolling window estimation method. We identify a time-varying behavior, with causal relations being stronger during the Subprime Financial Crisis (from oil prices to exchange rates) and in short periods of time after this crisis (from exchange rates to oil prices). Our results provide evidence supporting the hypothesis of the financialization of oil markets.

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