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Pass-through Effects of Oil Prices on LATAM Emerging Stocks before and during COVID-19: An Evidence from a Wavelet -VAR Analysis

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ABSTRACT

Vector Auto regression model (VAR) a time -varying parameter is applied to study the effect of oil price shocks on the returns of stocks in the LATAM (Latin American) markets. Coherent Wavelet analysis highlights possibilities of connectedness of the oil price and LATAM stock markets through the presence of different patterns in a time series. The structural demand shocks standard deviations during the COVID-19 era remain high and the pass-through effects on stock returns due to oil prices differ for different time frames. The fundamental linkages are demonstrated due to oil market specific demand. The main motive of the research work is to identify the influence of oil price on stocks and identify the fundamental source of contagion.A random effects model is applied to the panel data of LATAM markets with the Global stock market index, MSCI (Morgan Stanley Capital International World Index), domestic money market rates and currency exchange rates during the period of study, 15 March 2019 to 31 July 2021 with 684 observations of controlled non-observed characteristics from individual country. The findings of this research recommend the pass-through effect of the oil prices on the stock market returns are based on time frequency. The contribution of this paper helps the policy makers to restore the confidence amongst the investors in the stock markets and strategies to be adopted by the investors to mitigate the risk by ideal portfolio management.

Keywords: Wavelets, Wavelet-VAR, Oil Pass-Through, LATAM Stock Markets, Oil Price Volatility
JEL Classifications: C14, C32, G15, Q43

1. INTRODUCTION

Oil is considered to be one of the Globally traded commodities with fluctuant price with an increased influence on the economies of the nation. There is an extensive research work on the oil price volatility since the time of oil crises (1970 s) during past two decades. With the origin of oil crises in the 1970 s and the attention received from researchers on the works of Hamilton (1983) oil price increases and productivity positive related conclusions are on debate with different views on the relationship based on different factors and also widely accepted by many researchers along the most influenced work by Herrera et al., 2019).

Studies have analysed the impact of oil price volatility of international crude on developed economies (Barsky and Kilian 2004; Hamilton 2009; Kilian, 2008). It is anticipated that volatility in the oil price passes through to the prices of other goods directly and indirectly. Research on oil pass-through in economies has shown that investment expenditure responds to price shocks of the energy markets (Edelstein and Kilian, 2007). The impact of volatility of crude oil prices on inflation is an attributable direct or indirect impact on the energy components (ECB, 2010).

This study is motivated by and aligns with the work of Santillan-Salgado et al. (2017) and Kilian and Park (2009) and we aim to understand the pass-through effect on oil price and its effect on returns of the stocks in the emerging stock returns in LATAM markets.

This study uses a panel data model to examine the effect of oil prices on stock returns. We apply wavelet coherence analysis to decompose oil and stock time series into sub-time series. To decompose the series, a VAR (Vector Auto Regression model) is applied and impulse- response function identifies different time horizon and oil shock effects. This study contributes to the literature on emerging stock returns in LATAM markets-before and during the COVID-19 era.

The objective of the study is to identify: first, the interactions of oil shocks to stock markets over different time-frames; second, behaviour of the spread over time; third, the *contagion effects* and the fundamental sources with the research questions:

- At what times of the year do the interactions of oil and stock markets differ? (local correlation)
- In which periods do differences occur? (timing)
- How fast do interactions spread over time? (*pure contagion* or *fundamental linkages*)
- Does the oil price pass through to stock markets? (decomposed VAR)
- What is the extent of oil shocks on stock returns last indifferent time-frames? (decomposed impulse-response functions).

The remaining study is organized as follows- section 2 presents the literature review, section 3 puts forth the methodology, section 4 presents the results of the study, and finally, section 5 concludes the study.

2. LITERATURE REVIEW

There is an increasing popularity in the academic studies on Oil price volatility (Van Eyden et al., 2019). Movement in the crude oil price influence the global economies while stock market returns are influenced by the shocks due to asset allocations and management of portfolio risks. The review of literature in terms of the relationship between oil shocks and stock returns is divided into three different strands a negative relationship. International stock markets with the oil prices (Kaul and Jones, 1996); Kilian and Park, 2009; Kling, 1985); the second finds positive linkages (El-Sharif et al., 2005; Narayan and Narayan, 2010); and the third strand reports an insignificant relationship (Apergis and Miller, 2009; Henriques and Sadorsky, 2008).

Narayan and Sharma (2011) investigated the effect of the oil price volatility on the returns of 560 U.S. firms and find that the effect depends on their sectoral location. Additionally, five of the fourteen sectors analysed indicated the similar results. The study of Elyasiani et al. (2011) is a strong evidence for impact of oil volatility on excess stock returns in thirteen U.S. industries, the authors concluded presence of price fluctuations at the industry level. In the earlier years of research earlier studies focused mostly on western nations, *contagion* and *spillover effects* were studied from Asian crises to Latin American exchange markets and the investigation revealed that Asian crises had the impact on principal exchange markets significantly (Perry and Lederman, 1998). In the literature it is noted that "Not all Oil Price shocks are alike," accordingly a price hike is different for negative supply shock as compared to the increase in prices due to global demand of oil. Kilian and Park (2009) proposed SVAR approach to identify oil supply, oil demand and global demand shocks.

The other studies in the literature are also found to be based upon econometric methodologies such as Vector Auto regression for the study of dynamics of oil and stock (VAR; Kang et al., 2015), Vector Error Correction Models (VECM; Hammadache, 2012) or the GARCH approach (Alsalman, 2016). Also, an extensive work based on the wavelet approach which allows for the time scale and frequency analysis of time series (Akoum et al., 2012; Martín-Barragán, 2013; Reboredo and Castro, 2014; Thenmozhi and Srinivasan, 2015) is found in the literature. Thus, the wavelet coherency approach identifies the direction, causality and timing of occurrences between interactions of time series.

VAR models based on time varying parameter were estimated by Shioji and Uchino (2011) using monthly data of pass through from world oil prices to domestic prices and gasoline prices. Similarly, for Japan it is indicated by asymmetry in responses (Yanagisawa, 2012).

Gasoline prices in the daily data on US were collected from different cities and find different asymmetry across the cities in response to oil prices (Chesnes, 2016). Through estimate error correction model in weekly data of US as a substantial difference of oil pass through the regions is observed (Blair et al., 2017). A Structural VAR model was applied on US weekly data to study the oil pass through to domestic gasoline price and concluded that it was 13% for a week and 37% after 3 months and increased to 50% in the long run (Yilmazkuday, 2019). Another study it is evidenced through quicker oil pass through rate of 23% in the initial five working days and is increased to 48% after 20 days (Chudik and Georgiadis, 2019).

3. METHODOLOGY AND DATA

3.1. Wavelet Analysis

The wavelet analysis represents two frequency bands for the movements of stock return as long wavelet function with lower frequency movements and the short wavelet function with higher frequency movements (Aguiar-Conraria and Soares, 2011). The wavelet approach estimates spectral characteristics of time series and captures energy to provide analysis of temporality, non-stationarity, and volatility over time (Rua and Nunes, 2009; Wei et al., 1998) revealed the different time series in periodic components of time (Aguiar-Conraria et al., 2008), thus, isolates both the slow and persistent movements and describes the heterogeneous behaviour towards investment horizons of market participants in different terms. Wavelet coherence analysis is useful for risk management and portfolio diversification as it illustrates the *spillover effects* across international stock markets and commodity markets, along with revelation of contagion.

Figure 1 Summarizes the methodology applied to analyse using wavelets and software R 4.0.2 version is utlilized to estimate the performance.

The wavelet-based approach involves the decomposition of time series into multiple frequency-timescales that is decomposed with multi-resolution. Based Fourier series analysis approach, each resolution level refers a specific timescale, the frequencies in the time series are captured by sine-cosine functions. Wavelet analysis decomposes the components at different timescales through a filtering process at high and low frequencies separately. It is expected that high frequencies occur in very short time intervals, while the low frequencies can occur in longer time intervals. The decomposition of a time series $f(t)$ into its components occurring at different resolution levels is indicated in expression (1) given below:

$$f(t)=\sum_k s_{j,k}\phi_{j,k}(t)+\sum_k d_{j,k}\phi_{j,k}(t)$$
$$+\sum_k d_{j-1,k}\psi_{j-1,k}(t)+\cdots+\sum_k d_{1,k}\psi_{1,k}(t), \tag{1}$$

The father $\varphi(t)$ and mother wavelet $\psi(t)$ functions exist; approximation of smooth component of time series is enabled by father wavelet. The mother wavelet approximates $s_{j,k}$ smooth coefficients and $d_{j,k} \ldots d_{1,k}$ the detail coefficients, where j and k are obtained from wavelet transform representing the scaling and translation parameters. The following expressions (2) and (3) define the discrete form of the father and mother wavelets Daubechies (1988).

$$\phi_{j,k}(t)=2^{-\frac{j}{2}}\phi\left(2^{-j}t-k\right) \tag{2}$$

$$\psi_{j,k}(t)=2^{-\frac{j}{2}}\psi\left(2^{-j}t-k\right) \tag{3}$$

As per expression (4) the Mexican hat function represents the mother wavelet

$$\psi(t)=\left(1-t^2\right)e^{\frac{t^2}{2}}. \tag{4}$$

The time series $f(t)$ is decomposed in terms of its smooth (S_J) and detailed (D_J) series, as in expression (5):

$$f(t)=S_J(t)+D_J(t)+D_{J-1}(t)+\cdots+D_1(t) \tag{5}$$

Stock index returns are analysed using wavelet correlation and coherence. Maximal overlap discrete wavelet transform (MODWT) enables us to analyse and discrete a time series $f(t)$ into additive decomposition based on scales as shown in expression (1). The wavelet coefficients $s_{j,k}$ and $d_{j,k}$ are similar in length with the original time series at each scale considered to be an advantageous. Applying the least asymmetric Daubechies function of mother wavelet, unbiased estimation in wavelet correlation is performed as shown in expression (6):

$$\tilde{\rho}_{X,Y}\left(\lambda_j\right)=\frac{\gamma_{X,Y}\left(\lambda_j\right)}{v_X\left(\lambda_j\right)v_Y\left(\lambda_j\right)} \tag{6}$$

Covariance is indicated as $\gamma_{X,Y}$ between X and Y time series at scale λ_j, and variances of X and Y are v^2_X and v^2_Y respectively, at scale λ_j. Finally, $\lambda_j = 2^{j-1}$ represents the time frame at j-scale. Precisely, if the daily frame original data is taken at 1-scale, then the decomposed correlation will be obtained at a λ_1 = 1-day window, λ_2 = 2-day window, and at J-level successively.

Continuous wavelet transform (COWT) is used to perform the wavelet coherence is based on Graps (1995) and expressed in (7):

$$CWT_f(j,k)=\int_{-\infty}^{\infty} f(t)\frac{1}{\sqrt{j}}\overline{\psi\left(\frac{t-k}{j}\right)}dt,\ j>0, b\in\mathbb{R} \tag{7}$$

The complex conjugate of the mother wavelet indicated as $\overline{\psi(t)}$, s is a smoothing operator, j the scaling factor and the translation factor k as discussed in (2). Expression (8), W represents two time series $X(t)$ and $Y(t)$ cross wavelet transform (XWT) of Torrence and Compo (1998). This closely matches the correlation coefficient on a local basis as below (expression 9) to represent the COWT of the time series and complex conjugation.

$$W_{X,Y}=W_X W_Y^* \tag{8}$$

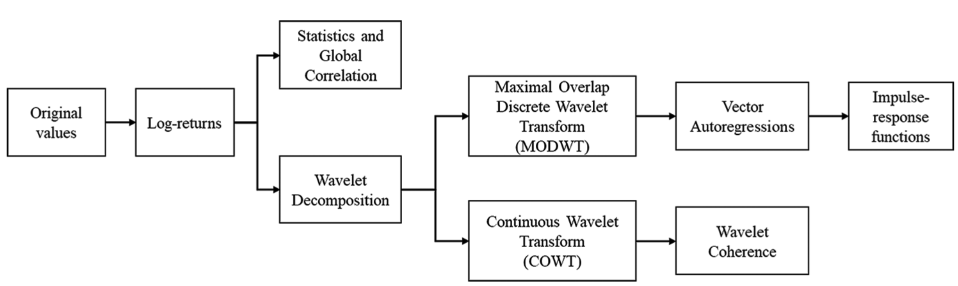
$$R_n^2(s)=\frac{\left|S\left(s^{-1}W_n^{XY}(s)\right)\right|^2}{S\left(s^{-1}\left|W_n^X(s)\right|^2\right).S\left(s^{-1}\left|W_n^Y(s)\right|^2\right)} \tag{9}$$

Wavelet coherence is one of the best tools to analyse linkages in two time series Grinsted et al. (2004). This was supported by the study of Aloui and Hkiri (2014) as they considered to be useful in stock market comovements. Finally, all estimations were performed in R version 4.0.5.

3.2. Data

The data set consists of 687 daily closing prices from March 15, 2019 to July 31, 2021, from the Latin American stock

Figure 1: The Wavelet-VAR approach



markets-which belong to the MSCI LATAM index-such as Argentina, Brazil, Colombia, Chile, Mexico and Peru. The West Texas Intermediate future crude oil prices were used and daily prices were transformed to log-returns as shown in expression (11):

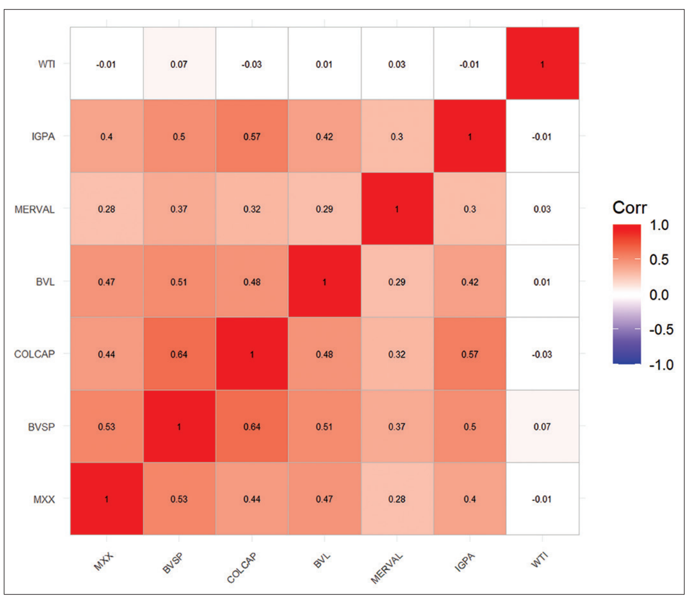
$$Ret_t = log\left(\frac{P_t}{P_{t-1}}\right), \tag{10}$$

Where P_t and P_{t-1} represent the current and previous stock index values and WTI prices, respectively.

The detail of log-returns are shown as Descriptive statistics in Table 1 represent maximum and minimum returns observed on the WTI oil and Brazil-MERVAL prices, respectively. WTI as shown by the standard deviation recorded the highest volatility, which is explained when future prices plunged to a negative zone in April 2020 and later boosted to levels greater than USD 30/barrel in less than a month. However, WTI shows a better risk-return trade-off among the equity indexes as indicated by the Coefficient of Variation.

The global correlation between oil and stock returns as indicated in Figure 2 reflects a weak association and in a few cases a negative asymmetry that support findings of (Alamgir and Amin, 2021). These results suggest the possibility of a diversification investment strategy considering the oil market as an asset that could work as a hedging instrument. From the macroeconomic perspective, it can be stated that oil prices have not fully passed through to stock markets even during the COVID-19 era.

Figure 2: Global correlation between oil and stock market returns



4. RESULTS

4.1. Wavelet Coherence Among Stock Exchanges

Figure 3 represents the wavelet coherence analysis of Mexican-IPC against other LATAM stock markets (see Appendix for complete estimations). In most cases, it is observed that the dynamic co-movement is from a low to medium degree of interaction at low scales (high frequencies). Red zones at low scales (high frequencies) mirror the excess of co-movement which may occur before and during the COVID-19 crisis.

However, at high scales (low frequencies) all cases show strong degrees of association which are interpreted as *fundamental linkages*. Even within this type of co-movement, which happened during COVID-19 crisis, more concentrated red zones at medium scales are found around March 2020, when most of the economies were shut down.

In a particular example, Mexico-IPC against Brazil-Bovespa, we observe that interactions differ at different times before September 2019 in most of the time-frames and that there are low relationships between the stock markets. After this date, an increasing co-movement occurs but at window times >64 days. Since not all market participants operate on the same time horizons, benefits of diversification would not have been collected in a long-term strategy as they were in the short term. After 2020, high interactions at low frequencies are registered, where window times are >56 days. This type of co-movement confirms that fundamental linkages still influence the long-term relationship between both markets. Some excesses of co-movements are found at low levels of window times which dissipate rapidly and are signals of *pure contagion*.

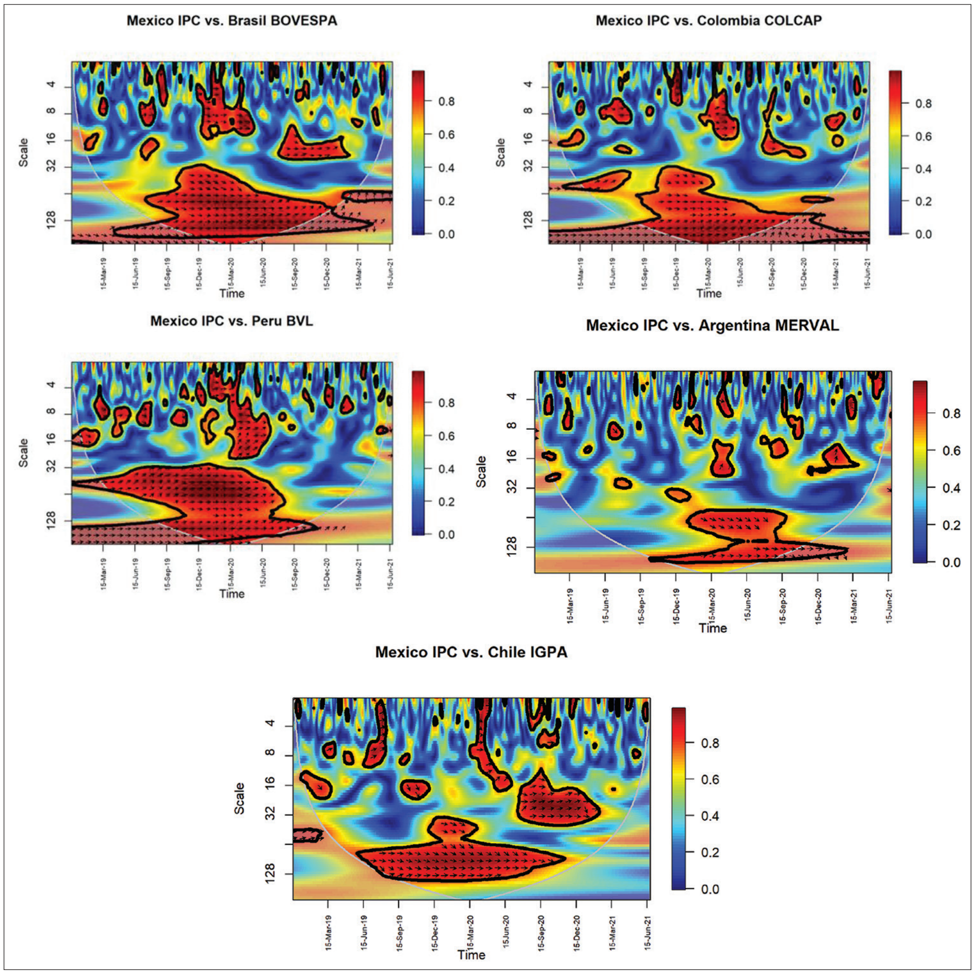
In another example, the pair Brazil-Peru (see Appendix) exhibit strong interaction at medium and high scales around March 2020, and return to its normal long-run interdependence after June 2020. The similar pattern is found between Mexico and Colombia.

On the contrary, all the pairs related to Argentina show an excess of co-movement which becomes stronger after March 2020 and may not last more than 6 months. An exception is found between Brazil-Argentina which continues co-moving until November 2020 but reflects a *pure contagion*.

Table 1: Descriptive statistics of oil and stock returns

	IPC (%)	BVSP (%)	COLCAP (%)	BVL (%)	MERVAL (%)	IGPA (%)	WTI (%)
Min	−6.86	−17.34	−17.69	−11.64	−61.11	−14.84	−32.61
Max	4.63	12.21	11.72	5.10	9.31	7.37	475.92
Mean	0.03	0.02	−0.01	−0.02	0.07	−0.03	0.98
Var	0.000134	0.000384	0.000250	0.000177	0.001281	0.000236	0.037754
Std. Dev.	1.16	1.96	1.58	1.33	3.58	1.54	19.43
Coef. Var.	42.77	97.56	−116.44	−59.83	48.09	−46.56	19.88
Skew	−0.62	−2.28	−2.81	−1.62	−7.66	−2.38	22.01
Kurtosis	4.04	23.42	40.59	13.85	125.66	22.75	527.67

Figure 3: Wavelet coherence among LATAM Stock Markets



4.2. Wavelet Coherence Between oil and Stock Returns

The global correlation shows a weaker level of association for oil prices and stock market returns. However, if the correlation structure is decomposed into different timescales, it is evident that both markets hold interdependence since at high scales (low frequencies) the degree of interaction is greater than at low and medium scales.

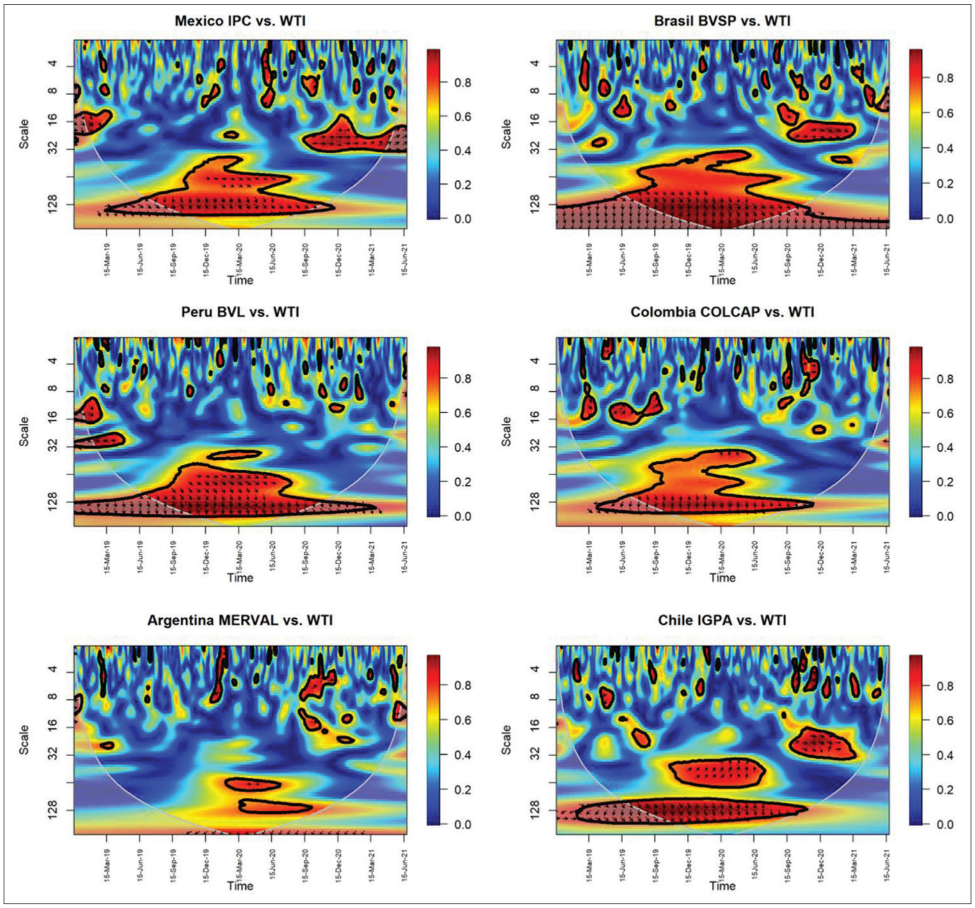
In the era before and during the COVID-19 crisis, a dynamic co-movement is observed, described as "fast and furious." At high scales, the pattern is better described as interdependence. The coherence shows greater concentration around March and April 2020, when most economies were shut down and oil futures prices plunged below zero. Conversely, the interaction is violent and relatively fast, lasting until August 2020 before returning to the normal co-movement observed before the COVID-19 crisis. The exception is Argentina, where no fundamental linkages between the stock and oil markets can be supported by the wavelet coherence; only contagion between markets.

By the end of 2020 and during the first half of 2021, interactions among equity indices and oil returns show low levels in most cases at different time scales. An exception is Bovespa-Brazil which continues to show high levels of association, which are evident even before COVID-19. Since Brazil, as major LATAM producer and exporter of oil compared to the rest of the countries, the high level of interaction is explained by *fundamental linkages* where co-movements pass through from 1 year to another. Peru is a similar case. In Mexico, a strong co-movement is shown during the medium term where the interactions between the stock market and oil returns do not pass through over 32 days. This reveal relationship between the Mexican stock market and the oil sector would only affect the most medium-term horizon investors and then long term does not require any portfolio adjustments.

A previous study by Santillan-Salgado et al. (2017) identified a positive relationship between oil prices and the stock markets of Argentina, Brazil, Chile, Colombia, Mexico, and Peru. They considered a data panel analysis with monthly prices from 2000 to 2015. The authors concluded that oil prices have a positive effect on the stock markets' returns irrespective of being the exporters or importer countries.

The results of Santillan-Salgado et al. (2017) partially converge with the findings in this research. First, the global correlation in the period of study signals no positive relationship between stock and oil market returns. However, when the correlation structure is decomposed into different time scales, the positive relationship holds long-term, which is described as a *fundamental linkage* between the markets. However, at low scales or short periods,

Figure 4: Wavelet Coherence among oil and stock returns at different scales



the interdependence does not hold and the pattern that better characterises the relationship is *excess of co-movement*.

Novel methodological proposals have paved a way for empirical analysis of the relationship between oil prices and the stock market Santillan-Salgado et al. (2017). In this context, the research findings based on the wavelet coherence approach are important to break down the correlation structure between the stock and oil market returns to better understand the dynamics of co-movement along time and across time-frames pre- and post-crisis, such as that experienced in the COVID-19 era. These findings may help investment managers to identify the time-frames when the interaction can be identified as *pure contagion* or *spillover effects* to better manage their holding positions and risk exposure.

The wavelet coherence results may answer the question regarding the time in which interactions occur, which show that correlation may differ at different time-frames. Weaker interactions between oil and stock returns have occurred up to window times of 64 days. After that period, joint behaviour strengthens. In addition, these stronger interactions have occurred in most cases since August 2019. Even during the COVID-19 era, there were no significant levels of associations when oil prices plunged below zero. It occurred for a very short window times and dissipated quickly. Since stronger interactions have occurred during long-term window times, the interconnectedness of oil prices and stock returns is best explained by *fundamental linkages*.

4.3. Decomposed Vector Autoregressions (VAR)

Expression (12) represents a first lag Vector Autoregression of two variables, VAR (1)

$$\begin{aligned} Y_{1,t} &= \alpha_1 + \beta_{11,1} Y_{1,t-1} + \beta_{12,1} Y_{2,t-1} + \varepsilon_{1,t}, \\ Y_{2,t} &= \alpha_2 + \beta_{21,1} Y_{1,t-1} + \beta_{22,1} Y_{2,t-1} + \varepsilon_{2,t} \end{aligned} \tag{11}$$

The decomposed-VAR (1) system is represented by expression (13)

$$\begin{aligned} Y_{1,j} &= \alpha_1 + \beta_{11,1} Y_{1,j-1} + \beta_{12,1} Y_{2,j-1} + \varepsilon_{1,j}, \\ Y_{2,j} &= \alpha_2 + \beta_{21,1} Y_{1,j-1} + \beta_{22,1} Y_{2,j-1} + \varepsilon_{2,j} \end{aligned} \tag{12}$$

Where $Y_{1,j}$ and $Y_{2,j}$ are the detail coefficients at *j*-scale of time series Y_1 and Y_2, respectively.

Table 2 shows VAR (2) estimations on the Mexico-IPC and WTI oil relationship at seven levels of resolutions (see Appendix for whole estimations). Figure 4 indicates that at low scales (high frequencies) the Mexico-IPC is not sensitive to oil price changes. However, as time-frame (level of resolution) increases, so does sensitivity. It can be stated that at high frequencies-within time-frames of <4 days-there is no evidence of a passing-through effect from oil prices to the stock market. But from time-frames >8 days, a pass-through effect is evident. These results could be supported by an indirect influence of oil prices on the stock market when market participants adjust their portfolio asset holdings over time, as companies may expect lower earnings caused by an increase in production or

Table 2: Estimation results for equation MXX

MXX=const+MXX(−1)+WTI(−1)+MXX(−2)+WTI(−2)						
Level (j)	Time-frame (days)	Variable				
		Const	MXX (−1)	WTI (−1)	MXX (−2)	WTI (−2)
d1	1-2	5.399E-06	−1.019E+00	−1.896E-03	−6.275E-01	−1.814E-03
		(0.026)	(−29.193)	(−0.827)	(−17.87)	(−0.797)
d2	2-4	6.898E-06	6.346E-01	1.619E-03	−8.359E-01	−3.087E-03
		(0.059)	(25.541)	(1.202)	(−33.550)	(−2.299)
d3	4-8	−2.985E-06	1.559E+00	−1.657E-03	−9.713E-01	1.373E-03
		(−0.131)	(141.844)	(−3.335)	(−88.213)	(2.77)
d4	8-16	−2.097E-07	1.884E+00	−6.461E-04	−9.829E-01	9.159E-04
		(−0.066)	(347.267)	(−2.954)	(−182.451)	(4.162)
d5	16-32	5.105E-08	1.985E+00	−4.482E-04	−1.007E+00	5.182E-04
		(0.082)	(736.78)	(−3.649)	(−372.271)	(4.233)
d6	32-64	1.76E-09	2.02E+00	−9.40E-04	−1.02E+00	8.48E-04
		(0.012)	(942.797)	(−8.618)	(−474.420)	(7.867)
d7	64-128	−3.778E-09	2.005E+00	3.121E-04	−1.006E+00	−3.351E-04
		(−0.135)	(1517.574)	(4.675)	(−751.369)	(−5.073)

*t-values in parenthesis

operational costs since oil price increases are expected to pass through the domestic prices.

As the Mexican stock market is smaller than that of the U.S. Also, there are no listed oil producer companies that could weigh in on the market capitalization in the Mexican Stock Exchange. So, this could also support in short term t a lower sensitivity of the stock market to oil prices. However, from the medium-to the long-term, *fundamental linkages* explain dynamic interaction.

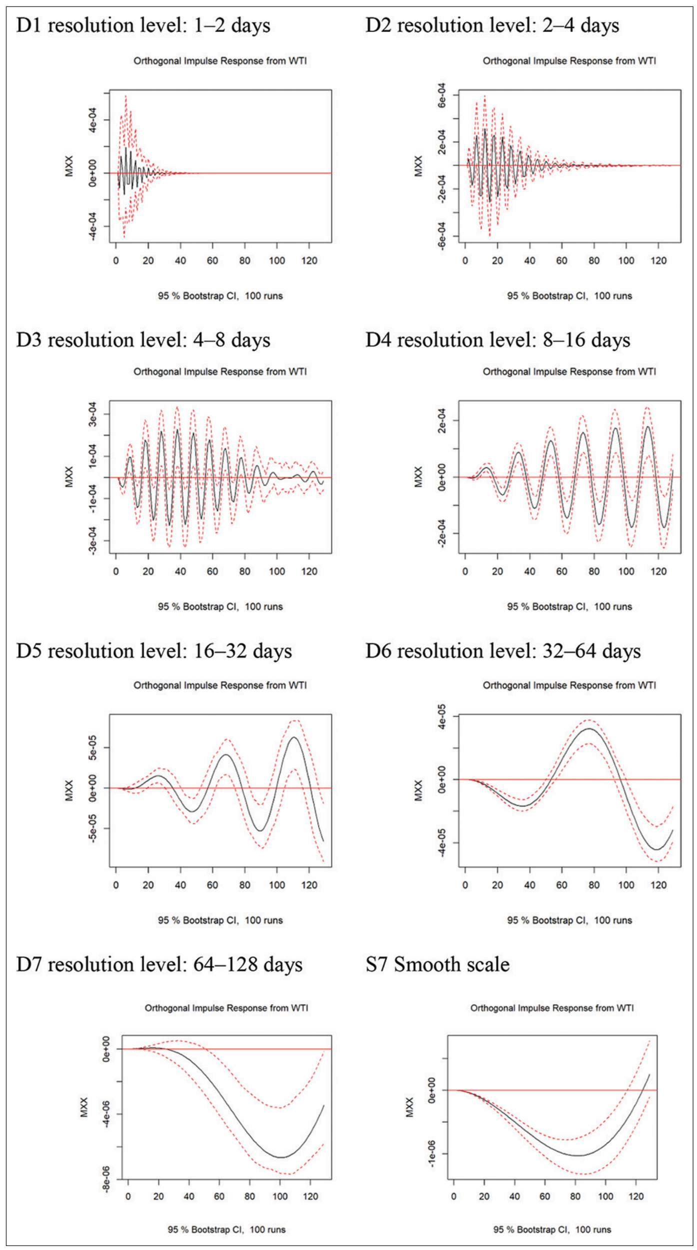
In contrast, Colombia shows a pass-through effect in the first scale (1–2 days window frame) and the stock market sensitivity to oil prices decreases in the second and third scales. Then, as the window frame increases, the pass-through effect returns. This is supported by the trading horizons of the market participants, where those who operate in very short-term runs quickly adjust their asset holdings. However, those whose investment horizons are within time-frames of 2–8 days may not have significant exposure to oil linkages. Even so, the stock market's sensitivity increases as the time frame is higher than 8 days, which could be explained by the indirect exposure of oil *fundamental linkages* to market participants' asset holdings.

The decomposed-VAR results may explain the pass-through effect of oil on stock markets. Since results have shown weak sensitivity in very short time-frames (1–8 days) compared to medium-to-long term, the existence of a pass-through effect may be explained by *fundamental linkages*. The importance of these results may help investment strategists to exploit risk diversification opportunities based on direct and indirect transmission mechanisms of oil to stock markets and among stock markets at different time-frames.

4.4. Impulse Response Function

Figure 5 represents the impulse-response functions of oil price one-standard deviation (shock) to stock returns of Mexico-IPC (see Appendix for complete estimations). In a timeframe of 1–2 days, a shock in oil prices has an initial negative effect on stock returns which takes about 20 days to dissipate. In contrast to Level 2, the response dies in about 60 days. At Level 3, the response

Figure 5: Impulse-response of oil shocks to Mexican-IPC returns



decreases in about 80 days but surges again after 100 days. At this resolution level, the stock market response to the oil impulse is never dissipated, which may be explained by indirect *fundamental linkages*.

The question to be answered is whether stock markets respond to oil shocks. Results show that responses vary across time-frames. A market participant whose investment horizon ranges within 1–2 days responds immediately to an oil shock where its reaction lasts for about 20 days. In this sense, it can be stated that a *pure contagion* has occurred since the spread over time was adverse and rapid. However, market participants whose investment horizons are >32 days react at a slower pace where decisions may rely on more fundamental factors and the shock effect lasts longer.

5. DISCUSSION AND CONCLUSIONS

Wavelets are filtering functions that allow us to capture oscillatory and smoothness properties of signals at the same time. The filtering process performed by wavelets is known as multiresolution decomposition (MRD) where time series are decomposed into high frequencies which occur at short time-frames and low frequencies which occur at long time-frames. Since the first application of wavelets in economics was to analyse the interaction among macroeconomic variables (Ramsey and Lampart, 1998), substantial research has been done in economic analysis based on wavelets such as the Phillips Curve Analysis (Gallegati et al., 2006), Monetary Policy (Aguiar-Conraria et al., 2008), and International Portfolio Diversification (Rúa and Nunes, 2009).

The de-noising process using wavelets has allowed us to discover hidden patterns (Graps, 1995), that traditional time series analysis could not perform among economic variables. This has resulted in the staking out of principles in economics and finance. As an example, Rúa and Nunes (2009) highlight the investment horizons of investors-who may exploit diversification opportunities when timing plays an important role in asset correlations across time. Since then, interactions have been distinguished into two types: the first when co-movement is “fast and furious,” named *pure contagion*. The second-when co-movement stays in the long term-is termed a *spillover effect* (Gallegati, 2012).

Distinguishing types of co-movements allows us to discover previously hidden patterns in the relationship between stock markets and crude oil prices. If the type of relationship is characterized as an instant association, which dissipates almost immediately, then a pass-through effect from oil to stock markets could be described as *pure contagion*. However, if the pass-through remains in long time-frames and across time, then *fundamental linkages* drive the relationship between stock markets and oil prices.

This study uses a hybrid approach of coherence wavelet analysis and vector autoregression models to explore the important connection between the oil and stock market returns which improves our understanding of the potential relationships in emerging markets from Latin America. Evidence shows that oil price stock return relationships have more structural shifts with time-varying volatility and may be of a non-linear type. Assessing the fact and source of time variation is crucial since it explains innovations in the variance-covariance matrix which are observed in the correlations that may vary at different periods. Instead of considering a global correlation, it could be understood as a structural term of correlation.

We examine the effects of oil price shocks on stock market real returns using a time-varying parameter VAR model to investigate the impact of oil price shocks on the emerging markets of LATAM stock exchanges. We find that oil price shocks contain information to forecast real stock returns and that coefficients and the nature of shocks have changed over time.

Maximum and minimum returns are observed on the WTI oil and Brazil-MERVAL prices, respectively WTI-as shown by the standard deviation-recorded the highest volatility. This is supported and explained by the plunge in futures prices to the negative zone in April 2020, which was then boosted to levels greater than USD 30/barrel in less than a month. WTI shows the better risk-return trade-off among the equity indexes as also indicated by the Coefficient of Variation Matrix.

The global correlation between oil and stock returns shows a weak level of association, and in certain cases, there are negative interactions, which supports previous findings. These results suggest the possibility of a diversification investment strategy-considering the oil market as an asset that could work as a hedging instrument. From the macroeconomic perspective, it is evident that oil prices have not fully demonstrated pass-through to stock markets even during the COVID-19 era.

Mexican-IPC, compared to other LATAM stock markets, observed the dynamic co-movement from low to medium degree of interaction at low scales (high frequencies). Wavelet coherence red zones at low scales (high frequencies) mirror the excess of co-movement which may occur before and during the COVID-19 crisis. Since not all market participants operate on the same time horizons, the benefits of diversification strategies are not collected in the long compared to the short term.

The Mexican stock market is small as compared to the U.S. and it does not list oil-producing companies that could weigh in on the market capitalization. This can be a support to the lower sensitivity of the stock market to oil prices in the short term. However, from the medium- to the long-term, *fundamental linkages* explain the dynamic interaction.

The main findings in this study answer the research questions as follows:
- In most cases, low interactions between oil and stock returns are observed at time-frames of <64 days. At certain time-frames, high co-movements are observed but dissipate rapidly. In all cases, interactions between oil and stock returns have been high at time-frames >128 days
- Oil and stock markets have co-moved in the long-term across time even before the COVID-19 era. This co-movement-that passes through time-is explained by *fundamental linkages*.

Interactions increased at the beginning of COVID-19 but the timing was short. If any degree of association remains it is explained by fundamental factors that are driving oil and stock markets. However, this pattern is hidden in the global correlation since it shows a negative relationship
- Interactions that may occur in short periods dissipate rapidly (*pure contagion*). However, a long-term relationship lasts longer since the linkage is due to fundamental factors (*spillover effects*)
- Hence, oil pass-through to stock markets varies across time. In short periods evidence of a pass-through effect is not be found. However, in longer time-frames, a pass-through effect from oil to stock markets is confirmed
- The pass-through effect in shorter time-frames could last no longer than 20 days. But in longer time-frames, the impact could last more than 128 days
- After the COVID-19 pandemic was declared in 2020, some markets stocks indicated high levels of interactions in the long term, which is a co-movement type named *spillover effects*, explained by *fundamental linkages*
- Only the Brazilian stock market indicates a high degree of association in the long term, which is explained by its economic structure, based on a high degree of oil production
- Any other excess of co-movement among stock markets and between oil returns indicates *pure contagion* if it dissipates rapidly-which could be explained by market participants that react immediately to economic events or market momentum shocks
- All the above could occur because market participants have different investment horizons. Those whose horizons are short-term may respond rapidly to any shock but may return to their "path" in a shorter time. However, those market participants whose horizons are long-term do not adjust their positions until more information arises that may allow them to reallocate their assets gradually.

In that way, the argument stated by (Santillan-Salgado, 2017) could be modified as "*It does not matter if countries are exporters or importers of oil, in the region as a whole, the effect of oil price innovations on stock market returns depends on timing*." The study also shows that positive effects endure, and trespass in the long term, while in short periods the trespass is rapid.

This study is limited to emerging markets stock returns in LATAM exchanges, with a time-frame of 2 years, and relating to relatively few industries. This work can be extended to the Asian markets, with an extended period, and comparisons over other regions.

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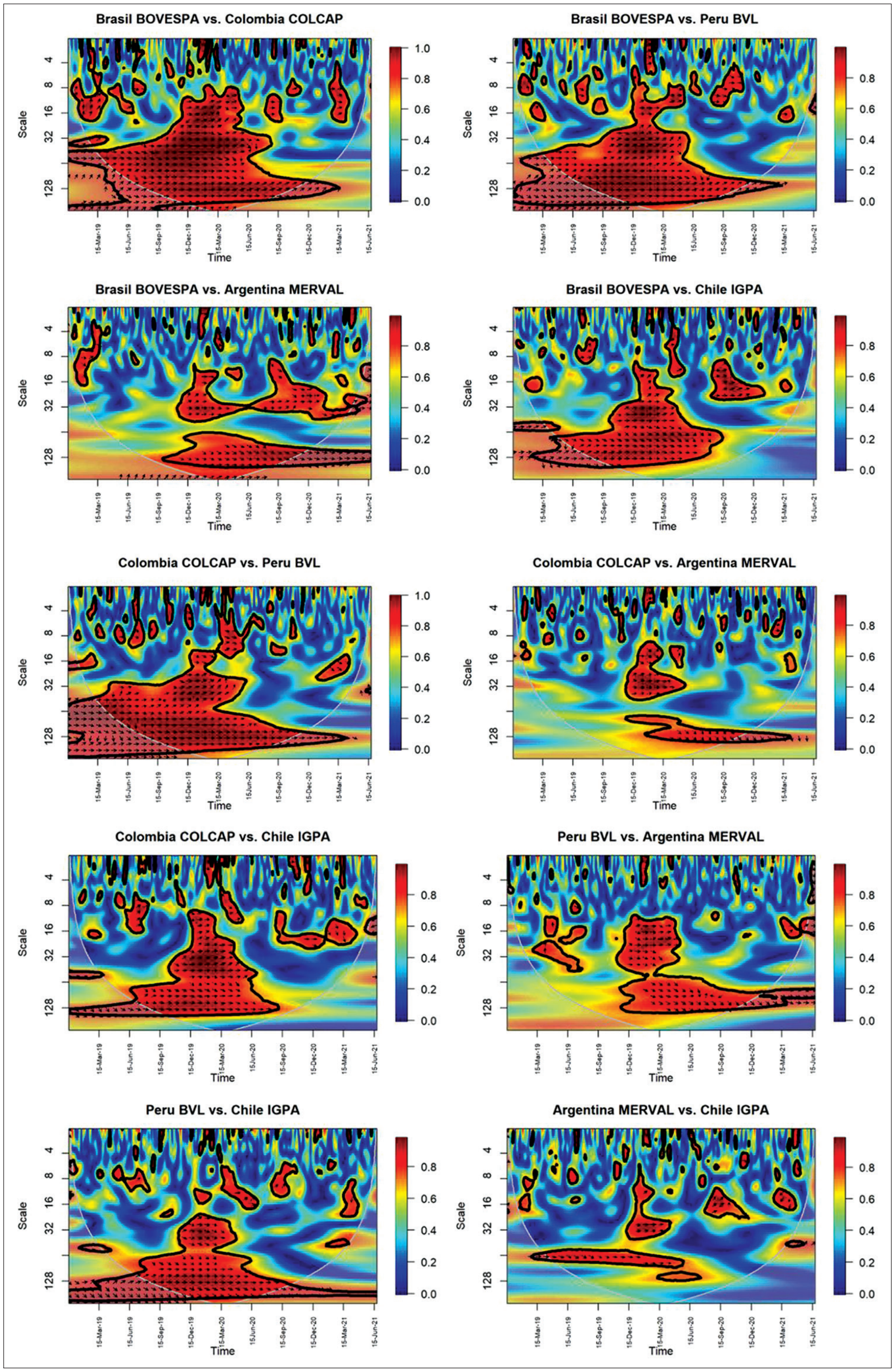
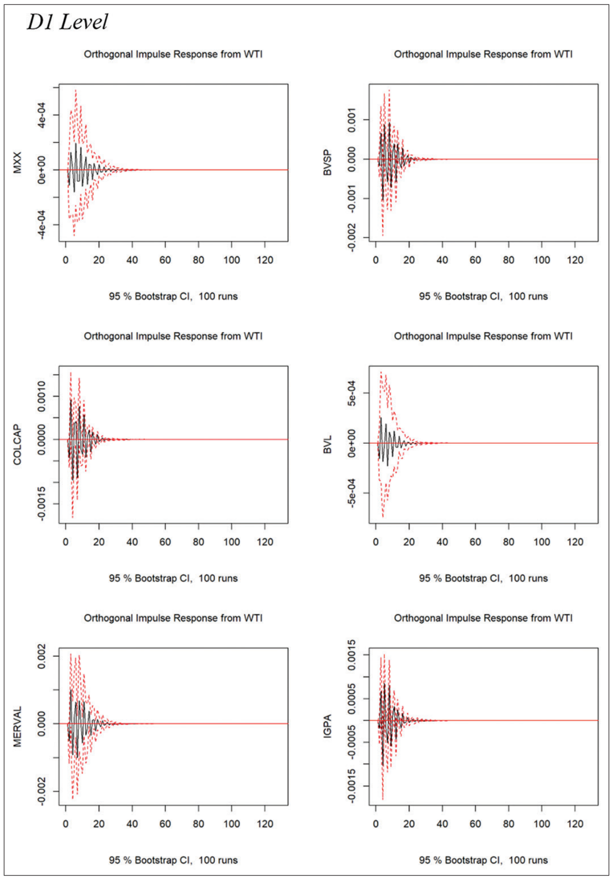
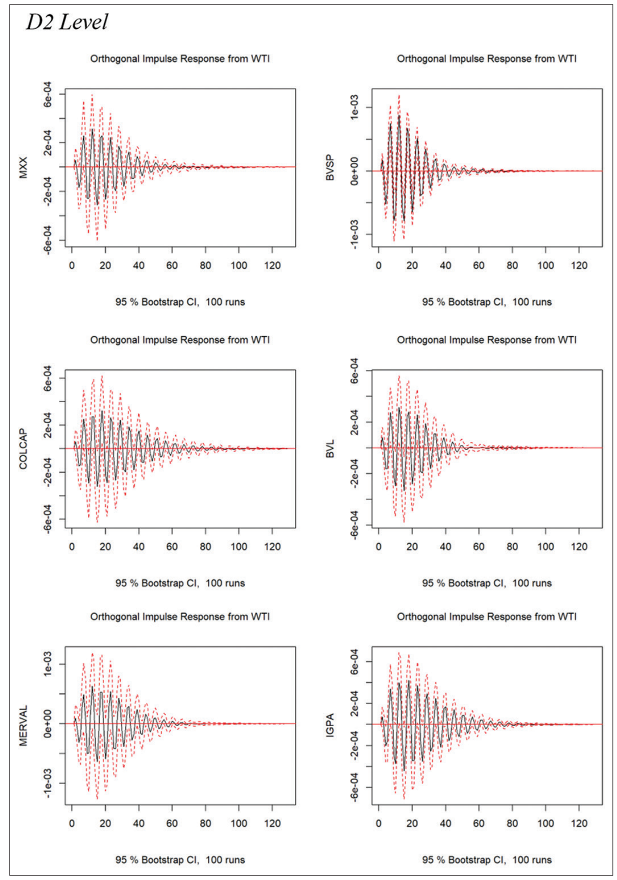
APPENDIX

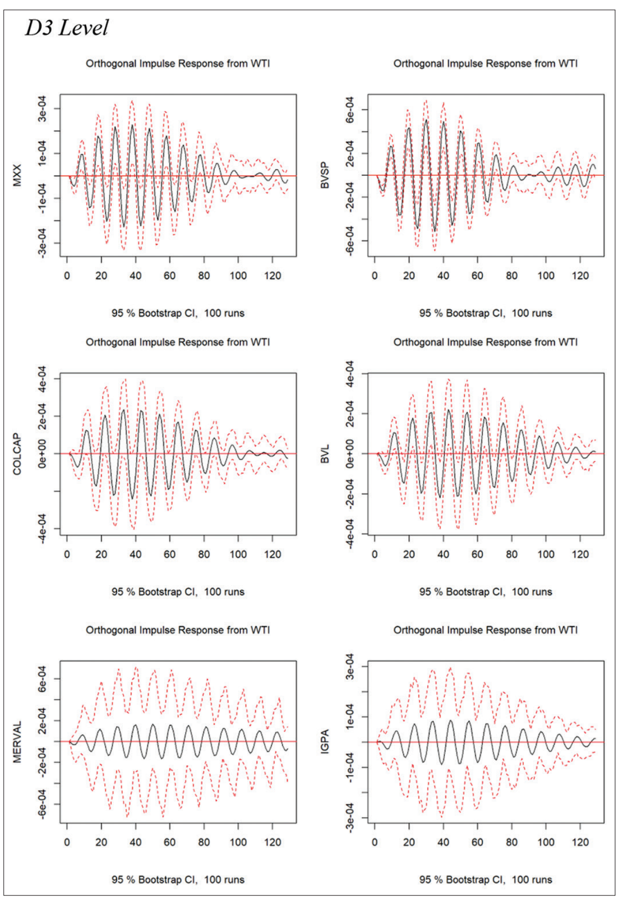
A. 1 Wavelet coherencies among stock markets

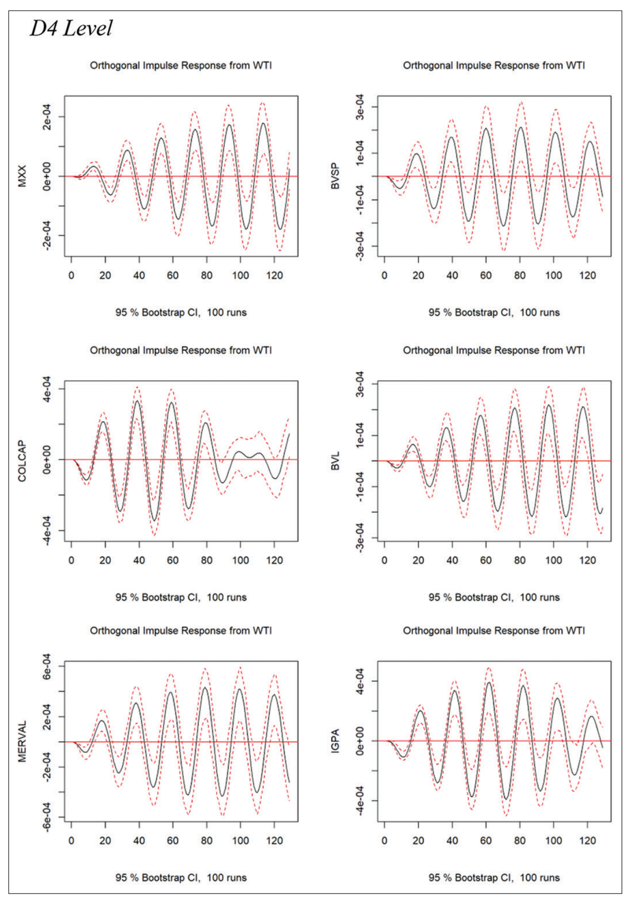


A.2 Impulse response functions

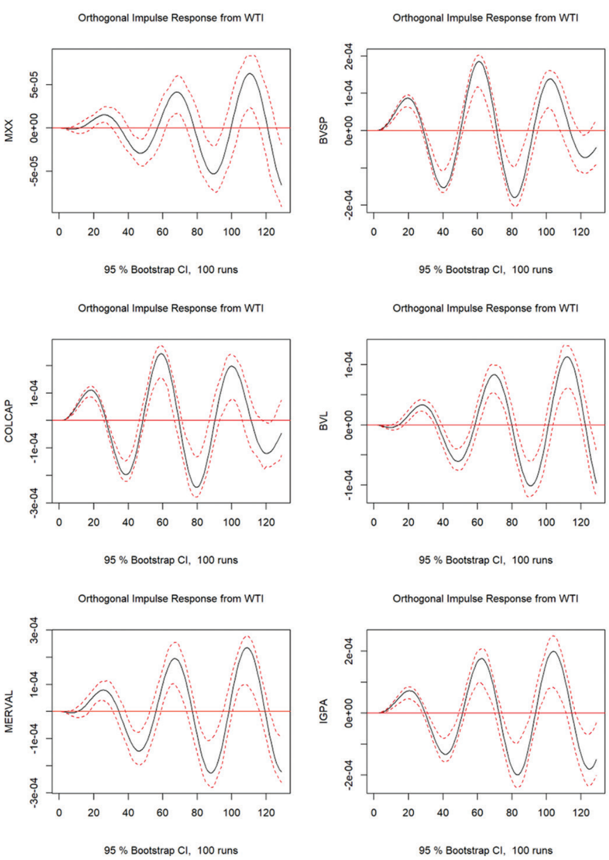




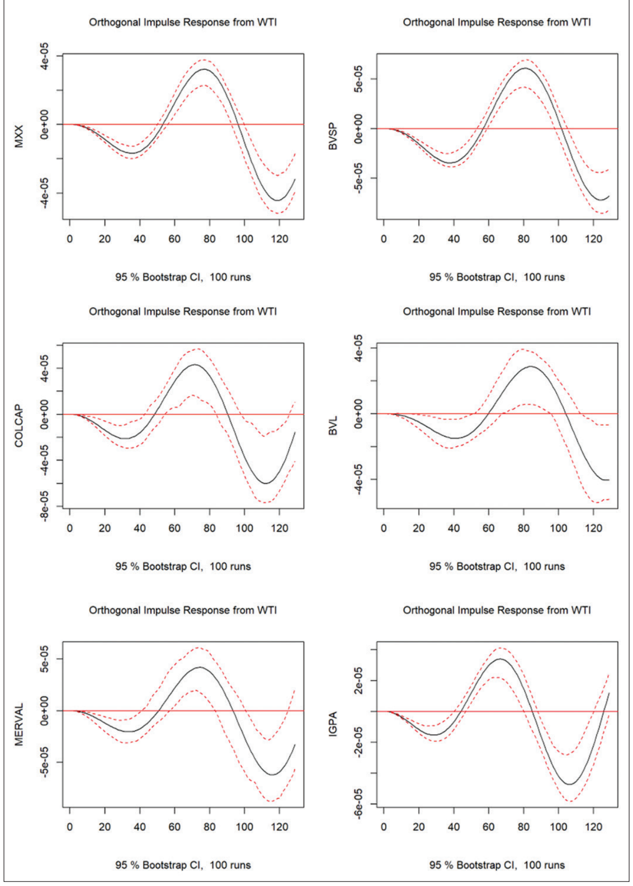




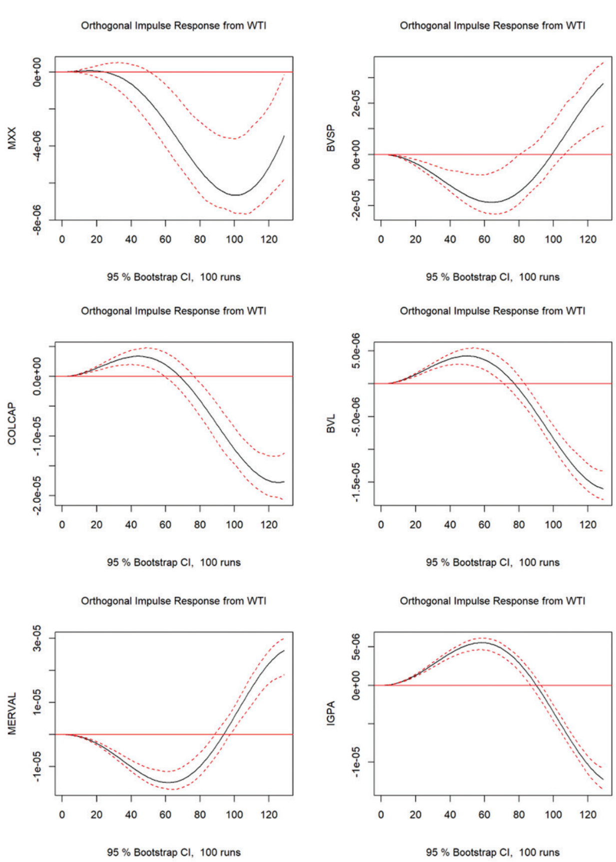
D5 Level



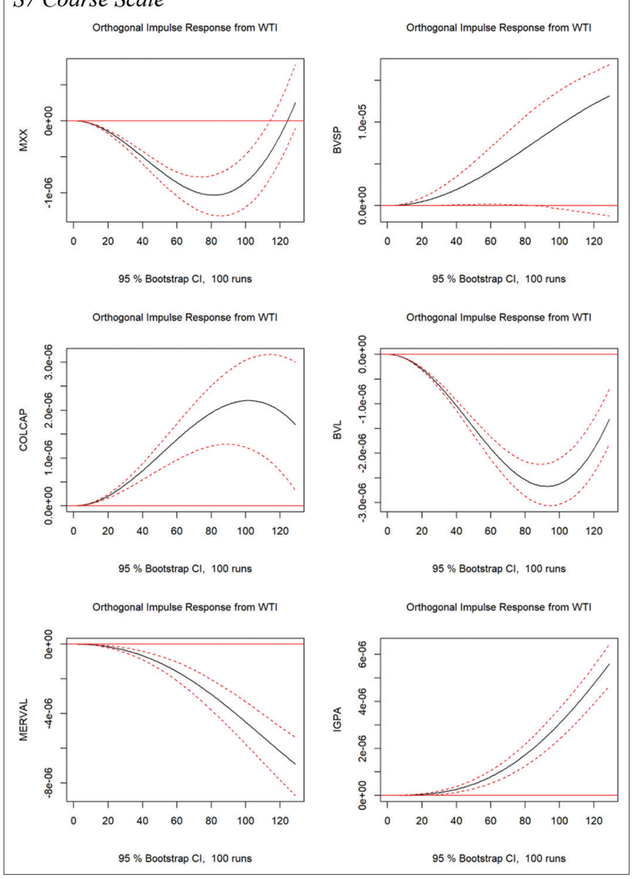
D6 Level



D7 Level



S7 Coarse Scale



A. 3 Vector Autoregression (VAR) estimations

Estimation results for equation BVSP-Brazil						
BVSP=const+BVSP(-1)+WTI(-1)+BVSP(-2)+WTI(-2)						
Level (j)	Time frame (days)	Variable				
		Const	BVSP(-1)	WTI(-1)	BVSP(-2)	WTI(-2)
d1	1-2	−7.235E-06 (−0.021)	−1.286E00 (−40.583)	−3.305E-03 (−0.866)	−7.026E-01 (−22.075)	4.959E-03 (1.306)
d2	2-4	4.536E-06 (0.031)	5.789E-01 (22.823)	4.983E-03 (2.891)	−7.939E-01 (−31.318)	−9.274E-03 (−5.394)
d3	4-8	−1.738E-06 (−0.052)	1.614E00 (133.129)	−3.548E-03 (−4.814)	−9.704E-01 (−79.404)	2.087E-03 (2.856)
d4	8-16	9.137E−08 (0.014)	1.907E00 (274.016)	−1.479E-03 (−3.429)	−9.947E-01 (−142.312)	1.052E-03 (2.452)
d5	16-32	3.780E-08 (0.045)	2.015E00 (884.019)	2.149E-03 (9.184)	−1.044E00 (−435.823)	−1.326E-03 (−5.910)
d6	32-64	−1.854E-08 (−0.101)	2.037E00 (970.182)	−2.464E-03 (−16.451)	−1.041E00 (−493.436)	2.247E-03 (15.258)
d7	64-128	−1.275E-09 (0-021)	2.004E00 (1376.863)	−5.517E-04 (−2.254)	−1.006E00 (−674.835)	5.271E-04 (2.164)

*t-values in parenthesis

Estimation results for equation COLCAP-Colombia						
COLCAP=const+COLCAP(−1)+WTI(−1)+COLCAP(−2)+WTI(−2)						
Level (j)	Time frame (days)	Variable				
		Const	COLCAP(−1)	WTI(−1)	COLCAP(−2)	WTI(−2)
d1	1-2	−5.719E-06 (−0.024)	−1.248E00 (−38.526)	−7.876E-03 (−3.028)	−6.861E-01 (−21.244)	−5.386E-04 (−0.206)
d2	2-4	1.912E-06 (0.017)	7.305E-01 (33.599)	1.830E-03 (1.424)	−8.715E-01 (−40.067)	−2.820E-03 (−2.194)
d3	4-8	−2.707E-06 (−0.086)	1.675E00 (150.892)	−8.687E-05 (−0.125)	−9.744E-01 (−87-269)	−7.987E-04 (−1.153)
d4	8-16	4.193E-07 (0.054)	1.918E00 (317.295)	−3.611E-03 (−7.064)	−1.008E00 (−164.228)	2.531E-03 (5.029)
d5	16-32	4.560E-08 (0.044)	2.017E00 (814.496)	4.329E-03 (13.914)	−1.048E00 (−400.773)	−3.376E-03 (−11.298)
d6	32-64	−2.410E-08 (−0.131)	2.019E00 (1033.33)	−1.959E-03 (−14.825)	−1.025E00 (−521.239)	1.894E-03 (14.405)
d7	64-128	3.772E-09 (0.10)	2.002E00 (1666.97)	1.320E-03 (13.29)	−1.003E00 (−827.71)	−1.337E-03 (−13.57)

*t-values in parenthesis

Estimation results for equation BVL-Peru						
BVL=const+BVL(−1)+WTI(−1)+BVL(−2)+WTI(−2)						
Level (j)	Time frame (days)	Variable				
		Const	BVL(−1)	WTI(−1)	BVL(−2)	WTI(−2)
d1	1-2	1.064E-05 (0.052)	−1.198E00 (−33.902)	−2.740E-03 (−1.225)	−6.056E-01 (−17.144)	−1.694E-03 (−0.757)
d2	2-4	−2.485E-06 (−0.207)	6.090E-01 (26.533)	2.113E-03 (1.973)	−8.566E-01 (−37.206)	−2.740E-01 (−2.568)
d3	4-8	−1.037E-06 (−0.054)	1.638E00 (137.684)	−2.799E-04 (−0.664)	−9.701E-01 (−81.235)	−5.483E-04 (−1.305)
d4	8-16	2.006E-07 (−0.057)	1.875E00 (290.549)	−1.690E-03 (−7.448)	−9.790E-01 (−151.592)	1.552E-03 (6.844)
d5	16-32	6.367E-08 (0.107)	1.997E00 (764.747)	−1.206E-03 (−9.667)	−1.019E00 (−386.152)	1.359E-03 (11.002)
d6	32-64	−1.760E-08 (−0.095)	2.008E00 (804.322)	−5.502E-04 (−3.663)	−1.013E00 (−402.910)	4.830E-04 (3.241)
d7	64-128	7.684E-10 (0.022)	2.005E00 (1248.041)	8.673E-04 (5.276)	−1.006E00 (−610.118)	−8.964E-04 (−5.521)

*t-values in parenthesis

Estimation results for equation MERVAL-Argentina						
MERVAL=const+MERVAL(−1)+WTI(−1)+MERVAL(−2)+WTI(−2)						
Level (j)	Time frame (days)	Variable				
		Const	MERVAL(−1)	WTI(−1)	MERVAL(−2)	WTI(−2)
d1	1-2	2.337E-05	−1.183E00	−8.480E-03	−6.669E-01	−1.523E-03
		(0.035)	(−35.747)	(−1.157)	(−20.166)	(−0.208)
d2	2-4	−1.011E-05	6.546E-01	2.659E-03	−8.676E-01	−5.572E-03
		(−0.032)	(29.861)	(0.729)	(−39.609)	(−1.528)
d3	4-8	−4.458E-06	1.609E00	−8.937E-04	−9.557E-01	7.427E-04
		(−0.065)	(123.049)	(−0.598)	(−73.108)	(0.498)
d4	8-16	−1.843E-07	1.895E00	−3.248E-03	−9.852E-01	2.698E-03
		(−0.015)	(286.303)	(−4.024)	(−148.718)	(3.345)
d5	16-32	1.154E-07	1.980E00	−1.677E-03	−1.004E00	2.167E-03
		(0.047)	(633.691)	(−3.972)	(−319.553)	(5.519)
d6	32-64	−9.727E-10	1.999E00	−1.242E-03	−1.004E00	1.193E-03
		(−0.002)	(1090.660)	(−4.209)	(−547.759)	(4.047)
d7	64-128	−1.677E-09	2.005E00	−2.034E-03	−1.008E00	1.987E-03
		(−0.043)	(5048.433)	(−25.877)	(−2508.326)	(25.382)

*t-values in parenthesis

Estimation results for equation IGPA-Chile						
IGPA=const+IGPA(−1)+WTI(−1)+IGPA(−2)+WTI(−2)						
Level (j)	Time frame (days)	Variable				
		Const	IGPA(−1)	WTI(−1)	IGPA(−2)	WTI(−2)
d1	1-2	−1.547E-06	−1.212E00	−2.668E-03	−6.123E-01	4.929E-03
		(−0.006)	(−34.535)	(−1.003)	(−17.366)	(1.865)
d2	2-4	1.566E-06	6.837E-01	2.066E-03	−8.638E-01	−3.621E-03
		(0.013)	(30.731)	(1.542)	(−38.799)	(−2.704)
d3	4-8	−2.274E-07	1.651E00	3.093E-04	−9.658E-01	−5.894E-04
		(−0.008)	(135.071)	(0.494)	(−78.842)	(−0.942)
d4	8-16	−2.760E-07	1.926E00	6.734E-05	−1.019E00	−1.295E-03
		(−0.050)	(392.478)	(0.169)	(−202.673)	(−3.331)
d5	16-32	5.924E-08	2.018E00	1.218E-03	−1.045E00	−5.018E-04
		(0.065)	(655.803)	(4.552)	(−323.973)	(−1.963)
d6	32-64	−2.539E-09	2.015E00	−1.763E-03	−1.020E00	1.729E-03
		(−0.017)	(1352.589)	(−20.409)	(−684.287)	(20.048)
d7	64-128	5.389E-10	1.991E00	5.805E-04	−9.924E-01	−5.714E-04
		(0.017)	(1738.319)	(7.014)	(−860.146)	(−6.886)

*t-values in parenthesis