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Information transmission across stock indices and stock index futures: international evidence using wavelet framework

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Abstract:

This paper provides international evidence on dynamic linkages between stock indices and stock index futures using daily data on 11 emerging and developed markets for the period from 3 October 2010 to 3 October 2014. In this study, we focus on the major wavelets tools: individual power spectrum, cross-wavelet power and wavelet coherency. The results show that the co-movement between spot and futures indices reveals an erratic behaviour. The paper also identifies the difference in patterns of comovements for emerging and developed markets, which makes empirical results highly significant for practitioners and policy makers. *Key words:* spot futures interlinkages, wavelet methodology, wavelet coherence, emerging markets

JEL Classification: G15; G11

1. Introduction

In theory, under the efficient markets hypothesis the returns on stock index futures and underlying stock indices have to be perfectly correlated since the information is simultaneously incorporated by both spot and futures prices (e.g., Brooks et al, 2001). In reality, empirical evidence shows that relationship between futures and spot returns are often instable, especially during the crisis periods, and may vary among markets across the globe, due the country's specific market regulations and different degree of economic development. Hence, the existence of lead-lag relationships between spot and futures markets, investigated for example by Harris (1989), Chan et al (1991), Antoniou et al. (1998), Antoniou et al. (2003), among others, challenge the financial regulators and policy makers, due to the common belief that futures trading increases the volatility of underlying stock markets. Indeed, due to the lower costs of trading and the greater leverage potential futures markets become attractive for both uniformed and informed traders (e.g., Antoniou et al., 2005; Chen & Gau, 2010). Stock index futures are also attractive financial instrument for those traders who willing to invest in diversified portfolio corresponding to index. Since stock indices cannot be traded by investors as financial instruments (investing in constituent stocks is costly and time-consuming), investors would prefer stock index futures which could be traded in a single transaction (Subrahmanyam, 1991; Yarovaya et al., 2016).

Introduction of stock index futures in emerging markets facilitated the debate about the spot-futures relationship in markets with different degree of financial development. More particularly, in China financial futures has been firstly traded in April 2010, which could potentially expand the channels of informational transmission in Asian region and beyond. However, the existing literature is often presented by single country studies and restricted to developed markets. For example, Tse (1995) and Chang et al. (1999) focused on the Japan; Brooks et al. (2001) provided evidence for UK; Antoniou et al. (2005) investigated this phenomena in industrialised markets of Canada, France, Germany, Japan, the United Kingdom, and the United States; to name but a few. To this stance we claim that there is a strong need in study providing international evidence of spot-futures relationships, because the pattern of spot-futures linkages may vary: i) across different regions, i.e. due to the existence of trading agreements between countries some markets can be donors or recipients of foreign shocks, increasing the volatility on futures and spot markets consequently changing the intensity of spillovers between them; ii) due to the level of economic development, i.e. the intensity of information transmission between stock indices and stock index futures could be higher on developed markets than emerging markets; iii) due to the different market openness and trading volume on futures markets among countries.

This paper aims to enrich the existing empirical evidence on information transmission between stock indices and stock index futures proving the evidence from wavelet methodology. This study contributes to existing knowledge in two ways. First, the paper analyses futures-spot relationships in 11 emerging and developed markets from three geographical regions. Selected markets play major role in the global economy, i.e. target markets are actively involved in the world trade and significantly important for international investors. The reason why this extensive data set is crucial is because the opportunity to provide international evidence can be offered, distinguishing this paper from previous studies in topic area. Second, the paper analyses spot-futures relationships from the new perspective. Wavelet methodology allows examining the time-and-frequency varying comovements between stock indices and stock index futures providing coherent visualization of empirical results.

2. Literature review

Even though that there are plenty of empirical literature on return and volatility spillovers across various financial assets it is surprising how much still left unknown about the channels, intensity and origin of transmission of information flows on the global markets. The information transmission mechanism across spot and futures markets is the area that requires further attention due to the ambiguity of the existing evidence presented in the literature. Ross (1989) showed that in absence of arbitrage the volatility in asset returns depends upon the rate of information flow, which means that information transmitted from one market can generate the excess of the volatility on the other market. Cox (1976) argued that the new information incorporated by futures markets first, due to the lower cost of trading attractive for investors, and only after information can be conveyed to the spot market. Thus futures trading increase the speed of information transmission to the spot markets. Indeed, Antoniou and Holmes (1995) analysed impact of futures contracts on underlying stock market volatility found that futures trading expanding the channels over which information can be transmitted to the market consequently increasing the volatility of spot market. Many studies analysed volatility of spot markets in pre-futures and post-futures periods provide the evidence of increased volatility after introduction of futures on the market (e.g., Harris, 1989; Chang et al., 1999). The issue of information transmission between spot and futures markets has been actively studied in respect to price discovery and volatility spillovers hypotheses. Continuous development of the new methodologies supported by the increase in computer power allows researchers to aggrandize knowledge in this area. This paper also contributes to the literature on information transmission between stock indices and stock index futures providing the evidence from the wavelet approach.

The methodological choice is motivated by increased popularity of the wavelet approach in empirical finance literature in the last decade. The wavelet methodology has been recently applied to the various financial tasks, such as noise removal (e.g., Sun & Meinl, 2012; Li, 2015), heterogeneity in the financial markets (e.g., Candelon et al., 2008; Ranta, 2013), structural features of financial time series (Lee, 2004; Rua & Nunes, 2009), and others.¹ The wavelet approach also demonstrated superior forecasting ability successfully dealing with various complexities of financial time series data, i.e. noise and non-stationarity (e.g., Bekiros & Marcellino, 2013). Nevertheless wavelet approach is still relatively unexplored in spillovers literature in comparisons to ARCH-family models, standard and asymmetric causality tests, and VAR methodologies. Several studies confirmed that combination of the traditional financial model with wavelet approach can significantly improve the performance of the standard models (e.g., Huang, 2011; Aloui & Jammazi, 2015).

¹ For the literature review on wavelet methodology please see, for example, Chakrabarty et al. (2015).

The cross-boarders spillover effect has been analysed by many scholars employed wavelet methodology to the stock indices of developed and emerging markets from the same geographical region (e.g., Graham et al., 2013; Tan et al., 2014; Sensoy & Tabak, 2015) or from different regions (e.g., Rua & Nunes, 2009; Loh, 2013). The spillovers of volatility across different financial assets have been also actively studied (e.g., Reboredo & Rivera-Castro, 2013; Barunik et al., 2015; Mart ń-Barrag án et al., 2015). However the waste majority of papers explored international transmission mechanism across financial markets used stock indices data only, while information transmission mechanism across stock indices and stock index futures are comparatively unexplored under the wavelet approach. The existing studies investigated spot-futures relationships (e.g., Gannon & Choi, 1998; Zhong et al., 2004; Yang et al., 2011; Antonakakis et al, 2015) employed standard finance methodologies, and evidence from wavelets approach is very limited (e.g., Li, 2015) and mainly restricted to commodity futures (e.g., Chang & Lee, 2015; Akoum et al., 2012; Ftiti, 2015). The paper fills this gap in literature, providing the results, which are significantly important for price discovery, predictability, and international portfolio diversification.

3. Data

Based on the existing literature gap we suggest the analysis of information transmission between stock indices and stock index futures in the international context. The selected country panel includes both developed and emerging markets, i.e. Canada, USA, Mexico, Brazil, Germany, France, India, Russia, Hong Kong, Japan and China, to capture the global perspective. The daily opening and closing prices of stock indices and stock index futures are obtained from Bloomberg database for the period from 3 October 2010 to 3 October 2014. The choice of estimation period is made based on the introduction of futures in China in 2010. This period covers Eurozone debt crisis and comparatively stable period. For each market there are several futures contracts with different maturity dates are traded simultaneously, therefore in order to generate continuous futures series we obtained data for those contracts that have the closest maturity date.

Table 1 below demonstrates trading hours in GMT for stock indices and stock index futures in regard to daylight saving time regimes in various markets.

[Table 1 to be here]

The trading day of stock index futures significantly exceed trading day of spot market for all countries in the sample. Additional electronic sessions make some of the futures markets tradable up to 20 hours per day. Information transmission from pit to electronic trading is separate area of research (e.g., Orlowski, 2015), which is beyond consideration of our study. Therefore, in this paper we focus on pit-trading phase only, which allows nonsynchronous trading hours on futures and spot markets to be kept to a minimum.

Daily returns are calculated as a difference between natural logarithm of closing price and natural logarithm of opening price. The series of preliminary tests have been employed to test data on stationarity, normality and heteroskedasticity2.

4. Wavelet theory and methods

There are two main reasons may explain why the continuous wavelet analysis based on the wavelet power spectrum and the cross wavelet coherence is particularly appropriate for this study. First, the wavelet methodology becomes one of the popular tools in the economics and finance field, due to its mature ability to uncover latent processes with changing cyclical patterns and trends, and non-stationarity (Aloui et al, 2015). There are two

² Tables with descriptive statistics and results of preliminary tests are available upon request.

types of wavelet analysis can be employed: i) continuous wavelet transform (CWT), which is useful for examining lead-lag interactions between time series in different time scales; ii) discrete wavelet transform (DWT), which has time-invariant property and the scales are strongly dependent on the data length (Ftiti et al., 2015). Thus we employ CWT to identify comovements between futures and spot markets during the target estimation period. Second, wavelets provide a more precise timing of shocks which cause changes in interrelationships between time-series. The wavelet power spectrum allows identifying the areas with high power in the series, which are often influenced by the period of turmoil, such as financial crisis.

4.1. Wavelet

The wavelets methodology allows to decompose a time series, a single function of time position (u) and scale (s) called the mother wavelet $\psi_{u,s}(t)$, into more elementary functions to detect the information contains in the time series. Using the same notations as in Aloui et al. (2015), and in earlier works by Torrence and Compo (1998), Grinsted et al. (2004), we define wavelets as:

$$\psi_{u,s}(t) = \frac{1}{\sqrt{s}}\psi\left(\frac{t-u}{s}\right) \tag{1}$$

where $\psi(.) \in L^2(\mathbb{R})$; $1/\sqrt{s}$ is the normalization factor that ensures the unit variance of the wavelet, $\|\psi_{u,s}\|^2 = 1$; the exact position of the wavelet is denoted by the location parameter u; s is the scale dilation parameter of the wavelet, higher scale of s is more suitable for the detection of lower frequencies as it implies more stretched wavelet.

Note that various types of wavelets have been adapted in the wavelet literature, and we choose the Morlet wavelet in this study for its overall applicability. The Morlet wavelet is generally defined as

$$\psi^{M}(t) = \frac{1}{\pi^{1/4}} e^{i\omega_{0}t} e^{-t^{2}/2}$$
(2)

where ω_0 is the central frequency of the wavelet, where we set $\omega_0 = 6$ (e.g., Grinsted et al., 2004, Rua & Nunes, 2009; Barunik et al., 2011). This choice of value for ω_0 enables a good balance between time and frequency localizations³.

4.2. Continuous wavelets

Following Nunes and Rua (2009) and Barunik et al. (2011) the continuous wavelet transform can be described as:

$$W_x(u,s) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{s}} \overline{\psi(\frac{t-u}{s})} dt$$
(3)

where $W_x(u, s)$ is obtained by projecting the specific wavelet $\psi(.)$ on the time series. One advantage of the continuous wavelet transformation is the ability of decomposing and reconstructing the function $x(t) \in L^2(\mathbb{R})$ such that

$$x(t) = \frac{1}{c_{\psi}} \int_{0}^{\infty} \left[\int_{-\infty}^{\infty} W_{x}(u, s) \psi_{u,s}(t) du \right] \frac{ds}{s^{2}}, \quad s > 0$$
(4)

The distinct feature of the wavelet transformation is that it prevents selected time series. For power spectrum analysis it specifies the variance in the following form:

$$\|x\|^{2} = \frac{1}{c_{\psi}} \int_{0}^{\infty} \left[\int_{-\infty}^{\infty} |W_{x}(u,s)^{2}| du \right] \frac{ds}{s^{2}}$$
(5)

4.3. Wavelet power spectrum

³ See for example Grinsted et al. (2004) and Rua and Nunes (2009), while the Morlet wavelet is centered at the point $(0, w_0/2\pi)$ in the time-frequency domain (see, Agiar-Conraria et al., 2008).

The wavelet power spectrum can be defined as $|W_n^x|^2$ and it simply assesses the local variance of each variable (Torrence and Compo, 1998; Aguiar-Conraria et al., 2008). Besides, the statistical significance is evaluated when comparing to the null hypothesis⁴.

It was shown by Torrence and Compo (1998) that through Monte Carlo simulations, we can use the white-noise and red-noise wavelet power at each time n and scale s, and to obtain the corresponding distribution for the local wavelet power spectrum such that:

$$D\left(\frac{|W_n^X(s)|^2}{\sigma_X^2} < p\right) \Rightarrow \frac{1}{2} P_f \chi_\nu^2 \tag{6}$$

where P_f is the mean of spectrum at the Fourier frequency *f* that corresponds to the wavelet scale $s \left(s \approx \frac{1}{f}\right)$, and *v* takes the values of 1 or 2 for real or complex wavelets.

4.4 Cross-wavelet power, wavelet coherence, and phase differences

The cross-wavelet power maintains the neighbourhood covariance of two period series in each frequency. In this study, the cross-wavelet power locates the areas where variables prices co-move in the time-frequency space (Aguiar-Conraria et al., 2008).

The cross-wavelet between two signals is specified by the cross-wavelet spectrum $W_n^{XY}(s)$ as following.⁵

$$W_n^{XY}(s) = W_n^X(s)W_n^{Y^*}(s)$$
(7)

where $W_n^{Y^*}(s)$ is the complex conjugate of $W_n^Y(s)$ and * is the complex conjugation. The cross-wavelet power is indicated by $|W_n^{XY}|$ and it captures the covariance variables. The

⁴The null hypothesis is that the variable has a significant power spectrum. As noted in Grinsted et al. (2004) the signal is generated by an AR (0) or AR(1) stationary process with mean background power spectrum (P_f)

⁵ See Hudgins et al. (1993) and Torrence and Compo (1998) for more details about the estimation process.

theoretical distribution of the cross-wavelet power of two signals with power spectra P_k^X and P_k^Y in the following form:

$$D\left(\frac{|W_n^X(s)W_n^{Y*}(s)|}{\sigma_X \sigma_Y} < p\right) = \frac{Z_v(p)}{v} \sqrt{P_k^X P_k^Y}$$
(8)

where σ_x and σ_y denotes the standard deviations of x and y, respectively. $Z_v(p)$ is the confidence interval level related to the probability p for a *pdf* (probability density function), as defined by the square root of the product of two χ^2 distributions.

The wavelet coherence is computed as the squared absolute value of the smoothed cross-wavelet spectra normalized by the product of the smoothed individual wavelet power spectra of each time series specifies the wavelet coherence as in Torrence and Webster (1999):

$$R^{2}(u,s) = \frac{|S(s^{-1}W_{xy}(u,s))|^{2}}{S(s^{-1}|W_{x}(u,s)|^{2})S(s^{-1}|W_{y}(u,s)|^{2})}$$
(9)

where *S* denotes the smoothing parameter where the squared wavelet coherence coefficient satisfies the inequality condition of $0 \le R^2(u, s) \le 1$. A value of $R^2(u, s)$ approaches zero signifies a week correlation, and it suggests the high correlation if the value is close to 1. And the earlier mentioned justifications make the wavelet coherence method best suited to inspect the chosen variables on its joint dynamics across time and all the way through frequencies.

Moreover, the phase difference of two time series variables (i.e. $\phi_{x,y}$) characterizes their phase relationships. This phase difference locates the positions in the pseudo-cycle and it is specified as:

$$\phi_{x,y} = \tan^{-1}\left(\frac{\mathfrak{X}\{W_n^{xy}\}}{\mathfrak{R}\{W_n^{xy}\}}\right) \text{ with } \phi_{x,y} \in [-\pi,\pi]$$

$$\tag{10}$$

The arrow directions characterize the phase relationship. In the event that arrows directed to the right it suggest variables are positively correlated, vice versa. In addition, if arrows approach to the right and up, the variable x is lagging and the two variables are

positively correlated; or if arrows approach to the right and down, the variable x is leading and the two variables are positively correlated. On the other hand, if the arrows move to the left and up, the first variable x is lagging and the correlation is negative, or if the arrows move to the left and down, the first variable x is leading and the correlation is negative.

5. Empirical results and discussion

The wavelet approach considers time and frequency domains concurrently, which allows us to interpret how a variable behaves at different horizons (i.e. frequency bands) and how the behaviour modifies over time. In our study, we focus on the major wavelets tools: individual power spectrum, cross-wavelet power and wavelet coherency.

5.1. The individual power spectrum

The individual wavelet spectrum plots are presented in Figure 1 (Fig 1.a to Fig 1.k). Regarding the behaviour of spot and futures indices, many observations merit emphasis. First, two general observations can be emerged; the spot indices appear to be more volatile than future indices regardless of the time scale. Second, variances of both spot and futures markets decline as the wavelet scale rises. More specifically, a close observation of wavelet power spectrums of futures index points out that, at the beginning of the sample period, the variance growing as the frequency period expands vertically downstairs beyond 4-32 days. As the period expands further, the variance vanishes for some markets, i.e. Germany (Fig.1c), Canada (Fig.1f), USA (Fig.1g) and France (Fig.1j) cases). For the other markets (Japan (Fig.1b), India (Fig.1d), Mexico (Fig.1h), Russia (Fig.1e) and Brazil (Fig.1i)), the variance vanishes at middle of the sample period and rises again at the end of the sample period (2013-2014). For the China's case, a weak variance is scattered over the sample period. It is also interesting to show that there are some common red islands between spot and futures indices mostly concentrated at the beginning of the period.

[Figure 1 to be here]

5.2. The cross-wavelet power

The movements of covariance between spot and futures indices are shown in the following Figure 2a and 2b. Overall, for all pairs, the co-movement between spot and futures indices reveals an erratic behaviour. For the emerging markets, there is more interesting covariance at low frequencies (high scales). The co-movements between time series are spotted over the sample period and mainly concentrated at the beginning of the period (2010-2012) for the Hong Kong, India, Mexico and Russia couples', at the end of the period (2012-2014) for the Japan and China pair and over the sample period for the Brazil case. For the developed markets, some interesting features deserve to be mentioned. When we look for all pairs we can observe that red islands are localized at the beginning of the period both at low and high frequencies indicating that the co-movement of covariance increases as the time scale increases. In addition, the Wavelet covariance between spot and futures indices increases weakly after the 2013 year. More precisely, after this date, there are no clear and general changes occurring for all spot-futures couples since the red power is increasingly weak until the end of the period.

[Figure 2 to be here]

5.3. The wavelet coherence

Based on the previous results, it is interesting to investigate whether volatility of one variable leads to another or merely a coincidence. As we mention above, the wavelet coherence measures the local correlation between time series. A perfect correlation between spot and futures at any frequency band over a specific period is perceived when the local correlation is equal to 1. The local correlation becomes less interesting when the value tends to 0. Figure 3 shows the estimated wavelet coherence respectively for emerging and

developed markets. We can clearly observe that, at all frequencies bands and over the time intervals, spot and futures move significantly. The arrows pointed to the right (left) indicate that spot and futures are in-phase or positively correlated, on the other hand, when the arrows are pointed to the left the variables are completely out of phase or negatively correlated. An arrow pointing up signifies that futures lead spot indices whereas arrow pointing down shows that spot indices lead futures.

For the emerging markets, for the cases of Hong-Kong, Russia, Brazil and China, the arrows are pointing to right and up indicating that futures lead spot indices. This result signifies that there is a unidirectional sequential causal relationship exists from futures market to spot markets. For the other cases (Japan and India), it is difficult to conclude which variables is leading because the tendencies of arrows are not reliable.

Looking for the developed markets, there is a significant local correlation between futures and spot indices at all time scales and over the sample period. For the US and Canada futures-spot cases, the arrows are pointing to the right and up most of the time which indicates that futures indices lead the spot prices. While the spot lead the futures, in the France context, as the arrows are pointing to the right and down, the trends of arrows for in the Germany case are not consistent making difficult to conclude about any bi-directional relationship between futures and spot.

6. Conclusion

The paper analyses the relationships between spot and futures markets using the daily data from October 2010 till October 2014. The empirical results show that the co-movement between spot and futures indices reveals an erratic behaviour. We found that the intensity of co-movement depends on the level of volatility of the markets, supporting the position the

volatility increasing the information flow and transmission of information across markets (Ross, 1989). At the beginning of the estimation period (2010-2012) when both futures and spot markets appear to be more volatile, the degree of co-movements between market are substantially higher than in the middle of the estimation period. This effect is especially observable for the Hong Kong, India, Mexico and Russia pairs. While in the middle of the period the variance declined significantly, it raised again at the end of the sample period (2013 – 2014), when the co-movements between futures and spot markets for the Japan and China couples are strong. Furthermore, the wavelet covariance between spot and futures indices increases weakly after the 2013 year and after this date there are no clear and general changes occurring for all spot-futures couples. Besides, the interesting pattern of co-movements shown in Brazil, where linkages between stock index futures and stock indices are strong during whole observation period.

While the stock indices appear to be more volatile than stock index futures for all markets, the lead-lag relationships have different patterns for developed and emerging markets. For example, the results for the emerging markets, i.e. Hong-Kong, Russia, Brazil and China, shows that unidirectional sequential causal relationship exists from futures market to spot markets. This findings support the position that futures trading increase the volatility of spot markets (e.g., Antoniou & Holmes, 1995; Antoniou et al., 2003). For the developed markets, there is a significant local correlation between futures and spot indices at all time scales and over the sample period. However, while for the USD and Canada futures-spot cases futures lead the spot prices, for the France the spot lead the futures. In the Germany case empirical results indicate bi-directional relationship between futures and spot markets.

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Table 1 Trading hours.

#	Country	Index	Stock Exchange trading hours (GMT)	Futures Exchange trading hours (GMT)	Daylight Saving Time (DST)	Trading hours during DSM
1	Germany	DAX 30	07:00-16:00	07:50-22:00	Mar–Oct	08:00-17:00
2	France	CAC 40	08:00-16:30	07:00-21:00	Mar-Oct	09:00-17:30
3	Russia	RTSI\$	06:00-14:45	07:00-15:45; 16:00- 20:50;	Mar-Oct	07:00-15:45
4	Hong	HSI	01:20-08:00	El. 09:00-15.45	n/a	01:20-08:00
	Kong		Lunch 04:00-05:00	Pit:01:15-04:00; Pit:		Lunch 04:00-
	-			00:00 - 06:15;		05:00
5	Japan	NKY	00:00 - 06:00	El. 07:30-18:00; Pit:	n/a	00:00 - 06:00
	-		Lunch 02:30-03:30	00:00-06:15		Lunch 02:30-
						03:30
6	India	NIFTY	03:45-10:00	El. 11:15-18:00 pit.	n/a	03:45-10:00
				01:00-10:15;		
7	China	SHSN	01:15-07:16	01:15-03:30; 05:00-	n/a	01:30-07:00
		300		07:15		
8	Canada	SPTSX60	14:30 - 21:00	06:00-16.15	Mar–Nov	15:30-22:00
9	USA	SPX	14:30 - 21:00	El: 17 :00 – 16:15	Mar–Nov	15:30-22:00
				Pit: 08:30-15:15		
10	Mexico	MEXBOL	14:30-21:00	13:30-21:00	Apr-Oct	15:30-22:00
11	Brazil	IBOV	13:00 -20:00	11:00-19:55	Oct–Feb	14:00-21:00

Figure 1 Individual power spectrum: Futures vs. Spot

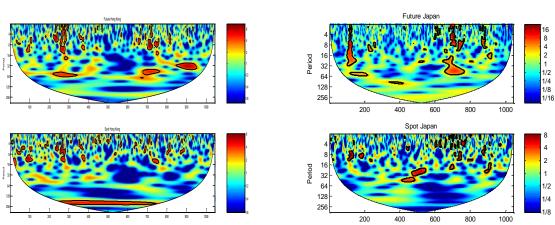


Fig. 1a Hong Kong

Fig. 1b Japan

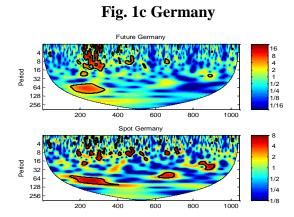


Fig. 1e Russia

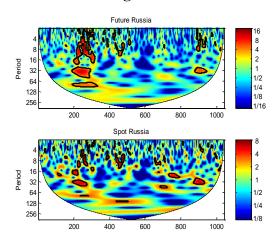


Fig. 1g USA

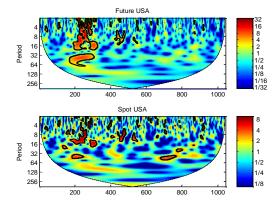


Fig. 1i Brazil

Fig. 1d India

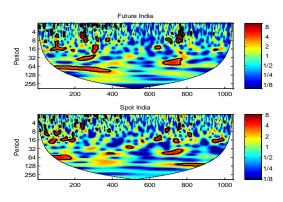


Fig. 1f Canada

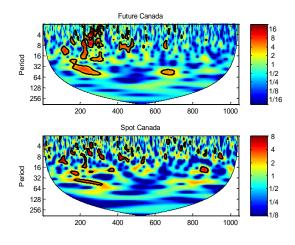


Fig. 1h Malaysia

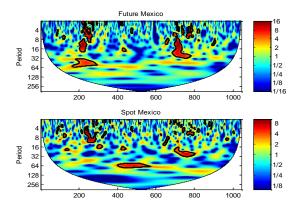


Fig. 1j France

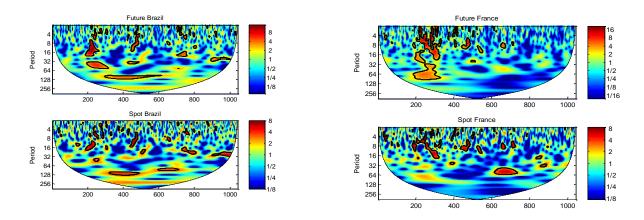


Fig. 1k

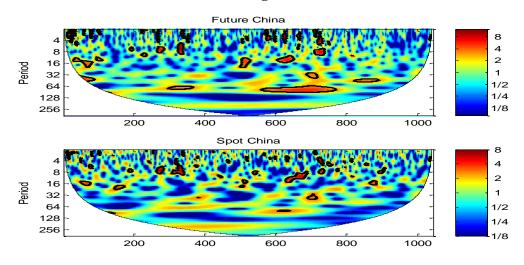
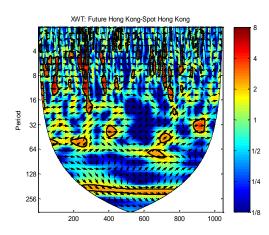
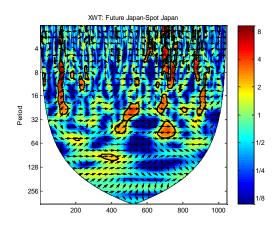
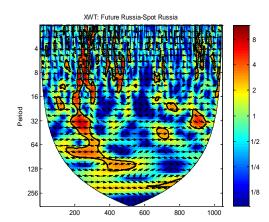


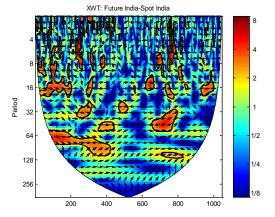
Figure 2 The cross-wavelet power: Spot vs. Futures

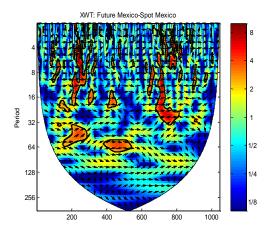
Figure 2a. Emerging Markets

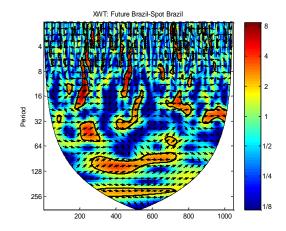


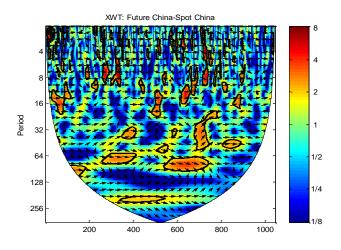


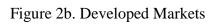


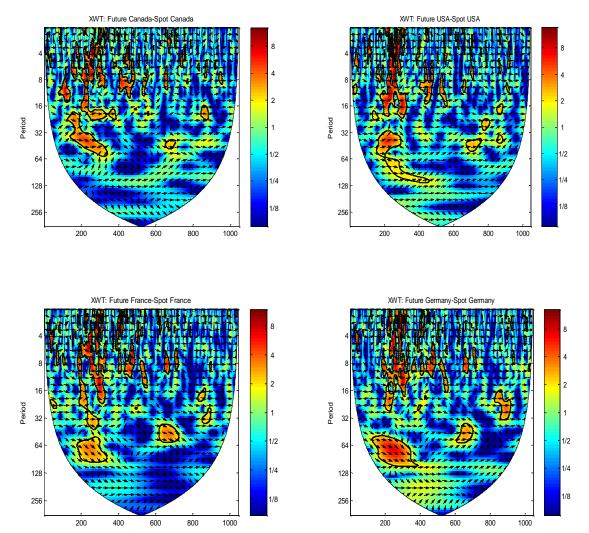












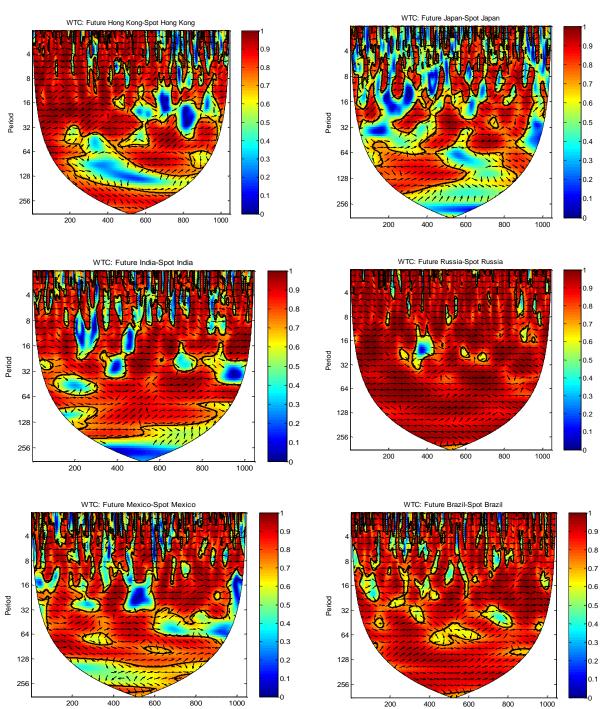


Figure 3 The wavelet coherence plots between future returns and spot returns

Figure 3a. Emerging Markets

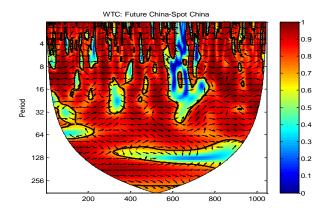
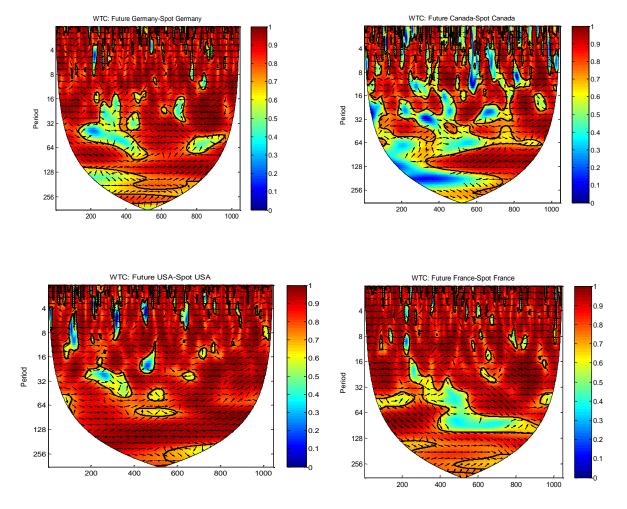


Figure 3b. Developped markets



Notes: The tick black contour encloses regions where the wavelet coherence is significant at the 5% level against the red noise estimated from Monte Carlo simulations using phase randomized surrogate series. The cone of influence (COI) is indicated by the lighter shade, which delimits the important power regions. The arrows indicate the phase difference between the two time series. The direction of arrows captures the phase difference between two time series. Arrows pointed to the right (left) indicate that variables are in phase (out of phase), to the right and up (down), the first variable is leading (lagging), and to the left and up (down), the first variable is lagging (leading). Time and frequency (year) are represented on the horizontal and the vertical axis, respectively.