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Abstract

We add to the discussion on the transmission of business cycles, by modeling worldwide banking sector indices cycle synchronization. We find that the respective physical distance and trade balance are able to impact the wavelet coherency. We also find regions of strong and significant coherency between NAFTA partners, and in the European core: France, Germany and United Kingdom. Concerning such trade blocs, based on the multiple coherence, partial coherence, partial phase-difference and partial gain, we find a strong performance in the period 2010-2012 in all frequencies, a period characterized by the sovereign debt crisis in some European countries.

Keywords: Sovereign debt crisis; Trade blocs; Banking contagion.

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1. Introduction

In the extensive literature on international financial system, one of the most analyzed issues is the convergence,[1] integration and contagion of some macro-finance variables for specific samples of countries.

With regards the debate on financial contagion and integration, irrespective of the concepts or measures used, it is necessary to distinguish between the nature of long-run and of short-run linkages among financial markets and then capturing the interaction between them as well. Aiming to infer about such relationships, there are many contributions assuming that from the methodological perspective there are comovements. Therefore, it is possible to synthesize complex systems into a simpler structure of common features, as cycles and trends. Some of the main theoretical and also empirical papers in this literature are Engle and Granger (1987) and Engle and Kozicki (1993), for instance.

According to this literature, international financial integration is commonly seen as increasing economic efficiency and growth, but it may also increase countries' vulnerability to contagion. On the one hand, Aharony and Swary (1983) find that failures of a dishonestly run banking institution, such as fraud and internal irregularities and even a large bank, need not cause panic and loss of public confidence in the integrity of the banking system as a whole. Otherwise, when there are macro fundaments, banking crises are overwhelmingly associated with the presence of both systematic and idiosyncratic contagion (Dungey and Gajurel, 2015). In both scenarios, some contributions following Meltzer (1967) use to suggest that the contagion effect of bank failure is one of the main reasons for bank regulation. So, our paper is relevant, since we add to this international financial system discussion, more specifically on the transmission of business cycles between countries and financial markets, by modeling worldwide banking sector indices cycle synchronization.

While applications in finance have not yet extensively utilized the properties of wavelets, there have been a number of interesting empirical exercises and the list is sure to grow fast. Some of the more recent closely related studies are Rua and Nunes (2009), Aguiar-Conraria and Soares (2011), Loh (2013), Dimic et al. (2016) and Lin et al. (2018). In this literature, we are the first, to our knowledge, to propose a metric to compare the Morlet continuous wavelet transform spectra and measure the degree of synchronization among the most relevant worldwide banking sector indices.

This methodology, explored by Grossmann and Morlet (1984) and Goupillaud et al. (1984) is well suited to our intent because it performs the estimation of the spectral characteristics of a time-series of return as a function of time. It enables us to study both the time varying and frequency specific behavior of the variables. Moreover, wavelets are mathematical functions that have advantages over traditional Fourier methods, besides improving the analysis of the non-stationary cycles on the comparison to the traditional method of understanding the trend and financial projections.

We perform an empirical exercise aiming to test if the synchronization is statistically significant by Monte Carlo simulations. Based on this metric, we fill a dissimilarity matrix which is used to map the countries into a two-dimensional axis in terms of banking cycle synchronization. We compare these banking cycle dissimilarities with geographical physical distances and foreign trade. We also use cross-wavelets and wavelet-phase difference analysis to study in more detail when and at what frequencies each country is synchronized or not.

In this context, we use a sample of the main worldwide financial sector indices, which are comprised of the banking, insurance and financial intermediation companies. Our final cross-section considering only G-20 economies is composed by financial sector indices of Australia, Brazil, Canada, Germany, France, India, Mexico, UK, USA, and Russia, covering the period from March 30, 2009, to December 31, 2013, 1255 observations. The return on these financial sector indices are stationary, heteroskedastic, leptokurtic and they are not Gaussian but rather driven by probability distribution functions as Johnson SU, Error, Hyperbolic Secant and Laplace. Finally, according to Matos et al. (2019), such banking sector indices exhibit nonlinear and nonchaotic characteristics, a sign of efficiency of the banking sector.

Summarizing our main findings, banking cycles in Australia and Russia are seem independent of all the other cycles, while wavelet transforms in France and United Kingdom behave similarly to five of nine other banking systems analyzed.

We find a synchronization between the main European economies: France, Germany and United Kingdom, highlighting the French banking cycle lowest dissimilarity with German cycle. Their longer-run cycles are strongly synchronized all the time, and we can conclude that Germany has been leading the French cycle during the year of 2010 for the 128-252 days frequency-band and France has been leading German cycle as of mid-2011. This finding

[1] To summarize previous findings, for small homogeneous groups convergence is likely, whereas for large samples such evidence is not common. According to Antozlautos et al. (2011), for a panel of 38 countries there is no convergence based on 13 different metrics.

complements in some sense the evidence reported in Aguiar-Conraria and Soares (2011) on the role played by France and Germany, both forming the core of the Euro land, based on the wavelet analysis for industrial production.

Our results suggest another pattern, a strong synchronization between Canada, United States and Mexico, precisely the countries that comprise the North American Free Trade Agreement (NAFTA), one of the largest trade blocs in the world. According to the wavelet coherency and its respective cone of influence, these economies exhibit many regions of high coherency and their phase difference analysis shows that their cycles are strongly synchronized all the time. United Kingdom is also synchronized with each country of this trade bloc.

Concerning emerging economies, Brazilian and Indian baking systems are also synchronized, likely because they belong to the BRIC trade bloc, although BRIC countries have heterogeneous profiles in terms of the cultural, political, social, demographic and macroeconomic contexts. Brazilian cycle has been leading the Indian cycle for the lowest frequency-band during the second half of the period. This finding corroborates that reported in Matos et al. (2016), according to which the Brazilian and the Chinese stock markets seem to be the first ones to react to global shocks, so that they are able to predict the common short run deviations and the Indian individual cycles.

This literature on business cycle synchronization is usually related to the optimal currency areas because it is seen as a necessary condition: a country with an asynchronous business cycle must face difficulties in a monetary union. We claim that it is also relevant to relate cycle synchronization to discussion on trade, as a useful tool for suggestion of admission of new commercial partners or even in evaluating the benefits of such commercial arrangements. In this context, we take a step forward by analyzing synchronization among the countries of each trade bloc.

Our results based on multivariate tools suggest a strong coherency in all frequencies for NAFTA economies. The partial phase-difference and partial gain results suggesting pro-cyclical relationship between USA and Mexico, with the first one leading the Mexican cycles of medium and low-frequencies at period of market instability. In the European core, the multiple coherency and partial analysis indicates a prevalence of cyclical co-movements at medium-term (32 ~ 64 days) and long-term (128 ~252 days). There is no integration at higher frequencies (4 ~ 25 days), and the French index lags UK and Germany cycles at long-term, with the relationship ranging between in-phase and out-phase.

This paper is structured as the following. Section 2 describes the methodology. The empirical exercise is reported in section 3, while concluding remarks are offered in the fourth section.

2. The wavelet analysis approach

2.1. Historical perspective

According to wavelet researchers, by using wavelets, we are adopting a whole new mindset or perspective in processing data, although the idea behind this technique is not exactly new: approximation using superposition of simple trigonometric functions has existed since the early 1800's, with Joseph Fourier. According to Graps (1995), a comprehensive survey on wavelet theory, in the history of mathematics, wavelet analysis has many different origins. Before 1930, the main branch of mathematics leading to wavelets began with Joseph Fourier with his theories of frequency analysis. Fourier's contribution played an essential role in the evolution of the ideas of mathematicians about functions. More specifically, by exploring the meaning of functions, Fourier series convergence and orthogonal systems, mathematicians gradually were led from their previous notion of frequency analysis to the notion of scale analysis. Since wavelet algorithm can process data at different scales and resolutions, it has advantages over traditional Fourier methods.

In the 1930s, some groups working independently researched the representation of functions using scale-varying basis functions, which is the key to understand wavelets. In 1980, Grossman and Morlet broadly defined wavelets in the context of quantum physics, thus providing a way of thinking for wavelets based on physical intuition. This literature claims that the coherent mathematical framework of wavelet analysis was originally developed and explored empirically by Grossmann and Morlet (1984) and Goupillaud et al. (1984). From there, this methodology, widely used in a vast range of areas, as physics and medicine, has also been used in economics, and more recently in finance.

2.2. The continuous wavelet transform

In a didactic way, this analysis performs the estimation of the spectral features of any time series as a function of time, revealing how the different periodic components of a particular time series evolve over time. While the Fourier transform breaks down a time series into constituent sinusoids of different frequencies and infinite duration in time, a wavelet function drops towards zero. This property allows for an effective localization in both time and frequency.

Our choice for this framework is particularly well suited to our intent of better understanding the behavior of the transmission of business cycles. According to Beveridge and Nelson (1981), wavelet method could improve the analysis of the non-stationary cycles of development on the comparison to the traditional method of understanding the trend and cycles, as cointegration and common feature-based approaches.

With respect to the specification, first we need to choose one among the several types of available wavelet functions. Since the wavelet coefficient $W_x(\tau,s)$ has information on $\psi(t)$ and $x(t)$, our choice of the wavelet function is important. Aiming to study synchronism between different time-series, analytic wavelets are ideal. This complex-valued wavelet is ideal for the analysis of oscillatory signals, since the continuous analytic wavelet transform provides an estimate of the instantaneous amplitude and instantaneous phase of the signal in the vicinity of each time/scale location (τ,s).

In this context, we follow most of the recent empirical contributions, by using the Morlet as the mother wavelet. It became the most popular of the complex-valued wavelets mainly because of four properties.[2]

According to Aguiar-Conraria and Soares (2010) there are three sensible ways to convert wavelet scales into frequencies: the peak frequency, the energy frequency and the central instantaneous frequency. In the case of the Morlet wavelet, these are all equal, facilitating the conversion from scales to frequencies. Moreover, the Morlet wavelet has optimal joint time-frequency concentration and the time radius and the frequency radius are equal, i.e. this wavelet represents the best compromise between time and frequency concentration. The Morlet function $\psi(t)$ is given by

$$\psi_{\varpi_0}(t) = \pi^{-1/4} e^{i\varpi_0 t} e^{-\frac{t^2}{2}} \tag{1}$$

In this analyzing function, all results are obtained using as the parametrization, the usual particular choice $\varpi_0 = 6$.

2.3. Univariate and bivariate tools

Following the terminology used in the Fourier case, the local wavelet power spectrum – a measure of the variance distribution of the time-series in the time-scale/frequency plane – is given by

$$WPS_x(\tau,s) = |W_x(\tau,s)|^2 \tag{2}$$

The concepts of cross wavelet power, wavelet coherency and phase-difference are natural generalizations of the basic wavelet analysis tools that enable us to deal with the time-frequency dependencies between two time-series. The cross-wavelet transform of two time-series, $x(t)$ and $y(t)$, is defined as

$$W_{xy}(\tau,s) = W_x(\tau,s)\overline{W_y}(\tau,s) \tag{3}$$

In the third equation, $W_x(.)$ and $W_y(.)$ are the wavelet transforms of x and y, respectively. The cross-wavelet power, defined as $|W_{xy}(\tau,s)|$, depicts the local covariance between two time-series at each time and frequency. When we compare with the cross-wavelet power, the wavelet coherency has the advantage of being normalized by the power spectrum of the two time-series. Thus, we define the wavelet coherency of two time-series, $x(t)$ and $y(t)$, as

$$R_{xy}(\tau,s) = \frac{|S(W_{xy}(\tau,s))|}{\sqrt{S(|W_{xx}(\tau,s)|)S(|W_{yy}(\tau,s)|)}} \quad , \tag{4}$$

where $S(.)$ is a kind of smoothing operator in both scale and time.

Following this methodology, first we propose using a metric for measuring the distance between a pair of given wavelet spectra. The measure can then be applied to each pair of spectra of all the countries in our dataset, thus allowing us to fill in a distance/dissimilarity matrix, suitable for cluster analysis. We follow Rouyer et al. (2008) by using the singular value decomposition of a matrix to focus on the common high-power time-frequency regions.

[2] See Aguiar-Conraria and Soares (2014) for a discussion of desirable properties of this wavelet function.

This method is analogous to Principal Component Analysis, but while with the latter one finds linear combinations that maximize the variance, subject to some orthogonality conditions, here we wish to maximize covariances instead. Therefore, the first extracted components correspond to the most important common patterns between the wavelet spectra. With that information, we just need to define a metric to measure the pairwise distance between the several extracted components. To compare the wavelet spectra of two banking systems we use the following equation:

$$dist(W_x, W_x) = \frac{\sum_{k=1}^{K} \sigma_k^2 [d(\mathrm{l}_x^k, \mathrm{l}_y^k) + d(\mathbf{u}_k, \mathbf{v}_k)]}{\sum_{k=1}^{K} \sigma_k^2} \tag{5}$$

where σ_k^2 are the weights equal to the squared covariance explained by each axis, $\mathbf{u}_k$ and $\mathbf{v}_k$ are singular vectors satisfying variational property and l_x^k and l_y^k are leading patterns. This distance is computed for each pair of countries and, with this information, we can then fill a matrix of distances, available in the subsection 3.2.

As we have already said, phase-difference is a natural generalization of the basic wavelet analysis tools. This is our second contribution: analyze the time-frequency dependencies between two time-series. In the literature on the theoretical distribution of the wavelet power and on the distribution of cross-wavelets, the available tests imply null hypotheses that are too restrictive to deal with economic data. Therefore, we follow Aguiar-Conraria and Soares (2011), for instance, by relying on Monte Carlo simulations for statistical inference.

One of the major advantages of using a complex-valued wavelet is that we can compute the phase of the wavelet transform of each series and thus obtain information about the possible delays of the oscillations of the two series as a function of time and scale/frequency, by computing the phase-difference. The phase difference is given by

$$\phi_{xy}(s,\tau) = tan^{-1}\left(\frac{\Im\left(W_{xy}(s,\tau)\right)}{\Re\left(W_{xy}(s,\tau)\right)}\right) \tag{6}$$

We also need the information on the signs of each part to completely determine the value of $\phi_{xy} \epsilon [-\pi, \pi]$. A phase-difference of zero indicates that the time-series move together at the specified frequency. If $\phi_{xy} \epsilon \left(0, \frac{\pi}{2}\right)$ the series move in phase, but the time-series y leads x, while if $\phi_{xy} \epsilon \left(-\frac{\pi}{2}, 0\right)$ then it is x that is leading. A phase-difference of $\phi_{xy} = \pm\pi$ indicates an anti-phase relation. Finally, if $\phi_{xy} \epsilon \left(\frac{\pi}{2}, \pi\right)$, then x is leading and time-series y is leading if $\phi_{xy} \epsilon \left(-\pi, -\frac{\pi}{2}\right)$.

See subsection 3.3 for this analysis and the appendix for the respective figures.

2.4. Multivariate tools (case of three series)

Following Aguiar-Conraria et al. (2018), we present the formulas for the wavelet multivariate tools, multiple wavelet coherency, partial wavelet coherency, partial wavelet phase-difference, and partial wavelet gain, for the simplest case in which we have three series of returns on banking indices x, y and z.

First, the multiple wavelet coherency between the series y and the series x and z, denoted by $R_{y(xz)}$ is given by

$$R_{y(xz)} = \sqrt{\frac{R_{yx}^2 + R_{yz}^2 - 2\Re(\xi_{yx}\xi_{xz}\overline{\xi_{yz}})}{1 - R_{xz}^2}} \tag{7}$$

The complex partial wavelet coherency between y and x, after controlling for z is given by

$$\xi_{yx,z} = \frac{\xi_{yx} - \xi_{yz}\overline{\xi_{xz}}}{\sqrt{(1 - R_{yz}^2)(1 - R_{xz}^2)}} \tag{8}$$

The absolute value and the angle of $\xi_{yx,z}$ are respectively the partial wavelet coherency and the partial wavelet phase difference between y and x, after controlling for z. They are analogue of the bivariate metrics given by (4) and (6), and they are denoted by $R_{yx,z}$ and $\phi_{yx,z}$.

3. Empirical exercise

3.1. Data and descriptive statistics

Major market indices are well known and they use to be composed of stocks of companies from several sectors of the economy. However, by incorporating all these companies, we lose the power of explaining a particular segment of the market. Aiming to deal with this issue, we observe the appearing of sectorial indices, with a proposal to complement the general market indices and also providing summary information about a specific sector of the economy. We implement an empirical exercise applying wavelet analysis in a sample of main worldwide financial sector indices of G20 economies. This sector consists of banks, insurance companies, and other financial intermediation companies and its idiosyncrasies make it more likely to be influenced by contagion and integration. Banks, insurance companies and other financial companies in major economies are often strongly connected, with interdependence in the short and long term.

We report in Table 1 a basic description of such financial indices.

Table 1
Main worldwide financial sector indices

Country	Financial Sector Index	Continent	Position in the ranking (GDP, 2013)
Germany	DAX All Banks	Europe	4th
Australia	ASX 200 Financials	Oceania	12th
Brazil	IFNC	South America	7th
Canada	TSX Financials	North America	11th
United States of America	KBW Bank	North America	1st
France	CAC financials	Europe	5th
India	CNX Finance	Asia	10th
Mexico	BMV	North America	15th
United Kingdom	NMX 8350	Europe	6th
Russia	Moscow Exchange Financials Index	Europe	9th

In principle, whenever econometric or statistical tests are performed, it is preferable to employ a large data set either in the time-series (T) or in the cross-sectional dimension (N). When working with worldwide financial sector indices, we have to deal with the trade-off between T and N. So, in terms of sample size, the main limitation for the time-series span used here is the appearing of this sectorial index across countries and the availability of a time series sufficiently extensive, at least one thousand daily observations, i.e., approximately four years.

In order to have a balanced database, we adjust data series to make these calendars uniform, since the countries have different calendars in terms of working days. The criterion is to use any day that was a working day in any of the economies, aiming to deal with the differences due to the holidays between the markets located on five continents, with a greater presence of European and North American countries. Unfortunately, the relevant financial markets, such as Japanese or Chinese, or do not provide time series of its respective sectorial indices or these series are very recent.

Figure 1 shows the cumulative gross return on the financial sector indices in terms of the local investor´s currency. Table 2 reports summary statistics and in Table 3, we report pairwise correlations.

We can highlight volatility clusters and higher oscillations, mainly between 2011 and 2012, a period characterized by the sovereign debt crisis in some European countries. The country whose index has the highest cumulative gain in the period is India, with 189%, while DAX All banks in Germany has the worst cumulative gain, only 26%, and the highest drawdown among these indices, 64%. TSX Financials in Canada is the smoothest index considering all volatility measures used here. Its semivariance is only 0.73%, for instance. All series are leptokurtic with a higher intensity for CNX Finance in India, suggesting the frequency of occurring large losses. These skewness and kurtosis are a strong evidence that the series do not follow a Gaussian distribution.

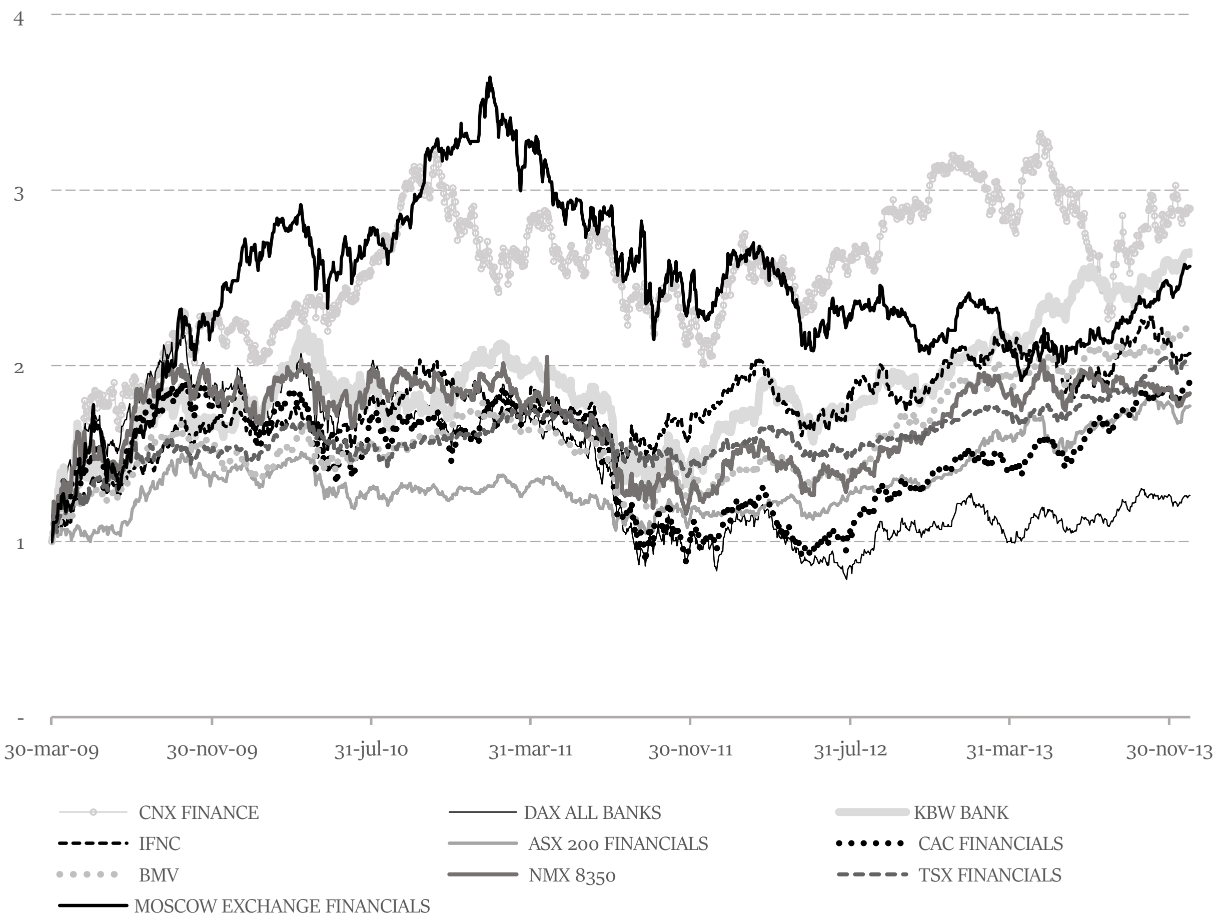


Fig. 1. Cumulative gross returns on main worldwide financial sector indices [a,b]

[a] This figure plots the nominal net return on financial sector index in terms of the local investor´s currency, based on the daily time series for the end-of-day quote, during the period from March 30, 2009 to December 31, 2013. [b] Data source: Bloomberg.

Table 2

Statistics of series of returns on main worldwide financial sector indices (March 30, 2009 to December 31, 2013. Data source: Bloomberg).

Statistics	CNX Finance (India)	DAX All Bankx (Germany)	KBW Bank (USA)	IFNC (Brazil)	ASX 200 Financials (Australia)	CAC Financials (France)	BMV (Mexico)	NMX 8350 (U. K.)	TSX Financials (Canada)	Moscow Exchange Financial (Russia)
Gain										
Mean	0.10%	0.04%	0.10%	0.07%	0.05%	0.08%	0.07%	0.07%	0.06%	0.09%
Cumulative	189.57%	26.29%	164.76%	107.04%	77.17%	91.30%	121.28%	84.29%	104.28%	156.61%
Risk										
S. D.	1.70%	2.09%	2.12%	1.43%	1.17%	2.16%	1.28%	1.82%	1.03%	1.70%
Semivariance	1.12%	1.46%	1.43%	1.00%	0.82%	1.49%	0.92%	1.22%	0.73%	1.21%
Drawdown	37.60%	64.27%	41.93%	32.09%	30.58%	53.98%	33.88%	43.55%	22.05%	47.43%
Other moments										
Asymmetry	1.34	0.26	0.79	0.05	0.04	0.55	-0.11	0.59	-0.05	-0.12
Kurtosis	17.82	5.91	15.83	4.83	4.33	9.73	8.21	9.03	6.65	7.12

Table 3
Correlations of daily series of returns on main worldwide financial sector indices (March 30, 2009 to December 31, 2013. Data source: Bloomberg).

Correlation		CNX Finance (India)	DAX All Bankx (Germany)	KBW Bank (USA)	IFNC (Brazil)	ASX 200 Financials (Australia)	CAC Financials (France)	BMV (Mexico)	NMX 8350 (U. K.)	TSX Financials (Canada)	Moscow Exchange Financial (Russia)
CNX Finance	(India)	1.00	0.31	0.18	0.28	0.24	0.29	0.23	0.32	0.20	0.34
DAX All Bankx	(Germany)	0.31	1.00	0.48	0.45	0.29	0.88	0.56	0.73	0.53	0.54
KBW Bank	(USA)	0.18	0.48	1.00	0.50	0.14	0.50	0.68	0.48	0.69	0.34
IFNC	(Brazil)	0.28	0.45	0.50	1.00	0.19	0.47	0.51	0.46	0.52	0.37
ASX 200 F.	(Australia)	0.24	0.29	0.14	0.19	1.00	0.34	0.21	0.29	0.24	0.26
CAC F.	(France)	0.29	0.88	0.50	0.47	0.34	1.00	0.58	0.77	0.55	0.52
BMV	(Mexico)	0.23	0.56	0.68	0.51	0.21	0.58	1.00	0.53	0.58	0.37
NMX 8350	(U. K.)	0.32	0.73	0.48	0.46	0.29	0.77	0.53	1.00	0.50	0.49
TSX Financials	(Canada)	0.20	0.53	0.69	0.52	0.24	0.55	0.58	0.50	1.00	0.41
Moscow E. F. I.	(Russia)	0.34	0.54	0.34	0.37	0.26	0.52	0.37	0.49	0.41	1.00

A simple but intuitive statistic that signals the expected results in terms of synchronization consists of the correlation, reported in Table 3. It is possible to observe on the one hand, that India and Australia are the banking systems that present less synergy with the others. The lowest correlation observed is between India and the United States, 0.14. On the other hand, the German and French banking indices are highlighted because they present the highest values of correlation with the indices of the other countries. The correlation between them is the highest reported, 0.88. In terms of blocs, Mexico, Canada and the United States share high correlations ranging from 0.58 to 0.69. We also find high correlations for the three major European economies, whose correlations range from 0.73 to 0.88.

We also apply Jarque and Bera (1981) test and the result suggests the rejection of the null hypothesis of normality at the 1% significance level for all indices. We propose ranking probability distribution functions considering a range with over 60 distributions, based on the metric proposed by Anderson and Darling (1952). Some of the best ranked distributions are Johnson SU, Error, Hyperbolic Secant and Laplace. Aiming to evidence the stationary or not of these time series, we perform the unit root test proposed by Dickey and Fuller (1979), in its augmented version, known as the ADF test. Based on such test, there is no unit root at the level of significance of 1%. We also use ARCH–LM test proposed by Engle (1982) and find that at 1% level of significance, eight series reject the null hypothesis of homoscedasticity, and at 10% of significance level, no series seems to be homoscedastic. These results are not reported here for the sake of space, but they are available upon request.

3.2. Business cycle dissimilarities

In Figure 2, we plot a useful map which enables us to infer that it is clear that there is a bloc formed by Canada, United States and Mexico, to which United Kingdom is also strongly aligned. This is exactly the composition of the NAFTA trade block. Therefore, we observe that different approaches lead to some overlapping findings. Further corroborating the previous evidences obtained in the correlation matrix, Australia confirms its distance from the other banking systems. Brazil and Russia are also distant from most other countries or colors. By correlations this was a predictable outcome as well.

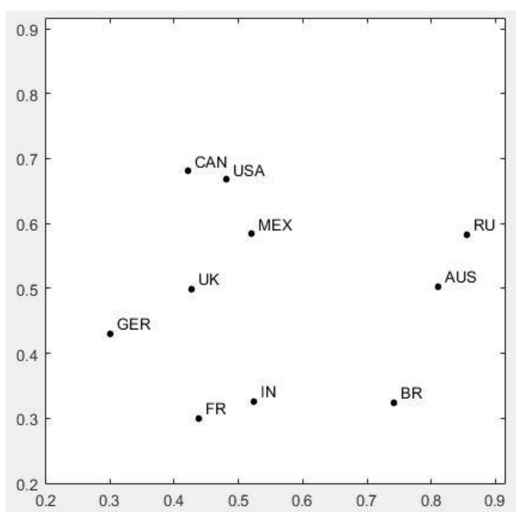


Fig. 2. Banking cycles dissimilarity of returns on main worldwide financial sector indices (March 30, 2009 to December 31, 2013).

In the upper triangle of Table 4, we report information on the physical distance between the cities where the respective stock exchanges are located (in km), while in the lower triangle of Table 4, we can find countries dissimilarities, computed with the formula (5) with the whole dataset, March 30, 2009 to December 31, 2013.

In the Table 5, the unique difference is that now we report in the upper triangle the trade balance, i.e. exports plus imports between partner countries (in U$$ bi), instead of physical distance.

Table 4

Banking cycles dissimilarities of returns on main worldwide financial sector indices, lower triangle, and the physical distance between the cities where the respective stock exchanges are located (in km), upper triangle. (* *p value* <0.05)

Dissimilarity		CNX Finance (India)	DAX All Bankx (Germany)	KBW Bank (USA)	IFNC (Brazil)	ASX 200 Financials (Australia)	CAC Financials (France)	BMV (Mexico)	NMX 8350 (U. K.)	TSX Financials (Canada)	Moscow Exchange Financial (Russia)
CNX Finance	(India)		6570	12537	13773	10156	7009	15645	7191	12488	5028
DAX All Bankx	(Germany)	0.536		6202	9829	16482	478	9559	638	6333	2021
KBW Bank	(USA)	0.484	0.480		7685	15988	5837	3359	5570	550	7510
IFNC	(Brazil)	**0.398***	0.507	0.491		13357	9401	7432	9470	8186	11806
ASX 200 F.	(Australia)	0.651	0.516	0.561	0.548		16960	12972	16993	15567	14495
CAC F.	(France)	0.469	**0.249***	0.444	**0.406***	0.527		9196	344	6000	2486
BMV	(Mexico)	0.493	0.420	**0.245***	0.524	0.516	**0.393***		8928	3261	10719
NMX 8350	(U. K.)	0.541	**0.324***	**0.385***	0.563	0.468	**0.275***	**0.386***		5712	2500
TSX Financials	(Canada)	0.495	0.521	**0.377***	0.518	0.552	**0.414***	**0.347***	**0.360***		7484
Moscow E. F. I.	(Russia)	0.545	0.454	0.453	0.538	0.588	0.456	0.472	0.428	0.472	

Table 5
Banking cycles dissimilarities of returns on main worldwide financial sector indices, lower triangle, and the trade balance – exports, FOB to partner countries + imports, CIF from partner countries between the countries in U$$ bi, upper triangle. (* *p value* <0.05)

Dissimilarity		CNX Finance (India)	DAX All Bankx (Germany)	KBW Bank (USA)	IFNC (Brazil)	ASX 200 Financials (Australia)	CAC Financials (France)	BMV (Mexico)	NMX 8350 (U. K.)	TSX Financials (Canada)	Moscow Exchange Financial (Russia)
CNX Finance	(India)		101	265	43	73	44	21	72	23	34
DAX All Bankx	(Germany)	0.536		720	109	65	1067	78	646	78	357
KBW Bank	(USA)	0.484	0.480		301	172	334	2151	512	2740	150
IFNC	(Brazil)	**0.398***	0.507	0.491		9	47	44	40	29	29
ASX 200 F.	(Australia)	0.651	0.516	0.561	0.548		27	10	62	17	6
CAC F.	(France)	0.469	**0.249***	0.444	**0.406***	0.527		20	337	38	109
BMV	(Mexico)	0.493	0.420	**0.245***	0.524	0.516	**0.393***		20	122	6
NMX 8350	(U. K.)	0.541	**0.324***	**0.385***	0.563	0.468	**0.275***	**0.386***		118	84
TSX Financials	(Canada)	0.495	0.521	**0.377***	0.518	0.552	**0.414***	**0.347***	**0.360***		12
Moscow E. F. I.	(Russia)	0.545	0.454	0.453	0.538	0.588	0.456	0.472	0.428	0.472	

Concerning this concept of dissimilarity, given that we use the Hermitian angle, the highest value the distance can take is $\pi/2$, while a value very close to zero means that two countries have a very similar wavelet transform. This which implies that the two countries share the same high-power regions and also that their phases are aligned. In other words, the contribution of cycles at each frequency to the total variance is similar between both countries and this contribution happens at the same time in both countries. We may also infer that the ups and downs of each cycle occur simultaneously in both countries.

According to the dissimilarities reported in Table 4, the most dissimilar is Australia, with an average higher than 0.547, while the other average dissimilarities for each country range from 0.404 (France) to 0.512 (India). In terms of cross-partner volatility, Australia is the country with more homogeneous dissimilarities, while Germany has more volatile dissimilarities. Australia also has the highest dissimilarities reported, 0.651 concerning India and 0.588 with regards Russia. The tighter pair of banking indices is USA and Mexico (0.245), followed by German and French systems (0.249).

Aiming to assess if the pairwise synchronization is statistically significant at 5%, we follow this literature by relying on Monte Carlo simulations (1000 times). First, corroborating the Figure 2 and the average dissimilarities, Australia and Russia have banking cycles that seem to be independent of other banking systems; they are not synchronized with any other country at 5%. This inference also enables us to identify two intuitive blocs: a European core, based on the strong and significant synchronization between France, Germany and United Kingdom and a strong synchronization between Canada, United States and Mexico, precisely the countries that comprise the North American Free Trade Agreement (NAFTA). United Kingdom is also synchronized with each country of this trade bloc, and the same holds for France, except for USA. Concerning emerging economies, Brazilian and Indian baking systems are also synchronized, likely because they belong to the BRIC trade bloc. We revisit this relationship discussion on synchronization and trade blocs, by analyzing multivariate coherency (subsection 3.4).

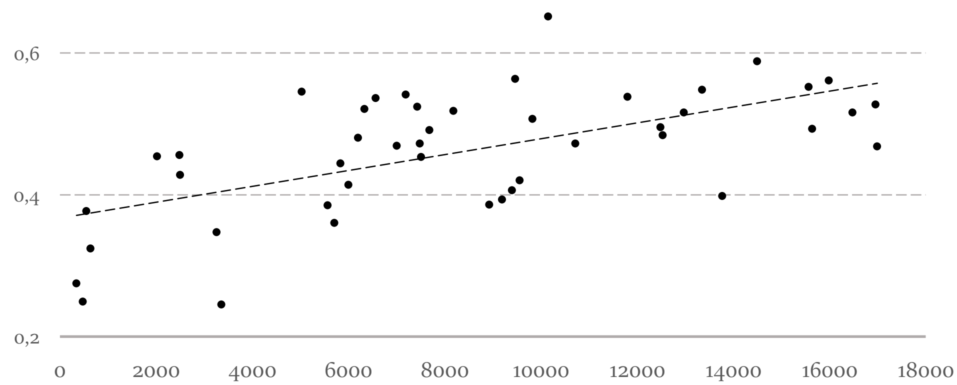
Observing the physical distance between the cities where the respective stock exchanges are located, banking cycle synchronization does not seem to be independent from geographical issue, based on the significative correlation of 0.607, as well as some common patterns for both metrics of distance/difference. The city with the longest average distance in relation to the others is Sidney, with more than 14,500 km, while the two cities with the least average distance are London and Paris, 7,89 and 7,154 respectively, the same pattern evidenced based on the dissimilarities. This finding is aligned to Aguiar-Conraria and Soares (2011), according to which the correlation between physical distance and dissimilarity based on industrial production for European countries is 0.67.

We also compare synchronization with trade between each pairwise of countries (Table 5). Once more, we find a significant correlation, -0.518. The negative sign is intuitive if we assume that commercial ties are useful to understand bank contagion, in the direction that stronger ties suggests lower dissimilarities. In addition to having the highest average dissimilarity and average physical distance, Australia has the lowest volume of foreign trade. USA, Germany and Canada have the highest average volumes in this order, and they are among the countries with the lowest dissimilarities in relation to the others. Analyzing each pair of foreign trade volumes, US commercial relations with Canada and Mexico are of the order of twice the relations between France and Germany, for example. Following, we highlight the strong German trade relations with UK and USA.

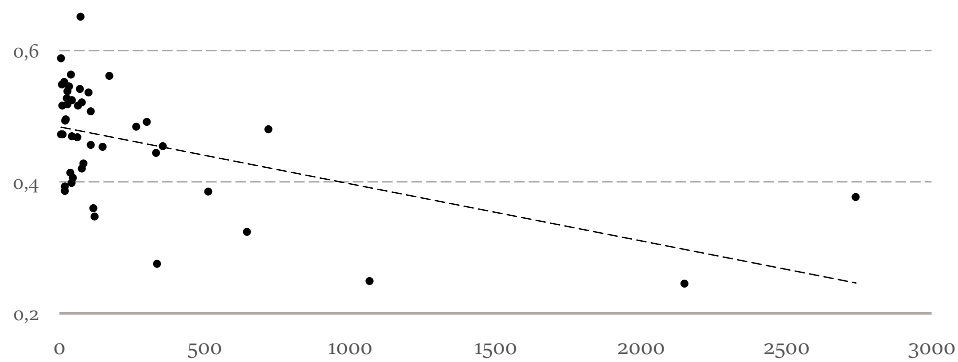
We summarize this finding by plotting in Figure 3 (a), the dispersion between physical distance in kms (horizontal axis) and dissimilarity (vertical axis) and in Figure 3 (b) the dispersion between trade balance in US$ bi (horizontal axis) and dissimilarity (vertical axis).

Finally, aiming to add to this discussion on the factors useful to better understand the 45 possible dissimilarities reported here, we follow Dimic et al. (2016) and Lin et al. (2018), by proposing a simple regression to measure the impact of related variables on wavelet coherency. We use the respective physical distance in kms and trade balance in US$ bi and the results are reported below. We find individual significance at 5% for the intercept, as well as for both variables, in the direction predicted by the associated fundamentals. We also find a joint significance and the explanatory power of this simple framework is higher than 0.407.

$$diss_{i,j} = 0.4016 + 8.58 \times 10^{-6} \times phydist_{i,j} - 4.92 \times 10^{-5} \times trade_{i,j} \tag{9}$$



(a) Dispersion between physical distance in kms (horizontal axis) and dissimilarity (vertical axis)



b) Dispersion between trade balance in US$ bi (horizontal axis) and dissimilarity (vertical axis)

Fig. 3. Dispersion between dissimilarity vs trade and physical distance [a, b, c]

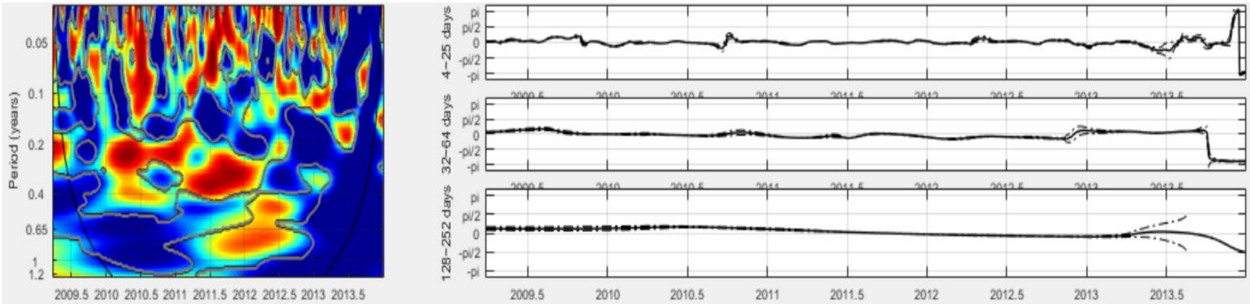
[a] Banking cycles dissimilarity of returns on main worldwide financial sector indices (March 30, 2009 to December 31, 2013). [b] Physical distance between the cities where the respective stock exchanges are located. [c] Trade balance – exports, FOB to partner countries + imports, CIF from partner countries between the countries in U$$ bi, from 2009:2 to 2013:4.

3.3. Wavelet phase difference and cross-wavelets

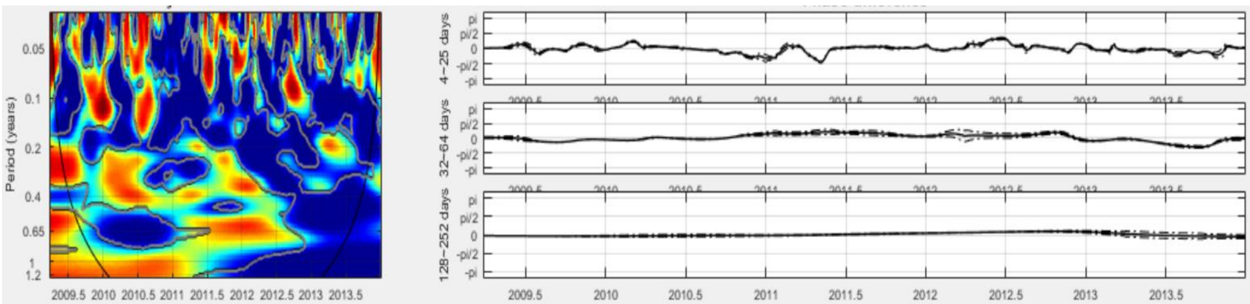
The phase-difference is a very useful tool to infer on the delay between oscillations of two banking indices, while the regions of high wavelet coherency suggest strong local correlation between pairs of banking cycles.

We follow the same procedure for all 45 pairwise available, given 10 banking indices used here: we plot the wavelet coherency on the left and phase-difference on the right. Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. With regards the phase-difference, we also plot it with plus and minus two standard deviations. In this subsection, we discuss the countries that we have identified as belonging to a bloc or group, based on previous finding.

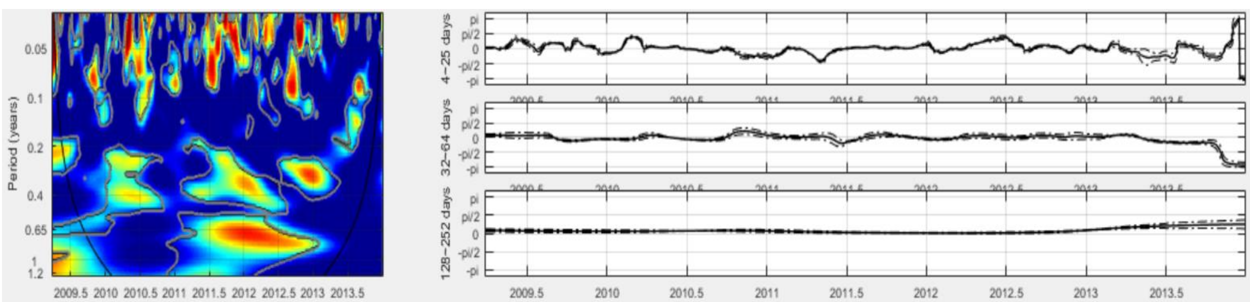
In Figure 4, we plot both frameworks for the European core: France, Germany and United Kingdom. Concerning up to one-month frequency-band, France exhibits many point and successive regions of high coherency with Germany and UK during almost the entire period. We find a somewhat similar pattern for UK and Germany, but with less intensity. We highlight the strong coherency between France and Germany from 2010 to 2012 for mid frequency-band and in the first two years between France and UK for the lowest frequency. There is no evidence on anti-phase even when we look at higher frequency-band and each of these countries is very much in-phase with each other when we look at longer-run frequencies. Finally, we find for the 128-252 days frequency-band that Germany has been leading the French cycle during the year of 2010 and France has been leading German cycle as of mid-2011.



a) Germany vs France



b) France vs UK



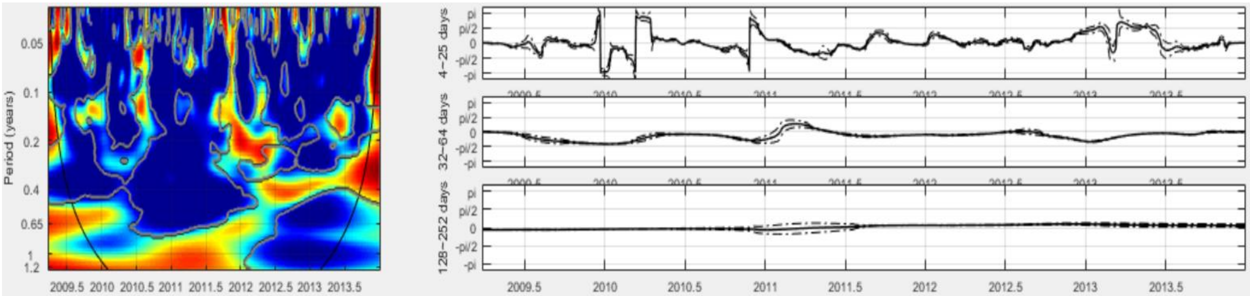
c) Germany vs UK

Fig. 4. European core: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

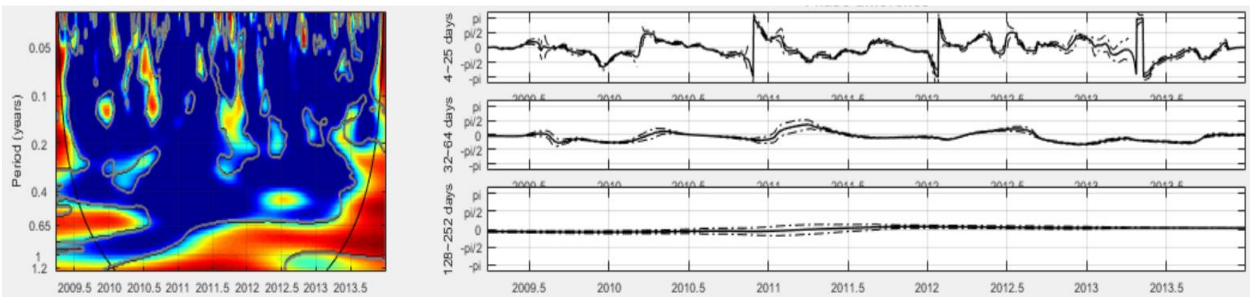
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

In Figure 5, there are regions of strong coherency between the high frequency cycles only for the USA and Mexico in 2011. The American cycles for the one-month to six-months frequency-band have regions of strong coherence in the beginning and at the end of the time with Canada and Mexico. With a frequency of six months or more, the cycles are coherent principally between Canada and USA during the first half of the time and between Canada and Mexico in the second half. To summarize the lower frequency pattern, these economies of NAFTA bloc behave as if they were highly synchronized all the time and we find some isolated out of phase behavior with the other partners only for the Canadian higher frequency cycles.

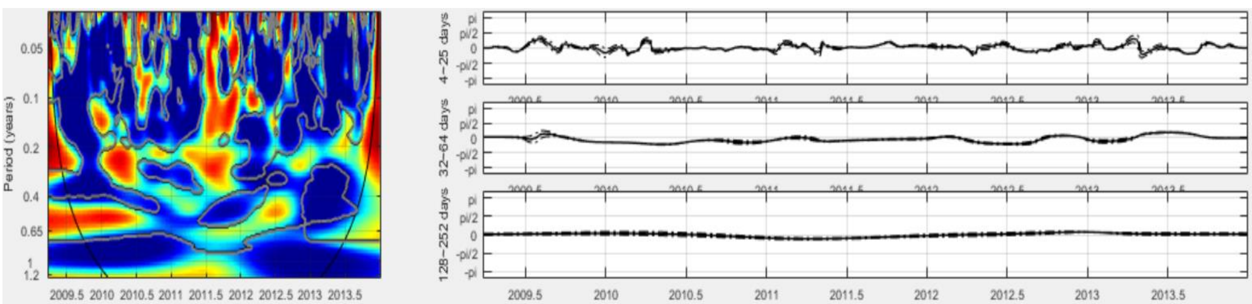
Concerning emerging economies (Figure 6), there is a clear high coherency region until mid-2010 frequency of two months or more. Brazilian and Indian baking systems are also aligned, mainly for lowest frequency-band, with the Brazilian cycle leading the Indian cycle during the second half of the period. We find some out of anti-phase regions for high- and mid-frequency bands after 2012. Other wavelet coherency maps and the respective phase-differences are reported in the appendix, from the Figures A1 to A10, given their minor relevance in terms of results and discussion.



a) USA vs Canada



b) Mexico vs Canada



c) USA vs Mexico

Fig. 5. NAFTA: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

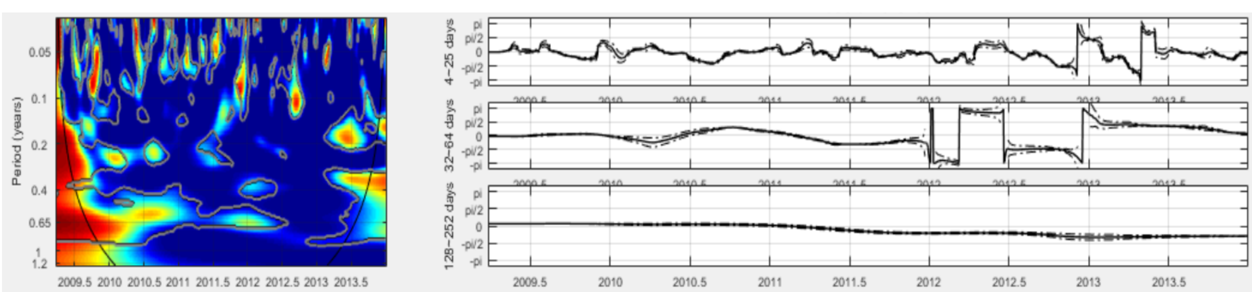


Fig. 6. India vs Brazil: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

3.4. Multivariate analysis

In the previous subsection, we find regions of strong coherency between NAFTA partners, as well as considering the European core: France, Germany and United Kingdom. Aiming to better understand the relationship in each of such blocs, we propose the use of the multiple coherence, partial coherence, as well as partial phase-difference and partial gain. The first one measures the degree of adjustment of the explanatory variables on the dependent variable in the time-frequency domain. The other measures calculate the relationship between the fluctuations of two markets, controlling the influence of a third party on the oscillations in the time-frequency space.

According to Figure 7, the presence of successive areas with significance statistics in the multiple coherence denotes a good overall fit in the model, reporting that the Canadian and American financial indices are useful to explain Mexico's financial index in the time-frequency location. At short-term (period 0.05 ~ 0.1 year) we find a regular pattern of absence of synchronization from the beginning of 2012. For mid-run frequencies (0.1 ~ 0.3 year), the multiple coherence is continuously significant from 2010 to 2013 in some location. At long-term horizon (0.5 ~ 1 year), the range of significance decreases to 2010 until the first half of 2012. Therefore, we are able to find a strong performance in the period 2010-2012 in all frequencies, characterized by greater uncertainties in the market due to the sovereign debt crisis in some European countries.

Controlling the effects of the US index, the partial coherence between Mexico and Canada shows greater coherence in the medium-term horizon and absence of synchronization in the long term. At short term, there is a region of coherence between second-half of 2011 and early of 2012, the partial phase-difference is set to zero, indicates strong contemporaneous co-movements among the Countries. On the other hand, for long-term frequencies (0.5 ~ 1 year), the partial coherency is significant between 2010 and first-half of 2012, with Mexico leading the Canada, but during 2011 the partial phase-difference is set to (0, $\pi/2$) indicating a positive co-movement, and in the early of 2012 the partial phase-difference is located between (-π, -$\pi/2$), and the index are out-phase.

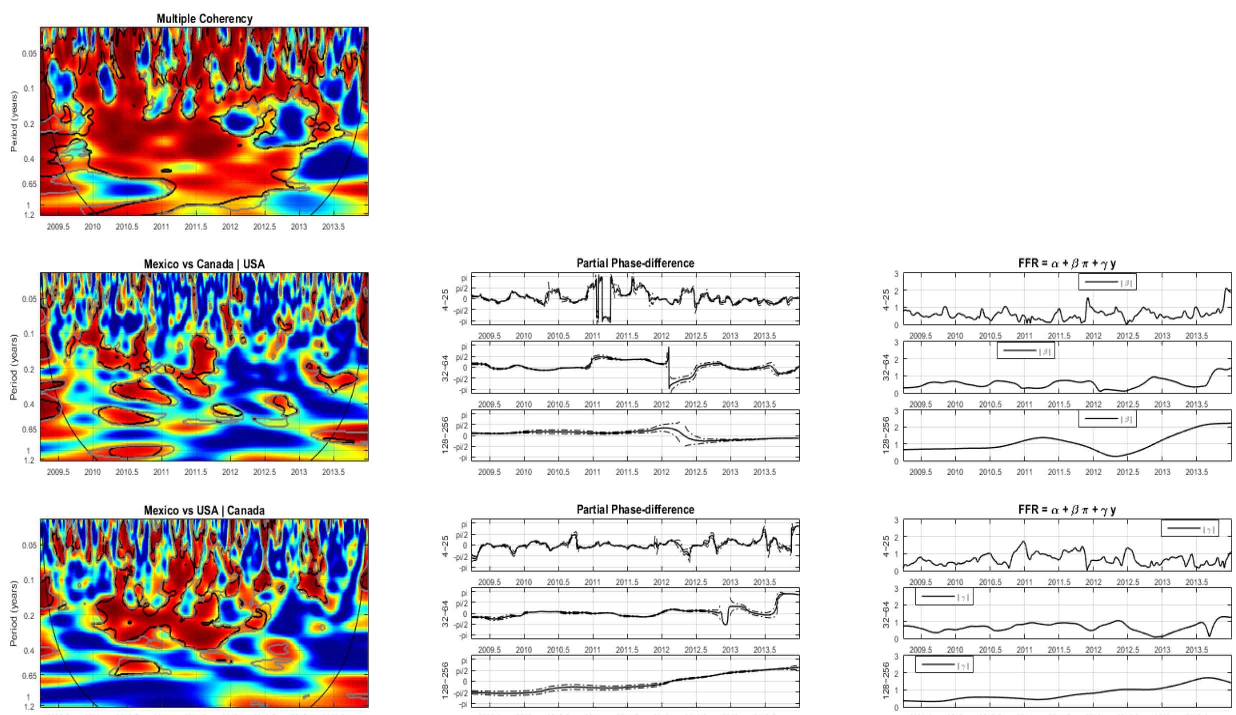


Fig. 7. NAFTA: joint wavelet coherency (on the left) and phase-difference (on the right). [a,b]

[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

The partial coherence between Mexico and USA repeats the pattern of the previous relationship, but with greater intensity in terms of synchronization. At higher frequencies (0.05 ~ 0.1 year), is predominant peaks with low duration from 2010-2012, the partial phase-difference are located in the interval ($-\pi/2, \pi/2$), indicates a positive synchronization, with irregular pattern of leads and lags. At medium-term, the partial coherence is only significant at the range 2010 until the first-quarter of 2012, the US is leading in the interval (quarters 2011:2-2011:4). At that range, the partial gain (coefficient of regression) increased, reaching a value slightly below 1.0. For low frequencies band (0.5 ~ 1.0 year) the partial phase-difference indicated that US leads Mexico when partial coherence is significant (second-half of 2010), with the partial gains' coefficient above 0.5.

In sum, US index anticipates fluctuations of the counterpart Mexican in the cycles of 0.1 ~ 0.3 year (medium frequency), and cycles of 0.5 ~ 1.0 year (long-term) during the period of instability in the market, with no contagion in another range.

Now, we analyze the multiple coherency between France versus Germany and United Kingdom (Figure 8).

There is a lack of high coherency in the short-term and we identify two regions with strong co-movements at lower frequency. The first one covers the period between the end of 2009 and the first half of 2010 (frequency band 0.65 ~ 1.2 years), while the most important covers the region of the year 2012 (frequency equal to or greater than 1 year). The medium-term banking cycles show statistical significance between the first and third quarter of 2010 (0.2 ~ 0.3 year), and a second period with weaker convergence in the year 2011. The partial coherence between France and Germany (controlling for the UK) indicates three regions of strong coherence at the horizon of medium-term (quarters 2012: 2-2012: 3) and long-term (quarters 2010: 2 and 2010: 2 - 2012: 4). At medium-term, the cycles move in-phase, with Germany leading, and the partial gain increased during the range, getting close to 0.5 in the third quarter of 2012. At frequency band located in 128 ~ 256 days, the first region statistically significant is associated with the partial phase-difference between $-\pi$ / 2 and 0 reporting again that Germany leads France, and the partial gain fluctuates slight of zero. On the other hand, during 2012: 2 - 2012: 4, Germany leads France, but they are out-phase, with the coefficient of regression below 0.5.

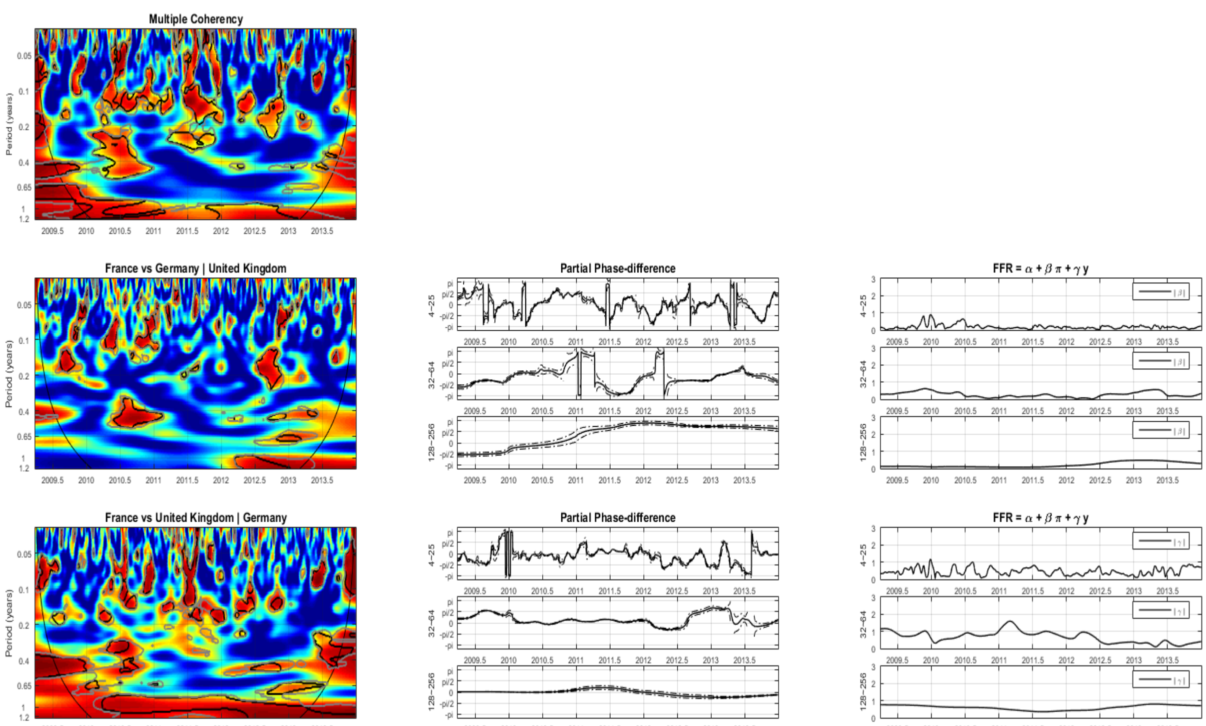


Fig. 8. EURO core: joint wavelet coherency (on the left) and phase-difference (on the right). [a,b]

[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

The partial coherence between France and the United Kingdom exhibits an important region of strong synchronization of long-term cycles after the beginning of 2010. More specifically, Germany leads UK throughout the year 2011, while UK is leading Germany from the second quarter of 2012 until the middle of 2013. In the last interval, the coefficient of partial gain increased, reaching a value close to unity in the first quarter of 2013. In other words, our results indicate strong co-movements between the series, with the cycle of UK contagious the France index. In the short and medium-term the statistically significant regions do not exceed one quarter, while the partial phase-difference presents an irregular pattern, which suggests the absence of synchronization.

4. Concluding remarks

Banking crises are costly, and a great deal of prudential effort is undertaken to avoid them. For instance, Bordo et al. (2001) estimate losses of around 6% of GDP associated with a banking crisis in the last quarter of the 20th century, while Laeven and Valencia (2013) report losses of about 30% of GDP during the last global financial crisis (2007–2009). According to OECD (2012), financial contagion shocks dramatically increase countries' risk of suffering a financial crisis: in periods where a country is not affected by financial contagion, its annual crisis probability is slightly above 1%, but rises to more than 28% in periods when it is hit by a strong contagion shock.

Regardless of the cause of the shocks in the banking system – due to fraud and internal irregularities in an institution or a consequence of macro fundaments –, the contagion effect of bank failure is seen by much of the literature on international finance as a relevant and worrying issue to be addressed. In practice, policy makers aim to avoid banking crises, and although they can to some extent control domestic conditions, internationally transmitted crises are difficult to tackle, which motivates banking crises as one of the main reasons for worldwide bank regulation mainly from the 80's. In this sense, Dungey and Gajurel (2015) identify international contagion in banking during this recent global crisis for more than 50 economies. They are able to find evidence at least one of the three channels of contagion, systematic, idiosyncratic and volatility in 45 countries. They claim that while policy makers and regulatory authorities are rightly concerned with the systematic transmission of banking crises, reducing the potential for idiosyncratic contagion can importantly reduce the consequences for the domestic economy. In other words, the systematic contagion effects present in these markets during this crisis could not have been reduced by further banking regulatory measures such as increased capital requirements. However, there is scope for further reduction in the probability of banking crises due to international linkages through idiosyncratic contagion.

Here we claim that potentially there is gain for regulators, researchers and policy makers to consider how does it work the transmission of business cycles between each pair of banking systems or even considering small group of countries. It is also relevant to measure the measure the impact of related variables on wavelet coherency, such as the respective physical distance and trade balance in US$ bi. It seems useful to identify which baking system is able to act as leader in the group of synchronized countries. In this context, our main findings can shed light on this discussion on business cycle synchronization and trade, as a useful tool for suggestion of admission of new commercial partners or even in evaluating the benefits of such commercial arrangements.

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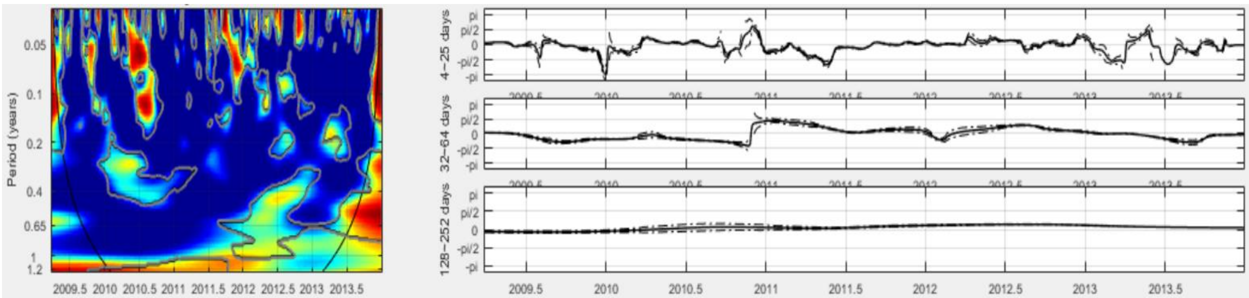
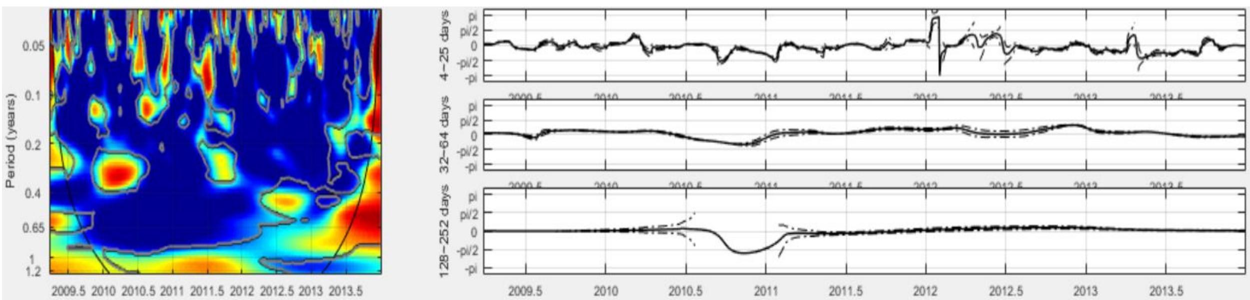
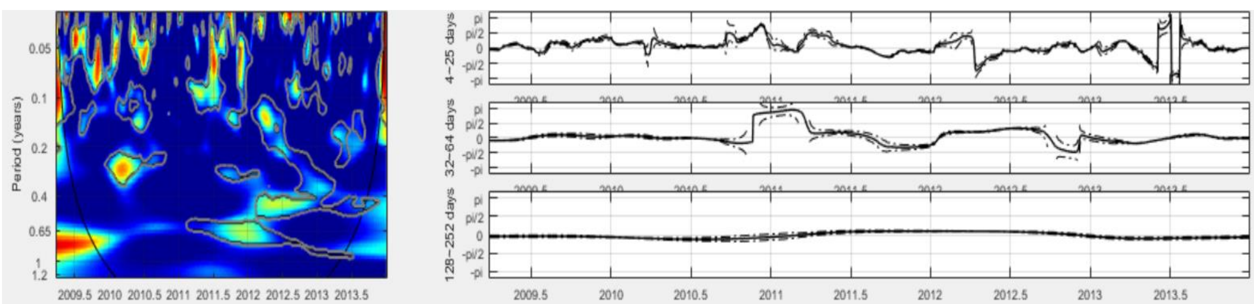
Appendix



a) France vs Canada



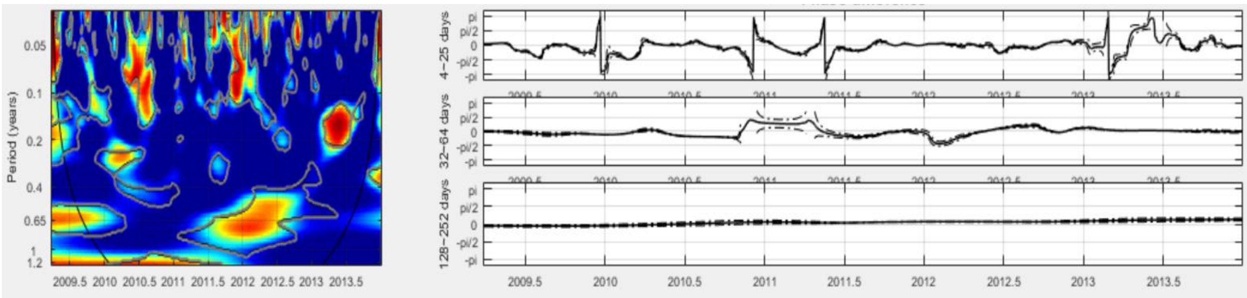
b) France vs Mexico



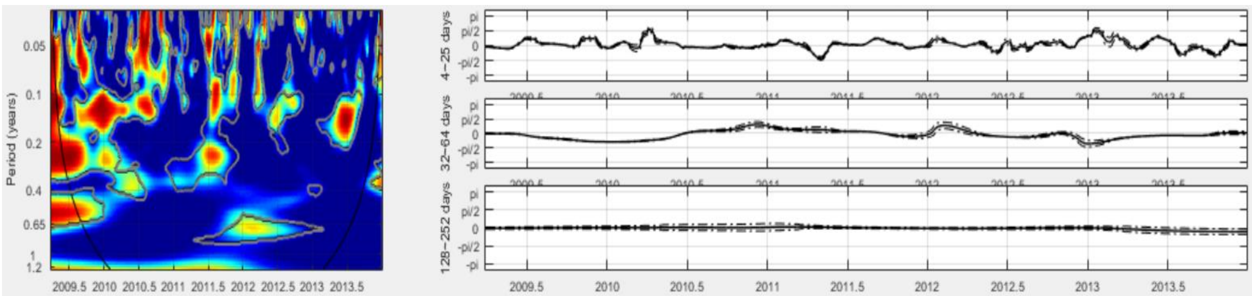
c) Brazil vs France

Fig. A.1. France vs Brazil, Mexico and Canada: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

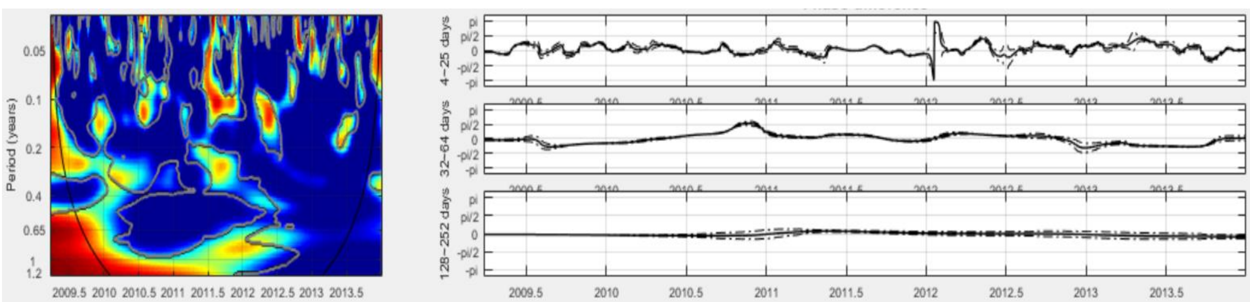
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



a) UK vs Canada



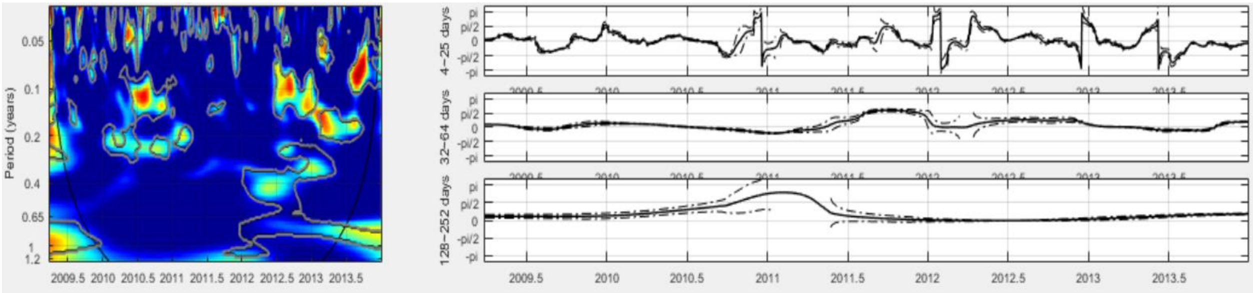
b) USA vs UK



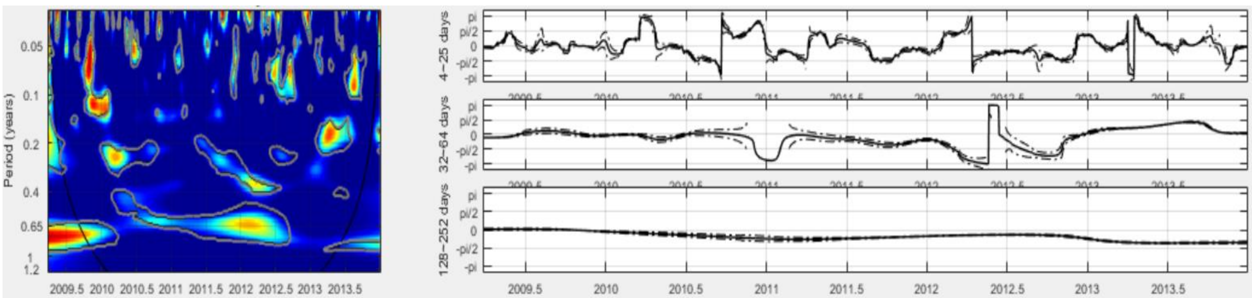
c) Mexico vs UK

Fig. A.2. UK vs NAFTA: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

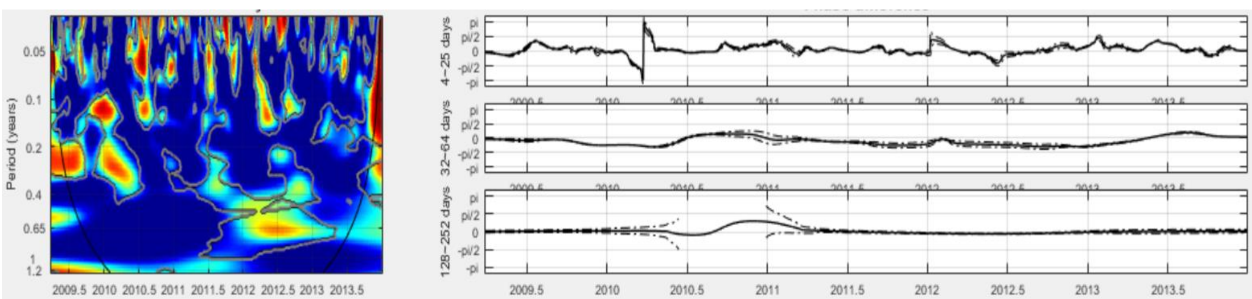
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



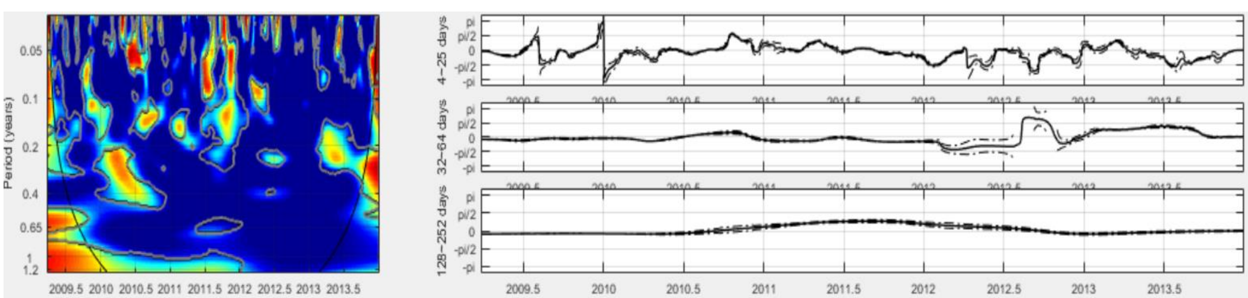
a) France vs Russia



b) India vs France



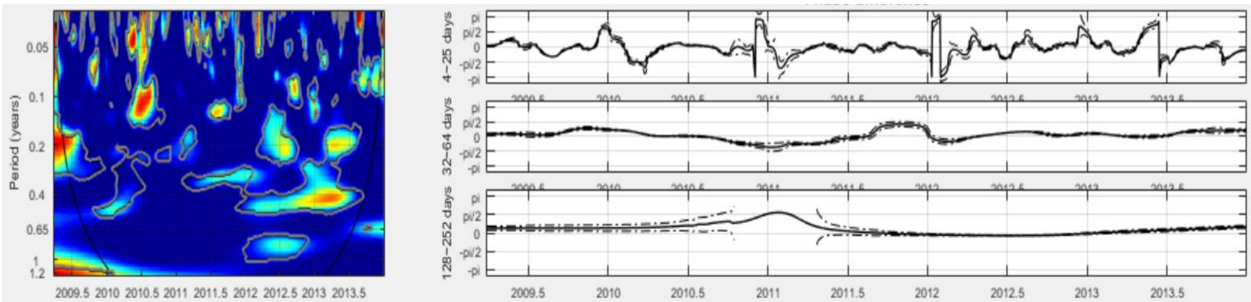
c) USA vs France



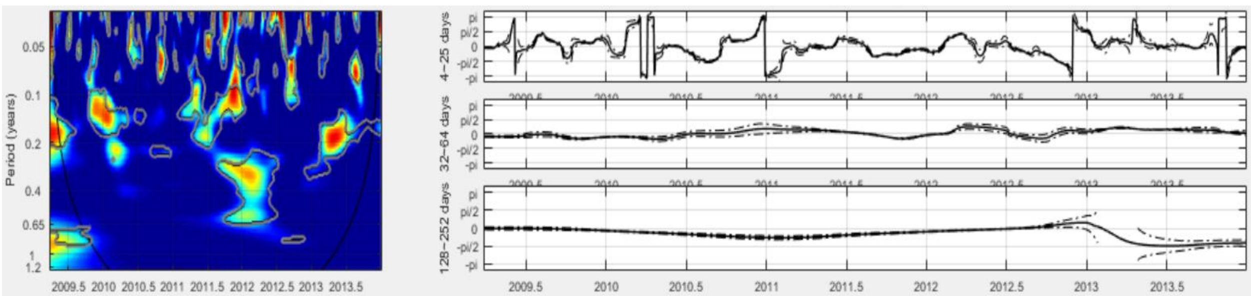
d) Australia vs France

Fig. A.3. France vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

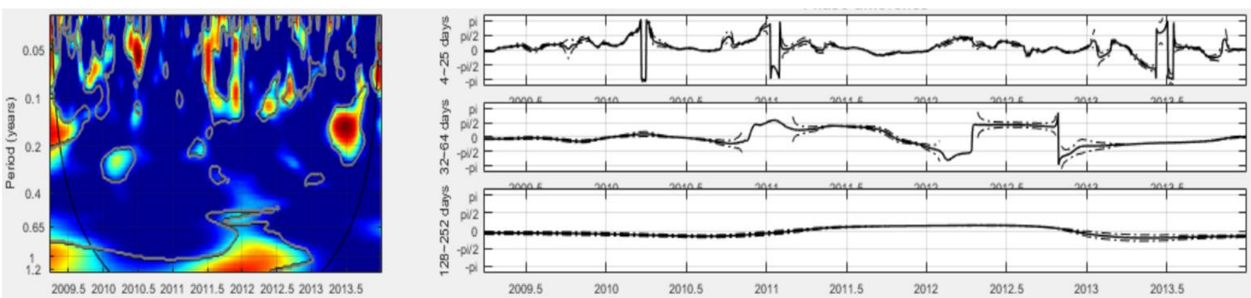
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



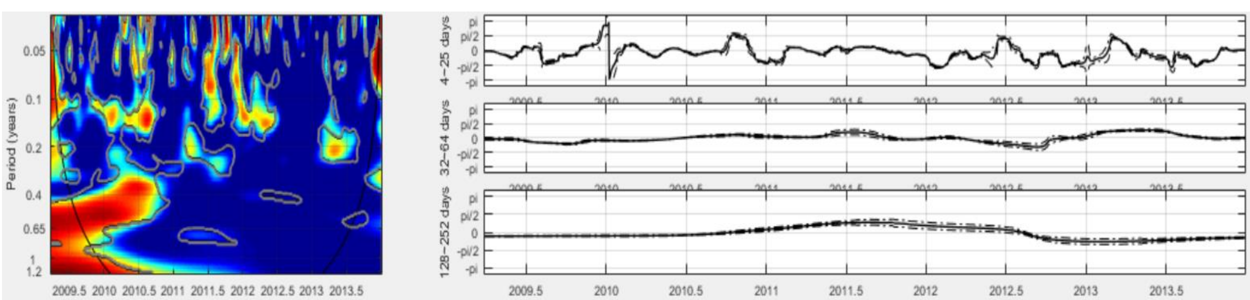
a) UK vs Russia



b) India vs UK



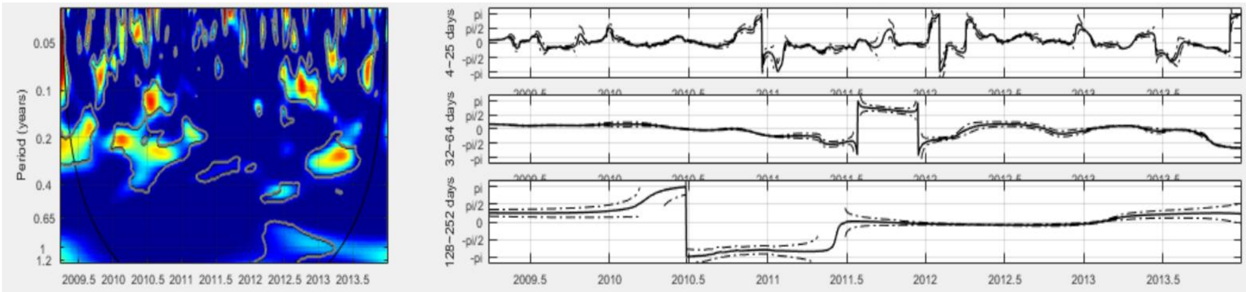
c) Brazil vs UK



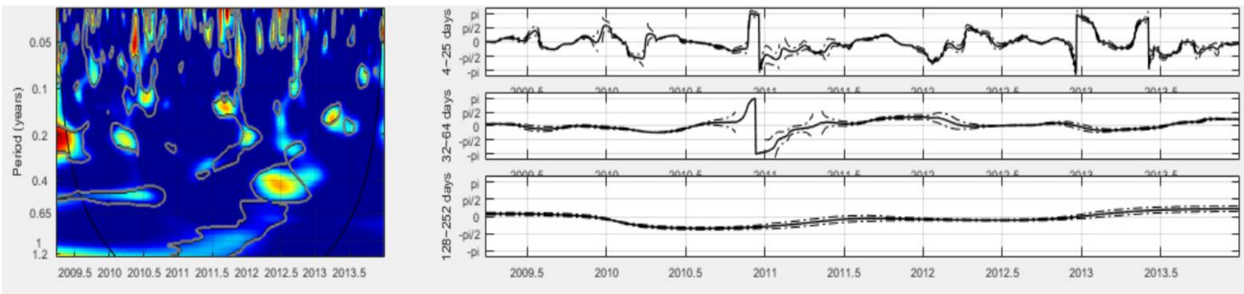
d) Australia vs UK

Fig. A.4. UK vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

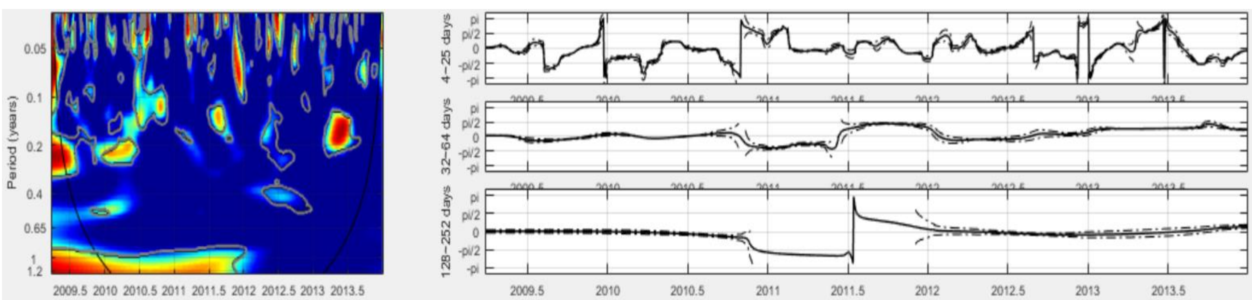
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



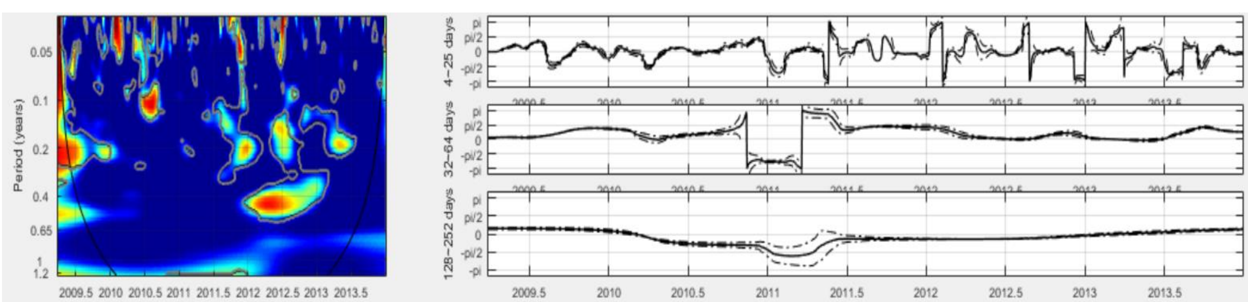
a) Germany vs Russia



b) USA vs Russia



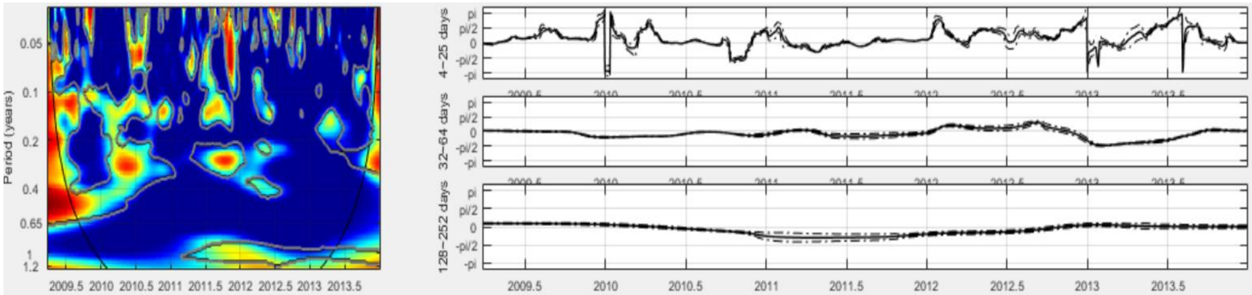
c) Australia vs Russia



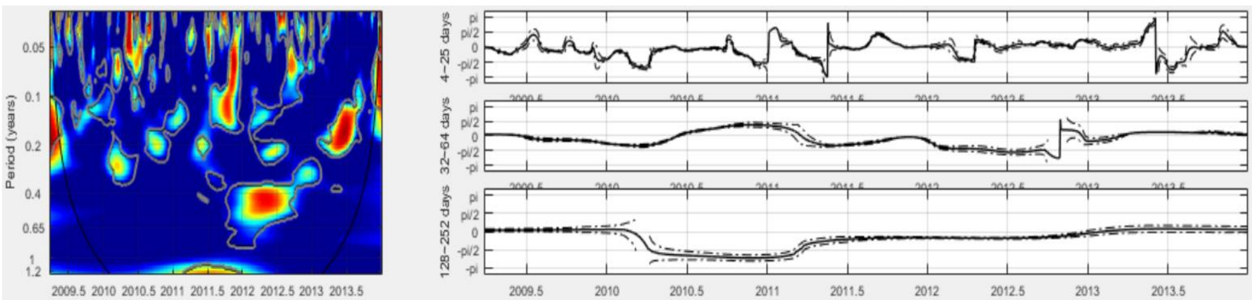
d) Canada vs Russia

Fig. A.5. Russia vs developed economies: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

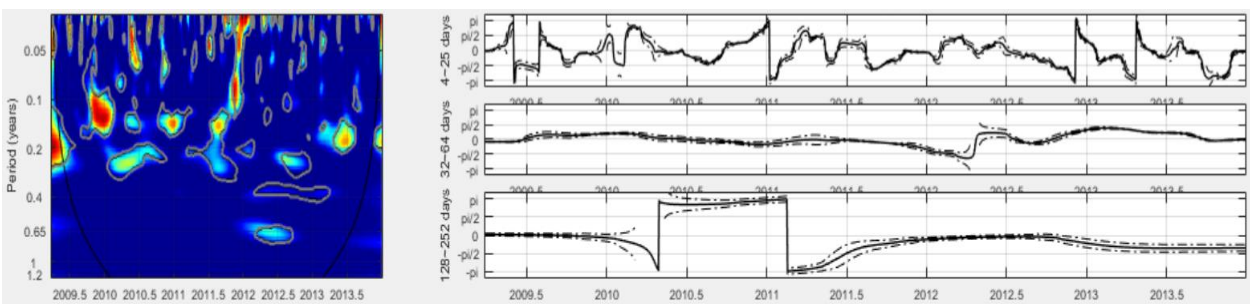
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



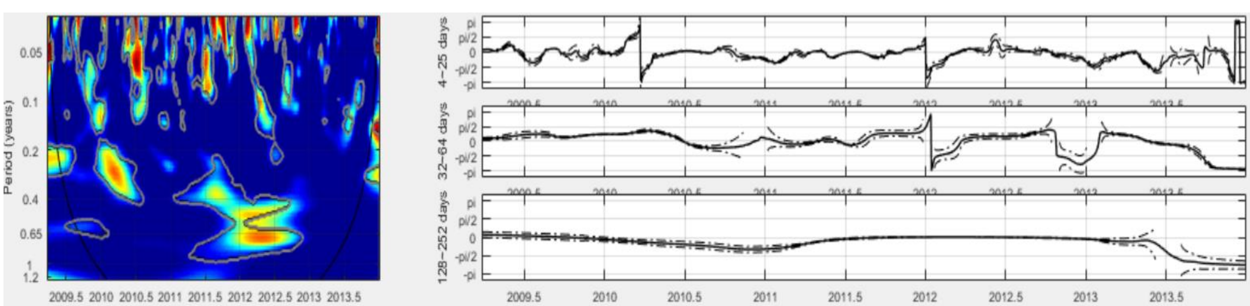
a) USA vs Australia



b) USA vs Brazil



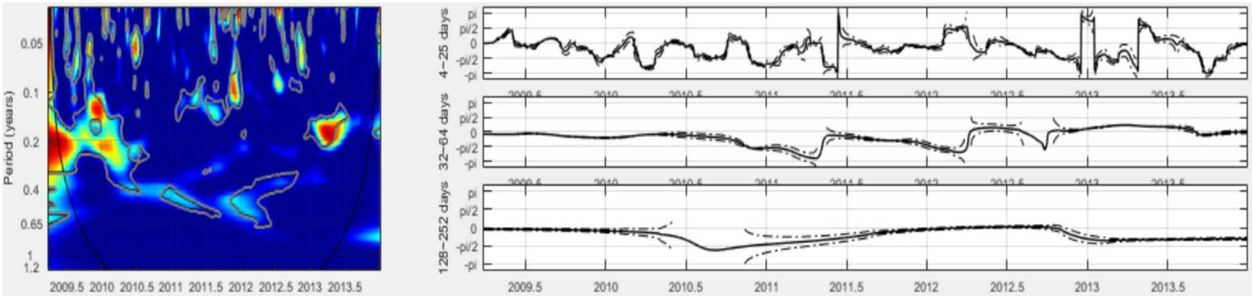
c) India vs USA



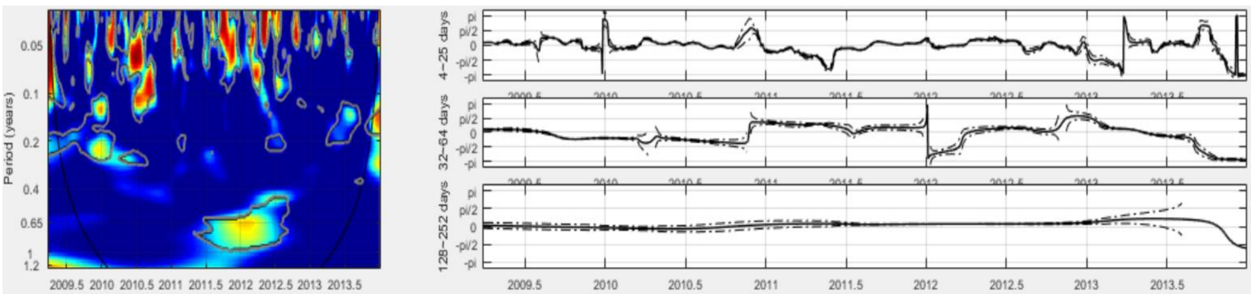
d) Germany vs USA

Fig. A.6. USA vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

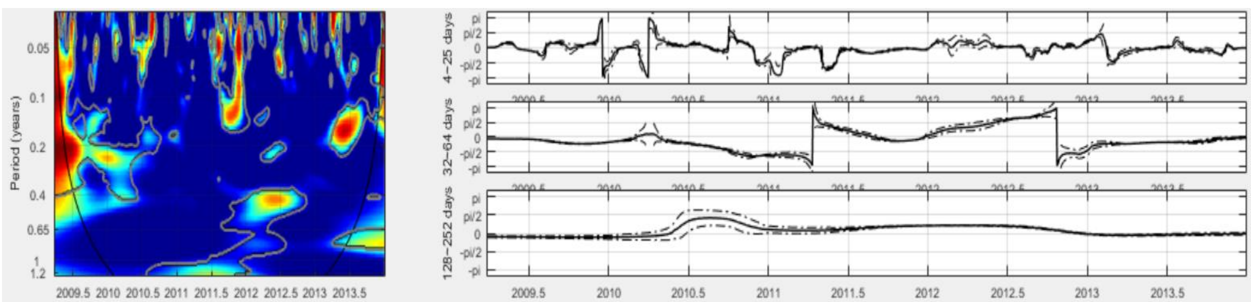
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



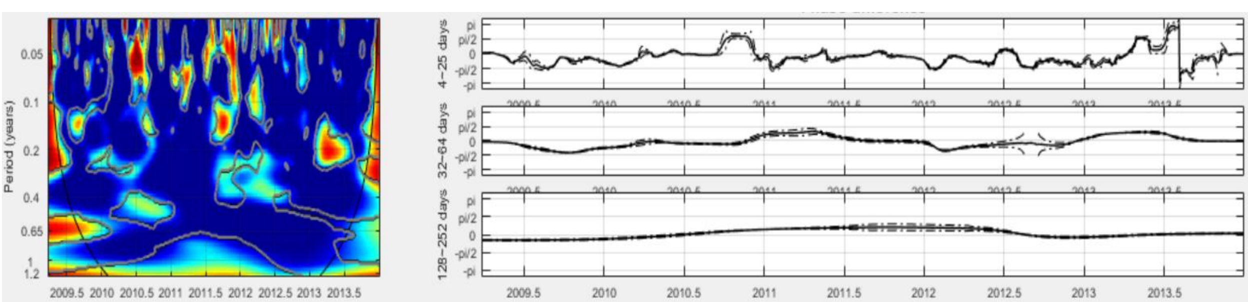
a) India vs Canada



b) Germany vs Canada



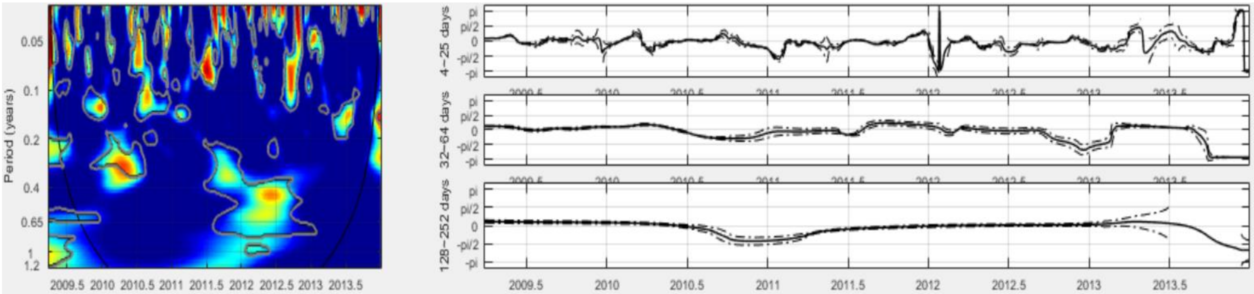
c) Brazil vs Canada



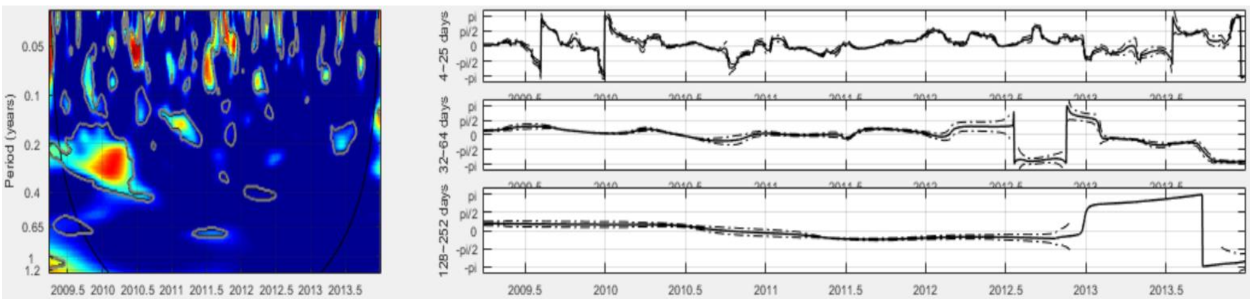
d) Australia vs Canada

Fig. A.7. Canada vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

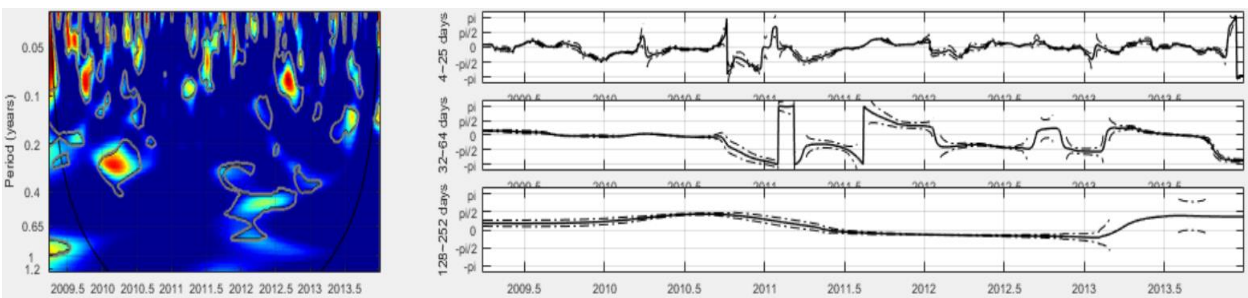
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



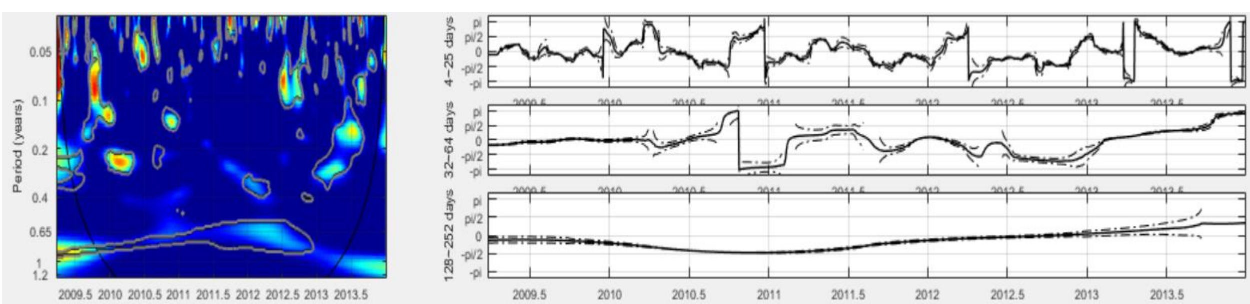
a) Germany vs Mexico



b) Germany vs Australia



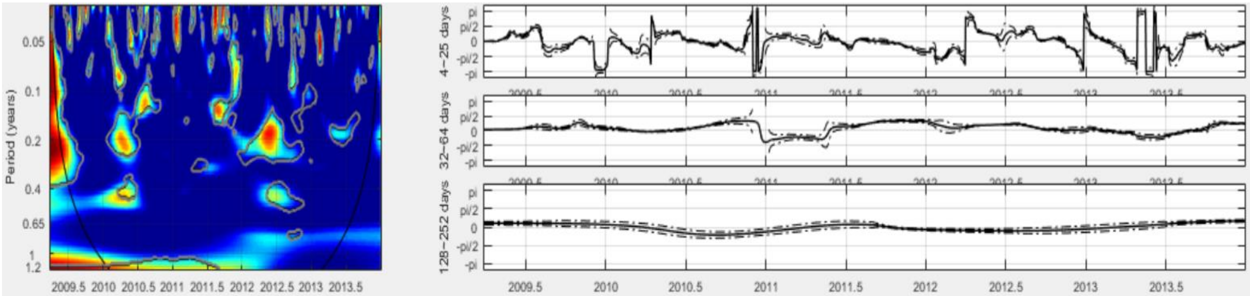
c) Germany vs Brazil



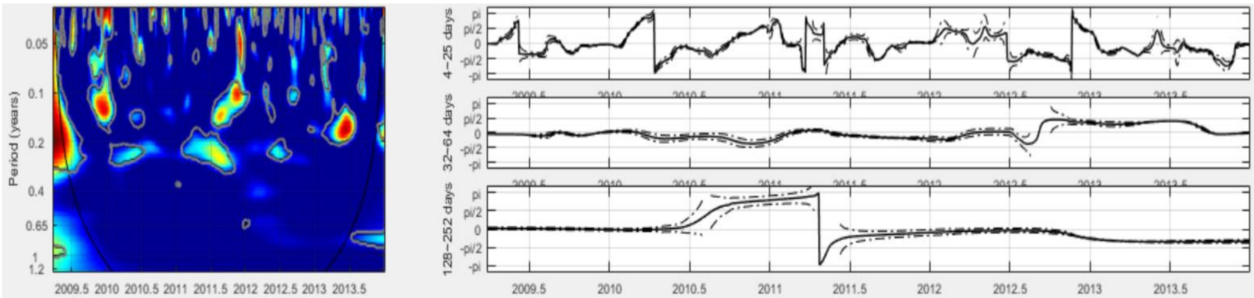
d) India vs Germany

Fig. A.8. Germany vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

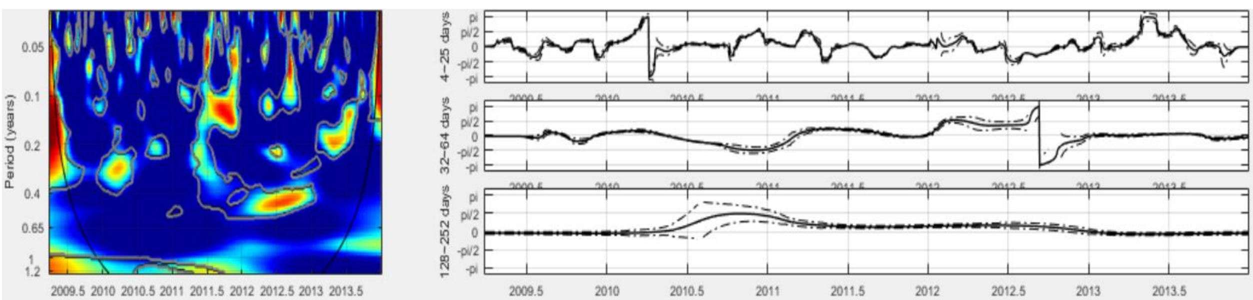
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



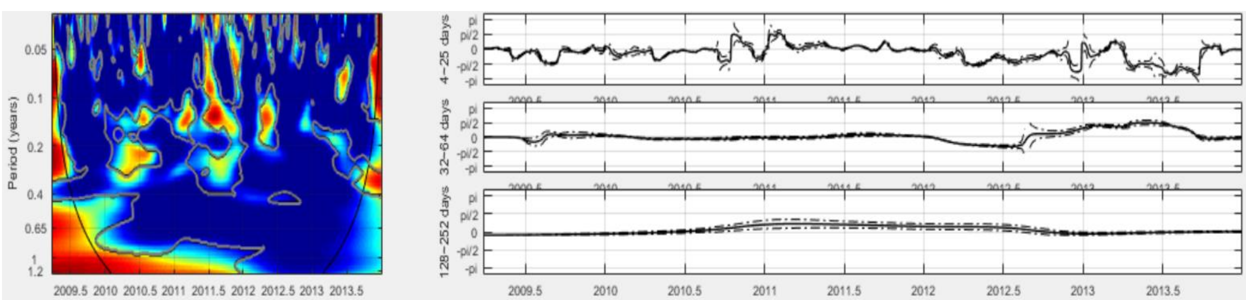
a) Mexico vs Russia



b) India vs Mexico



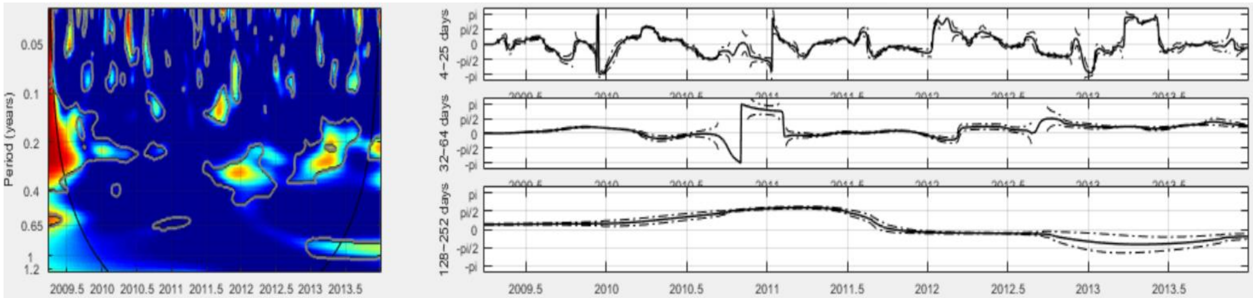
c) Brazil vs Mexico



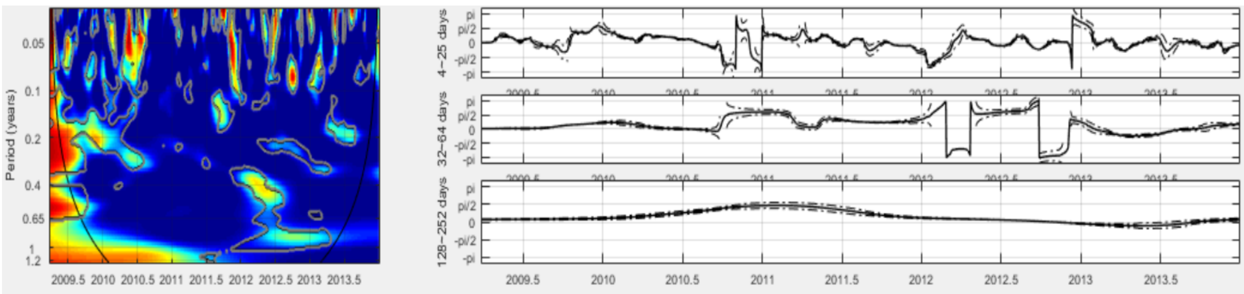
d) Australia vs Mexico

Fig. A.9. Mexico vs some other countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

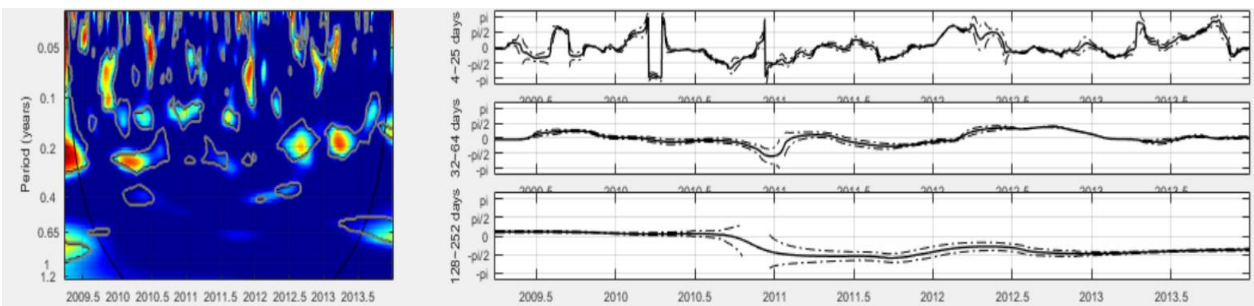
[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.



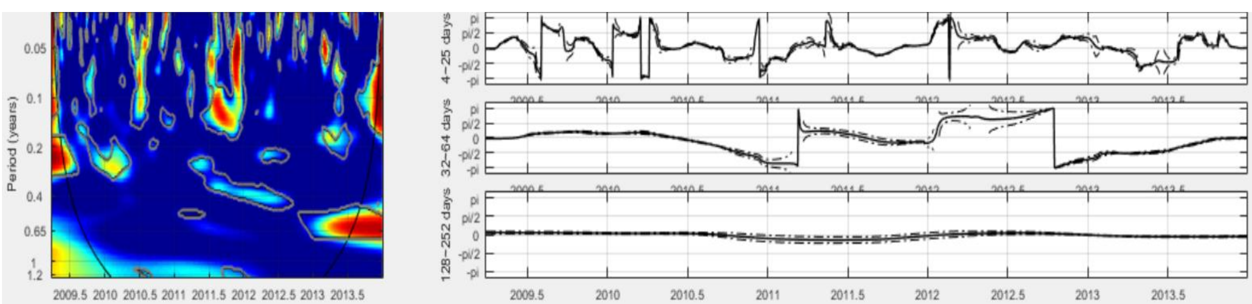
a) India vs Russia



b) Brazil vs Russia



c) India vs Australia



d) Brazil vs Australia

Fig. A.10. Residual pairwises of countries: wavelet coherency (on the left) and phase-difference (on the right). [a,b]

[a] Concerning the coherency, it ranges from low coherency in blue to high coherency in red and the respective cone of influence is shown with a black line, designating the 5% significance level. [b] With regards the phase-difference, we also plot it with plus and minus two standard deviations.

We add to the discussion on the transmission of business cycles, by modeling worldwide banking sector indices cycle synchronization. We find that the respective physical distance and trade balance are able to impact the wavelet coherency. We also find regions of strong and significant coherency between NAFTA partners, and in the European core: France, Germany and United Kingdom. Concerning such trade blocs, based on the multiple coherence, partial coherence, partial phase-difference and partial gain, we find a strong performance in the period 2010-2012 in all frequencies, a period characterized by the sovereign debt crisis in some European countries.

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