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How far is gas from becoming a global commodity?[*] [†]

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Abstract

While we can say that there is a global market for crude oil, we cannot say the same cannot for natural gas. There is a strand of literature that argues that, in the last decades, gas markets have become less regional and more global. We use wavelets to test this hypothesis and conclude otherwise: although the European and Japanese gas markets are significantly synchronized, they are much less than the oil markets, which we take as the benchmark. We also show that the North American gas market fluctuations are independent of the other gas markets. Finally, we show that the existing synchronization between gas markets almost vanishes once one filters out the effect of oil price variations, suggesting that it is the global oil market that connects the regional gas markets.

Keywords: Gas markets; Oil market; Wavelet Power Spectrum; Wavelet Coherency; Wavelet Phase-Difference

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[†]Our data, our Matlab toolbox and the replication codes are available at https://sites.google.com/site/aguiarconraria/joanasoares-wavelets

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1 Introduction

This paper analyzes the North American, European, and Asian natural gas markets integration and its relation to oil markets. Although the literature on these topics is extensive, as far as we know, nobody has looked at this problem from a time-frequency perspective. To do that, we rely on multivariate wavelet analysis, which gives us a very natural framework to estimate how these relationships behave at different frequencies and how they evolve. As we will see, energy markets integration has changed, not only over time, but also across frequencies. We reach some results that would be difficult to disentangle with more traditional time-series methods.

Until 2000, most authors would consider "crude oil as a world market while coal and natural gas belonged to geographically segmented markets"; see Bachmeier and Griffin (2006) and references therein. From that point on, the literature has evolved from a yes or no answer to a more nuanced view of market integration. In particular, some authors started to assess the degree of market integration.

Because we work with prices, we must rely on prices' behavior to operationalize the concept of integrated markets. If the markets are truly integrated, prices must be the same in the different regions, by the law of one price. In a global market, shocks are felt globally. An increase in the demand for gas in Russia should lead to a price increase everywhere. On the other hand, if markets are entirely segmented, only the Russian prices would react. In segmented markets, we expect prices to be independent. In that sense, we can use price synchronization in different regions as a proxy for market integration. The stronger the synchronization, the more integrated the markets are. In the context of the wavelet analysis that we employ, as we explain later, that amounts to say that coherency between prices is very high. We will take the oil market as the benchmark for a global market[1] and show that the coherency between West Texas Intermediate (WTI) and Dubai oil prices is consistently close to one.

Several authors investigated the impact of decreasing transport costs of Liquefied Natural Gas (LNG). Neumann (2009) concluded that the increase in LNG trade had accelerated the

[1]See Plante and Strickler (2021) for the most recent evidence that we can indeed treat the oil markets as one.

integration of previously segmented markets in North America, Europe, and Asia. At about the same time, Aune et al. (2009) argued that gas markets integration would keep increasing, thanks to the LNG effect. This prediction was later confirmed by some authors, like Barnes and Bosworth (2015). However, Chiappini et al. (2019) concluded that, despite the increasing interdependence between European and American prices, gas markets were still not global. Oglend et al. (2020) provided one possible explanation. They argued that time commitments associated with inter-continental Liquefied Natural Gas trade increase other types of costs, weakening the ties between global natural gas markets.

Although not as many, some authors also investigated the impact of the shale gas revolution. It seems that the main contribution of shale gas was to separate the markets, not to integrate them. For example, Wakamatsu and Aruga (2013) concluded that the U.S. market had a one-side influence on the Japanese market before 2005, but, thanks to the shale gas revolution, that influence disappeared afterward. Aruga (2016) also concluded that the U.S. gas market became independent after the shale gas revolution. The price linkage between the U.S. and international gas markets became weaker than before.

Overall, there is ample evidence that gas markets are regionally very integrated. We can, therefore, treat them as a single market (e.g., Renou-Maissant 2012, Asche et al. 2013, Yorucu and Bahramian 2015, Bastianin et al. 2019, and Garaffa et al. 2019, regarding European markets, and Park et al. 2008 and Avalos et al. 2016, for North American markets). Nevertheless, they are not globally integrated. It is worth noting that most studies identified some degree of integration between the European and the Asian markets. It is the North American market that is mostly independent. E.g., Li et al. (2014) concluded that there is some convergence between European and Asian markets. However, they also pointed out that this is probably the result of the contract structure that links gas prices to the oil price. Siliverstovs (2005) had reached a similar conclusion earlier: high natural gas market integration between the European and Japanese markets, but not with North America. Chai et al. (2019) even concluded that "the price linkage relationship between the United States and European natural gas markets had gradually declined in recent years."

Another strand of literature, which explains some of the described stylized facts, explores the relationship between oil and natural gas markets. Because oil and gas are substitutes, and the oil market is global, oil prices tie the gas markets together (Brown and Yücel 2008) or, at least, coordinate gas prices across different regions (Brown and Yücel 2009). With very few exceptions, notably Batten et al. (2017), the consensus is that causality runs from oil to gas markets (see, e.g., Erdős 2012 or Geng, Ji, Fan 2017). Most studies also concluded that this relation is more robust for Europe and Asia than North America (Geng et al. 2016, Zhang et al. 2018 and Zhang and Ji, 2018). Lin and Li (2015) concluded that European and Japanese gas prices are co-integrated with Brent oil prices, but the U.S. gas price is decoupled from oil due to natural gas market liberalization and shale gas expansion. Additionally, they confirmed the results of other authors when they claimed that their results support the presence of price spillover from crude oil markets to natural gas markets, but not the reverse.

One controversial issue in the oil gas relationship is its stability. For example, while Ji et al. (2018) found a stable contemporaneous causal flow from crude oil to natural gas, Brigida (2014) only found a co-integration relationship once he allowed for shifts in the co-integrating vector. Ramberg and Parsons (2012) also concluded that the co-integrating relationship is not stable through time.

The paper proceeds as follows. Section 2 starts with a discussion showing why wavelet analysis is particularly well-suited to study market synchronization and energy markets, followed by a very brief description of the Continuous Wavelet Transform tools used in this study. We leave the technical details about these tools to an appendix, and in, this section, instead, we apply them to the oil markets, which will serve as a global market benchmark. In Section 3, we present our data, and Section 4 delivers our first results regarding gas market synchronization between North America, Asia, and Europe. In Section 5, we explore the gas-oil relationship and describe how it helps to explain the results of Section 4. Surprisingly, we uncover a long-run relationship between the regional gas markets. It started in the early 2000s and had not been revealed before, to the best of our knowledge. Section 6 concludes.

2 Methodology and the definition of the oil market benchmark

We use wavelet analysis to study market prices synchronization. We do not claim that wavelet analysis is better than other more traditional methods. We only argue that this technique is particularly appropriate to investigate this issue. It performs the estimation of the spectral characteristics of a time-series as a function of time, revealing how its different periodic components evolve, which is crucial, because market equilibria are a combination of features operating on different frequencies. Moreover, relations may be different for different frequencies, since different economic agents are concerned with different time-horizons. Some agents focus on short-run (high frequencies) movements and co-movements, while other agents are concerned with longer horizons (lower frequencies). It is entirely conceivable that, at high frequencies, markets may be independent, but they are together at low frequencies. For example, Nick and Thoenes (2014) found that, in the short-run, the German natural gas market is affected by local conditions, like temperature, storage, and supply shortfalls. In the long-run, oil and coal are key determinants. With a global oil market, and assuming that it impacts all gas markets, it is likely that regional gas markets synchronization looks very different in the short- and long-run. Additionally, causality relations need not be the same at different frequencies. It is possible that, at high frequencies, shocks in the gas markets have impacts in the oil markets but that, in the long-run (at lower frequencies), causality runs from oil to natural gas prices.

It is also a fact that energy price dynamics are firmly non-stationary with unit roots, volatility clustering, structural breaks, etc. Therefore, it is essential to use methods that do not require stationarity. Moreover, Kyrtsou et al. (2009) showed that several energy markets display consistent nonlinear dependencies. Thanks to its localized nature, wavelet analysis is particularly well-suited to study data with all these characteristics.

There are mainly two ways to apply wavelets to data. One uses the discrete wavelet transform (DWT) and the other the continuous wavelet transform (CWT), which is the technique used in this paper. With DWT, one decomposes a time-series into a sum of time series of different frequencies. It is similar to applying several bandpass filters to isolate the behavior of a variable for each band. Yogo (2008) showed that multi-resolution with wavelet analysis (very quickly performed with DWT) allows for the decomposition of a variable into a trend, cycles of different periodicities, and noise, in a way very similar to bandpass filtering. Yang (2019) combined this technique with the connectedness measure proposed by Diebold and Yilmaz (2009). Thanks to this combination, they were able to study the connectedness between economic policy uncertainty and oil price shocks at different frequencies (also called timescales). Their approach allowed them to conclude that the connectedness relationship is robust across frequencies. However, it did not allow them to study how that connectedness evolves across time. CWT provides an elegant and efficient way to integrate both analyses, as we will show.

Before us, other authors have relied on wavelets to analyze the energy markets or the relationship between energy prices and other financial or macroeconomic variables. Aguiar-Conraria and Soares (2011b), Naccache (2011), Jammazi (2012), Tiwari et al. (2013) have already used wavelets to study the evolution of oil prices, and Aloui and Hkiri (2014) used them to analyze stock market returns for the Gulf Cooperation Council Countries. Vacha and Barunik (2012) looked to other energy commodities and found interesting dynamics of correlations between crude and heating oil, gasoline, and natural gas. Vacha et al. (2013) relied on wavelet coherencies to relate biofuels to several commodities. Other authors, such as Rua and Nunes (2009), Flor and Klarl (2017), Aguiar-Conraria et al. (2018), or Verona (2000), have applied wavelets to study co-movements in financial data.

In this section, we give a brief description of the continuous wavelet tools used in our analysis. We refer the readers to Aguiar-Conraria and Soares (2014) and Aguiar-Conraria et al. (2018) for more technical details. For a broader view of the digital signal processing and spectral analysis, including the Continuous Wavelet Transforms, we suggest Alessio (2016).

2.1 Continuous Wavelet Transform and Wavelet Power

Researchers have used the Fourier transform and Fourier spectral analysis to determine whether frequencies play predominant roles in explaining the overall variance of a time-series, by decomposing the observed pattern over time into a spectrum of cycles of different lengths.

Fourier analysis theory can be traced back to 1807, when Joseph Fourier showed that almost any periodic function could be written as a weighted sum of sines and cosines of different frequencies. Even if the function is not periodic, it still may be expressed as a combination of sines and cosines under some conditions. The typical approach is to map the original variable, say x_t, into the frequency domain, employing the Fourier transform. The main limitation of Fourier analysis is that the information about time is lost under the Fourier transform. Therefore, we can identify which are the predominant cycles, but we cannot tell when they were the most important.

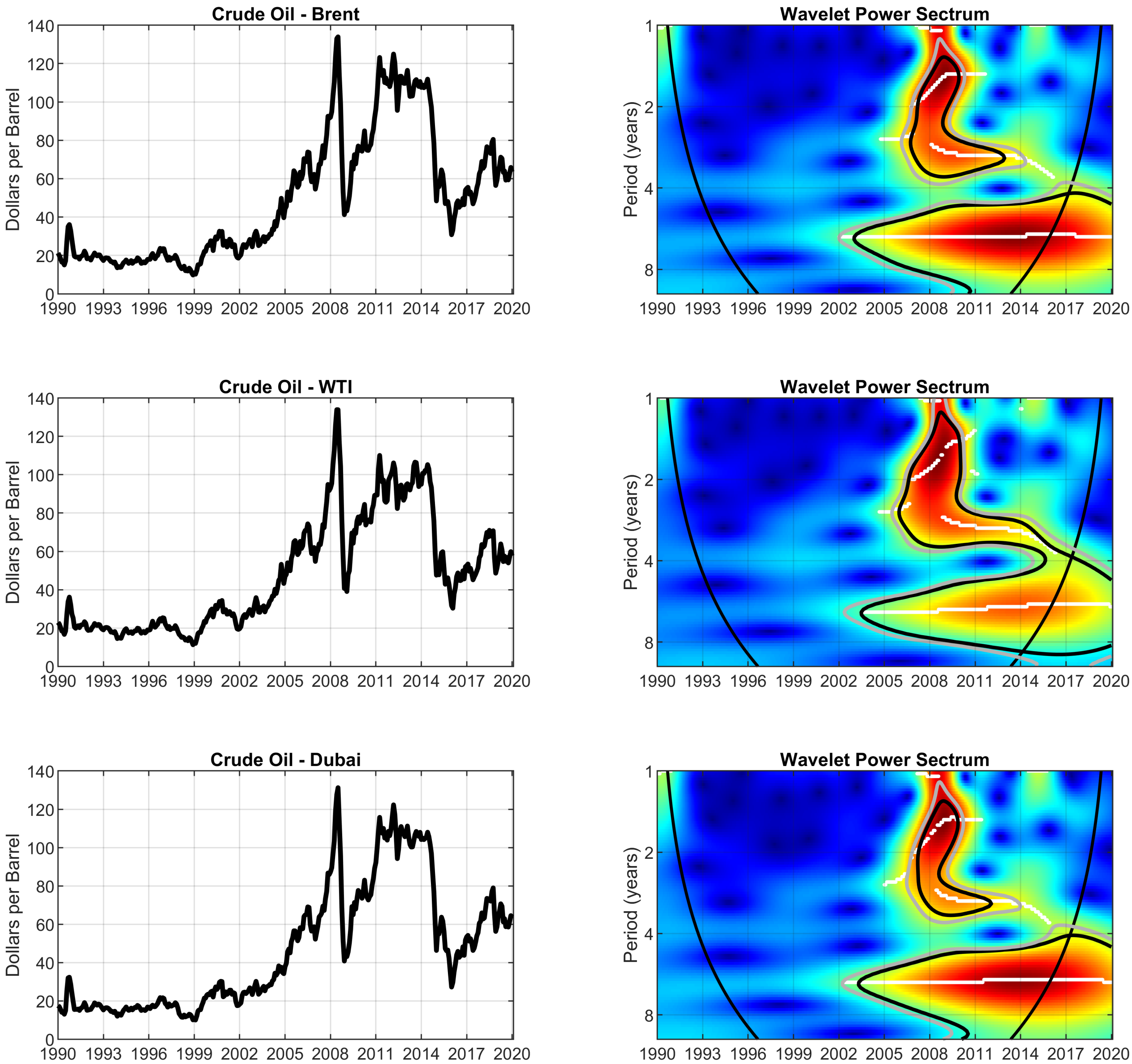

Figure 1: Crude Oil prices and their Wavelet Power Spectra. The color spectrum depicts the extent of variability, and evolves from low power (blue color) to high power (red color). The white lines within the power spectra represent the local maxima. The black contour signifies 5%

significant level while the gray contour represents the 10% significant level. The cone of influence, represented by the black conic line, indicates that the results are unreliable outside this line and should be interpreted with special care.

The Continuous Wavelet Transform overcomes this problem by mapping x_t into the time-frequency domain, which is just a way to say that CWT is a function of two variables: time and frequency. That is why while the Fourier Power Spectrum gives us information on which cycles play predominant roles in explaining the variance of a time-series, the Wavelet Power Spectrum (WPS) tells us which cycles play predominant roles and when.

In Figure 1, we display the WPS of the oil prices in three markets: Brent, West Texas Intermediate (WTI), and Dubai. How should we interpret this picture?

We use colors to depict the power spectrum. It goes from low power (blue) to high power (red). The higher the power, the higher the volatility. We can see that the wavelet power spectra become statistically significant around the year 2002 (the gray/black contour represents 10%/5% significance) at low frequencies. Around the year 2006 and until 2014, integrating the international financial crisis, we also observe high volatility at higher frequencies.

The white stripes within the power spectra represent the local maxima, giving us the best estimate of the dominant cycle period. This means that a 6-year cycle is dominant, starting in 2006 and going until the end of the sample. We also identify less predominant cycles at higher frequencies, especially after 2007, coinciding with the international financial crisis.

2.2 Wavelet transform de-synchronization matrix

Aguiar-Conraria and Soares (2011a) introduced a procedure to measure the dissimilarity between the wavelet transforms of two time-series; this technique was also used by Flor and Karl (2017). To measure the dissimilarity between two markets x and y, we simply measure the dissimilarity between their wavelet transforms, by using the referred technique.

Looking at Figure 1, it should be apparent that comparing the wavelet spectra of two variables is similar to comparing two images. Direct comparison is not suitable, because there is no guarantee that low power regions will not overshadow the comparison. In the appendix, we explain how we use the Singular Value Decomposition to focus on the common high power time-frequency regions and measure how far apart the wavelet spectra are.

If the two wavelet spectra are very similar, the variables share the same high power regions, and their phases are aligned. In turn, this means that their cycles are very synchronized: the contribution of cycles at each frequency to the total variance is similar for both variables, and they occur simultaneously.

	Brent	WTI	Dubai
Brent		**0.063**	**0.026**
WTI	**0.063**		**0.065**
Dubai	**0.026**	**0.065**	

Black cells stand for 1% significance, corresponding to rejecting the null hypothesis of no synchronization

Table 1: Oil markets de-synchronization matrix.

Table 1 displays our results. As we can see, the oil markets are very synchronized. Every pair is synchronized at 1%, with Brent and Dubai being more synchronized with each other than with WTI. As gas and oil are substitutes and it is common to compare both markets, this table provides a useful benchmark.

2.3 Wavelet Coherency and Wavelet Phase-Difference

While the wavelet power spectrum is useful for describing the spectral characteristics of a single variable, here we are interested in studying the synchronization between two or more variables. For that purpose, we will rely on two tools. The first is wavelet coherency, which calculates the correlation between two variables in time. The pictures will be similar to Figure 1, with warm colors representing high coherency regions and cold colors corresponding to low coherencies.

Given that we use a complex-valued wavelet, we can compute the phase of the wavelet transform of each series and, hence, compute the corresponding phase-difference. The phase-difference, which is an angle, is another tool that we will use, in order to obtain information about the possible delays in the two series' oscillations, as a function of time and frequency. A phase-difference of zero indicates that the time-series move together at the specified time-frequency value. If the phase difference between x and y is between 0 and $\frac{\pi}{2}$, then the series move in phase with x leading ; if it is between $-\frac{\pi}{2}$ and 0, then it is y that is leading; a phase-difference of π (or $-\pi$) indicates an anti-phase relation (negative correlation); if it is between $\frac{\pi}{2}$ and π, then y is leading; series x leads if the angle is between $-\pi$ and $-\frac{\pi}{2}$.

We will also use the partial wavelet coherency and the partial wavelet phase-difference, which are simply the multivariate analogs of the wavelet coherency and the wavelet phase-difference. For three variables, e.g., x, y, z, the *partial wavelet coherency* of x and y, after controlling for z, is the wavelet coherency between x and y, after removing the influence of z.

In Figure 2, we estimated the coherency and phase-difference between prices of the different oil markers. We can see that, in all the three cases, the color red dominates the picture. Therefore coherency is very high, close to one, across the entire sample and for all frequencies. On the right, we can observe that the phase-difference is zero or very close to zero, meaning that the markets co-move without anyone leading the other.

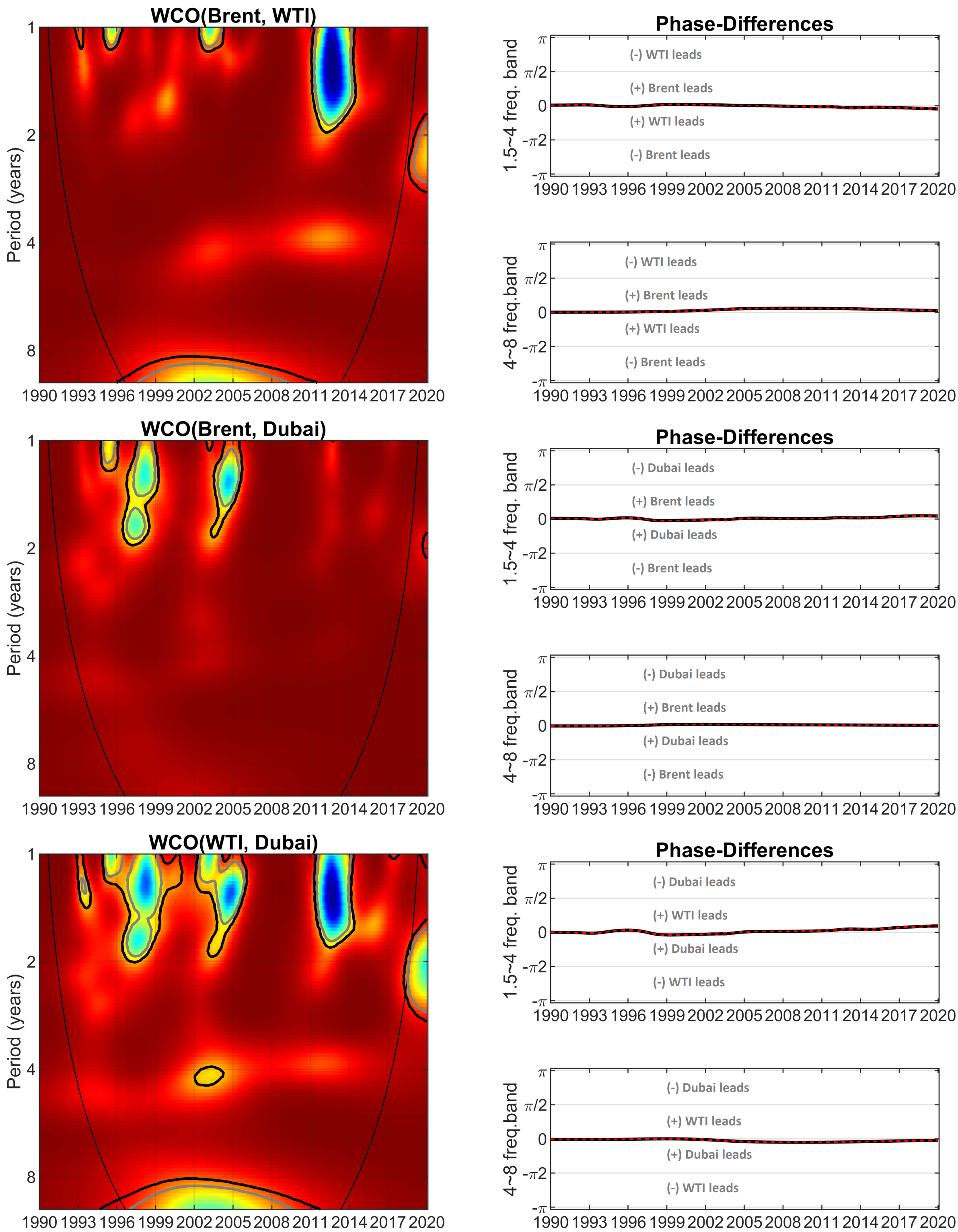

Figure 2: on the left – the wavelet coherency between oil prices of two different markers. The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). On the right — Corresponding phase-differences for the frequency bands of $1.5 \sim 4$ and $4 \sim 8$ years.

3 A first look at the gas data

We use monthly data from 1990M01 to 2019M12 for Natural Gas prices ($/MMBtu) in the U.S., Europe, and Japan. For crude oil prices ($/bbl), we consider the Brent marker, which is light and sweet. Brent is the reference for more than half of the oil traded around the world. In the previous section, we used the Dubai marker, which is heavier and sour, and WTI, which is somewhat similar to Brent, but slightly lighter. We retrieved all our data from the World Bank Commodity Price Data (The Pink Sheet). In Figure 3, on the left, we display our data for the three gas markets. On the right, we can see the wavelet power spectrum of each variable. In the power spectra, the colors reflect the degree of volatility, with cold colors (blue) depicting low variability and warm colors, such as red, depicting high volatility. A thick black/gray contour identifies the regions of 5/10% significance against the null of a flat power spectrum. The white stripes identify local maxima and are, therefore, an estimation of the period of the most relevant cycles.

The wavelet power spectra of the gas markets in Europe and Japan are quite similar (and also similar to power spectra of the oil markets in Figure 1). In both cases, the power spectrum becomes statistically significant around the year 2000 (2005 in the case of the gas in Japan) at low frequencies. The white stripes indicate that the period of the dominant frequency is about six years. This 6-year cycle remains dominant until the end of the sample. Around the year 2008 and until at least 2012, coinciding with the international financial crisis, we also observe high volatility at higher frequencies, particularly in Europe.

The wavelet power spectrum of the gas prices in the U.S. displays a different behavior. At higher frequencies, the power spectrum is statistically significant from the mid-1990s to mid-2010s, with a dominant 3-year cycle. Between 2005 and 2008, at even higher frequencies, corresponding to 1.5-year cycles, we have another region of high volatility. Contrary to the previous cases, volatility at low frequencies does not seem to play a dominant role, despite being statistically significant.

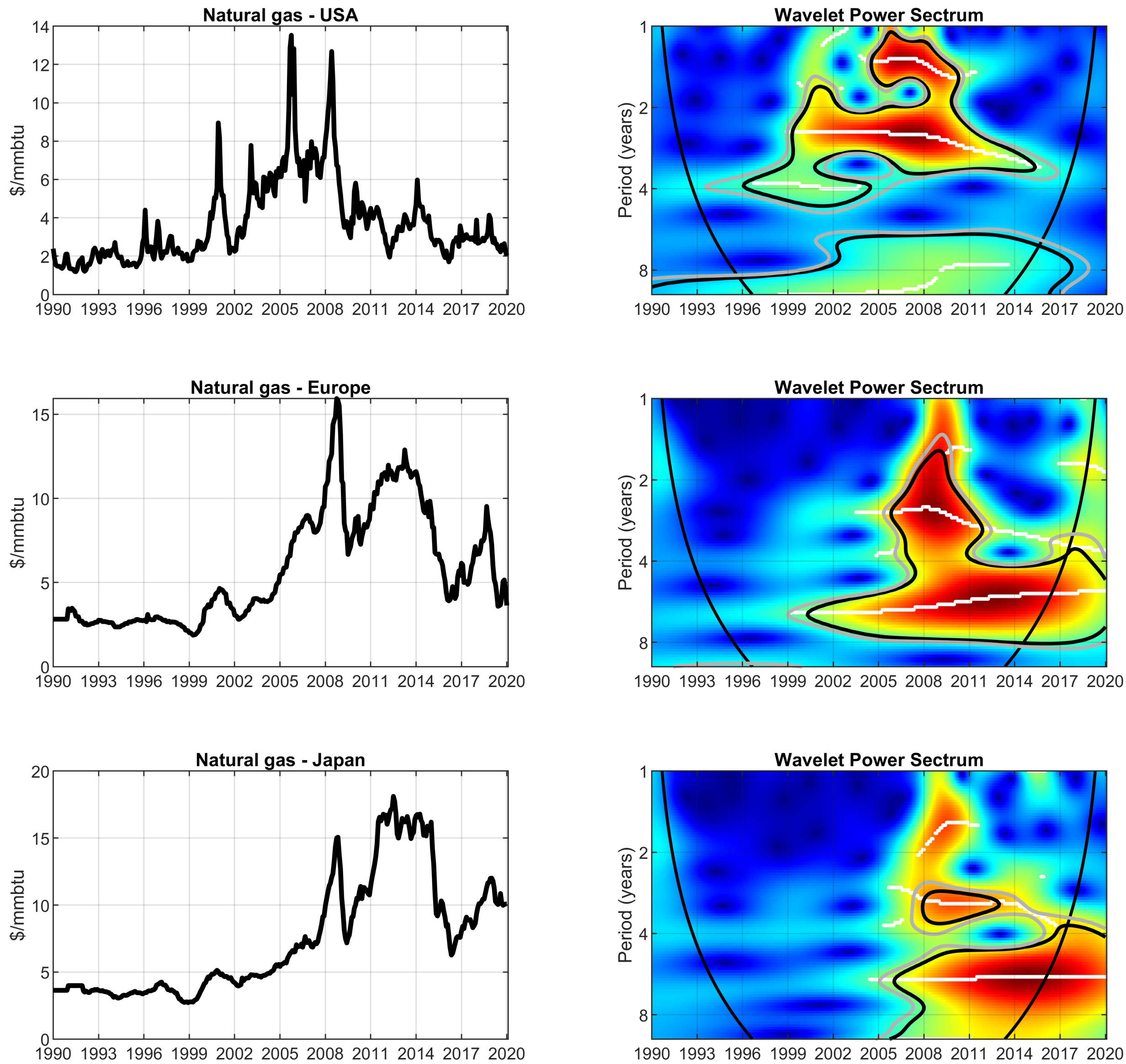

Figure 3: Natural Gas prices and their Wavelet Power Spectra. The color spectrum depicts the extent of variability, and evolves from low power (blue color) to high high power (red color). The white lines within the power spectra represent the local maxima. The black contour signifies 5% significant level while the gray contour represents the 10% significant level. The cone of influence, represented by the black conic line, indicates that the results are unreliable outside this line and should be interpreted with special care.

In Table 2, we display the wavelet transform dissimilarity index developed by Aguiar-Conraria and Soares (2011), also applied by Flor and Klarl (2017). As we have seen, a value close to zero means that two markets have a similar wavelet transform, implying that the two countries share the same high power regions and also that their phases are aligned. More specifically, this means that the contribution of cycles at each frequency to the total variance is similar between both markets, that this contribution happens at the same time, and, finally, that the peaks and troughs of each cycle coincide in both markets. To test for significance, we rely on Monte-Carlo simulations, in which the null hypothesis is that the two series are independent.

	NGas - USA	NGas - Eur	NGas - Jpy	Crude - Brent
NGas - USA		0.353	0.351	0.350
NGas - Eur	0.353		**0.167**	**0.135**
NGas - Jpy	0.351	**0.167**		**0.101**
Crude - Brent	0.350	**0.135**	**0.101**	

Black cells stand for 1% significance, corresponding to rejecting the null hypothesis of no synchronization

Table 2: Gas markets de-synchronization matrix.

One interesting result that we observe in Table 2 is that each gas market is closer to the oil market than to any other gas market. It is also worth noting that the North American gas market seems independent of the other markets. We do not reject the null of no synchronization even at 10%. The other markets form a cluster, and we reject the null of being independent. Note, however, that the dissimilarity between the European and the Japanese markets (0.167) is between 2.5 and 6.4 times larger than the dissimilarities between the oil markets (Table 1). In the next two sections, we explore these results in detail.

4 Gas Markets Integration

In Figure 4, on the left, we estimate the pairwise wavelet coherency between the three different gas markets. On the right, we have the phase-difference. If the phase-difference between market A and market B is between 0 and $\pi/2$ ($-\pi/2$ and 0), that means that the markets are in-phase (positive correlation), with A (B) leading. If the phase-difference is between $\pi/2$ and π ($-\pi$ and $-\pi/2$), then they are out-of-phase (negative correlation) with B (A) leading. The interpretation of our econometric results proceeds along with the standard approach in related literature. First, we check the time-frequency regions where the coherency is statistically significant. In those episodes, we may confidently say that there has been a significant co-movement between the two series for cycles of the indicated period. For the statistically significant time-frequency locations, we analyze the phase-differences to detect whether the co-movement is positive or negative, and which variables are leading and lagging.

The picture on top gives us the relation between the American and European gas markets. In the $1.5 \sim 4$ year frequency band, we observe a large region of high coherency statistically significant at 10% (or to smaller regions if one focuses on 5% significance). Loosely speaking, it runs from the mid-1990s to mid-2010s. Apart from the beginning, the phase difference is consistently between 0 and $\pi/2$, indicating that it is the American market that leads the European market. Towards the end of the sample, the coherency becomes significant again at very high frequencies, with the phase-difference being almost zero, suggesting that cycles are almost simultaneous. At lower frequencies, the regions of significant coherencies are scarce. There is one small region until 2000, with the U.S leading and, again, around 2014, with Europe leading. However, these regions are so small that we do not attach any particular meaning to them.

Regarding the U.S. and Japan, the regions of statistically significant coherency are smaller. The most surprising result, which contradicts part of the earlier literature, is that after 2005 there is a region of high and statistically significant coherency at higher frequencies ($1.5 \sim 4$ year frequency band) with the phase-difference indicating that the U.S. market is leading. Therefore, and this applies both to Europe and Japan, we find no evidence that the shale gas revolution has led to a decoupling of the American market. At most, we can say that the existing co-movement moved from lower to higher frequencies.

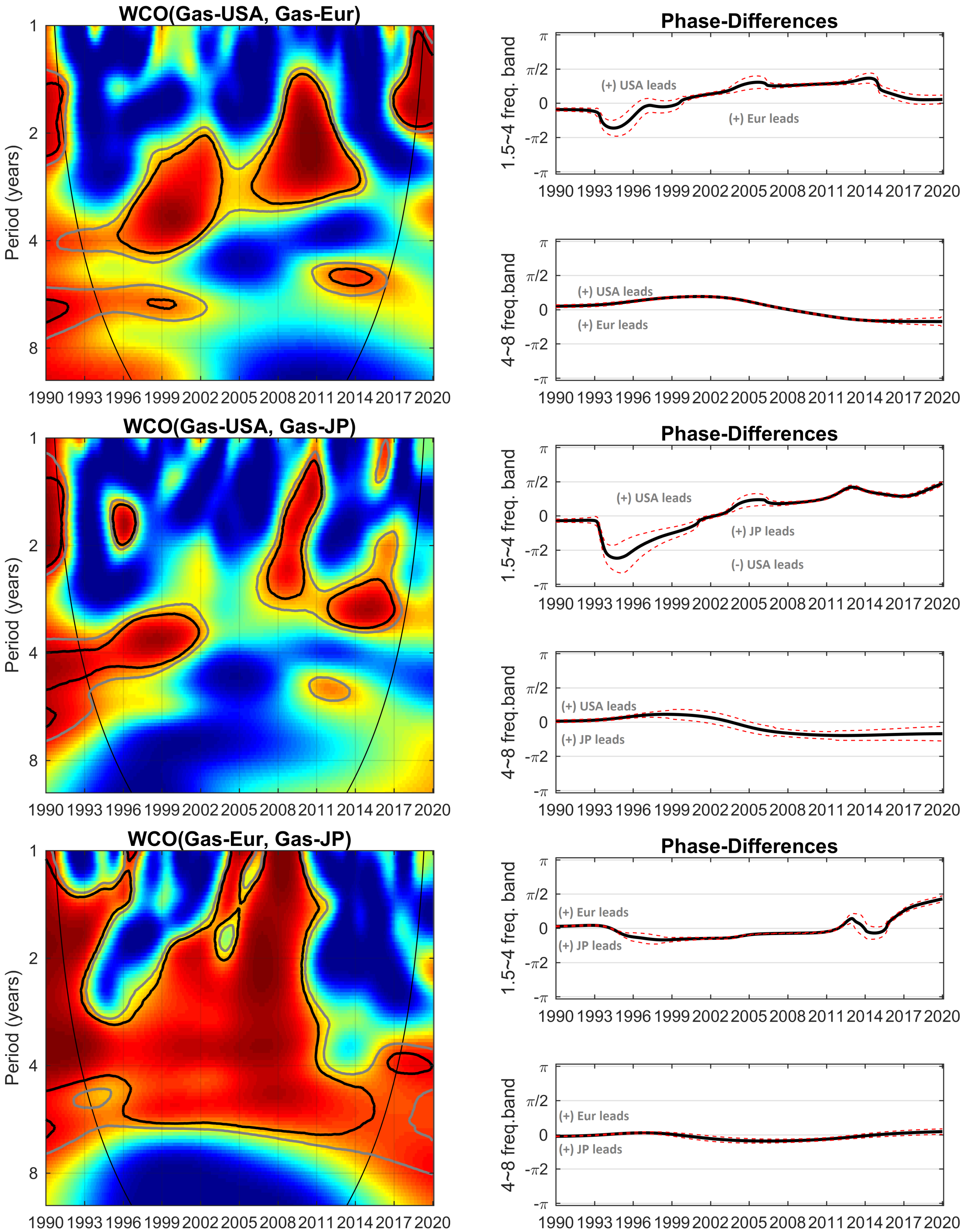

Figure 4: on the left – the wavelet coherency between Natural Gas prices in the three different regional markets. The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). On the right — phase-differences for the frequency bands of 1.5 $\sim$ 4 and 4 $\sim$ 8 years.

The picture of Europe and Japan confirms the result we had before: these two markets are significantly synchronized. The red (and statistically significant) region is vast, and it covers both high and low frequencies. Most of the time, the phase-difference is slightly negative, indicating that the European gas market slightly lags the Asian market.

However, it is noteworthy that towards the end of the sample, the regions of high coherency diminish, suggesting that, in this last decade, these two markets are becoming less, not more, synchronized.

Given these results, is the degree of synchronization such that we can consider that these two markets are integrated and that we can treat them as one? The answer is no, at least if we take the oil markets as the benchmark (see Figure 2). Therefore, we can discuss how integrated the gas markets are, especially the European and Japanese markets, but we should keep in mind that, no matter how synchronized, they are still far from a global market such as the crude oil world market.

5 The role of oil in connecting the gas markets

As we saw in the introduction, there is a considerable literature about the oil and gas market relation and on the role of oil in connecting the gas markets. This kind of association is expected given that, in many ways, these two forms of energy are substitutes, sometimes even close substitutes. In Table 2, we materialized this relation under our framework: except for the North American gas market, we can safely reject the hypothesis that the oil and gas prices are not connected.

In the first subsection, we explore this connection, checking which market leads which, when, and at what frequencies. Then, in the second subsection, we reanalyze the connectedness of the gas markets after removing the coordinating effect of the oil prices.

5.1 Gas and oil markets integration

In Figure 5, we estimate the wavelet coherency and the phase difference between the gas prices in each market and the price of crude oil (Brent). Confirming the results of several other authors, we can see that the links between oil and gas in the U.S. are much weaker than between oil and the other gas markets. Until 2000, at lower frequencies, the two markets were tied (high coherency and zero phase-difference). After that, the longer run link disappeared. In the shorter run ($1.5 \sim 4$ years), there is a region of high coherency at the beginning of the sample, but the phase-difference is too erratic to be able to make sense of this result. After 2005, at higher frequencies, coherency becomes significant again. The slightly negative phase difference suggests that the gas prices follow the oil prices. This is one possible explanation for the result we found in the previous section linking the North American gas market to the European one (and, to a lesser extent, also to the Japanese).

Regarding the connection between the European and Japanese gas markets with the oil market, we can observe a much more stable relationship and, actually, stronger than the relationship we found in the previous section between the two regional gas markets. One can safely conclude that these two gas markets are more connected with the oil market than with each other.

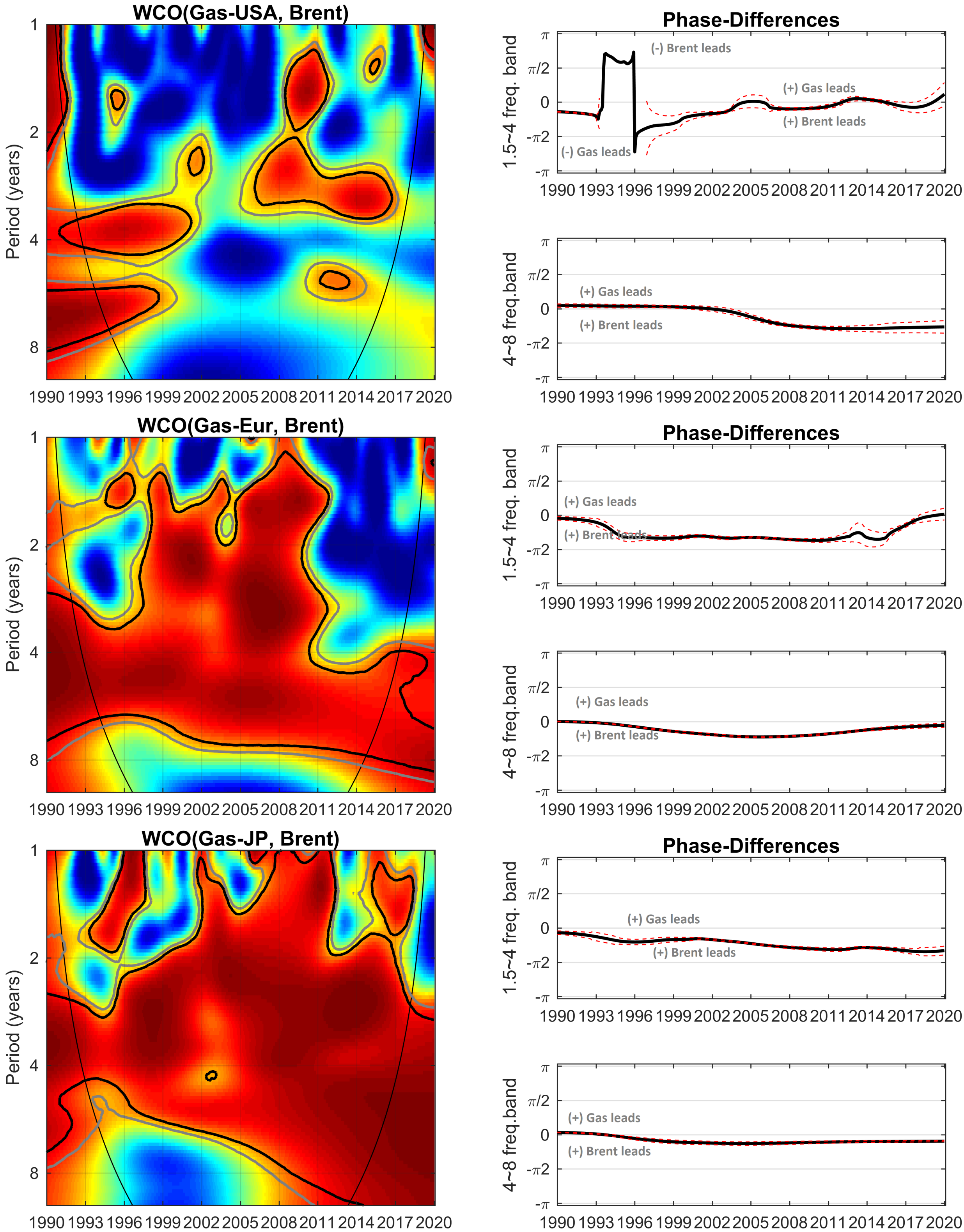

Figure 5: on the left – the wavelet coherency between Natural Gas prices and crude oil (Brent). The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). On the right — phase-differences for the frequency bands of 1.5 $\sim$ 4 and 4 $\sim$ 8 years.

The red region is more extensive in the case of the Japanese gas market than in the case of the European one, suggesting that the relation between oil and gas is more substantial in the former case. Note that the phase-difference is consistently negative, meaning that it is the oil market that consistently leads the gas markets, confirming the consensus in the literature that that causality runs from oil to gas markets.

One possible take from these results is that it is not the European gas market that is connected to the Asian market, as suggested by Figure 4, but it is the oil connection that is the common factor.

This brings us (ou leads us) to next natural question, which is to know what would happen to their relationship if we removed the oil effect. We try to answer this question in the following subsection.

5.2 Gas markets integration without the oil connection

To control for the oil market effect, one must rely on multivariate analysis. That is what we do in Figure 6. We estimate the partial wavelet coherency between each pair of gas markets, after controlling for the oil market effect. The results are staggering. Regions of high coherency almost disappear, and the phase-differences become quite erratic. This result, not only reinforces previous conclusions that it is the global oil market that connects the regional gas markets, but also suggests that once we remove this link, gas markets become mostly independent.

There is one peculiar result, though, which is common to the three pictures. In 2005, at the lowest frequencies, we observe a region of high coherency that dies off by the end of the sample. The phase-difference between the U.S. and Japan fluctuates between π and $-\pi$. This means that there is an almost instantaneous negative relationship between these two markets, at these frequencies. Analyzing the U.S. and Europe, we observe an in-phase relation with the U.S. leading and, naturally, between Japan and Europe, we observe an anti-phase relation, with the Japanese prices leading.

Overall, the conclusion is that once one removes the oil coordinating effects, the three markets become primarily independent.

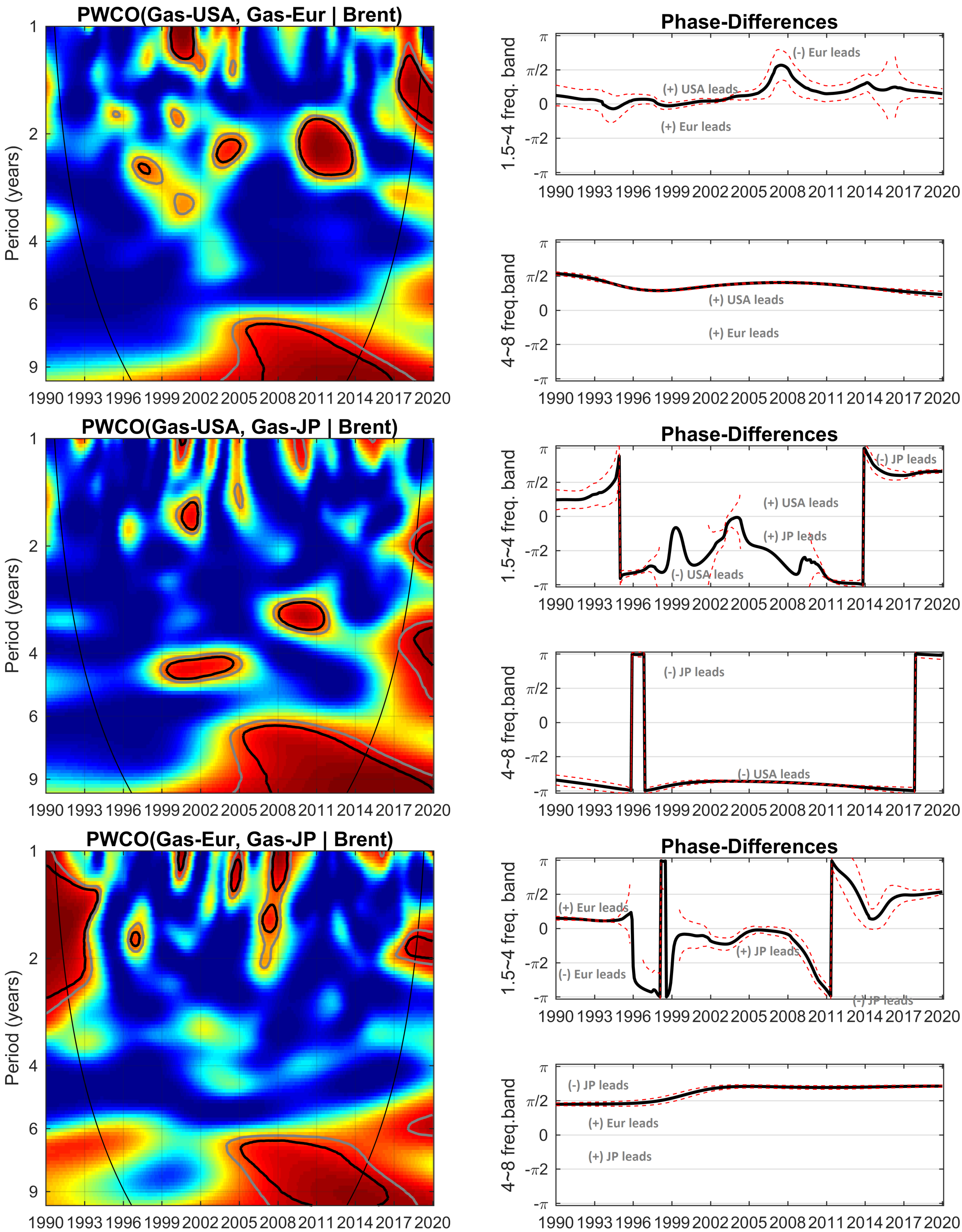

Figure 6: on the left – the partial wavelet coherency between prices of different gas markets after controlling for oil prices. The black/gray contour designates the 5%/10% significance level. The color code for coherency ranges from blue (low coherency – close to zero) to red (high coherency – close to one). On the right — partial phase-differences between for the frequency bands of $1.5 \sim 4$ and $4 \sim 8$ years.

6 Conclusions

While we can say that there is a global market for crude oil, we cannot say the same about natural gas. Still, there is a strand of literature that argues that, in the last decades, gas markets have become less regional and more global. We applied the Continuous Wavelet Transform tools to test the global integration of regional gas markets and its relation to the oil market. This approach offers the opportunity to look at this subject simultaneously from a time and frequency perspective.

Among other results, we concluded that the Japanese and European markets are synchronized (although their coordination is far smaller than what we observe in the global oil market) at $1.5 \sim 6$ years frequencies, with a slight lead from the Asian market. However, in the last decade, coordination has been decreasing. The North American market is independent; however, some evidence points to some coordination with the European market at high frequencies.

We also looked at the relation between the gas and oil markets. Each gas market is more synchronized with the oil market than with any other gas market. It is the oil market that links the gas markets, mostly the Japanese and the European ones. Once we remove the oil prices' arbitraging effect, the gas markets become independent from each other.

Can we find economic reasons that explain the detachment of the North American gas market? Natgas.info (2021) provides several clues: one possible explanation is the extensive pipeline network present in the United States, with roughly equivalent gas specifications, many buyers and many sellers, facilitating the existence of an independent market. Moreover, regional gas supply and demand set gas prices, where gas competes with other gas (gas-on-gas pricing). It is common in the other markets to have gas prices directly linked to oil prices (Garaffa et al., 2019). To be more precise, in Europe, gas prices are a function of energy substitutes, which naturally include oil products. According to Natgas.info (2021) and Agerton (2017), it is common to have pure oil-linked pricing in North Asia, especially Japan, Korea, and Taiwan. This contract structure explains the results we found in Table 2 and Figures 5 and 6. Note that we concluded that the oil market is very connected with the Asian gas market, and (less) with the European market, and even less with the North

American market.

In this study, we analyzed gas markets synchronization. We considered the role of oil in coordinating these markets. We did not consider other factors that may also be relevant. For example, Nick and Thoenes (2014) show that, in the short-run, natural gas prices in Germany suffer shocks from several sources and that, in the long-run, not only oil but also coal are vital determinants. In future work, we will study the role of coal in explaining the dynamics that we found. Still, our results are of interest to several economic agents. It is still not the time for industry strategists to think of regional gas markets as being one market. That means that geographical diversification reduces obviously local risks, like political risks, and also reduces exposure to price shocks. The fact that our analysis is frequency varying allows for portfolio managers to adjust their choices to their clients' time-horizons. Consider, for example, the case of the Japanese and European gas markets. After 2013, coherency between the two markets decreased at higher frequencies and increased at lower frequencies (corresponding to cycles of a period above four years). If the clients' time-horizon is less than four years, then portfolio investment in both markets will help risk diversification. For a more extended time-horizon, the investor should consider that markets are (imperfectly) tied, and risk diversification will be harder to achieve. It should also be clear that, at these lower frequencies, any spillover effects will run from oil to gas markets. All this information helps portfolio managers to define their risk strategies more adequately.

Our results reinforce the need to decouple gas pricing from oil prices in Europe and Japan (especially in the latter case) for policymakers. Given the typical contract structure of gas transactions, an increase in oil prices will increase gas prices. This may lead to overpriced gas, which will hurt consumers. Moreover, because of environmental concerns, a policymaker may prefer that gas consumption share increases. With both prices tied together, there is not much incentive to substitute gas for oil when the latter increases.

7 Appendix — The Continuous Wavelet Transform and the de-synchronization matrix

7.1 Continuous Wavelet Transform and Wavelet Power

For all practical purposes, a *wavelet* is simply a small wave: a *wave*, in the sense that it is a function $\psi(t)$ whose graph oscillates up and down the t-axis (integrating to zero) and *small* meaning that it rapidly decays as $t \to \pm\infty$. To obtain the phase information about the various cycles in a time series, which will be essential to assess the lead/lag relationships between two variables, it is necessary to work with a complex-valued wavelet. The wavelet we used in our computations is the particular member of the so-called *Morlet family*, introduced by Grossmann and Morlet (1984) and defined by $\psi(t) = \pi^{-\frac{1}{4}} e^{i6t} e^{-t^2/2}$, see Aguiar-Conraria and Soares (2014) for a detailed discussion on the optimal characteristics of this particular wavelet.

Given a function (time-series) $x(t)$, its *continuous wavelet transform* (CWT) (with respect to the wavelet ψ) is a function of two-variables, $W_x(\mathtt{t}, \mathtt{s})$:

$$W_x(\mathtt{t}, \mathtt{s}) = \frac{1}{\sqrt{|s|}} \int_{-\infty}^{\infty} x(t)\, \overline{\psi}\left(\frac{t - \mathtt{t}}{\mathtt{s}}\right) dt, \mathtt{t}, \mathtt{s} \in \mathbb{R}, \mathtt{s} \neq 0. \tag{1}$$

In the above formula, and in what follows, the over-bar is used to denote complex conjugation.

The wavelet transform W_x is complex-valued and can be expressed in polar form as $W_x(\mathtt{t}, \mathtt{s}) = |W_x(\mathtt{t}, \mathtt{s})|\, e^{i\phi_x(\mathtt{t}, \mathtt{s})}$, $\phi_x \in (-\pi, \pi]$. The angle ϕ_x is referred to as the *(wavelet)-phase* and the square of the modulus of W_x is called the (local) *wavelet power spectrum* and is denoted by $(WPS)_x$, i.e.

$$(WPS)_x(\mathtt{t}, \mathtt{s}) = |W_x(\mathtt{t}, \mathtt{s})|^2 . \tag{2}$$

We can interpret the wavelet power spectrum as depicting the local variance of a time-series in the time-scale (or time-frequency) plane.

7.2 Wavelet Coherency and Wavelet Phase-Difference

To deal with the time-frequency dependencies between two non-stationary time-series, we use the wavelet coherency and wavelet phase-difference, which naturally generalized the basic wavelet analysis tools to the bivariate case.

Remark 1 *As for the wavelet power spectrum, all the wavelet measures that we are going to introduce are functions of the two variables, t and s. To simplify the notation, we will describe these quantities for a specific value of the argument, (t, s) , which will be omitted in the formulas.*

Given two time-series, $x(t)$ and $y(t)$, their *cross-wavelet transform*, W_{xy}, is simply defined as $W_{xy} = W_x\overline{W_y}$, where W_x and W_y are the wavelet transforms of x and y. The *complex wavelet coherency* ϱ_{xy} of series x and y is given by:

$$\varrho_{xy} = \frac{S\left(W_{xy}\right)}{\left(S\left(|W_x|^2\right) S\left(|W_y|^2\right)\right)^{1/2}}, \tag{3}$$

where S denotes a smoothing operator in both time and scale; smoothing is necessary, because, otherwise, coherency would have modulus one at all scales and times.

As with the wavelet transform, the complex wavelet coherency can be written in polar form, as $\varrho_{xy} = \left|\varrho_{xy}\right| e^{i\phi_{xy}}$. The absolute value of the complex wavelet coherency is called the *wavelet coherency* and is denoted by R_{xy} and the angle ϕ_{xy} of the complex coherency is called the (*wavelet*) *phase-difference*. The angle ϕ_{xy} is obtained form the real part $\Re(\varrho_{xy})$ and the imaginary part $\Im(\varrho_{xy})$ of ϱ_{xy} by using the formula

$$\phi_{xy} = \arctan\left(\frac{\Im(\varrho_{xy})}{\Re(\varrho_{xy})}\right), \quad \phi_{xy} \in (-\pi, \pi], \tag{4}$$

together with the information on the signs of $\Re(\varrho_{xy})$ and $\Im(\varrho_{xy})$ to determine to which quadrant the angle belongs to.

A phase-difference of zero indicates that the time-series move together at the specified time-frequency value; if $\phi_{xy} \in (0, \frac{\pi}{2})$, then the series move in phase, but the time-series x leads u; if $\phi_{xy} \in (-\frac{\pi}{2}, 0)$, then it is y that is leading; a phase-difference of π indicates an anti-phase relation; if $\phi_{xy} \in (\frac{\pi}{2}, \pi)$, then y is leading; time-series x is leading if $\phi_{xy} \in (-\pi, -\frac{\pi}{2})$.

7.3 Partial Wavelet Coherency and Partial Wavelet Phase-Difference

The partial wavelet coherency and the partial wavelet phase-difference are simply the multivariate analogs of the the wavelet coherency and the wavelet phase-difference. For three variables, e.g. x, y, z, the *complex partial wavelet coherency* of x and y, after controlling for z, is given by the formula

$$\varrho_{xy\,.\boldsymbol{z}} = \frac{\varrho_{xy} - \varrho_{xz}\overline{\varrho}_{yz}}{\sqrt{(1 - R^2_{xz})(1 - R^2_{yz})}}. \tag{5}$$

The *partial wavelet coherency,* $r_{xy\,.\boldsymbol{z}}$, is the absolute value of $\varrho_{xy\,.\boldsymbol{z}}$ and the *partial phase-difference of* x over y, given z, is the angle of $\varrho_{xy\,.\boldsymbol{z}}$. We can interpret $r_{xy\,.\boldsymbol{z}}$ as the wavelet coherency between x and y, after removing the influence of z.

7.4 Wavelet transform de-synchronization matrix

We will also use a measure of the dissimilarities between the wavelet transform of two time-series proposed by Aguiar-Conraria and Soares (2011a), also applied by Flor and Klarl (2017).

To measure the dissimilarity between market x and y, we start by computing the Singular Value Decomposition (SVD) of the matrix $W_x W_y^H$, where W_y^H is the conjugate transpose of W_y, to focus on the common high power time-frequency regions.[2] Because this method extracts the components that maximize covariances, the first extracted K components correspond to the most important common patterns of the wavelet transforms.[3] The wavelet distance between the wavelet spectra of series x and y, denoted by $\mathrm{dist}(W_x, W_y)$, is computed as:

$$\mathrm{dist}\left(W_x, W_y\right) = \frac{\sum_{k=1}^{K} \sigma_k^2 \left[d\left(\mathbf{l}_x^k, \mathbf{l}_y^k\right) + d\left(\mathbf{u}_k, \mathbf{v}_k\right)\right]}{\sum_{k=1}^{K} \sigma_k^2}. \tag{6}$$

In the above formula, $\mathbf{u}_k$ and $\mathbf{v}_k$ are the singular vectors and σ_k the singular values obtained in the SVD and $\mathbf{l}_x^k$ and $\mathbf{l}_y^k$ are the so-called leading patterns, given by $\mathbf{l}_x^k = \mathbf{u}_k^{\mathrm{H}} W_x$ and $\mathbf{l}_y^k = \mathbf{v}_k^{\mathrm{H}} W_y$. We compute the distance $d(\mathbf{u}, \mathbf{v})$ between two vectors $\mathbf{u}$ and $\mathbf{v}$ (leading vectors or leading patterns) by measuring the angle between each pair of corresponding segments, defined by the consecutive points of the two vectors, and take the mean of these values; see Aguiar-Conraria

[2] In practice, the CWT of a time-series is computed only for a finite number of values of the time and scale parameters, so the computed wavelet spectrum of a series ends up being simply a matrix.

[3] The value of K is, in general, an integer much smaller than the rank of the matrix $W_x W_y H$; in our case, we considered $K = 3$.

(2011) for more details.

The above distance is computed for each pair of markets and, with this information, we can then fill a de-synchronization matrix.

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