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Co-movement between some commodities and the Dow Jones Islamic Index: A Wavelet analysis

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Abstract

The objective of this paper is to study the common movement of three commodities (Oil, gas and gold) and the Dow Jones Islamic Market index (DJIM) using daily price observations, covering the period from January 2, 2006 to February 21, 2019. The Wavelet Squared Coherence (WSC) indicates that there is a co-movement between DJIM and oil prices and to a lesser extent with the price of gas, notably for the long run. However, a decline in dependence observed in 2014 confirms a gradual comeback to the situation before 2008. Moreover, using the Windowed Scalogram Difference (WSD), we confirm these findings but we detect other elements such as a more regular relationship between gas and Islamic stock. The results show that investors in Islamic stock market indices do not base their decisions on oil, gas or gold prices.

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1. Introduction

Islamic stock indexes have become increasingly popular since they created opportunity for investment portfolio diversification (Nagayev et al., 2016). An extensive literature is dealing with the interaction between Islamic stocks and oil/gas markets (eg: Abdullah et al., 2015; Chebbi and Derbali, 2015. Ghorbel et al. 2014 ; Hussin et al., 2013 ; Badeeb and Lean, 2018; Mensi et al., 2017; Narayan et al. 2019 ; Shahzad et al. 2017). Since Islamic financial institutions and investors in Islamic stock indexes are mainly concentrated in oil and gas-producing countries of the Gulf Cooperation Council (GCC), it can be argued that Islamic investors' behavior is sensitive to oil/gas market evolution. Obviously, Islamic stocks react differently to changes in the oil price compared to conventional stocks (Narayan el al. 2019)

The objective of this article is to study the causal relationship between the price of three commodities (Oil, gas and gold) and the Dow Jones Islamic Market (DJIM) index by analyzing the common movement of these commodities and the Islamic index. Despite a growing body of evidence confirming the relationship between the commodity market and Islamic stock return dynamics, the evolution of the relationship over the period following the financial crisis of 2008 is still poorly understood. By using a wavelet approach, we analyze the co-movement and its variation in time and in scale between these commodities and the selected index. DJIM is chosen because it is the most important Islamic stock market index in terms of capitalisation. The gold is also included to verify the reliability of the method used, which is the wavelets technique.

While the literature studying the oil-stock price interdependence is generally inconclusive (Arouri and Fouquau, 2009; Smyth and Narayan, 2018), studies specifically examining the effect of the oil and gas markets on Islamic indices find similar results. For instance, using a combination of the DCC GARCH approach and wavelet technique, Nagayev et al. (2016) report that the financial crisis of 2008 strengthened the correlation between crude oil/natural gas prices and Islamic equity. Similarly, Khan and Masih (2013) and Shahzad et al. (2017) confirm the role of the 2008 crisis in strengthening crude oil/Islamic stock price interdependence. Using the wavelet technique, Kamarudin and Masih (2015) identified a significant co-movement for crude oil – stock market relationship for the long term, but this observation was not identified for the short and medium terms. Conversely, Hussin et al. (2013) establish that Islamic stocks in Malaysia react to oil prices only in the short term. Other studies are more skeptical about the existence of a significant correlation between the price of oil and stock returns. For example, in their study of 2178 Islamic stocks, Narayan et al. (2019) found that only 32% of the stock returns are significatively affected by oil prices.

The aim of this article is to enhance the existing literature by using a dual wavelet approach. The advantage of the wavelet method is that it allows a clear distinction between short and long-term investor behaviors, which are pertinent in a co-movement analysis and enable us to consider time and frequency simultaneously when analyzing the correlation between the two time-series. The wavelet squared coherence methodology is the one most used. However, this paper uses a combination between the Wavelet Squared Coherence (WSC) and the Windowed Scalogram Difference (WSD) to refine the observations. According to Bolós et al. (2017), the WSD can detect features that the WSC is not able to identify. The advantage of the WSD is to restrict the analyses to a finite window in time and scale. Therefore, this method is more flexible since it enables the choice of window size according to the interest of the investor on a scale.

The outline of this paper is as follows. The next section describes the econometric methodology. Section 3 presents briefly the data and the empirical results according to the wavelet technics used. Section 4 concludes.

2. Econometric Methodology

The wavelet transform approach was introduced to overcome the limitations of the Fourier transform. The basic requirement for the Fourier transform is that the time series under study should be periodic and assumes that frequencies do not evolve in time etc. In the wavelet transform, its window is adjusted routinely to high or low frequency. This is because it uses a short window at high frequency and conversely by utilizing time compression or dilatation, rather than a variation of frequency in the modulated signal, which is achieved by separating the time axis into a sequence of successively smaller segments. The starting point in such analysis is based on decomposing a time series on a scale-by-scale basis. This theory has its roots in Fourier analysis. Nevertheless, significant differences exist between the two transforms. As a matter of fact, to represent a given function, the Fourier transform uses complex exponential functions which are inherently nonlocal and stretch to infinity. Conversely, wavelet building blocks are mathematical functions which are defined over a finite domain and possess remarkable localization properties. Furthermore, the wavelet transform utilizes a basic function (called the mother wavelet), then dilates it and translates it to capture the features that are local in time and in frequency and can describe local characteristics of a given signal in a parsimonious way.

2.1. Continuous wavelet transforms

The continuous wavelet transform (CWT) is a function $W_X(u,s)$, defined as a projection of the time series $X(t) \in L^2(\mathbb{R})$ onto a particular wavelet $\psi(\bullet) \in L^2(\mathbb{R})$

$$\forall s > 0,\ \forall u \in \mathbb{R},\ W_X(u,s) = \int_{-\infty}^{+\infty} X(t)\overline{\psi(t)}dt = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} X(t)\overline{\psi\left(\frac{t-u}{s}\right)}dt, \tag{1}$$

where $\overline{(\bullet)}$ denotes the complex conjugate, u is a location parameter that indicates the exact position of the wavelet (the translation parameter determines where the wavelet is centered) and the scale parameter s that controls the length of the wavelet (the scaling factor controls how the wavelet is stretched or compressed). If the scaling factor is lower, the wavelet is more compressed. If the scale factor is higher the wavelet is stretched. Thus, the wavelet is able to detect higher or lower frequency components of the examined time series $X(t)$.

A wavelet must satisfay the admissibility condition

$$C_\psi = \int_0^{+\infty} \frac{|\hat{\psi}(f)|^2}{|f|} df < \infty, \tag{2}$$

where $\hat{\psi}(f)$ is the Fourier transform of a wavelet $\psi(\bullet)$.

The time series $X(t)$ can be reconstructed using the wavelet coefficients as

$$X(t) = \frac{1}{C_\psi}\int_0^{+\infty}\int_{-\infty}^{+\infty} W_X(u,s)\frac{1}{\sqrt{s}}\psi_{u,s}\left(\frac{t-u}{s}\right)du\frac{ds}{s^2}. \tag{3}$$

The continuous wavelet transform preserves energy of the analyzed time series

$$\int_{-\infty}^{+\infty}|X(t)|^2 dt = \frac{1}{C_\psi}\int_0^{+\infty}\int_{-\infty}^{+\infty}|W_X(u,s)|^2\, du\frac{ds}{s^2}. \tag{4}$$

The most commonly used mother wavelet is the Morlet wavelet: $\psi^M(t) = \pi^{-\frac{1}{4}}e^{-\frac{1}{2}t^2}e^{ift}$.

2.2.Wavelet analysis of coherence and phase spectra

Since we study the interactions between two time series, we introduce a bivariate setting called wavelet coherence. The cross wavelet transform of two time series $(X(t), Y(t))$ is defined as

$$W_{XY}(u,s) = W_X(u,s)\overline{W_Y(u,s)}, \tag{5}$$

where $W_X(u,s)$ and $W_Y(u,s)$ denote the continuous wavelet transforms of $X(t)$ and $Y(t)$, respectively, u defines a time position, and s denotes the scale parameter. Thus, the cross wavelet power is obtained via $|W_{XY}(u,s)|$ that represents the local covariance between the examined time series at the specific scale u. In other words, it indicates where the time series have high common power in the time-frequency domain. Following Torrence and Webster (1999), we define the wavelet squared coherence coefficient as follows

$$0 \le WSC(u,s) = \frac{\left|A\left(s^{-1}W_{XY}(u,s)\right)\right|^2}{A\left(s^{-1}\left|W_X(u,s)\right|^2\right)A\left(s^{-1}\left|W_Y(u,s)\right|^2\right)} \le 1, \tag{6}$$

where A is a smoothing operator in both time and scale which is essential in coherence analysis, otherwise the ratio would be equal to one. By computing wavelet squared coherence (WSC) we find regions in time-frequency space where the two time series co-vary. The WSC can be conceived as a local linear correlation (R^2) between two time series at a particular scale. To distinguish between negative and positive correlation[1], we use the wavelet coherence phase differences which indicate delays in the oscillation between the two examined time series. We test the statistical significance of the wavelet coherence estimates using Monte Carlo methods. The testing procedure is based on the approach of Grinsted *et al.* (2004) and Torrence and Compo (1998).

The delay in the oscillation between two time series at some specific time and scale can be obtained by evaluating the wavelet coherence phase difference. Following Torrence and Webster (1999), the wavelet coherence phase differences is defined as

$$-\pi \le \theta_{XY}(u,s) = arctan\left[\frac{Q_{XY}(u,s)}{C_{XY}(u,s)}\right] \le \pi, \tag{7}$$

where $C_{XY}(u,s) = \Re\left\{A\left(s^{-1}W_{XY}(u,s)\right)\right\}$ and $Q_{XY}(u,s) = \Im\left\{A\left(s^{-1}W_{XY}(u,s)\right)\right\}$ are the real and the imaginary parts of the smoothed cross wavelet transform.

A phase-difference of zero shows that the time-series move together at the specified frequency, which indicates co-movement. If $\theta_{XY} \in \left(0, \frac{\pi}{2}\right)$ then the series move in phase, but the time series Y leads X. If $\theta_{XY} \in \left(-\frac{\pi}{2}, 0\right)$ then it is X that is leading. A phase-difference of π or $(-\pi)$

[1] The WSC is simple to interpret since it is resembling the squared correlation coefficient in regression.

indicates an anti-phase relation. If $\theta_{XY} \in \left(\frac{\pi}{2}, \pi\right)$ then X is leading. Time-series Y is leading if $\theta_{XY} \in \left(-\pi, -\frac{\pi}{2}\right)$.

2.3.Windowed Scalogram Difference

As it was mentioned in the previous section, the concept of WSC is particularly useful for determining the regions in the time frequency domain where two time series have a significant co-movement, reflecting the local linear correlation between the series. In contrast, the concept of windowed scalogram difference (WSD) of Bolós et al.(2017) compares the behavior of two time series through their respective scalograms for different windows in time and scale; thus, it allows one to ascertain the particular scales and time intervals in which both time series exhibit a similar pattern, compare their scalograms and determine if they give the same weight to the different scales.

Consequently, the Windowed Scalogram Difference (WSD) can be considered, in some cases, as an alternative to the wavelet squared coherence (WSC) which is widely used in wavelet analysis. Indeed, the WSD is able to detect features that the WSC is ineffective to identify and quantify the extent to which two time series follow a similar pattern over time by comparing their scalograms and determining if they give the same weight to the different scales. This measure, which is based on the concept of wavelet scalogram, was designed to identify scales that are most representative in the time series, restricted to a finite window in time and scale. It is worth highlighting that the great flexibility of the WSD arises from the possibility of shifting the length of time and scale windows.

Contrary to the WSC, the WSD examines the behavior of two time series through their respective scalograms for different windows in time and scale, thus allowing one to ascertain the particular scales and time intervals in which both time series exhibit a similar pattern, comparing their scalograms and determining if they give the same weight to the different scales. Hence, the WSD is able to detect features that go unnoticed by the WSC.

The WSD of these two time series $\left(X(t), Y(t)\right)$ centered at (t,s) with time radius τ and log-scale radius r, is defined as

$$WSD_{\tau,r}(t,s) = \left(\int_{s-r}^{s+r} \left(\frac{WS_{\tau}(t,s) - WS'_{\tau}(t,s)}{WS_{\tau}(t,s)} \right)^{2} ds \right)^{\frac{1}{2}}, \tag{8}$$

where WS_τ , $WS_\tau^{'}$ denote the windowed scalogram of X , Y respectivelys, given by

$$WS_\tau\left(t,s\right)=\left(\int_{t-\tau}^{t+\tau}\left|W_X\left(u,s\right)\right|^2\,du\right)^{\frac{1}{2}}. \tag{9}$$

As shown in equation (8), the WSD measures the difference between the windowed scalograms of two time series. It enables us to quantify the level of similarity between two time series for different finite time and scale intervals.In the same case, the WS has the ability to determine the importance of different scales windowed around a specific time point. When the wavlet are discretely sampled, i.e. family of dyadic wavelet, the dyadic version is given by time variable $u=2^k j$ and scale $s=2^k$.

3. Empirical Results

3.1 Data description

This study employs daily closing stock price of the Dow Jones Islamic Market Index (DJIS) which measures the performance of stocks traded globally that pass rules-based screens for adherence to Shariah investment guidelines. We also use daily oil (OILW), gas (GASS) and gold (GOLD) prices. All these data are extracted from Datastream.

The daily sample spans the period from January 2, 2006 to February 21, 2019, totalising 3431 daily observations, enabling us to study the volatility of sectorial Islamic indices during the last twelve years including few important financial shocks.
As stated earlier, the objective of this research is to analyze the co-movement between the Dow Jones Islamic Market Index and three commodities prices (Oil, gas and gold).

3.2 Continuous wavelet Coherence transform

We use wavelet coherence transform to identify the presence of a cause-and-effect relationship between series.

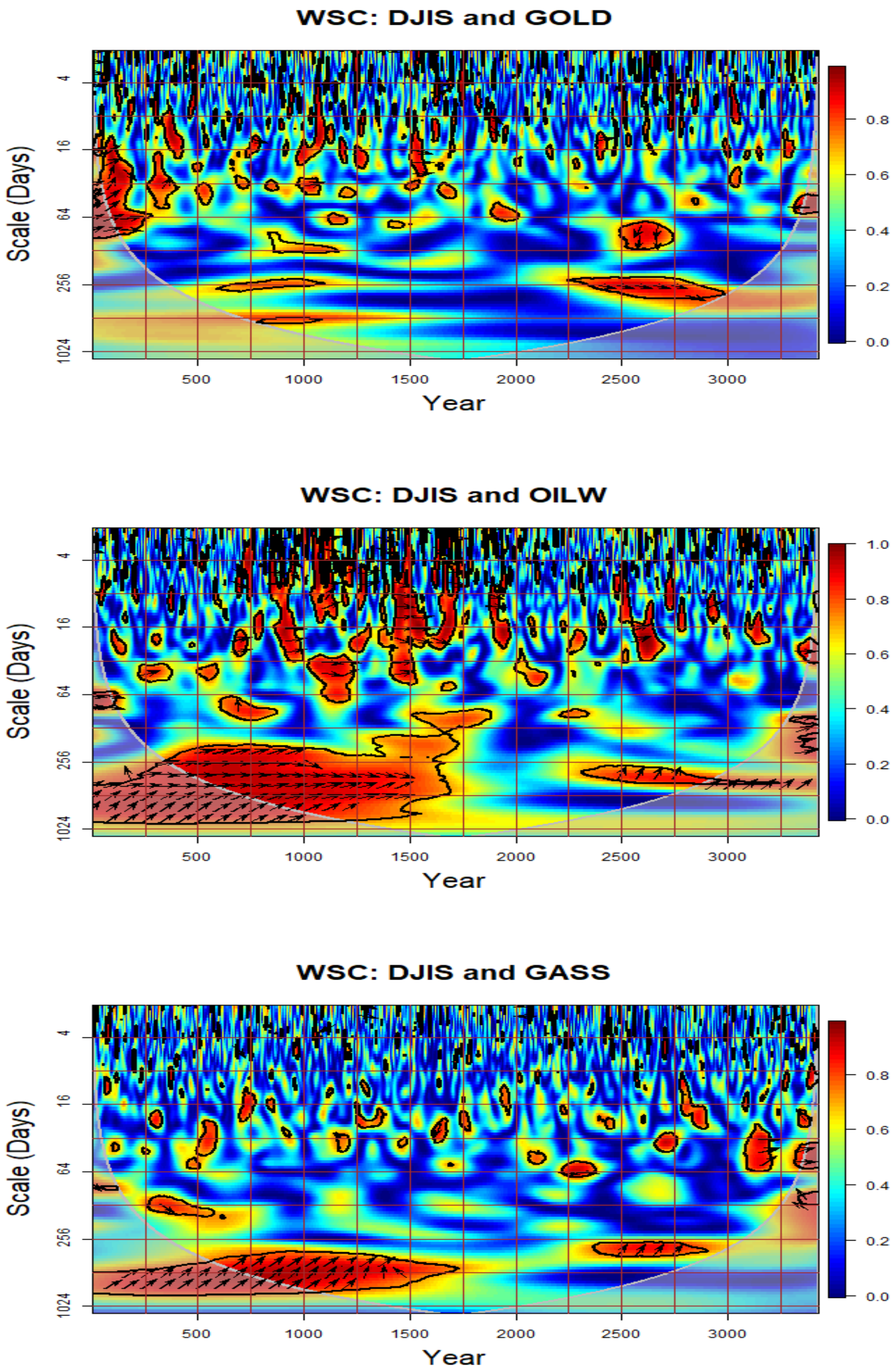


Figure 1 : Wavelet Squared Coherence of Oil, Gaz, Gold and the Dow Jones Islamic Market Index

Figure 1 shows the Wavelet coherence of DJIS and GOLD (top), DJIS and OILW (in the middle), DJIMI and GASS (bottom).

To analyze co-movement of indices, we consider the evolution of the correlation between all selected indices in the time as well as the frequency domain. Time (from January 2, 2006 to February 21, 2019 totalizing 3431 observations) appears on the x-axis, while frequencies (or scale), are expressed in days, on the y-axis; the lower the frequency, the higher the scale.

The cone of influence, where edge effects should be considered, is shown as a lighter shade. The color scale represents the magnitude of R-squared.

The black line contours denote areas with significant coherence ($p < 0.05$). The darker red (areas with arrows) the regions are, the higher the degree of co-movement. These areas represent the spaces with high dependence, i.e. where the R^2 is close to 1. The blue areas are signaling a low dependence meaning a low co-movement.

These figures provide a visualization of time-series behaviors using arrows. An arrow pointing down and to the right indicates that the first series is leading the second series with positive correlation, while an arrow pointing up and to the right indicates that the first series is being led by the second series with positive correlation and an arrow pointing only rightwards indicates that these prices are comoving without any leading or lagging relationship.

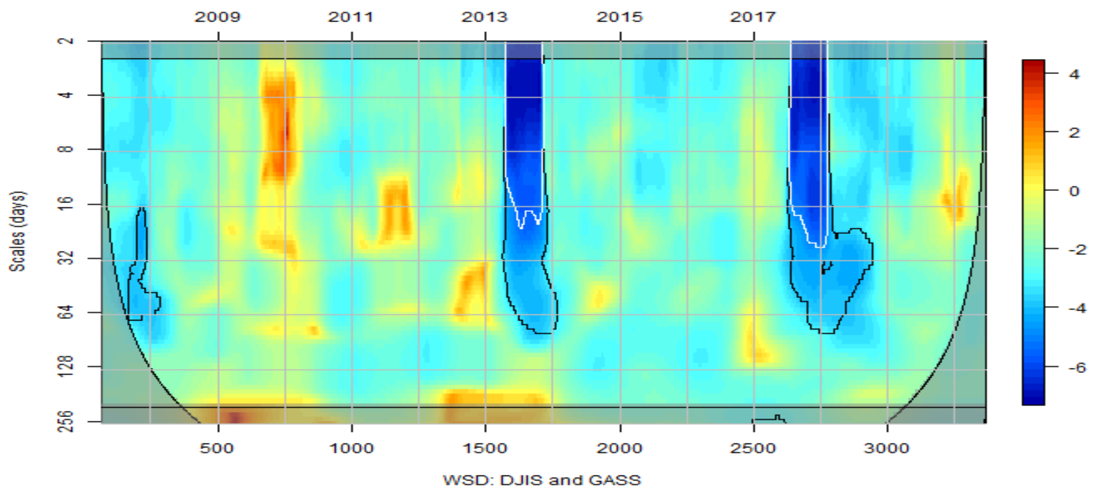
As expected, the Islamic index shows more dependence with oil and gas than with gold, in particular for the long run, confirming for example the findings of Kamarudin and Masih (2015) although the dependence is stronger with oil. The direction of the arrows indicates that it is the price of oil and gas that influences the Islamic stock prices. However, from the end of 2013, there is a decline in this co-movement. This result is consistent with findings of Nagayev et al. (2017) who indicated that the relation between oil/gas (among other commodities) and Islamic equity are heading towards their pre-crisis equilibrium.

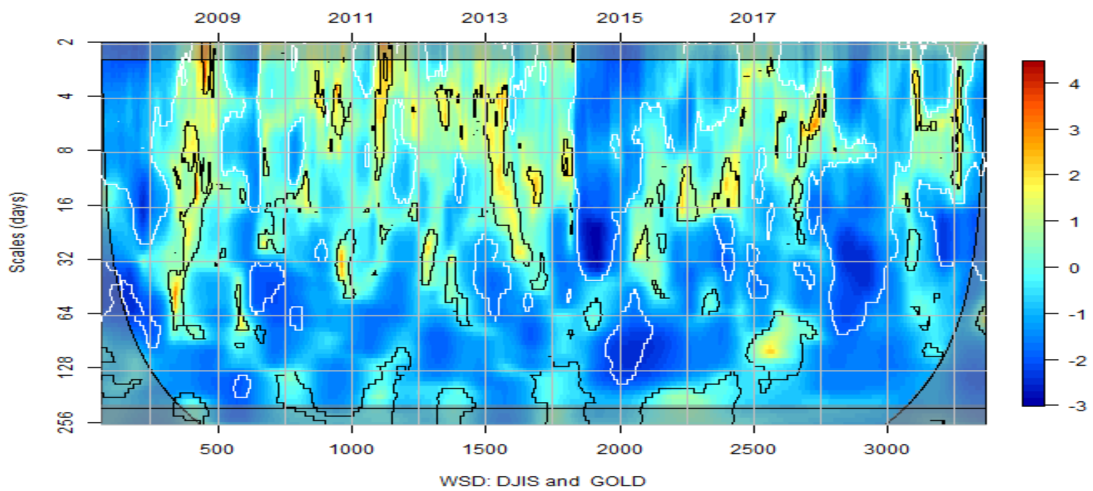
The co-movement during the 2007-2010 crisis is normal since the wavelet technique detects the simultaneous decline in oil/gas prices and stock market indices during the crisis and a simultaneous gradual increase in the post-crisis period. The decline in co-movement witnessed from mid-2014 coincides exactly with the beginning of the fall in the price of a barrel of oil due to the effects of the slowdown in the Chinese economy. Hence, between July 2014 and February 2016 the price of Brent dropped more than 65 percent from $ 110 to $ 35 per barrel (Henry Hub natural gas prices decreased from \$ 5.26 to \$ 1.76 between February 2014 and March 2016). As oil and gas prices fall, Islamic index continues to rise gradually.

It seems that investors in the Islamic stock markets do not base their investment decisions on the dynamics of the oil and gas market. The co-movement effect observed in 2007-2013 is due to a decrease and then a simultaneous rise in both prices caused by the dynamics created by the financial crisis.

Nevertheless, we use another wavelet approach (the WSC) to further explore linkages between selected variables. This concept is useful for determining the regions in the time frequency domain where two time series have a significant co-movement, reflecting the local linear correlation between the series. to clarify and confirm this result.

3.3 Windowed Scalogram Difference (WSD)





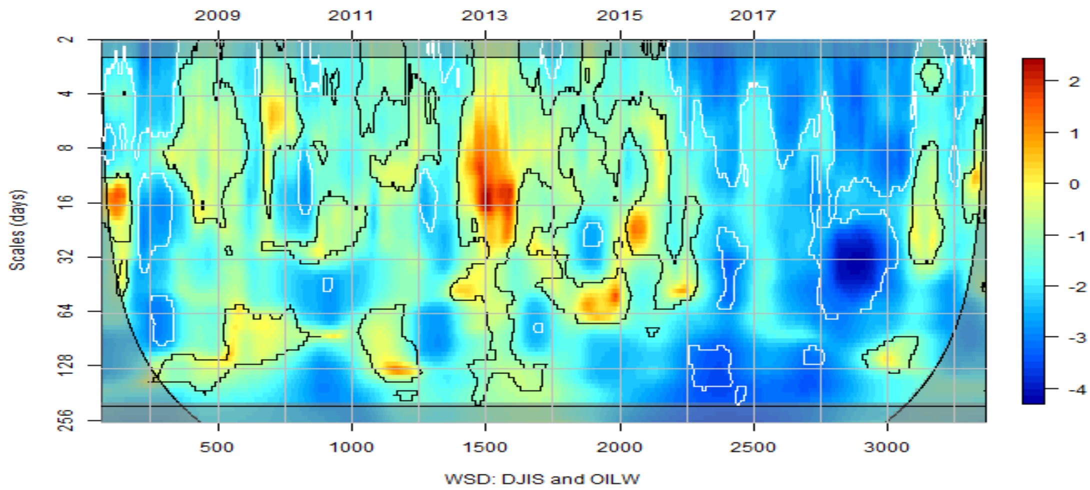


Figure 2 : Windowed Scalogram Difference of Oil, Gaz, Gold and the Dow Jones Islamic Market Index

Figure 2 shows the Windowed Scalogram Difference of DJIS and GOLD (top), DJIS and OILW (Middle), DJIS and GASS (bottom). The hotter the colour, the higher the similarity is between time series. The black-line regions are regions of statistical significance at the 5% level (high similarity) and the white-line regions are regions of statistical non-significance at the 5% level (low similarity) estimated using Monte Carlo simulations. The cone of influence is shown as a lighter shade.

Once again, the Islamic stock market index shows the higher correlation with oil. Gold shows the weakest correlation with DJIS confirming that this metal does not have much influence on the prices of the Islamic index. The WSD shows more accurately than the Wavelet Coherence a decline in the correlation between DJIS and OILW/GASS from 2014. This decline could indicate that Islamic investors' financial decisions are not dependent on oil and gas prices.

The WSD makes it possible to establish a more precise image of the correlation dynamics between the variables studied. It shows that even though there is a simultaneous decline in the co-movement between oil / gas prices and DJIS from 2014, gas continues to show a stronger correlation than oil (although declining) during this period. This can be explained by the fact that gas prices have been more resilient and are less volatile than oil prices.

While the co-movement is less marked between gas prices and the Islamic index than between oil and this index, this relation supported periods of strong declines notably in 2013 and 2016 but is characterized by a more regular relation except for these periods of decline.

4. Conclusion

This study contributes to the literature on the relationship between the prices of certain strategic commodities and stock returns, focusing on an Islamic stock market index. The Wavelet Squared Coherence (WSC) indicates that there is a co-movement between the Islamic stock returns and the oil/gas prices notably for the long run between 2007 and 2014 but that is explained by a simultaneous downward trend then the rise in commodity prices and the Islamic index. Meanwhile, it is impossible to establish whether the decisions of investors in the Islamic index are based on oil/gas prices since this fall and rise in prices follows a logic of market and economic context.

The decline in correlation observed since 2014 confirms a gradual return to the situation preceding 2008. The Windowed Scalogram Difference (WSD) confirms these findings but detects other elements such as a more regular relationship between gas and Islamic stock except some sudden and punctual decline in the correlation.

Understanding the influence of strategic commodities on Islamic stock prices is important for both regulators and investors. These results can be exploited by investors to increase the benefits of diversification since oil, gas and gold do not behave in the same way in their relationship with stock markets.

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