LITHIUM INDUSTRY IN THE BEHAVIOUR OF THE MERGERS AND ACQUISITIONS IN THE U.S. OIL AND GAS INDUSTRY

Manuel Monge, Francisco de Vitoria University (UFV), Madrid, Spain

and

Luis A. Gil-Alana*, University of Navarra, Pamplona, Spain

October 16, 2018

Abstract

Is lithium affecting the U.S. oil and gas industry strategies? Lithium has an increasingly strategic role as clean technologies emerge, affecting the strategies of oil and gas companies in response to energy trends. This paper contributes to this literature, studying the dynamics of lithium industry and mergers and acquisitions in the U.S. oil and gas industry in time-frequency domain. We use methodologies based on Continuous Wavelet Transform (CWT) and Vector AutoRegressive Models (VAR), and the results indicate that both time series are correlated in the long term, where M&A U.S. oil and gas industry dependence on lithium industry has increased, starting in the early 2014 until the end of the sample. Evidence of causality is not found between both time series.

Keywords: Lithium Industry; oil and gas industry; mergers and acquisitions; wavelet analysis; causality.

JEL Classification: COO; C22; E30; Q42.

Correspondence author: Dr. Manuel Monge
Francisco de Vitoria University
Faculty of Law and Business
E-28223 Madrid
SPAIN

Email: manuel.monge@ufv.es

*. The second-named author gratefully acknowledges financial support from the Ministerio de Economía y Competitividad (ECO2017-85503-R). Comments from the Editor and two anonymous reviewers are gratefully acknowledged.

1. Introduction

Lithium has an increasingly strategic role as clean technologies emerge. The most important use of lithium is in rechargeable lithium-ion batteries for electric vehicles and hundreds of electronic devices. Since Hubbert (1956) the imminent demise of oil as the world's main energy source has been widely heralded. Schurr and Netschert (1960) argued that the U.S. energy and fuel mix went through two dramatic transitions within a century. First, coal toppled wood as the main component of the U.S. fuel base roughly between 1850 and 1895. The share of wood in the fuel base went from about 90 to 30 percent, while coal's soared from 9 to 65 percent. In turn, oil and gas replaced coal between roughly 1910 and 1955. Within the span of four and one-half decades, the share of coal declined from 77 to 28 percent, while the combined share of oil and gas increased from 9 to 65 percent.

The transition between crude oil to the renewable energies in transport sector is a relevant topic because according to BP Energy Outlook (2017), the transport sector consumes most of the world's liquid fuel (petroleum), and its share of global demand remaining under 60% over the outlook, accounting for almost two-thirds of the growth in overall demand, 10 million barrels per day (Mb/d). This fact is important because the increasing production of electric cars joint with the decelerating transport demand for oil cause growth in total oil demand to slow gradually and could affect oil prices.

After examining recent developments in transportation and renewable energy as well as past technology transitions, Cherif and Hasanov (2017) conclude that oil as the main fuel for transportation and a major energy source in general, could change in the next 10 to 25 years, assuming in their projection that oil could lose its role as the main fuel for transportation, converging towards the level of coal prices, coupled with the ascent of renewables for power generation.

Germeraad et al. (2017) documented in their research the declines in the use of oil, gas and coal and the synchronous increases in energy production from renewable sources. The cause of such large-scale economic disruption is the climate and general environmental concerns. They also argue that such change is the advent of portable electric power on a cost and performance adjusted basis competing favorably with traditional oil or coal powered power. While, there are many sides to the story of how fossil fuels will migrate to renewable energy sources and some oil companies and oil-producing nations have recognized this and are now in the process of changing their strategies for the future.

The most important technological advancement that has had the greatest impact on the adoption of renewables is that of energy storage, led by lithium, using for the next generation technologies such as energy storage, electric mobility and cordless devices, among others. Vacha and Barunik (2012) argue that commodity markets are complex systems of interacting agents with different term objectives, and the time series methods usually considered by the literature are based on frequency and time components separately. The introduction of wavelets thus helps to uncover interactions which are hard to see using other econometric methods and which would otherwise stay hidden. In addition, the wavelet analysis is a nonparametric spectral method that eliminates the need of parametric data modelling, encountering facilities such as certainty in model parameters and the ability to fit data with complex spectral contents. In this context, to our knowledge this is the first paper that proposes to answer the question whether the interconnection between lithium industry and mergers and acquisitions (M&A) in the U.S. oil and gas industry changes significantly across different time horizons.

We use wavelet analysis (Aguiar-Conraria 2011a, b)[1] to detect the evolution in time-frequencies, paying particular attention to the trend or long-run component in the

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[1] https://sites.google.com/site/aguiarconraria/joanasoares-wavelets

time series (low frequency) and the seasonality or the short-run component and the rapid changes in the time series (high frequency). We focus on dynamic correlations based on wavelet coherence between lithium industry, represented by Solactive Global Lithium Index, and M&A in the U.S. oil and gas industry using monthly data. We analyze the evolution of these correlations in time as well as for different frequencies. In addition, we analyze the wavelet phase-difference. This approach distinguishes between different behaviors with different horizons. Finally, in relation with causality and wavelets, Olayeni (2016) argues that measuring causal effects using continuous wavelet transform has been particularly problematic because such measures as wavelet coherence only embodies amplitude between the variables; the information on the direction necessary for scooping out causal links is unavailable. However, the useful information on lead-lag relationships is encoded in the phase-difference. In addition, Dhamala et al. (2008), which try to undertake causality in non-parametrical wavelets, mention that the trouble lies in computing the spectral matrix factors in order to derive the minimum phase. This process involves inverse Fourier to communicate between the time and frequency domains. For this reason, we use Granger causality test after VAR model estimation to examine the causality direction between both time series.

The paper is organized as follows. In Section 2 we analyze the company strategies in response to energy trends. In Section 3 we provide a brief introduction to the mathematics of wavelets and explains how to derive the metric that is used to compare the Solactive Global Lithium Index and M&A in the U.S. and international oil and gas industry. Section 4 describes the data and the main empirical results, while Section 5 concludes the paper.

2. Mergers and acquisitions in response to energy trends

Brealey and Richard (1995) and Gregoriou and Renneboog (2007) suggest that M&A activities are typically pursued for strategic purposes and efficiency gains by achieving operational and financial synergies. As a result, Bruner (2004) identifies several factors that influence firms' M&A activities. In the same line, Hsu et al. (2017) argue that mergers and acquisitions (M&A) activities in the oil and gas industry (O&G) have momentum building periods, i.e. occur in waves, and show that M&A is largely driven by industry-specific factors rather than by general economic conditions.

According to Germeraad et al. (2017), oil companies investments (China and Saudi Arabia in particular), are being used as part of an economic development program. These are investments in renewable energy sources. Germeraad et al. (2017) argue that these are not showing up because when one looks closely at the investment activity of oil companies, they find this is done through external M&A activity versus internal R&D spending (which shows up in patent information). They argue that this M&A approach occurs because oil companies lack sufficient core competence in the new renewable technology areas at this point in time. Thus, energy companies are using open innovation from outside to experiment and gain knowledge in renewables areas.

On the other hand, Coase (2009) and Gort (1969) explained that economic factors are behind industrial organization and structure, as well as firms' investment behavior. They affirm that industries react to economic or industry shocks by reallocating assets through mergers and acquisitions. Economic or industry shocks (including technological, regulatory and so on) provide motivation for mergers and acquisitions. Harford (2005) added that while economic, technological, and regulatory shocks provide the fundamental reasons for mergers and acquisitions, overall capital market liquidity conditions cause these activities to occur in waves.

The literature related to the merger waves in the U.S. of mid-1980s have been described by Nelson (1959), Golbe and White (1988, 1993) and Mitchell and Mulherin (1996). The merger waves of the mid-1990s have been described by Andrade et al. (2001) and Harford (2005). Ravenscraft (1987), Shleifer and Vishny (1990) and Holmstrom and

Kaplan (2001) have been able to research the causes that trigger the merger waves from the previous cited researches. Also, Golbe and White (1993) tried to identify waves applying a sine curve's methodology to historic merger data. Clark et al. (1988), Chowdhury (1993) and Barkoulas et al. (2001) have modeled the wave behavior using autoregressive processes.

Related with the link between oil/gas prices and the M&A in the U.S. oil and gas industry, Monge and Gil-Alana (2016) modelled the wave behavior using autoregressive (AR) processes, concluding that an increase in the crude oil price produces an increase in the M&A between 2 and 3 months after the initial shock. On the other hand, Monge et al. (2017) studied the wave behaviour applying wavelet tools and found a potential change in the pattern of the relation between the two variables around 1995. Finally, Monge (2018) studies the interconnections between the main components of the lithium industry and the WTI crude oil prices in time-frequency space. He concludes that in the long-term, WTI crude oil prices dependence on lithium industry have increased, starting early 2014 and reaching the high levels of dependence in 2015 (from 48 to 70 days). Other works conducted for example by Town (1992) and Resende (1999) modeled the merger series by using switching models. Following the research done by Monge et al. (2017), this is the first paper that try to find evidence of the interconnection between lithium industry and M&A in the U.S. oil and gas industry.

2. Methodology

2.1 Wavelet Analysis

The wavelet transform offers localized frequency decomposition, providing information about frequency components. Wavelets have significant advantages over basic Fourier analysis when the series under study is stationary – see Gençay et al. (2002), Percival and Walden (2000) and Ramsey (2002). In our research, we use continuous wavelet analysis tools, mainly wavelet coherence, measuring the degree of local correlation between two-time series in the time-frequency domain, and the wavelet coherence phase differences.

The continuous wavelet transform

The continuous wavelet transform of a time series $x(t)$, with respect to the wavelet ψ, is a function $WT_x(a, \tau)$ defined as:

$$WT_x(a, \tau) = \int_{-\infty}^{+\infty} x(t)\psi_{a,\tau}^{*}(t)dt, \quad (1)$$

where $WT_x(a, \tau)$ are the wavelet coefficients of $x(t)$ at a certain scale a and a shift τ, where,

$$\psi_{a,\tau}^{*} = \frac{1}{\sqrt{a}}\psi^{*}\left(\frac{t-\tau}{a}\right) \quad (2)$$

is the complex conjugate of the wavelet function ψ. The parameter a is a scaling factor that controls the stretching factor of the wavelet and τ is a location parameter in time. Then, $WT_x(a, \tau)$ will be a matrix of time series. The scaling factor a is a positive real number that simply means stretching it if $a > 1$, or compressing it if $a < 1$. If a is positive, we assume that we are using an analytic or progressive wavelet, i.e., its Fourier transform is defined by the positive frequency axis, $\Psi(\omega) = 0$ when $\omega < 0$.

The lower the value of the scaling factor, the more higher frequency components are reflected in the continuous wavelet transform, thus we are dealing with the short-run components of the signal. As the scaling factor increases, we are dealing with lower frequency components of the time series, focussing on the long-run components. Then, the continuous wavelet transform is a multidimensional transform; from one time series we obtain a matrix of time series that show different frequency components (depending on the scaling factor) of the original one. If the wavelet function ψ is complex, then the wavelet transform $WT_x(a, \tau)$ will also be complex, with amplitude, $|WT_x(a, \tau)|$, and phase, $\phi_x(a,\tau)$. The real part of the wavelet transform, $\Re\mathrm{e}\{WT_x\}$, and its imaginary part, $\Im\mathrm{m}\{WT_x\}$ define the phase or phase-angle of the wavelet transform:

$$\phi_x = \mathrm{Arctan}\left(\frac{\Im\mathrm{m}\{WT_x\}}{\Re\mathrm{e}\{WT_x\}}\right). \tag{3}$$

The phase of a given time-series $x(t)$ is measured in radians, ranging from $-\pi/2$ to $+\pi/2$. Then, the phase is also a matrix containing the angle of each frequency component of the original time series. The phase will be used to extract conclusions of the synchronism between two time series, applying the wavelet coherency and the phase difference between time series (Aguiar-Conraria and Soares, 2011a,b, 2014).

The wavelet or mother wavelet used to analyze the time series must satisfy certain technical conditions to provide effective time-frequency location properties (Daubechies, 1992). First, it has to be a function of finite energy, $\int_{-\infty}^{+\infty}\psi(t)dt = 0$. There are many different wavelet families, but the election of a certain wavelet will depend on the application itself.

Related to time localization properties, we can normalize the wavelet function so that $\int_{-\infty}^{+\infty}|\psi(t)|^2dt = 1$. $|\psi(t)|^2$ defines a probability density function, and therefore we can obtain the mean, μ_ψ, and the standard deviation, σ_ψ, of this distribution. They are called the center and the radius of the wavelet, respectively. If we consider the Fourier transform of the mother wavelet, $\Psi(\omega)$, in a similar way we can calculate its mean and standard deviation, μ_Ψ and σ_Ψ. These quantities define the Heisenberg box in the time-frequency plane: $[\mu_\psi - \sigma_\psi, \mu_\psi + \sigma_\psi] \times [\mu_\Psi - \sigma_\Psi, \mu_\Psi - \sigma_\Psi]$. We say that ψ is localized around the point (μ_ψ, μ_Ψ) of the time–frequency plane with an uncertainty given by $\sigma_\psi\sigma_\Psi$. In our context, the Heisenberg's uncertainty principle establishes that $\sigma_\psi\sigma_\Psi \geq 1/2$.

The Morlet wavelet,

$$\psi(t) = \pi^{-\frac{1}{4}} e^{i\omega_0 t} e^{-t^2/2} \quad (4)$$

is a complex sine wave within a Gaussian envelope, so we are able to measure the synchronism between two-time series. This wavelet has optimal time–frequency concentration, in the sense that $\sigma_\psi \sigma_\Psi = 1/2$. Therefore, using this wavelet, we have the optimum trade off between time and frequency resolution. On the other hand, the Morlet can be considered as a wavelet (with finite energy, defined as before) when the frequency parameter $\omega_0 = 6$. For this value of the Morlet wavelet, the wavelet scale, a, satisfies the inverse relation f $\approx 1/a$, as the rest of the most used mother wavelets. Aguiar-Conraria and Soares (2011b) argue that the Morlet wavelet is frequently used due to the following four properties: (1) the three sensible ways of converting wavelet scales into frequencies are equal; (2) it has optimal joint time-frequency concentration; (3) the time radius and the frequency radius are equal; and (4) it is an analytic wavelet.

Wavelet and cross wavelet power spectrum, and wavelet coherency

The wavelet power spectrum (WPS) or the scalogram of a time series $x(t)$, as it is called, is the squared amplitude of the wavelet transform, that is: $WPS_x(a,\tau) = |WT_x(a,\tau)|^2$. The wavelet power spectrum lets us know the distribution of the energy (spectral density) of a time series across the two dimensional time–frequency representation. While the wavelet power spectrum shows the variance of a time series in the time-frequency plane, the cross wavelet power spectrum (CWPS) of two time series $x(t)$ and $y(t)$ shows the covariance between these time series in the time-frequency plane:

$$CWPS_{xy}(a,\tau) = \left|WT_x(a,\tau) WT_y(a,\tau)^*\right|, \quad (5)$$

where * represents the complex conjugate, as before. Therefore, the complex wavelet coherency between two time series $x(t)$ and $y(t)$ is defined as the ratio of the cross-spectrum and the product of the power spectrum of both series:

$$WCO_{xy} = \frac{SO(WT_x(a,\tau)WT_y(a,\tau)^*)}{\sqrt{SO(|WT_x(a,\tau)|^2)SO\left(\left|WT_y(a,\tau)\right|^2\right)}}, \tag{6}$$

where *SO* is a smoothing operator in both time and scale. Without the smoothing operator, the wavelet coherency would be always one for all times and scales (see Aguiar-Conraria et al. (2008) for details).

As the WCO_{xy} is a matrix of complex time series, we can split it again into amplitude and phase, $WCO_{xy} = \left|WCO_{xy}\right|e^{i\phi_{xy}}$. The amplitude matrix is the wavelet coherency, WC_{xy} and the angle ϕ_{xy} is called the phase difference between both time series:

$$\phi_{xy} = \text{Arctan}\left(\frac{\Im\text{m}\{WCO_{xy}\}}{\Re\text{e}\{WCO_{xy}\}}\right), \tag{7}$$

ϕ_{xy} is the phase difference between the two time series $x(t)$ and $y(t)$, and tells us about the synchronism between those time series. ϕ_{xy} ranging from $-\pi$ to π. If $\phi_{xy} = 0$ then both time series move in phase. This will mean that both time series increase or decrease their values at the same time. If $\phi_{xy} \epsilon \left(-\frac{\pi}{2}, 0\right)$, they move in phase but the time series $x(t)$ is leading; if $\phi_{xy} \epsilon \left(0, \frac{\pi}{2}\right)$, the time series $y(t)$ is leading. Therefore, in these cases we can find that one time series anticipates the increase or decrease of the other one. On the other hand, a phase difference of π or $-\pi$ indicates an anti-phase relation, when one time series increases, the other one is decreasing in time. Finally, if $\phi_{xy} \epsilon \left(-\frac{\pi}{2}, -\pi\right)$, both time series are out of phase but $x(t)$ is leading; and if $\phi_{xy} \epsilon \left(\frac{\pi}{2}, \pi\right)$, $y(t)$ is leading. In this case this means that one time series has a time delay with respect to the other.

2.2 Significance tests, Monte Carlo simulations

The theoretical distribution of the wavelet coherence coefficient is unknown. To check the statistical significance of the wavelet coherency, WC_{xy}, we rely on Monte Carlo simulations (Schreiber and Schmitz, 1996 and Torrence and Compo, 1998).

We model each time series as an ARMA (p, q) process where $p = q = 1$, with no pre-conditions. Then we assess the statistical significance of the amplitude, not of the phase.

The phase difference is not tested as there is no agreement in the scientific community about how to define the procedure. We should only take into account the phase difference when the amplitude of the wavelet coherency is statistically significant[2].

2.3 Vector Auto-Regression (VAR) model

Sims (1980) presented the vector autoregression model (VAR) for the dynamic analysis of the economic system. The VAR model treats all the variables as endogenous, and evaluates the estimation of the dynamic interaction between the economic variables. The VAR model can be expressed as follows:

$$y_t = \phi_1 y_{t-1} + \cdots + \phi_t y_{t-p} + \varepsilon_t, \quad t = 1, 2, \dots, T,$$

where y_t is a k-dimensional endogenous variables column vector, p is the lag length, and T is the number of observations in the sample.

[2] The seminal paper by Torrence and Compo (1998) is one of the first works to discuss significance testing for wavelet and cross-wavelet power. Based on a large number of Monte Carlo simulations, these authors concluded that the local wavelet power spectrum of a white noise or an AR(1) process, normalized by the variance of the time series, is well approximated by a chi-squared distribution. Torrence and Compo (1998). also derived empirical distributions for cross-wavelet power. On the other hand, Ge (2007, 2008) reconsidered the discussion of the significance testing for the wavelet, cross-wavelet power and wavelet coherency.
Aguiar-Conraria and Soares (2011c) concentrate on the use of a specific wavelet (the Morlet wavelet) and, assuming a Gaussian white noise process, analytically derive the corresponding sampling distributions. However, these sampling distributions were shown to be highly dependent on the local covariance structure of the wavelet, a fact that makes the significance levels intimately related to the specific wavelet family used, meaning that they cannot be generalized. Naturally, no work has been done on significance testing for the partial coherency, as, this measure has not been introduced elsewhere. Maraun, Kurths and Holschneider (2007) argued that pointwise significance tests, like the ones described, generate too many false positive. They proposed an areawise test which aims at correcting false positives of pointwise tests, based on the area on shape of the significant regions. Lachowicz (2009), however, shows that some more work needs to be done in this area.
Following the examples and the toolbox provided by Aguiar-Conraria and Soares (2011c), the tests of significance are either based on very simple Monte Carlo simulations or bootstrapping. They fit an ARMA (p, q) model and then construct new samples by bootstrap or by drawing errors from a Gaussian distribution. In the first option, they use the very basic bootstrap technique described in section 2.1 of Berkowitz and Kilian (2000). Related with the statistical test for the phase difference, Ge (2008) showed that, under the null of no linear relation between two variables, the phase angle will be uniformly distributed. Hence it will be dispersed between $-\pi$ and π. Because of that, Ge (2008) argues that one should not use significance tests for the wavelet phase-difference. Instead, its analysis should be complemented by inspection of the coherence significance.

2.4 Causality

The Granger causality test is used after the VAR model estimation to examine the causality direction between two stationary series x_t and y_t. The linear causality test is based on a bivariate VAR representation of the two series, as follow:

$$x_t = a_1 + \sum_{i=1}^{k} \alpha_i x_{t-i} + \sum_{i=1}^{k} \beta_i y_{t-i} + \epsilon_{1t}$$

$$y_t = a_2 + \sum_{i=1}^{k} \gamma_i x_{t-i} + \sum_{i=1}^{k} \delta_i y_{t-i} + \epsilon_{2t}$$

where k is the lag length of the variables. We can thus test the following null hypotheses: (1) y does not cause x, which is represented as $H_{01} = \gamma_1 = \cdots = \gamma_k = 0$. In this case, causality runs from y_t to x_t when the null is rejected; in the second case, $H_{o2} = \alpha_1 = \cdots = \alpha_k = 0$, causality runs from x_t to y_t when the null is rejected; and finally, bivariate causality means that both hypotheses are rejected. The test statistic for these hypotheses has a standard Chi-squared distribution.

3. Empirical results

3.1 Data description

The data examined in this work correspond to the Solactive Global Lithium Index and the mergers and acquisitions in the U.S. oil and gas industry[3] between January 2011 and September 2017 using monthly data. The database was obtained from Bloomberg database.

In Figure 1 we observe the comparison between the M&A in the U.S. oil and gas industry and the Solactive Global Lithium Index.

[3] This study uses the daily number of mergers and acquisitions in the U.S. oil and gas industry to form the aggregate monthly series from 2011 to 2017.

[Insert Figure 1 about here]

We notice in Figure 1 that during the period after the Global Financial Crisis in 2008 there was a major recovery after 2010 (United States Geological Survey (2011) and Maxwell, 2014).

3.2 Empirical Results

Continuous Wavelet Transform

Figure 2 displays the wavelet coherency and the phase difference for the monthly prices of Solactive Lithium Index and the monthly M&A in the U.S. oil and gas industry showing evidence of varying dependence between both time series across different frequencies and over time.

[Insert Figure 2 about here]

The left panel (a) has the wavelet coherency between Solactive Global Lithium Index and M&A in the U.S. oil and gas industry. Frequencies are shown on the vertical axis, from scale 2 (a single month) up to scale 64 (approximately five years and four months), whereas time is shown in the horizontal axis, from the beginning to the end of the sample period.

The statistical significance of local correlations in the time-frequency domain was evaluated using Monte Carlo simulations. The regions surrounded by the black contour are the high coherence regions with significant values at 5%, that are the outcomes obtained. This analysis presents regions in time-frequency space where two time series are highly dependent, plotting those regions with cooler colors and plotting less dependence using warmer colors. The right panel has the phase differences: on the top (b) is the phase difference in the 1.5-16 frequency band; at the bottom (c) is the phase difference in the 16.5-64 frequency band. The frequency band helps to understand how the movement of both time series is, one in relation to the other. By analyzing the wavelet coherency between Solactive Global Lithium Index and M&A in the U.S. oil and gas industry, we appreciate at lower frequencies that M&A in the U.S. oil and gas industry dependence on lithium industry increased. The level of dependence starts at early 2014, reaching high levels of dependence centered at lower frequencies (from 8 to 16 months) until the end of the sample.

If we analyze the phase difference during the period of dependence, between 0 and $-\pi/2$, the correlation of the series is positive, and they move together and suggests that mergers and acquisitions are lagged the lithium industry. This result reinforces the M&A hypothesis, where M&A activities are pursued for strategic purposes and efficiency gains by achieving operational and financial synergies.

Unit roots methods

The VAR model is implemented to explore the lithium industry and mergers and acquisitions in the U.S. oil and gas nexus. Initially, unit root tests are used to examine the statistical properties of the series. We selected the Augmented ADF test (Dickey and Fuller, 1979), the PP test (Phillips and Perron, 1988) and the KPSS test (Kwiatkowski et al., 1992) to check for robustness. Table 1 displays the results, which clearly suggest that mergers and acquisitions in the U.S. oil and gas industry is stationary I(0) and Solactive Global Lithium Index is nonstationary I(1). These methods clearly indicate that we need to take first differences on the Solactive Global Lithium Index series to construct the VAR model.

[Insert Table 1 about here]

Granger causality test

The Granger causality test is used to examine the interactions between Solactive Global Lithium Index and M&A in the U.S. oil and gas industry. The Granger causality test is based on the VAR model with the variables placed in the following order: first difference of Solactive Global Lithium Index and mergers and acquisitions in the U.S. oil and gas industry. The test results are displayed in Table 2.

[Insert Table 2 about here]

The test, which is asymptotically distributed as a chi-square with four degrees of freedom is not statistically significant. The same happens when testing causality of mergers and acquisitions in the Solactive Global Index equation.

4. Discussion of the results and conclusions

Germeraad et al. (2017) concluded that the national oil companies are reacting to change by continuing to invest their internal research and development (R&D) in specialized exploration and production (E&P) areas advantageous to extraction of oil and gas in their own geographic regions. Also, oil companies are investing in M&A activities in renewable energy technology companies because oil companies lack sufficient core competence in the new renewable technology areas at specific points in time and they are using open innovation from outside to experiment and gain knowledge in renewable areas.

This paper contributes to the literature by reaching the interconnections between the main components of the lithium industry and M&A U.S. oil and gas industry in the time-frequency space. The novelty of our approach lies in the application of wavelet tools to solve it. To reinforce our results, we also use Granger causality tests after VAR model estimation to examine the causality direction between both time series.

The main finding of this paper, using wavelet coherence, is that the relationship between both time series were highly related at lower frequencies (long-term) from 8 to 16 months, where M&A U.S. oil and gas industry dependence on lithium industry increased, starting in the early 2014 until the end of the sample. Analysing the phase difference, we conclude that mergers and acquisitions are lagged the lithium industry during the period of dependence, reinforcing the argue that M&A activities are typically pursued for strategic purposes and efficiency gains by achieving operational and financial synergies.

In the last part of the paper, we use causality tests, and did not find any evidence of causality between the two time series examined. In relation with the present research we are now working in a new research paper implementing partial wavelet coherency following the works by Ng and Chan (2012) and Tiwari et al. (2016). In future papers we are also planning to look at this relationship from a different perspective allowing, for instance, for long range dependence and structural breaks endogenously determined by the model itself. Work in this direction is now in progress.

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Figure 1. M&A in the U.S. oil and gas industry and the Solactive Global Lithium Index.

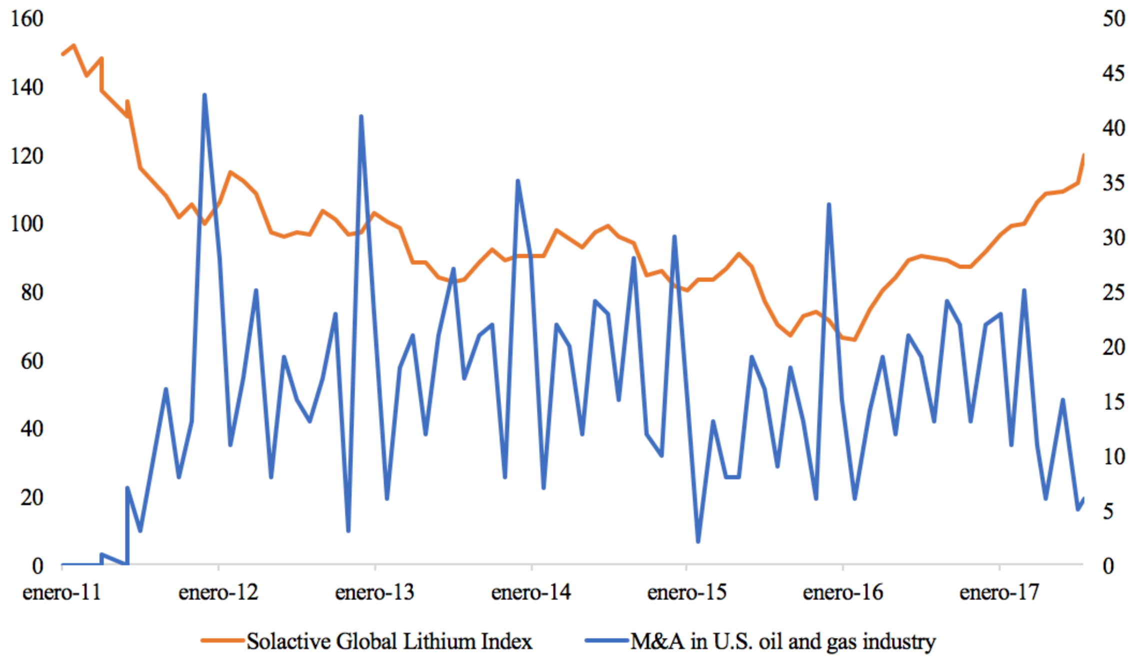
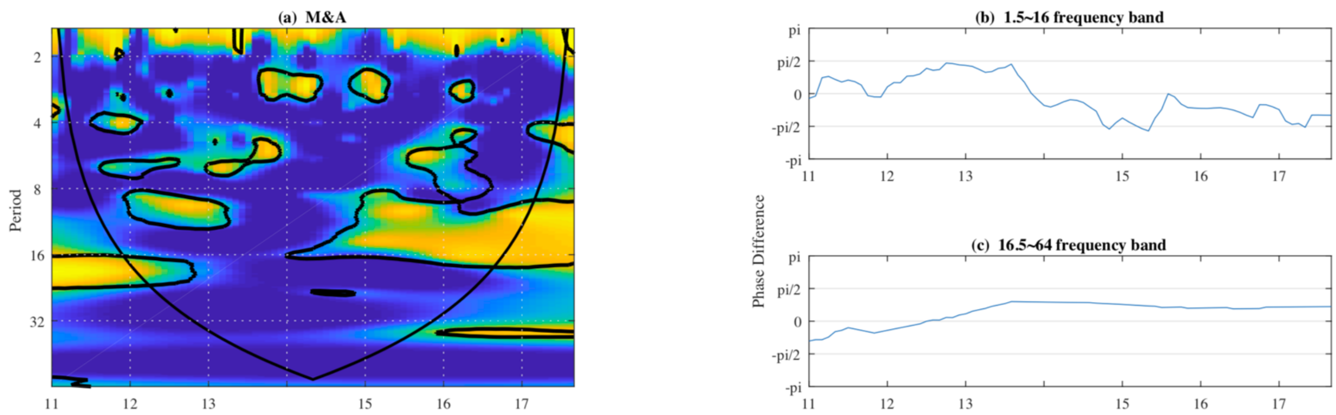


Figure 2. Wavelet coherency and phase difference between M&A in the U.S. oil and gas industry and Solactive Global Lithium Index.



The contour designates the 5% significance level. Coherency ranges from blue (low coherency) to yellow (high coherency). Left: Wavelet coherency between M&A in the U.S. oil and gas industry and Solactive Global Lithium Index. Right: Phase difference between M&A in the U.S. oil and gas industry and Solactive Global Lithium Index at 1.5-4 year (top) and 4.5-8 year (bottom) frequency bands.

Table 1: Unit root test results

	ADF				PP				KPSS	
	C		C&T		C		C&T		C	C&T
	TS	p-value	TS	p-value	TS	p-value	TS	p-value	TS	TS
M&A	-2.906792	0.0491	-2.667385	0.2529	-7.641971	0.0000	-7.600470	0.0000	0.172083	0.164025
Lithium Industry	0.918903	0.9953	2.626834	1.0000	0.615205	0.9894	2.423040	1.0000	0.253675	0.243672

Notes: TS - test statistic; C - Constant; T - trend.

Table 2: The Granger causality test results for the VAR model

Dependent	Independent	Chi-sq	Prob
D(Solactive)	M&A	4.788977	0.3096
M&A	D(Solactive)	6.444132	0.1683