HOW LITHIUM PRICES AFFECT MERGERS AND ACQUISITIONS IN THE LITHIUM INDUSTRY

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ABSTRACT

Is lithium affecting business strategies in the sector? We employ methodologies based on Continuous Wavelet Transform (CWT) and fractional integration and cointegration vector autoregressive models (FCVAR) models to analyze how lithium prices influence mergers and acquisitions (M&A) in the lithium industry over the world. The univariate and the multivariate results obtained using long memory methods support the nonstationary nature of the data, but they seem to be linked in the long-term through a fractional cointegrated relationship. In addition, analysis in the time-frequency domain indicates that both series are highly correlated from 2015 to 2017, finding that the lithium prices explain the M&A behavior after mid-2016 until early 2017.

Keywords: Lithium industry, lithium prices, M&A, fractional integration, fractional cointegration, wavelets.

JEL Codes: C22; E30; G30; Q02.

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1.- INTRODUCTION

Concern about issues related to natural resources has become especially relevant in recent years. The appearance of new uses and applications, especially of mineral resources and their derivatives, has caused companies to modify their behavior patterns at an economic level. Furthermore, the control of certain natural resources, considered strategic, is also a tool of geo-political control of enormous interest to governments at the global level, which in turn has unleashed innumerable conflicts of all kinds.

On the other hand, in recent years the notion and concern about climate problems has clearly increased. Along these lines, there is an important change in the socio-economic conception in favor of the use of more sustainable and less harmful energies against the environment. This has led to the generalization of the use and application of clean energy to the detriment of the traditional sources that mainly led by oil and coal. At this point, certain mineral resources have become key in the market, influencing in a decisive way the behavior of companies dedicated to their treatment and use.

In particular, this acceleration process in the use and implementation of clean energy has positioned lithium as a key mineral resource, as it is used as the main source of energy storage for them. This transition is especially remarkable in transportation, consuming most of the world's liquid fuel (BP Energy Outlook, 2017). Its wide applications in the development of different electronic components and especially for the manufacture of lithium-ion batteries for electronic devices of great importance in industries such as those of the electric car must be especially highlighted.

The increase in the demand for this type of technology has led to the consequent increase in the demand for lithium in the market, in addition to the increase in its perception as a strategic mineral resource for the industry. This fact, largely explained by the rapid growth of the electric car industry, has led to an increase in the price of lithium (Narins, 2017), in turn causing significant changes in the behavior of companies operating in this market.

The rich mineral area located in the intersection between Bolivia, Chile and Argentina and called "Lithium Triangle of South America" owns 50% of the planet's lithium resources and has become one of the focus of attention for investors in this sector, especially from China. It´s particularly in these regions where more mergers and acquisitions (M&A) are expected.

Moreover, during the past few months, it has been observed that there is a disconnect between the demand for electric vehicles and the battery industries that is explained by their dependence on supplying stocks from lithium mining.

Over the last months, the lithium market outlook has focused on supply consolidation through mergers and acquisitions in the industry. This process of consolidation of lithium resources through mergers and acquisitions, amid rising demand for the battery metal, may be broadly explained by its price behavior.

This paper examines how lithium prices influence mergers and acquisitions (M&A) in the lithium industry, applying methodologies based on Continuous Wavelet Transform (CWT) and fractional integration and co integration vector autoregressive (FCVAR) models. In particular, we use CWT to detect the evolution in the time-frequency domain, paying particular attention to the trend or long-run component in the time series (low frequency) and seasonality or the short-run component and the rapid changes in the time series (high frequency). Aguiar-Conraria (2011a) argues that this methodology is useful because stationarity is not required in the wavelet analysis and also because we can observe how relations evolve between time and frequencies. This is even more important as energy markets in particular, display consistent non-linear dependencies (Kyrtsou et al., 2009).

2.- LITERATURE REVIEW

Shock in a particular economy or industry can produce a profound reallocation of assets through mergers and acquisitions (Gort, 1969, and Coase, 2009). There are some authors that have studied the effect of prices on mergers and acquisitions (M&A) in several industries. Particularly, Monge et al. (2017) analyze how mergers and acquisitions in the petroleum industry is affected by oil prices. Studying its dynamics in the time-frequency domain, their results suggest that there have been some periods in which there was a clear influence of prices on M&A. In the same line, Boss et al. (2018) provides a novel perspective to the oil-stock market nexus by examining the predictive ability of M&A over West Texas Intermediate (WTI) oil returns and volatility using non-parametric quantile-based methodologies. Their findings suggest that M&A behavior plays an important role on predicting oil returns and market volatility. Harford (2005) affirms that economic, technological and regulatory shocks provide the fundamental reasons for M&A, and overall capital market liquidity conditions cause these activities to occur in waves. The literature review confirms that there are several papers dealing with merger waves including, among others, Nelson (1995), Golbe and White (1988, 1993), Mitchel and Mulherin (1996), Andrade et al. (2001), Harford (2005), Ravenscraft (1987), Shleifer and Vishny (1990) and Holmstrom and Kaplan (2001). Moreover, there are also papers such as Town (1992) and Resende (1999) that use switching models which should capture wave structure if it is present in the data and thus model the merger series.

EY Outlook (2018) show the key trends in mergers, acquisitions and capital raising in mining and metals. Monge et al. (2020) aim to analyze the time-series properties of M&A activity in the behavior of the lithium sector, applying statistical methods based on long memory and fractional integration models. Their results show that the series has a long memory and fractionally integrated behavior with an order of integration smaller than 1, so they can conclude that the impacts are transitory, expected to disappear in the long term by their own.

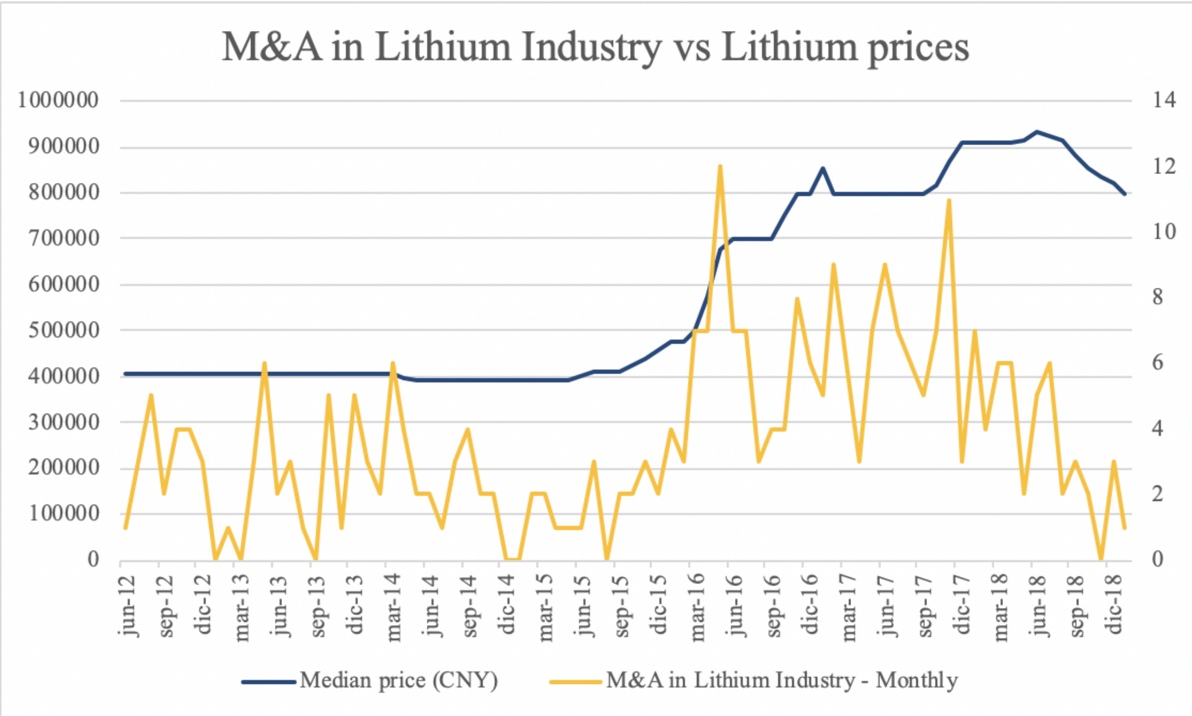
As far as we know, no previous studies have applied econometric methods to analyze the influence of prices on mergers and acquisition in the lithium industry. Therefore, this paper contributes to the literature by employing Continuous Wavelet Transform (CWT) and long memory and fractional integration and cointegration methods in order to see how price behavior affects M&A in the lithium industry.

The rest of the paper is organized as follows. The following section describes the dataset, while Section 4 presents the methods employed in the paper. In Section 5 we report the empirical results while Section 6 concludes the paper.

3.- DATA

Figure 1 details the data examined in this paper, which correspond to the mergers and acquisitions in the lithium industry all over the world from June 2012 to January 2019. These were obtained from the Thomson Reuters Eikon database. Also, we use the SMM Lithium Metal Spot Price Daily from the Shanghai Metals Market to get the lithium median prices from June 2012 to January 2019, obtained from Thomson Reuters Eikon database. For prices, we use monthly, weekly and daily data.

Figure 1: Time series plots



In line with the United States Geological Survey (2011) and Maxwell (2014), we observe that the M&A and the lithium prices series both increase after the Global Financial Crisis in 2008.

4.- METHODOLOGY

4.1 Fractional integration and cointegration

4.1.1. Fractional integration

Fractional integration means that the number of differences required in a time series to render it stationary I(0) is a fractional value. In other words, assuming that u_t is an I(0) process, we say that x_t is integrated of order d, or I(d), if it can be expressed as:

$$(1 - B)^d x_t = u_t, \qquad t = 1, 2, \ldots, \tag{1}$$

where B is the backshift operator ($Bx_t = x_{t-1}$) and u_t is I(0). If d > 0, x_t is said to be long memory, based on the large degree of dependence (or memory) between the observations. Moreover, as long as d is smaller than 1, the series is mean reverting in the sense that the shocks will have temporary effects unlike what happens with values of d which are equal to or higher than 1. The natural generalization of the concept of fractional integration to the multivariate case is fractional cointegration which is briefly presented in the following sub-section.

4.1.2 Fractional Cointegrated VAR

Johansen (2008) introduced a method to check for multivariate fractional cointegration denominated Fractionally Cointegrated Vector AutoRegressive (FCVAR) model. Johansen and Nielsen (2010, 2012) expanded this model. It is a further step of the Cointegrated Vector AutoRegressive model (Johansen, 1996), named also CVAR, which allows for fractional processes of order d that cointegrate to order d–b (b > 0). We could introduce the FCVAR model by referring first to the non-fractional CVAR model.

Let Y_t, $t = 1, \dots, T$ be a p-dimensional I(1) time series. The CVAR model is:

$$\Delta Y_t = \alpha\beta' Y_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Y_{t-i} + \varepsilon_t = \alpha\beta' L Y_t + \sum_{i=1}^{k} \Gamma_i \Delta L^i Y_t + \varepsilon_t. \quad (2)$$

To derive the FCVAR model we must replace the difference and lag operators Δ^b and $L_b = 1 - \Delta^b$, respectively, with $\Delta = (1 - L)$, and $Ly_t = y_{t-1}$. We then obtain:

$$\Delta^b Y_t = \alpha\beta' L_b Y_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \quad (3)$$

which is applied to $Y_t = \Delta^{d-b} X_t$ such that

$$\Delta^d X_t = \alpha\beta' \Delta^{d-b} L_b X_t + \sum_{i=1}^{k} \Gamma_i \Delta^b L_b^i Y_t + \varepsilon_t, \quad (4)$$

where ε_t is p-dimensional independent and identically distributed, with mean zero and covariance matrix Ω. Thus α and β are $p \times r$ matrices, where $0 \leq r \leq p$. The columns of β are the cointegrating relationships in the system, that is to say the long-run equilibria. Γ_i is the parameter that governs the short-run behavior of the variables. The coefficients in α represent the speed of adjustment responses to deviations from the equilibria and the short-run dynamics of the system.

Matlab computer programs for the calculation of estimators and test statistics were provided by Nielsen and Popiel (2018) and they have been employed in several empirical papers (Jones, Nielsen and Popiel, 2014; Baruník and Dvořáková, 2015; Maciel, 2017; Dolatabadi et al., 2018; Gil-Alana and Carcel, 2018; Yaya and Gil-Alana, 2019; Yaya et al., 2019; Tule et al., 2019; etc.).

4.2 Wavelet Analysis

The wavelet methodology is used to analyse time series in the time-frequency domain. Following Vacha and Barunik (2012), Aguiar-Conraria and Soares (2011, 2014), Dewandaru et al. (2016), Tiwari et al. (2016), Jammazi et al. (2017), and others that apply Continuous Wavelet Transform (CWT) in finance and economics research, two tools are used in this paper:

wavelet coherency and wavelet phase-difference.

There are two reasons for using this methodology: firstly, stationarity is not a requirement to carry out a wavelet analysis and, secondly, it is interesting to study the interaction of both the time and the frequency domains of the time series themselves to find evidence of the potential changes in their patterns.

The wavelet coherency is a two-dimensional diagram that correlates time series and identifies hidden patterns or information in the domain of time and frequency. The $WT_x(a,\tau)$ of a time series $x(t)$, that is obtained by projecting a mother wavelet ψ, is defined as:

$$WT_x(a,\tau) = \int_{-\infty}^{+\infty} x(t) \frac{1}{\sqrt{a}} \psi^* \left(\frac{t-\tau}{a}\right) dt, \tag{5}$$

where $WT_x(a,\tau)$ are the wavelet coefficients of $x(t)$; the position of a wavelet in the frequency domain is defined by a, and τ is the position in the time domain. Thus, the wavelet transform provides information concurrently on time and frequency by mapping the original series into a function of τ and a. The Morlet wavelet has been chosen as a mother wavelet to carry out our analysis since it is a complex sine wave within a Gaussian envelope, enabling the measurement of the synchronism between the time series. (see Aguiar-Conraria and Soares, 2014 for the properties of this wavelet).

To understand the interaction and the integration between the two series we use the wavelet coherence defined as:

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

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. 2014, for details). Matlab computer programs for the calculation of the estimators and test statistics in the CWT are provided in Aguiar-Conraria's website[1].

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

5.- EMPIRICAL RESULTS

5.1 Fractional integration

We start by presenting the results of the univariate time series. For each of the three series (daily, weekly and monthly) we consider the following regression model,

$$y_t \;=\; \beta_0 \;+\; \beta_1 t \;+\; x_t\,, \qquad (1-B)^{d_o}\, x_t \;=\; u_t\,, \qquad t \;=\; 1,\, 2,\, \ldots, \qquad (7)$$

where y_t refers to each of the individual series~~,~~; β_0 and β_1 are the coefficients referring respectively to an intercept and a linear time trend, and d is the potentially fractional differencing parameter.

Across Table 1 we display the estimates of d in (7) under three different set-ups: i) with no deterministic components, i.e., imposing $\beta_0 = \beta_1 = 0$ in (7); with a constant/intercept, i.e., $\beta_1 = 0$; and with a linear time trend, i.e., β_0 and β_1 both freely estimated from the data, and we report in bold in the table the relevant cases for each series according to the corresponding t-values of these deterministic terms. We make two assumptions on the error term. Thus, in the upper panel of the table, we refer to the case where u_t in (7) is a white noise process, while in the lower part (panel ii)~~)~~ we report the estimates of d under weak autocorrelation in u_t; however, instead of imposing here a specific ARMA modelling framework, we use a non-parametric approach due to Bloomfield (1973) that accommodates very well in the context of fractionally integrated processes (see, Gil-Alana, 2004).

Table 1: Estimate and confidence bands of d for the prices of lithium

i) No autocorrelation			
Data frequency	No terms	An intercept	A linear time trend
Daily	1.00 (0.96, 1.03)	0.97 (0.94, 0.99)	**0.97 (0.94, 0.99)**
Weekly	0.98 (0.92, 1.07)	**1.16 (1.10, 1.25)**	1.16 (1.10, 1.25)
Monthly	0.95 (0.82, 1.14)	**1.46 (1.31, 1.68)**	1.46 (1.32, 1.68)
ii) with autocorrelation (Bloomfield)			
Data frequency	No terms	An intercept	A linear time trend

Daily	0.99 (0.94, 1.05)	**1.06 (1.02, 1.09)**	1.06 (1.02, 1.09)
Weekly	0.98 (0.86, 1.11)	**1.08 (0.99, 1.16)**	1.08 (0.99, 1.16)
Monthly	0.86 (0.64, 1.21)	**1.25 (1.07, 1.50)**	1.25 (1.05, 1.50)

In bold, the significant cases in relation with the deterministic terms. In parenthesis, the 95% confidence bands of the values of d.

The first thing we observe across Table 1 is that the time trend coefficient is significant in only a single case, corresponding to the daily data under the assumption of white noise errors; in all the remaining cases the intercept is sufficient to describe the deterministic part of the data. Looking at the degree of persistence by means of the estimates of d we see that mean reversion only takes place in the case of the daily data under the assumption of uncorrelated (white noise) errors, while in all the other cases the estimates of d are in the I(1) interval or they are significantly above 1, implying lack of mean reversion. Thus, we observe nonstationarity and high degrees of persistence in the three series.

5.2 Fractional Cointegrating VAR

We use the FCVAR approach to analyze the relationship between the time series and measure its degree of integration. We force *d* to be equal to *b*, assuming then that the cointegration residuals are I(0), which is consistent with the classical cointegration approach. However, we allow the individual series to display an order of integration different from 1.

First, we determine the lag augmentation in the system. We provide two estimations for the corresponding lag levels for each variable. For each level, we check the significance through likelihood ratio (LR) tests. Following Jones, Nielsen and Popiel (2014), we use k = 3 as a lag value.

The next step is to select the number of the cointegrated vectors in the system determined by rank. Testing the following hypothesis: $H_0\colon rank = r$ and $H_1\colon rank = p - 1$, here $r = 0,1,2, ...$ and p is the number of variables in the system. For the alternative ranks, the first non-rejected value is the number of cointegrated vector in the system. Following MacKinnon and Nielsen (2014) we accept $r = 1$ because a single lag seems to be sufficient in the fractional model to capture the serial correlation in the residuals. The estimated parameters in the FCVAR are displayed in Table 2.

Table 2. Results FCVAR model

	d	Cointegrating Equation Beta (ß)	
		M&A	Lithium prices
Panel I: M&A and Lithium prices	0.698 (0.072)	1.000	-0.000
	$\Delta^d\left(\begin{bmatrix} M\&A \\ Lithium\ Prices \end{bmatrix} - \begin{bmatrix} 2.251 \\ 404416.690 \end{bmatrix}\right) = L_d \begin{bmatrix} -0.566 \\ 1809.296 \end{bmatrix} v_t + \sum_{i=1}^{2} \hat{\Gamma}_i \Delta^d L_d^i (X_t - \mu) + \varepsilon_t$		

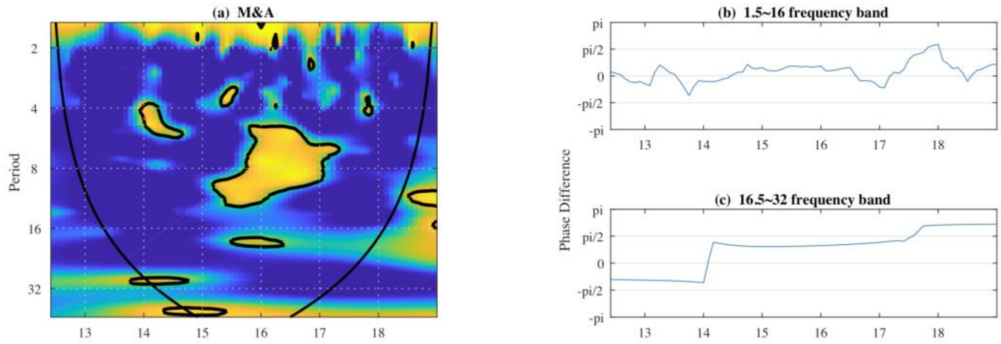
Analyzing the results from the FCVAR model, we conclude that a negative impact in the lithium industry affects mergers and acquisitions in the industry. Also, we observe that the value of the fractional differencing parameter in the joint representation of the variables is 0.698 (0.072), meaning that the series are clearly nonstationary and close I(1). Note that since we impose d = b in the model, the residuals must be I(0) and thus, cointegration errors are mean reverting, meaning that in the long term there are no deviations in the stock prices. Therefore, the beta behavior will be fulfilled.

5.3 Wavelet analysis

After the cointegrating analysis between Mergers and Acquisitions (M&A) in the lithium industry and prices, we analyze, in the time-frequency domain, the dynamic correlation to achieve a robust analysis.

Figure 2 displays the wavelet coherency and the phase difference for the monthly data of the cited time-series, showing evidence of varying dependence between both time series across different frequencies and over time.

Figure 2. Wavelet coherency and phase difference between time series.



Left: Wavelet coherency. The contour designates the 5% significance level. Coherency ranges from blue (low coherency) to yellow (high coherency). Right: Phase difference prices at 1.5-16 months (top) and 16.5-128 months (bottom) frequency bands. The cone of influence is shown with a thick line, which is the region subject to border distortions

Analyzing the wavelet coherence between M&A in the lithium industry, we notice that the level of dependence starts early in 2015, reaching high levels of dependence centered at higher frequencies (from 5 to 12 months) in the year 2017. After 2017, the dependence for the short run dissipates.

If we analyze the phase difference during the periods of dependence, it is between 0 and $\pi/2$ until mid 2016, having a positive correlation between the time series which suggests that M&A leads the behavior of the lithium industry. After mid-2016 and until early 2017 the correlation is negative (between 0 and $-\pi/2$), concluding that the prices in this period explain M&A in the lithium industry.

6.- CONCLUDING REMARKS

In this paper, we have examined how lithium prices influence mergers and acquisitions (M&A) in the lithium industry applying methodologies based on Continuous Wavelet Transform (CWT) and fractional integration and cointegration vector autoregressive (FCVAR) models.

Focusing on the results based on long memory methods, both the univariate and the multivariate results support the nonstationary nature of the data, though they seem to be linked together in the long run throughout a fractional cointegration relationship. Thus, exogenous shocks affecting the individual series will have permanent effects, not disappearing by themselves in the long run; however, in the joint representation of the two series, we find a long run equilibrium relationship between the two.

The results obtained from the wavelet coherency in the time-frequency domain analysis indicate that both series are highly correlated from 2015 to 2017, extending from 5 to 12 months. Moreover, from 2015 to mid-2016 there is a positive correlation between prices and M&A with this last leading. However, after mid-2016 and until early 2017 the correlation is negative, what means that prices are leading and explain M&A behavior.

DATA AVAILABILITY STATEMENT

The data employed in this evaluation is downloaded from Thomson Reuters Eikon database. In accordance with International Journal of Finance and Economics we will make all data available upon request.

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