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Exploring Correlations and Volatility Linkages between Lithium and Oil Markets

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NOVA Information Management School
Instituto Superior de Estatística e Gestão de Informação
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EXPLORING CORRELATIONS AND VOLATILITY LINKAGES BETWEEN LITHIUM AND OIL MARKETS

By

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Master Thesis presented as partial requirement for obtaining the Master's degree in Statistics and Information Management, with a specialization in risk management and analysis

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STATEMENT OF INTEGRITY

I hereby declare having conducted this academic work with integrity. I confirm that I have not used plagiarism or any form of undue use of information or falsification of results along the process leading to its elaboration. I further declare that I have fully acknowledge the Rules of Conduct and Code of Honor from the NOVA Information Management School.

Leonardo Nogueira

Lisboa, 2023

DEDICATION

I dedicate this thesis to my loving family, whose unwavering support have been my anchor throughout this academic endeavor.

To my advisor, for his constructive criticism and for having accompanied this work so that it had the best possible version.

I also extend my appreciation to my friends, colleagues and professors who have shared this academic voyage with me. Your camaraderie and collaborative spirit have made the challenges more manageable and the successes more joyful.

Last but not least, to my girlfriend who was and is my pillar and without her encouragement and insights this project wouldn't have been the same.

Thank you!

ABSTRACT

There is an urgent need for an energetic transition, and we are increasingly feeling this pressure from the world's population, and lithium is one of the elements necessary for that. There are indications that electric cars could be the future of the automotive industry, replacing cars powered by fossil fuels. To do this, we need to produce batteries with that precious element, lithium. This study analyses the correlations between five of the largest lithium mining companies based in the USA and China and WTI crude oil. In this paper we focus on the returns of the companies to study their correlations and on the volatilities to study their Volatility Spillovers. It’s known that lithium mining companies and crude oil are not strongly correlated, however they have a strong persistence in their correlation. WTI also doesn't have much influence when it comes to changing the prices of lithium companies, as it is much more self-correlated. Even in these unstable times when we have been through a pandemic and are currently going through a geopolitical conflict, there have been no significant changes in the correlations between these markets.

KEYWORDS

LITHIUM; WTI CRUDE OIL; CORRELATION; VOLATILITY SPILLOVERS; GARCH

Sustainable Development Goals (SGD):

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LIST OF ABBREVIATIONS AND ACRONYMS

ALB – ALBERMARLE CORPORATION

SQM – SOCIEDAD QUIMICA Y MINERA DE CHILE

LAC – LITHIUM AMERICAS CORPORATION

GAF – GANFENG LITHIUM CORPORATION

TIA – TIANQI LITHIUM

WTI – WEST TEXAS INTERMEDIATE

GARCH - GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSKEDASTICITY

CNY – CHINESE YUAN RENMINBI

USD – UNITED STATES DOLLAR

1. INTRODUCTION

The rapid development of new technology has led to the emergence of numerous new sectors, many of which are dependent on essential minerals. As a result, the dynamics of supply and demand in the global energy and mineral sectors have significantly changed (Liu D, Gao X, An H, Qi Y, Wang Z, Jia N, Chen Z, 2020). To be more specific, advances in green technology have increased energy efficiency and encouraged the use of renewable energy sources, thereby decreasing dependency on fossil fuels. In the United States, approximately 25 percent of greenhouse gas emissions are related to the driving activities of passenger cars on the roads. Fossil fuels, namely gasoline and diesel, constitute nearly 90% of the fuels used in that type of automobiles. Shifting passenger cars to renewable energy sources, such as low-carbon electricity and biofuels, is considered one of the most promising approaches to significantly decrease greenhouse gas emissions (Agusdinata, Liu, Eakin & Romero, 2018).

The main mineral in this study will be lithium, although this mineral is used in many other activities like ceramics, medicine, metallurgy, or warfare, its major and principal use nowadays is in rechargeable batteries, often known as lithium-ion or Li-ion batteries. With the global environmental crisis and with the fickle oil prices, there's a rising demand for electric and hybrid vehicles. The battery module's capabilities have a huge impact on how well electric cars perform. Due to their high energy density, lack of memory effect, and long lifespan, among other advantages, lithium-ion batteries are widely used as the main power source for electric cars (Cheng, Shuai, Tang & Changfa, 2023). The growing demand for these cars leads to an increase in the production of these batteries which is emerging as the primary driver for the increasing lithium consumption.

Despite this increasing number of hybrid and electric cars on the roads, we still have oil as the main source of energy for automobiles and there are studies that still expect oil to continue to be the principal type of fuel, due to a not so fast energy transition and also due to the fact that crude oil is one of the principal materials influencing the global economy (Batten, Ciner & Lucey, 2017).

Global inflation is increasing, there is an environmental awareness and an intention to reduce carbon emissions, and also a geopolitical battle is currently ongoing. All of this has a significant impact on the oil markets with the prices being very unstable. In addition, there was recently a pandemic that had an impact on all the markets (Samitas, Kampouris & Polyzos, 2022). Later in this research, we will examine what occurred at that time in the markets for lithium and oil.

Investing directly in lithium as a commodity is subject to restrictions, unlike other industrial metals, so there are two different indirect methods for investing in lithium. The first includes buying Exchange

Traded Funds (ETFs) that specialize in lithium and battery technology, such as Global X Lithium & Battery ETF. Investors may invest money into companies that are specifically engaged in lithium mining thanks to these ETFs. The second strategy involves acquiring shares in firms involved in the lithium sector, giving investors exposure to lithium prices (Będowska-Sójka & Górka, 2022).

This dissertation aims to find out if there is any correlation and volatility between the oil and lithium markets. In uncertain times, where inflation, war and COVID-19 were in the news every day around the world, how did these two materials behave in terms of their stock markets.

The rest of the paper runs as follows. Section 2 gives a Literature Review that was made for this study, Section 3 we present the data, Section 4 we give a brief overview about the methodology used, Section 5 is where we discuss the results obtained and finally in Section 6, we make a short conclusion about this work and talk about future projects that could be carried out.

2. LITERATURE REVIEW

Before moving on to the practical part and the data, we did a literature review where we tried to understand more about the subject and what other researchers have studied.

In a research conducted by Irfan, Rehman, Liu & Razzaq (2022), it is suggested that mineral markets play a crucial role in influencing the worldwide progress of clean energy and the development of low-carbon power generation. Also, they say that the extraction of minerals used to manufacture batteries (namely those used in electric vehicles) will increase, and in the realm of advanced technologies related to energy transitions and low-carbon power generation, certain minerals such as copper, lithium, nickel, and graphite are projected to hold a prominent position. In addition, the authors refer that economic growth, renewable energy adoption, and foreign direct investment, particularly in mineral-rich developed countries, play a positive role in promoting energy transition, aligning with the goals of sustainable development.

Another research more focused on the lithium market, Li, Sengupta, Mohammed & Jamaani (2023), tried to forecast lithium prices using a comparison of machine learning approaches and reliable time series forecasting methodologies, he estimates lithium mining companies have an opportunity to enter new markets due to the lithium prices and the continuous demand of the element. On the other hand, they say, from an investing point of view, the downside risk lies in the volatility and uncertainty in the demand and supply of lithium, which can result in losses for investors who are considering doing it.

Moreover, regarding the oil market, we have Singh, Kumar, Nishant (2019), who show in the results of their paper that crude oil holds a vital position as a commodity that connects important asset markets around the world. Syed & Bouri (2021) conducted a study examining the impact of economic policy uncertainty and oil prices on stock market volatility for both oil importers and exporters. The findings indicate that the spillover effects of global economic policy uncertainty and oil prices have distinct implications on the returns of importers and exporters, with the outcomes varying based on whether the countries involved are classified as developing or developed. In addition, Adekoya, Asl, Oliyide & Izadi (2023), studied the cross-correlation between crude oil from European and non-European markets during the Russia-Ukraine war. This war, indirectly, has increased the price of crude oil, influencing the economy of both oil-importing and oil-exporting countries. Then through the cross-correlation analysis, strong evidence suggests that oil has a more significant influence on the persistence of stock markets during the war compared to the pre-war period. While oil prices had a minimal impact on stock market performance before the war, the opposite holds true during the war, leading to a loss of market efficiency.

In recent research, Wei, Qi, Ren & Gozgor (2023), continued the existing literature about the relationship between oil markets and green bonds, but considering the impact of COVID-19 on their dynamic correlation, they conclude that significant changes observed at the extreme quantile level indicate that during extreme market conditions, the stability is disrupted, potentially resulting in a highly influential relationship.

Naeem, Hamouda, Karim & Vigne (2023) performed a research considering cryptocurrencies and commodity markets before and during Covid-19 and Ukrainian-Russian war periods. It was noted that spillovers during these two periods were particularly high, so there is evidence health and geopolitical conflicts affect the return and volatility system.

Oliyide, Adekoya & Khan (2021) conducted an analysis to explore the dynamic relationship between the oil and metal markets, including gold, silver, aluminum, copper, and iron. Their findings reveal an increasing trend of financialization within the oil market, accompanied by a limited capacity to effectively hedge globally traded metals. Additionally, Youssef & Mokni (2021), conduct a study investigating the influence of oil shocks on gold prices. They discover that the state of both markets affects how gold prices respond to oil shocks.

Furthermore, in our literature, we found other studies that have forecasted crude oil and refined products volatilities and correlations using multivariate GARCH models Marchese, Kyriakou, Tamvakis & Di Iorio (2020). Another method is to study the tail dependence of the oil markets using copula method Li & Wei (2018). However, there's a study, closed related to ours, Będowska-Sójka & Górka (2022) performed a study on the independence and connection between lithium mining companies (Chinese and American) and the price of oil. According to this paper American lithium mining stocks exhibit a weak correlation with oil price changes, yet their correlation is stronger than that of Chinese companies. Regarding their correlations, they are similar within markets but differ across markets. Although the tail dependence is strongest between American and Chinese companies, there is no dependence between oil and lithium producers.

Other study that study lithium industry and crude oil prices is conducted by Monge & Gil-Alana (2021). However, this paper only refers to the American markets, and uses a different methodology to investigate the relationship between the prices of these two markets. They use ARFIMA (p,d,q) model, Fractional cointegrated VAR and Wavelet analysis. They state that at short-run the lithium industry are weakly correlated with WTI crude oil prices and in long-term the time series showed a high level of dependence between late 2021 and mid 2016, concluding that the lithium mining companies reflect and foreshadow the responsiveness of the WTI crude oil prices during that period.

Following the research line started by Monge & Gil-Alana (2021) and Będowska-Sójka & Górka (2022), to the best of our knowledge, this is the first research to verify the correlation and volatility of WTI crude oil prices with lithium mining industry stock prices from two different countries, considering the global inflation we are going through in the world, and also the geo-political conflict between Ukraine and Russia.

In our study, we intend to show how the markets of oil and lithium are correlated and their volatility spillover. To do so, we purpose the use of multivariate GARCH models to study the dynamic conditional correlation between these markets and also see the difference between American and Chinese markets. For the volatility spillover, we're going to study it in two different ways, the first in a static way between all the stock markets and WTI and the second in a dynamic way from WTI to all the other markets together and in pairs with WTI and each one of the lithium producer companies' stock prices. For this method we will use the spillover index model.

3. DATA

Since the trading dynamics of lithium differ from other metals, our study centers on examining the performance of lithium producers and their sensitivity to changes in oil prices. Our study considers five of the most significant companies from two stock exchanges that are actively involved in lithium mining and/or production. These companies are: Ganfeng Lithium, Tianqi Lithium, Albermarle, Sociedad Quimica y Minera de Chile and Lithium Americas Corporation. The first two are listed in the Chinese stock exchange and the last three companies listed in the US stock exchange. While the stocks of these companies are listed on both the US market and the Shenzen Stock Exchange in China, it is important to note that some of these companies operate their businesses in other countries. For the crude oil, our intention is to use West Texas Intermediate (WTI) prices to further analysis with the lithium companies previously denoted.

Our data was imported from two different websites, for the lithium companies it was from Yahoo! Finance, and for the WTI crude oil prices was from investing.com. It will cover the dates from January 1, 2016 and March 31, 2023. America and China have different holidays and we considered that, so we only consider the days that both markets were open, having the samples the same number of days. So, in total we have 1698 observations for each company and WTI.

Also, the lithium companies based in the Shenzen Stock Exchange were with their prices in Yuan, so to convert the values to US dollars we used the historical data for CNY/USD from Yahoo! Finance. Thus, we multiplied the given prices of the companies on a specific day with the conversion value of the respective day. This analysis is performed on the logarithmic returns of the samples, this can be calculated using the formula

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (1)$$

where Pt and Pt−1 are the closing price in time t and t−1, respectively.

We will present the descriptive statistics for the data we have available. These results are shown in Table 1. According to the statistics presented, LAC has the highest rate of returns with 17% and WTI the lowest with only 4,1%. We can also see that all of them have a positive average rate of return. From the standard deviation we can see that LAC has the highest volatility, while ALB and SQM both have a low and approximate volatility value. We can verify that TIA and LAC have a positive value in skewness and all of them have positive value in Kurtosis which means all are leptokurtic, however ALB, SQM and specially WTI have a big value meaning that they have excess kurtosis. Also, we did the Jarque-Bera test for assessing whether this dataset follows a normal distribution or not (Jarque & Bera, 1980), and the Ljung-Box test to check any significant autocorrelation in our dataset (Ljung & Box, 1978). From the Jarque-Bera test there's no statistical evidence from the data to admit the normality of results. The Ljung-Box test shows that the data for the SQM, TIA and WTI have a p-value of less than 0.05 and high values, confirming that these companies show auto-correlation.

Table 1 – Descriptive statistics and tests regarding rates of returns

	ALB	SQM	LAC	TIA	GAF	WTI
Min	-0.22202	-0.18106	-0.24297	-0.13019	-0.12838	-0.41765
Max	0.20414	0.18800	0.26726	0.12016	0.11836	0.40352
Mean	0.00087	0.00107	0.00170	0.00063	0.00093	0.00041
St. Dev.	0.02824	0.02933	0.04890	0.03702	0.03542	0.03212
Skewness	-0.45026	-0.27643	0.35035	0.12718	-0.00670	-1.72930
Kurtosis	6.77852	3.95428	2.40486	0.99314	1.22749	49.19333
Jarque-Bera	3317.4	1131.9	445.88	74.99	107.42	172389
Ljung-Box	5.6078	16.3930	1.9469	21.1780	0.3127	50.1300
p-value	0.2304	0.0025	0.7455	0.0003	0.9890	0.0000

Note: Jarque-Bera test for normality has a p-value inferior than 1%; Ljung-Box test for auto-correlation with lag 4

4. METHODOLOGY

To assess whether there exists any dependence, correlation, or volatility between the lithium and oil markets, we will employ two distinct methods. We will start by performing unit root tests, which are crucial for our research because we need our data to be covariance stationary. There are several ways to perform them, but to maintain consistency with past investigations, we shall apply the techniques frequently used in earlier researches. The tests we're talking about are: ADF tests, developed by Dickey & Fuller (1979) and the PP tests introduced by Phillips and Perron (1988).

After these tests were finished and reaching conclusions from them, we moved on to the main objective of this study, which is the estimation of correlation and volatility. First, we use conditional correlation models (GARCH Models) to examine correlations and their potential fluctuations. The other method used for this study is the volatility spillover, which enables us to verify if the fluctuations in the volatility of the lithium companies impact the volatility of the crude oil or vice-versa.

4.1. DYNAMIC CONDITIONAL CORRELATION

In this section, we describe the models used to estimate the dynamic conditional correlation for our dataset. Given our data and what we want to analyze, we will use the generalized autoregressive conditional heteroscedasticity model, mostly known as GARCH model. Engle (1982) first introduced the ARCH model and Bollerslev (1986) later brought the generalized ARCH model known as GARCH(p,q). The mathematical expression for GARCH may be written as it follows:

$$l_t = \theta + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i l_{t-i} \quad (2)$$

The first time dynamic conditional correlation model was mentioned was by these two independent studies Engle (2002) and Tse & Tsui (2002) which is based on the constant conditional correlation (CCC) model introduced by Bollerslev (1990). The CCC-GARCH model is simpler than the one used in this study because it assumes that all conditional correlations remain constant. Then it was developed the DCC-GARCH model which allows the estimation of the changing conditional correlations and conditional variances among multiple distinct variables over time. Engle (2002) defined the DCC-GARCH model with the following equations:

$$H_t = D_t R_t D_t \quad (3)$$

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha \widetilde{e_t}\widetilde{e_t}' + \beta Q_{t-1} \quad (4)$$

$$\rho_t = Q_t^{*-\frac{1}{2}} Q_t Q_t^{*-\frac{1}{2}} \quad (5)$$

$$\varepsilon_t = \sqrt{H_t} z_t \quad (6)$$

In these equations we have the matrix H_t which is the dynamic condition covariance matrix and is calculated by multiplying two different matrices the first one D_t which denotes the conditional standard deviation of all the returns and the other one ρ_t represents a time varying correlation matrix of the z_t. Also, we have $\overline{Q}$, a matrix representing the unconditional covariance matrix of the standardized errors, Q_t is a symmetric positive definite matrix, $\widetilde{e_t}$ is the standardized error vector and α and β are non-negative scalar parameters satisfying $\alpha + \beta < 1$. z_t is a vector of the standardized error residuals ε_t.

Despite the availability of the ADCC-GARCH model, introduced by Cappiello, Engle & Sheppard (2006), which assesses asymmetry in time-varying conditional volatility spillover among asset returns, this paper opts for employing the DCC-GARCH model.

Estimating the DCC-GARCH model can be accomplished through a two-stage process employing the quasi maximum likelihood (QML) technique. Firstly, the univariate GARCH models are estimated for each asset series, then in the subsequent stage, we conduct the estimation for the conditional correlation equation.

There are various models in the GARCH family, but taking into account previously published and studied articles, and considering the data we have at our disposal, we realize that the best models belonging to the GARCH family to use are: GARCH, EGARCH, IGARCH, GJR-GARCH and AVGARCH. We opted for the GARCH model based on the Akaike (AIC) and Bayesian (BIC) information criteria. Although we have estimated all the GARCH models mentioned above for all the companies and WTI, we will only detail the models that best suit each one[1].

The exponential GARCH (EGARCH), developed by Nelson (1991), provides an alternative asymmetric model considering the leverage effects of price change on conditional variance and it follows the following equation:

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \alpha \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \left[\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right] \quad (7)$$

Where β is defined by the reflection of the degree of fluctuation and γ shows the asymmetry. Comparing this EGARCH with the original model GARCH the advantage is that it can distinguish the distinct impacts of positive and negative news.

[1] The results of all GARCH models for all companies and for WTI are available upon request.

Another best fitted model is the Integrated GARCH, another linear GARCH class model, developed by Engle & Bollerslev (1986) is as below:

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{p}(\alpha_i)\varepsilon_{t-i}^2 + \sum_{j=1}^{q}\beta_j\sigma_{t-j}^2 \quad (8)$$

The IGARCH model closely resembles the standard GARCH model, but the parameter constraint ω_0 is greater than 0 and it is recommended the use this model when $\sum_{i=1}^{q}\alpha_i + \sum_{i=1}^{p}\beta_i \approx 1$ and for IGARCH it is assumed that:

$$\sum_{i=1}^{q}\alpha_i + \sum_{i=1}^{p}\beta_i = 1 \quad (9)$$

GJR-GARCH is a simplification of the EGARCH model that was developed by Glosten et al. (1993) and can capture asymmetry in the time-varying volatility and is defined as it follows:

$$\sigma_t^2 = \omega_0 + \sum_{i=1}^{q}\alpha_i\gamma\left(\varepsilon_{t-i}^2\right)d_{t-i} + \sum_{j=1}^{p}\beta_j\sigma_{t-j}^2 \quad (10)$$

In this equation we have a dummy variable d_t and the asymmetry parameter γ which will be relevant when ε_{t-i} is less than zero causing $d_t = 1$.

4.2. VOLATILITY SPILLOVER

In order to measure the volatility spillover effects among lithium companies and the oil market we employ the spillover index model of Diebold & Yilmaz (2012). It relies on the forecast error variance decomposition of the VAR model and enables the computation of volatility spillover indices. Furthermore, this method can measure both the strength and direction of spillover effects among various variables.

To begin, we will define a VAR(p) model as:

$$Y_t = \sum_{i=1}^{p}\theta_i\, Y_{t-i} + \varepsilon_t \quad (11)$$

This formula (11) can be written as moving average form with this equation:

$$Y_t = \sum_{k=0}^{\infty}A_k\,\varepsilon_{t-k} \quad (12)$$

Where A_k is a matrix of coefficients of order n x n, obeying the following recursive process:

$$A_k = \sum_{k=0}^{p}\theta_i\, A_{k-p} \quad (13)$$

In the estimation of the VAR(p) model, a variance decomposition is employed to assess how much each variable contributes to explaining the variations observed in the other variables within the set.

According to Diebold & Yilmaz (2012) we can define the H-step-ahead prediction error variance decomposition as:

$$\vartheta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \sum e_j)^{2}}{\sum_{h=0}^{H-1}(e_i' A_h \sum A_h' e_i)} \quad (14)$$

In this formula $\sum$ is the covariance matrix of the error vector ε_t, σ_{jj} is the standard deviation of the j-th error term and e_i is the n x 1 dimensional i-th element. Hence, to normalize each element in the decomposition matrix, we can achieve this by dividing the sum of the rows, as follows:

$$\widetilde{\vartheta_{ij}^{g}}(H) = \frac{\vartheta_{ij}^{g}(H)}{\sum_{j=1}^{K}\vartheta_{ij}^{g}(H)} \quad (15)$$

With these values obtained in the eq. (15) we can construct four different formulas to calculate spillover indexes:

$$S^{g}(H) = \frac{\sum_{i,j-1,i\neq j}^{K}\widetilde{\vartheta_{ij}^{g}}(H)}{\sum_{i,j=1}^{K}\widetilde{\vartheta_{ij}^{g}}(H)} \times 100 \quad (16)$$

$$S_{i\cdot}^{g}(H) = \frac{\sum_{j-1,i\neq j}^{K}\widetilde{\vartheta_{ij}^{g}}(H)}{\sum_{i,j-1}^{K}\widetilde{\vartheta_{ij}^{g}}(H)} \times 100 \quad (17)$$

$$S_{\cdot i}^{g}(H) = \frac{\sum_{i,j-1,i\neq j}^{K}\widetilde{\vartheta_{ij}^{g}}(H)}{\sum_{i,j-1}^{K}\widetilde{\vartheta_{ij}^{g}}(H)} \times 100 \quad (18)$$

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H) \quad (19)$$

The first equation (16) is the Total Spillover index, it basically measures spillovers across all stock markets we have in the database. Next, in equation (17) we have the From Spillover, which indicates the volatility spillover received by stock i from all other stocks and in equation (18) it's the opposite, the spillover transmitted by stock i to all other stocks, called To Spillover. The last one (19) is the Net Spillover where it is the difference between the To and From Spillovers.

The findings were obtained through the utilization of R programming, using the package developed by *Krehlik (2023)* 'frequencyConnectedness' and other package named "Spillover".

5. RESULTS AND DISCUSSION

We initiate the analysis by conducting the typical unit root tests for our returns (the measure used in this work) that are described in Section 4. We perform these tests because we need our series to be covariance stationary and as shown in Table 2 the results present large negative values in ADF and PP tests rejecting the null hypothesis of a unit root at the 1% level significance, leading to the stationarity of daily closing price returns.

Table 2 – Unit Root Tests

	ALB	SQM	LAC	TIA	GAF	WTI
PP	-1592.6	-1634.2	-1598.7	-1622.5	-1656.2	-1584.7
p-value	0.01	0.01	0.01	0.01	0.01	0.01
ADF	-11.489	-12.322	-12.183	-10.72	-10.958	-12.234
p-value	0.01	0.01	0.01	0.01	0.01	0.01

Note: PP – Phillips–Perron Unit Root Test; ADF - Augmented Dickey–Fuller Test.

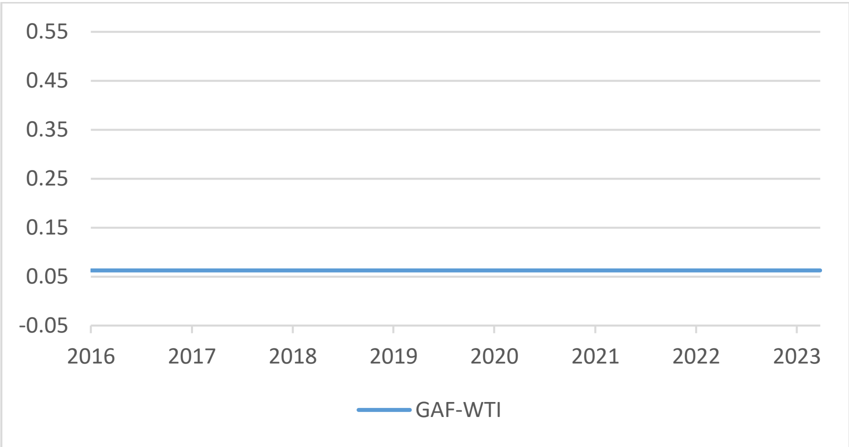
5.1. OUTCOME OF DCC-GARCH MODEL

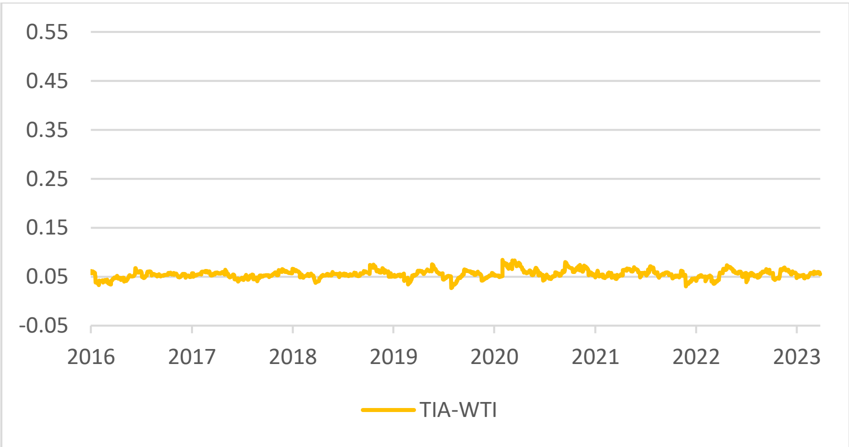
The first step was to obtain the estimates from univariate GARCH models. The models follow to different distributions, such as Student's t-distributions, the Generalized Error Distribution (GED), and a skewed adaptation of each. The motivation for exploring distributions beyond the normal lies in the fact that a GARCH model with conditional normal errors presents heavier tails than the normal distribution. This choice is particularly relevant because, in the context of financial time series, the standardized innovations continue to display leptokurtic characteristics. Hence, it appears more suitable to assume a leptokurtic unconditional distribution for the models. The outcomes of the models that most suitably match each of the stocks in the dataset are presented in Appendix Table 1.

In the next part of the analysis, we will apply the DCC-GARCH model estimation, which has the capacity to accommodate time-varying conditional correlation, enabling the consideration of dynamic beta values. We paired each lithium company with the WTI return values and Table 3 displays the estimations of DCC-GARCH (1,1) for the sample. The statistically significant estimated DCC parameters, α and β, indicate a substantial level of persistence in the conditional correlation process. If the sum of both parameters it's close to 1, it means that the pair shows a strong persistence in correlation. For our data, we can see in Table 3 that for the ALB/WTI and SQM/WTI pairs the persistence in the correlation is lower than that on the other pairs, which have a sum of approximately 0.789 and 0.725 respectively, while the other pairs all exceed 0.9 in the sum of their parameters. We also built a graph (Figure 1), where we can see the conditional correlations compared for each pair over time. It is easy to see from the Figure 1 that the values of the conditional correlation between WTI crude oil and companies based in America are almost always higher than those of companies based in China. There were also some sharper swings during the initial Covid-19 period for American companies, with the SQM-WTI pair reaching values close to 0.45 and the ALB-WTI pair reaching values even higher than 0.45. However, in the beginning of 2023 we can note that for these two pairs there's a peak with values near 0. In the annex section, we can see in the same graph (Annex Figure 1) all the pairs where we can get a different sense of this contrast between the pairs of companies based in America and the others based in China.

Table 3 – Dynamic Conditional Correlation GARCH estimations

		Estimate	Std. Error	t-value	p-value	AIC	BIC
WTI-ALB	α	0.0261	0.0177	1.4751	0.1402	-8.9903	-8.9551
	β	0.7624	0.172	4.4317	0		
WTI-SQM	α	0.0208	0.0236	0.8829	0.3773	-8.885	-8.8498
	β	0.7037	0.1132	6.2175	0		
WTI-LAC	α	0.0064	0.008	0.7914	0.4287	-7.8414	-7.8062
	β	0.9419	0.0386	24.4168	0		
WTI-TIA	α	0.0026	0.0054	0.4833	0.6889	-8.3748	-8.3395
	β	0.9393	0.0256	36.1295	0		
WTI-GAF	α	0	0	0.001	0.992	-8.416	-8.3808
	β	0.9221	0.1225	7.5277	0		





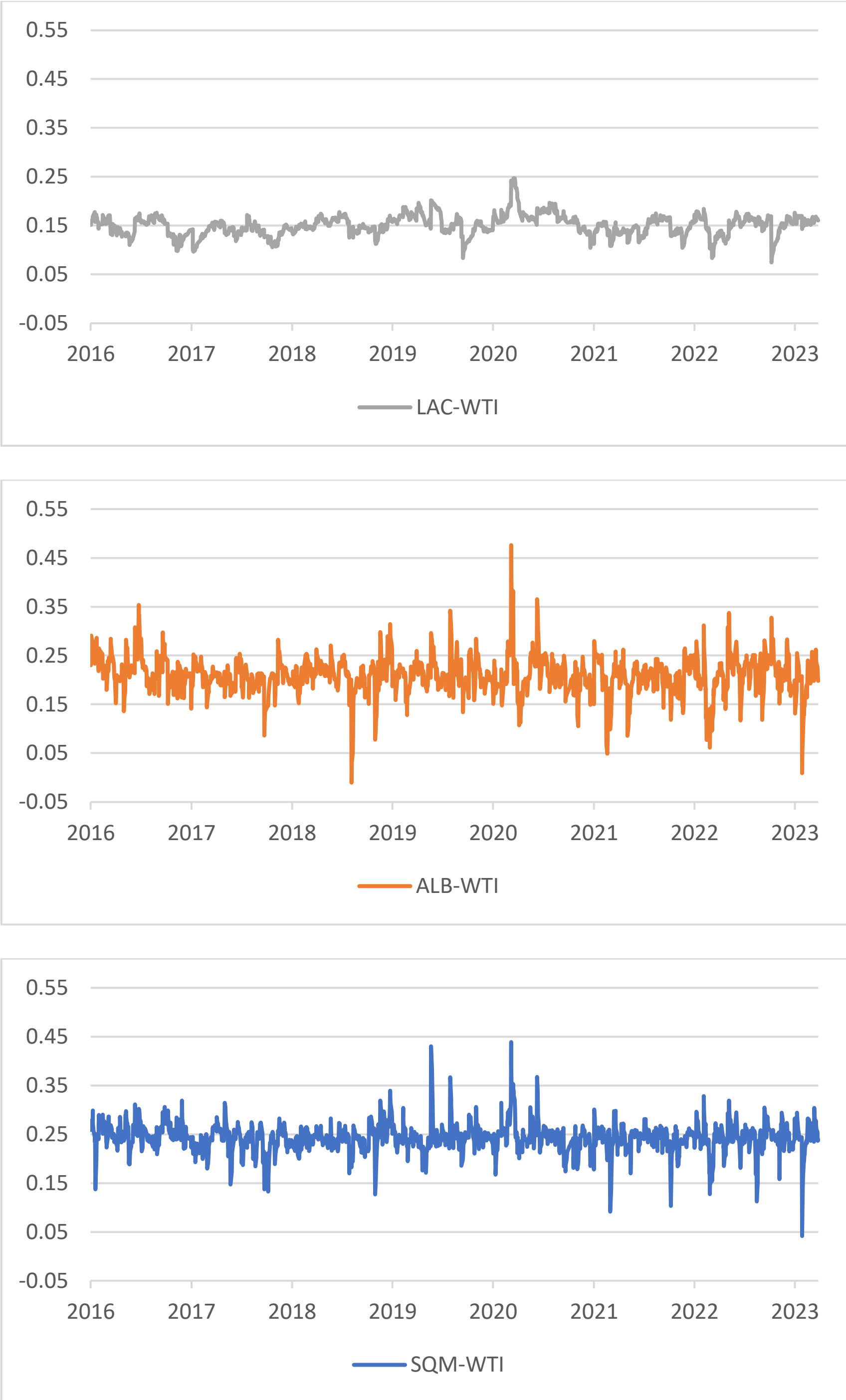


Figure 1 – Conditional correlation between each mining company and WTI oil

5.2. OUTCOME OF VOLATILITY SPILLOVERS

Before starting to estimate the volatility spillover, we first had to estimate the VAR. To do this, we used the Ordinary Least Squared (OLS) method. According to Diebold & Yilmaz (2012) the VAR model's optimal lag order is set to 5, and the forecast horizon (H) is set to 10 days, so these were the measures we used. Table 4 contains the calculated static volatility spillover index. Within the table, the diagonal elements signify the portion of the forecast variance contribution, denoting the connection between each market and itself. On the other hand, the non-diagonal elements represent the spillover between each market and other markets. In practical terms, the element positioned in the ith row and jth column indicates the degree of the spillover effect from variable *j* to variable *i*. The last column of the table showcases the average spillover of each variable to shocks originating from all other variables, excluding themselves. The last two rows represent the average spillover from each variable to all variables, excluding themselves, and the net spillover index which is the subtraction between the To and From spillovers.

The diagonal elements provides the own-variable spillovers of volatility and we can conclude from the results that the variance comes mainly from themselves. With this, we can see that the interaction between the markets is relatively weak, especially regarding WTI. WTI has a weak correlation with the five lithium companies' markets considered in this study at the volatility level because as the table shows, the values in the column and row corresponding to WTI are significantly small. We can verify an average transmitted spillover of 1.73% and an average received spillover of 2.28%, which are a relatively low values even compared to lithium companies, which are already low.

We can also verify that both the ALB and the SQM are the biggest contributors and receivers of volatility, with fairly identical values for To and From, although there is a higher value for volatility transmission in comparison to the volatility received. We can also see that the companies based in China are highly dependent on each other because the transmission to each other is relatively high, with spillover values for both companies above 33%.

Table 4 – Static Volatility Spillover indices between lithium mining stocks and WTI oil – cross-correlations included.

	ALB	SQM	LAC	GAF	TIA	WTI	FROM
ALB	58.10	23.99	12.71	1.15	0.80	3.25	6.98
SQM	23.74	58.17	11.27	1.70	1.19	3.93	6.97
LAC	14.59	12.99	67.52	1.55	1.20	2.15	5.41
GAF	2.11	2.67	2.06	59.04	33.57	0.57	6.83
TIA	2.74	2.40	1.57	33.62	59.18	0.49	6.80
WTI	3.99	5.87	2.80	0.59	0.46	86.29	2.28
TO	7.86	7.99	5.07	6.43	6.20	1.73	TSI = 35,28
NET	0.88	1.02	-0.34	-0.40	-0.60	-0.55	

Note: The i,j entry, where i indicates the row and j represents the column, denotes the contribution of volatility from market j to market i. The column FROM denotes the sum of the elements in the row except the diagonal value divided by 6. The row TO denotes the sum of the elements in the column except the diagonal value divided by 6. The row NET denotes the difference between the correspondent values of TO and FROM. TSI denotes the Total Spillover Index.

In Figure 2 we are doing an analysis for the WTI dynamic spillovers so we can better understand its performance over time. For this we used other VAR estimation, using the Garman-Klass volatility estimator, where we calculate these volatility values with the following equation

$$\sigma_i^2 = \ln\left(\frac{H_i}{L_i}\right)^2 \times \frac{1}{2} + \ln\left(\frac{C_i}{O_i}\right)^2 \times (2\ln(2) - 1) \quad (20)$$

where H_i is the highest price registered in the ith day, L_i is the lowest price registered in the ith day, C_i is the close price in the ith day, O_i is the open price in the ith day and σ_i^2 is the volatility estimated in the ith day.

To run this analysis, we use a rolling window of 180 days. In 'From Spillover' graph it's possible to verify a higher transmission of shocks in the first months of 2020, when it coincides with the initial period of COVID-19, with the Spillover Index reaching a value superior to 40, and a slight increase in transmission can also be seen around the beginning of 2022, when it coincides with the initial period of the conflict between Russia and Ukraine, but nothing like what we see at the beginning of 2020. In 'To Spillover' it is possible to observe the same behavior, a higher transmission in the same time periods as 'From Spillover'. However, there is nothing comparable to the values recorded in 'From', where the maximum spillover index seen in 'To' is around 15. Finally, the last graph shows the Net Spillover, if the net spillover is positive, the market would function as a transmitter of volatility spillover, and a receiver otherwise. From the graph we can see that the values are mostly below zero, which means that the WTI is more of a receiver than a transmitter of spillover, with only one outlier in the specific COVID period.

Figure 3 shows the net pairwise spillovers between each of the lithium companies and WTI, with a rolling window of 180 days. Values greater than zero signify that the spillover originated from the lithium stock to oil, whereas values less than zero indicate transmission was from oil to the lithium stock. It should be noted that all pairs have a negative transmission peak in the initial period of COVID-19, possibly when the lockdown occurred, which then stabilizes and becomes positive, apart from LAC, which continues with spillover transmission from WTI. What is also interesting to note is that during the period of war between Russia and Ukraine, companies based in America have a negative peak, unlike companies based in China. And all companies transmit spillover to WTI in this war period, except LAC which receives more spillover from WTI instead of transmitting, because as shown in Figure 3, in 2022 coinciding with the beginning of the war, we can see that all companies have values above 0 but LAC values are slightly below 0 in the corresponding period. It is important to note that up to the most recent day that we have data available, the transmission of spillover, both from WTI to lithium companies and from lithium companies to WTI is close to 0, as Figure 3 shows there are very little volume in the graphs in the most recent days. However, we can see that most of the time the net values are above zero, which indicates that there is more transmission of spillover shocks from lithium stocks than the other way around, from WTI to lithium.

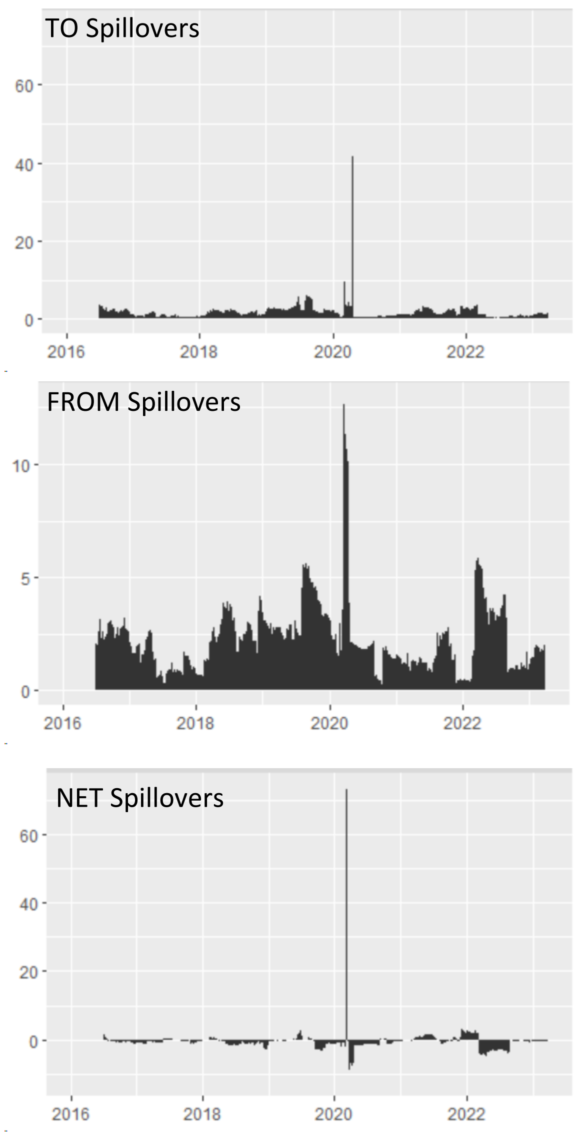


Figure 2 - Spillovers for WTI

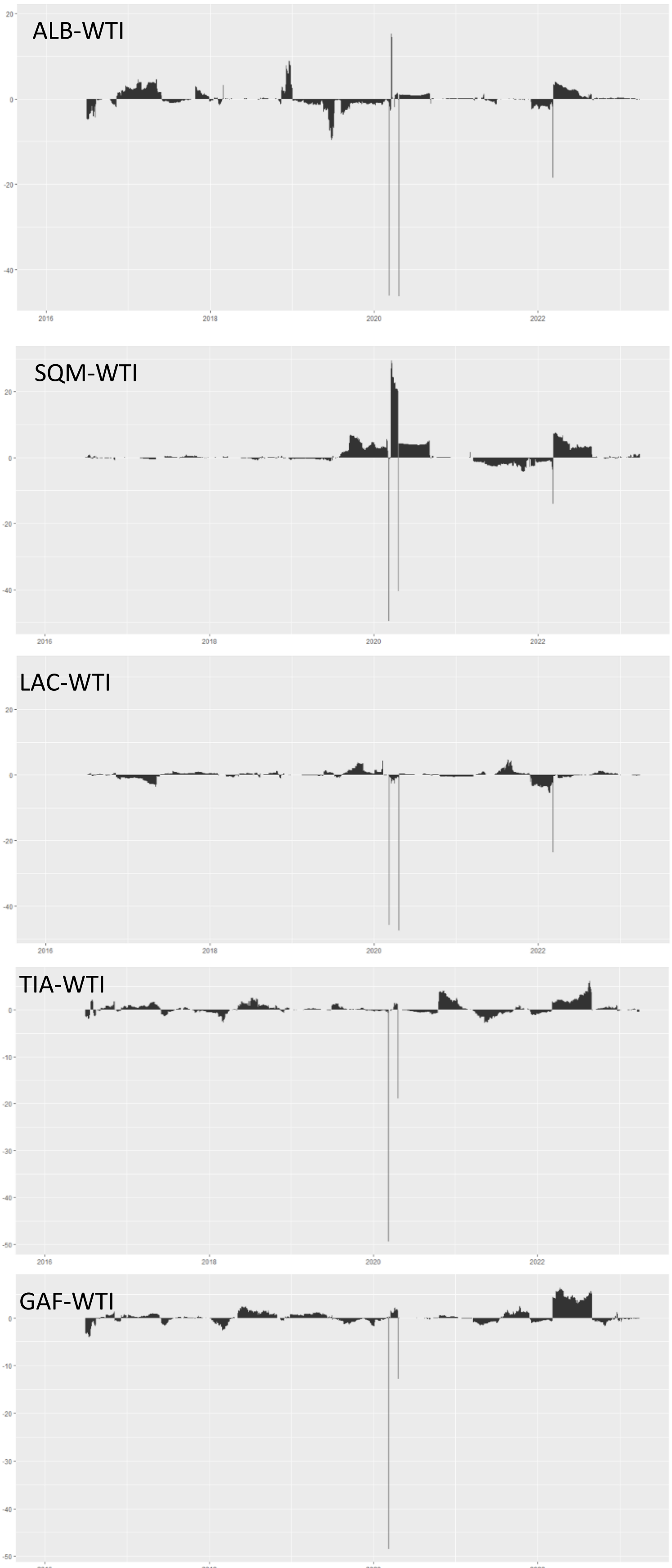


Figure 3 - Pairwise spillovers between each mining company and WTI

6. CONCLUSIONS AND FUTURE DEVELOPMENTS

The global energy landscape is currently undergoing a profound and imperative transformation toward sustainable and renewable sources. This energetic transition is driven by escalating concerns about climate change, a decreasing in fossil fuel reserves, and the need to ensure energy security. For this transition the world needs more and more rechargeable batteries, used mainly in the automobile sector. These batteries have a key component, lithium. This is where the main point of this study came from. With an increasingly technological world and evidence for the end of fossil fuels, lithium could be a key element in this. So, what could be the relationship between these two markets? To do this, we focused on studying the correlation and volatility between the two energy sources, using the share price of the current five largest lithium producing companies and the share price of the West Texas Intermediate (WTI) oil series.

We can see from this study that there is a weak correlation between the different markets as the α values calculated above in the dynamic conditional correlation are close to 0 for every pair but instead we verify a strong persistence in their correlation as we have high values in the sum from α and β values form the DCC estimation. Despite facing the challenges posed by the pandemic and the ongoing war, there is no indication that lithium has a significant correlation with fluctuations in oil prices. As far as volatility is concerned, we found a total spillover index value of approximately 35.28%. However, this is only because most of the transmission of shocks is between lithium companies based in the same area. The representation of volatility transmitted and received by WTI is small, further affirming the little influence between these two markets.

With this study we concluded that both energy sources are very important in our lives, but for the time being, there is little or no connection between them. Perhaps because the energy transition is still in its early stages, or perhaps because oil itself is still so embedded in our lives so we cannot "say goodbye" to it at a glance, given the results that persistently point to a low correlation and low volatility.

Our results could provide valuable insights for institutions and companies affected by fluctuations in the crude oil market. Moreover, our findings have the potential to enhance the understanding among market participants regarding the influence of the lithium industry on movements in crude oil prices, thereby informing and optimizing their hedging strategies.

Future developments could extend this research for other types of markets related to activities focused on obtaining sources of energy from natural resources. These activities include the production of renewable, nuclear, and other fossil fuel derived sources of energy, and for the recovery and reuse of energy that would otherwise be wasted.

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ANNEXES

Annex table 1 - GARCH models that most suitably match each of the stocks in the dataset.

	ALB	SQM	LAC	TIA	GAF	WTI
Model	EGARCH	EGARCH	IGARCH	IGARCH	GJRGARCH	EGARCH
Distribution	sstd	std	sstd	sged	ged	sstd
ω	0.0012	0.0013	0.0016	-0.0003	0	0.0008
p-value	0.0058	0.0214	0.1186	0.4815	0.9523	0.1625
Ω	-0.0995	-0.2493	0	0	0	-0.1638
p-value	0	0	0.0252	0.5997	0.2590	0
α	-0.0145	-0.0142	0.0989	0.0428	0.0483	-0.0649
p-value	0.3845	0.4469	0	0	0	0
β	0.9864	0.9653	0.9011	0.9573	0.9548	0.9781
p-value	0	0			0	0
ϒ	0.1605	0.1769			-0.0185	0.1389
p-value	0	0			0.1170	0.0020
skewness	0.9289		1.2056	1.0432		0.8725
shape	4.1926	5.5148	5.1789	1.2022	1.2701	4.6359
AIC	-4.6090	-4.3977	-3.3904	-3.9457	-3.9759	-4.7008
BIC	-4.5866	-4.3785	-3.3744	-3.9297	-3.9567	-4.6784

Annex figure 1 - Conditional correlation between each mining company and WTI oil in the same graph.