MODELLING THE IMPACT OF COBALT AND LITHIUM PRICE FLUCTUATIONS ON VOLATILITY OF TESLA MOTOR INC. SHARES

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Abstract

The development and current technological innovation has triggered the importance of certain metals called critical such as cobalt and, to a lesser extent, lithium. These metals are necessary for the production of batteries, and specifically those of electric vehicles. The spectacular increase of demand for these metals has led to a high increase of the price, due to its reduced availability. Tesla Motors Inc., that has developed the most efficient and long-lasting batteries for the manufacture of its electric vehicles, belongs to companies that are most sensitive to a change of cobalt and lithium prices. The aim of this paper is to examine effects of cobalt and lithium price fluctuations on volatility of Tesla Motors Inc. shares. In order to model mutual relationships between cobalt and lithium prices shocks and Tesla Motors Inc. volatility, we utilized the DCC GARCH model. Empirical analysis is provided on daily data in the period of 2013 - 2017 years. The overall results indicate that changes in lithium prices may have significant impact on volatility of Tesla Motors Inc. shares over time.

Key words: cobalt, dynamic conditional correlations, lithium, Tesla Inc., volatility

JEL Code: C58, G15, Q43

Introduction

In recent years, the great development and implementation that have experienced products whose source of power are lithium-ion batteries has radically changed the demand map of basic products in its creation, such as lithium and cobalt, called critical metals because of their properties (Slack, Kimball, and Shedd, 2017).

Since 2007, smartphones production has skyrocketed, (Sommer, Rotter, and Ueberschaar, 2015) which has considerably increased these materials demand, but the electric vehicle is the most determining factor in the recent concern around these metals, since it is highly required for batteries manufacture.

This increase in demand has generated a supply crisis due to the scarcity of these materials in the earth's crust (Sonoc and Jeswiet, 2014), as well as geopolitical problems for the main supplying regions, which has caused a considerable increase in the market value of these metals.
Cobalt is a silver gray metal that has various uses based on certain key properties including ferromagnetism, hardness and wear resistance when alloyed with other metals. It is used, above all, in rechargeable batteries cathodes and, in combination with other metals, to form super-alloys for jet turbine engines manufacture. It is an indispensable material to prolong lithium batteries life.
In 2016, approximately 123,000 metric tons of Cobalt (Mineral commodity summaries, 2018) were produced, of which 55% were extracted from the Democratic Republic of the Congo. The future substitution of vehicles powered by fossil fuels would require a much higher production than the current world reserve of this metal is available to offer. This has caused strong speculative positions in the markets in recent times, by large investment funds, around this metal. Also, governments like United States and companies dependent on this metal are beginning to accumulate reserves, such as Apple or Tesla Inc.
On the other hand, lithium is the lightest metal that exists, and it is extracted through brine and granitic pegmatite minerals, usually as a trace element. The main countries that produce this metal are Chile and Australia (U.S. Geological Survey, 2015). This element has a wide variety of uses, the most outstanding uses are for mobile phones, laptops and electric and hybrid vehicles batteries; that take advantage of its light weight and its high electro-chemical potential.
Unlike fossil fuels, lithium and cobalt have a characteristic that makes them more sustainable (Izatt et al, 2014), it is their repeated recyclability. This a fundamental factor, since it turns the products that consume these metals resources into future suppliers.
The increasing high demand for these two metals is a handicap for the main electric vehicles manufacturers, especially Tesla, General Motors and Ford, which are currently involved in the development and marketing of these type of cars. About 50% of the value of an electric vehicle falls on its battery, thus an increase in the price of the two basic metals used for its manufacture has a direct and marked effect on the manufacturing cost and, therefore, on commercialization.
Tesla Inc. is a US company responsible for the design, manufacture and marketing of electric vehicles and energy storage systems through the creation of highly efficient lithium ion batteries (Berdichevsky, et all 2006). Therefore, at present, their dependence on these two metals is complete.
The analysis of the volatility of the prices of these metals and their modeling can allow us to measure the risk of Tesla Inc.'s assets and, therefore, its price in the Nasdaq market. The main

objective of this paper is to analyze the impact of the critical Lithium and Cobalt metals fluctuations value on the stock market value of a company with a high dependence on these metals, such as Tesla. To this end, data on the value of these metals and on the stock market quotation of this electric vehicle production and marketing company were collected from September 2013 until the same month of 2017.

To carry out this objective, in the next section, we will first introduce the multivariate conditional heteroskedasticity model with time-varying conditional correlations and the associated estimation techniques. Next, an analysis of the collected data for these metals and for Tesla company stock market value will be carried out, as well as the estimation of the DCC GARCH estimation models and the corresponding dynamic conditional correlations and the valuation of the company, which will finally be analyzed. Finally, the obtained results will be discussed and the main conclusions obtained from this work will be shown.

1 Methodology

The estimation models used to analyze the potential impact of fluctuations in the price of lithium and cobalt metals on Tesla, Inc.'s stock market value are briefly described below; this analysis is justified in the great dependence of these materials for this company manufacture and in the high influence that a significant increase in prices could have on it.

1.1 Multivariate GARCH Models with Dynamic Conditional Correlations

In this subchapter, the basic information on multivariate GARCH model with time varying dynamic conditional correlations (DCC GARCH) including the estimation procedure will be described. Univariate volatility models as defined by Engle (1982) or Bollerslev (1986) can be utilized only when modelling the volatility of just one-time series. However, modelling the dependencies in the comovements of different time series is important as well. Identifying this feature of financial time series using a multivariate model should deliver more precise empirical models than in the case of separate univariate models. Thus, the DCC GARCH model represents a useful tool for analyzing volatility of time series when the volatility changes over time. This class of models is based on the idea of the conditional variances and correlations. The conditional covariance matrix is decomposed into a correlation matrix and related conditional standard deviations.

Engle (2002) proposed to estimate the DCC GARCH model in following three steps. First, the univariate volatility models including standardised residuals should be estimated to obtain standardized residuals. For the purpose of this paper, GARCH (Bollerslev, 1986) and EGARCH (Nelson, 1991) model are considered. Second, when the univariate GARCH models were estimated, standardized residuals were utilized to estimate the correlations. The variance covariance matrix of paired residuals can be decomposed to where represents a diagonal matrix of time-varying conditional standard deviations as estimated by univariate ARCH models (Seďa, 2015). The specification of the DCC GARCH model takes the following form:

$$\begin{aligned} & r_t \mid \Omega_{t\text{-}1} \sim N(0, D_t \rho_t D_t), \\ & D_t^2 = diag\left\{\Sigma_t\right\}, \Sigma_t = \operatorname{cov}(r_t \mid \Omega_{t\text{-}1}), \\ & \varepsilon_t = D_t^{-1} r_t, \\ & \rho_t = diag\left\{Q_t\right\}^{-1/2} Q_t \ diag\left\{Q_t\right\}^{-1/2}, \\ & Q_t = \left(1-\alpha-\beta\right)\bar{Q}_t + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1}, \end{aligned} \tag{1}$$

where r_t is logarithmic return, $\Omega_{t\text{-}1}$ represents information set available at time *t*-1, ρ_t is the time-varying correlation matrix, $\bar{Q}_t$ is the matrix of unconditioned variances ε_t, ε_t denotes standardised residuals, α, β are nonnegative parameters that have to be positive, and $\alpha + \beta < 1$. Univariate and multivariate GARCH models are estimated with a help of the maximum likelihood method. Finally, the correlation matrix is normalized and adjusted to fulfil properties of correlation matrix (Engle, 2002). The bivariate dynamic conditional correlation $\rho_{1,2,t}$ then can be expressed as follows:

$$\rho_{1,2,t} = \frac{E_{t-1}(\sqrt{E_{t-1}(r_{1,t}^2)}\varepsilon_{1,t}\sqrt{E_{t-1}(r_{2,t}^2)}\varepsilon_{2,t})}{\sqrt{E_{t-1}(r_{1,t}^2)E_{t-1}(\varepsilon_{1,t}^2)E_{t-1}(r_{2,t}^2)E_{t-1}(\varepsilon_{2,t}^2)}} = E_{t-1}(\varepsilon_{1,t}\varepsilon_{2,t}). \tag{2}$$

The bivariate dynamic conditional correlation between Tesla and Lithium is then regressed on a constant, time trend, and conditional volatilities of both time series (Tesla and Lithium):

$$\rho_{1,2,t} = \beta_0 + \beta_1 t + \beta_2 \rho_{1,2,t-1} + \beta_2 \sigma_{1,t} + \beta_2 \sigma_{2,t} + \varepsilon_{1,2,t}, \tag{3}$$

where *t* is the time trend as some conditional correlations may exhibit a trend that means changing integration between markets, $\rho_{1,2,t-1}$ represents lagged value of the DCC, $\sigma_{1,t}$ is the conditional standard deviation of Tesla index, and $\sigma_{2,t}$ is the conditional standard deviation of Lithium market.

Conditional volatilities as estimated by univariate ARCH models usually have high persistence. If we don´t use any lagged value of the DCC in equation (3), it may lead to high values of autocorrelation in residual term. That is why; we estimated equation (3) with lagged value of the DCC by one period. The potential presence of autocorrelation in residuals is verified by

Ljung-Box testing procedure (Ljung and Box, 1979). Further, we will test for the presence of heteroskedasticity with a help of White test (White, 1980).

2 Results

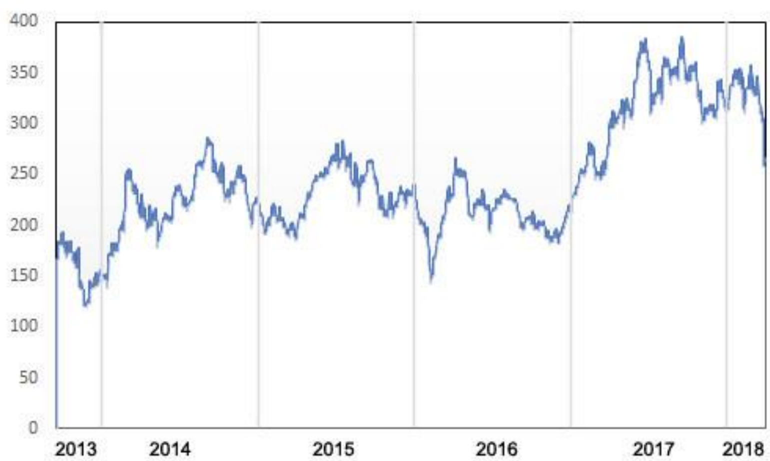
In this section, we first analyze the sample used in this research, which consists of three time series with the evolution of the value of Tesla company in the Nasdaq market, the price of Cobalt that is quoted on London's metals stock exchange and lithium value, which has the disadvantage of not quoting in any market, since its price depends on characteristics such as type, volume or purity. Its value will be measured through the Global Lithium Index, developed by the Solactive engineering company index, admitted as the main indicator of this metal price, and of which daily values are available. The analyzed data correspond to daily values between September 2013 and March 2018.

2.1 Time evolution of Lithium, Cobalt and Tesla company value analysis

Tesla Inc. company began its journey in 2003 with the corporate purpose of manufacturing and marketing electric vehicles, getting financed through different rounds of private funds. In June 2010, it went public at a price of $ 17 per share. At the end of September 2017, its value amounted to more than 300 dollars.

During 2013, its value increased by 372%, although during the month of October it lost 17% due to the negative results obtained in the second quarter of the year. At the beginning of 2014, it experienced a strong promotion sponsored by the production results of the previous year, Apple's interest in acquiring the company and the high revaluation expectations granted by the rating consultancies.

Fig. 1: Quote value of Tesla Inc.



Source: own calculations in Eviews from Investing.com data.

Between September 2014 and April 2015, there was a significant decrease due to oil lower price and the delay in the company's profit expectations until 2020.

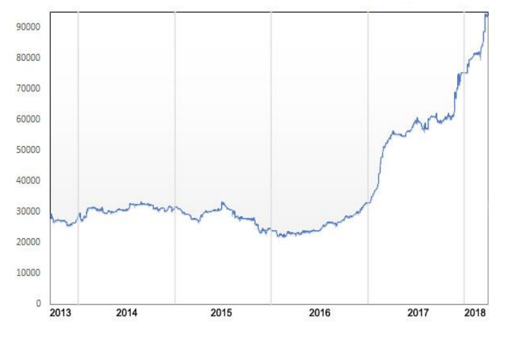
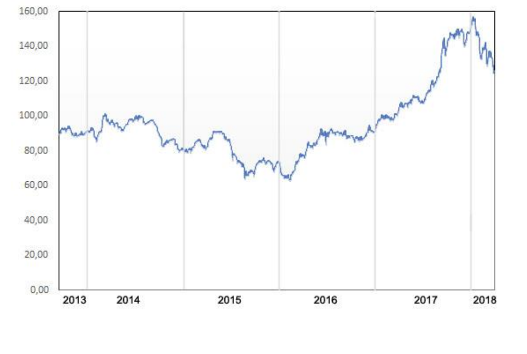
As can be seen in Fig. 1**Chyba! Nenašiel sa žiaden zdroj odkazov.**, at the beginning of 2016, there was a sharp decrease after reporting losses of more than 800 million dollars the previous year, which is fully balanced by the presentation of its new model of electric vehicle, Tesla Model 3, and the important improvements of its emblem product, Tesla Model S.

From January 2016 to September 2017, although with some ups and downs in the quote, their value has continued increasing to settle at values close to $ 400. Since then, the value of the company has dropped below $ 270, coinciding, as we will see now, with a sharp increase in cobalt price.

Next, we will analyze the evolution of the value of metals associated with the company production, cobalt and lithium. As can be seen in **Chyba! Nenašiel sa žiaden zdroj odkazov.**, the valuation of both metals shows a clear upward trend, that is more pronounced from the end of 2016. However, while the value of cobalt continues rising sharply, lithium's one has fallen since the beginning of 2018.

Both metals reached their minimum and maximum values in the considered period and in very close dates. While cobalt minimum value was 21665 dollars per metric ton and lithium's one was 69.79% of its beginning value, in 2010, both in February 2016, the maximum values were obtained at the beginning of 2018, with $ 94300 / Tn and an index of 156.80, respectively. In addition, the decrease observed since the end of 2014 until the beginning of 2016 coincides with the sharp drop in oil price, which began to rise from that moment.

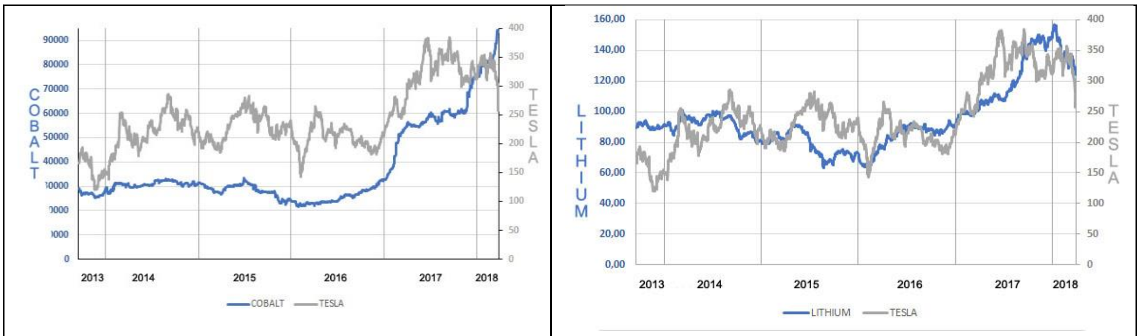
Fig. 2: Cobalt and lithium value

	
Cobalt	Lithium

Source: own calculations in Eviews from Investing.com data.

Chyba! Nenašiel sa žiaden zdroj odkazov. shows the evolution of the price of the considered metals compared to Tesla, Inc. company market value, it is done in the same chart and for two different scales. A strong correlation is observed in both cases, so that, although a sharp rise in the price of metals would increase manufacturing costs in the medium term, the increase in the value of cobalt and lithium is accompanied by a revaluation of Tesla company. This behavior seems to be reversed when cobalt price exceeds $ 75,000 per metric ton.

Fig. 3: Comparison of Cobalt and Lithium prices against Tesla Inc. evolution price.



Cobalt and Tesla, Inc.	Lithium and Tesla, Inc.

Source: own calculations in Eviews from Investing.com data.

Once the evolution of the two considered metals and the price of Tesla have been analyzed, the daily returns have been defined as the difference of the logarithm of the price in one day and the previous day: $r_t = \ln(p_t) - \ln(p_{t-1})$

This has allowed us to eliminate the stationarity lack problem of the three considered series so that multivariate conditional heteroscedasticity models can be estimated with conditional correlations between each of the metals and the company's price.

2.2 Estimation of models

Once analyzed the possible existence of correlation between the volatility of the cobalt and lithium raw materials price, and the quote of the electric vehicle company, Tesla Inc., we will quantify the dynamic conditional correlation between these by means of the estimation of DCC GARCH models presented previously.

Tab. 1: Estimation of the linear GARC DCC model between Lithium and Tesla Inc

	Coefficient	Std. Error	z-Statistic	Prob.
theta(1)	0.066208	0.021571	3.069272	0.0021
theta(2)	0.807251	0.066637	12.11407	0.0000
Log likelihood	6100.624	Schwarz criterion		-13.5189
Avg. log likelihood	3.400571	Hannan-Quinn criterion		-13.5553

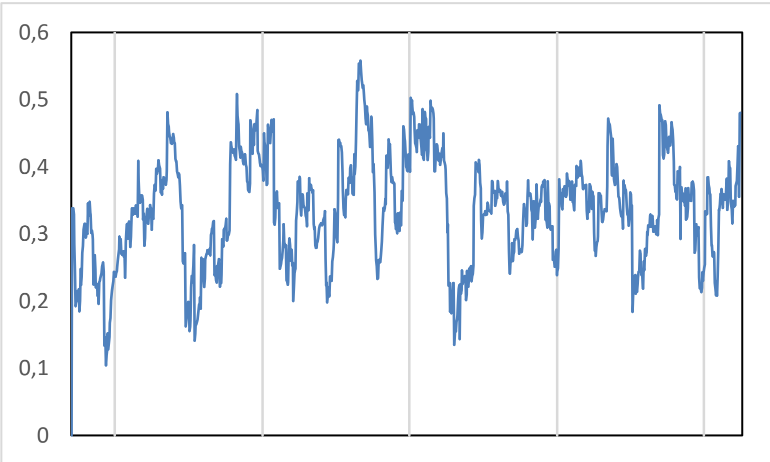
		Akaike info criterion	-13.5778

Source: own calculations in Eviews from Investing.com data.

The estimation for the model between Lithium and Tesla is shown in **Chyba! Nenašiel sa žiaden zdroj odkazov.**, as well as the dynamic correlations graphical representation. As it can be seen, the stability condition of the model is verified, since the sum of the coefficients, denoted by α and β, in the previous section and that are identified by theta (1) and theta (2) in the table, is less than 1, the significance of both coefficients, as well as the positivity condition, allows us to affirm that the matrix is positive definite. This indicates a high temporal relationship between the lithium index and Tesla. In this way, the estimated model for Lithium and Tesla is as follows:

$$Q_{i,j,t} = \omega_{i,j} + 0.066208\varepsilon_{i,t-1}\varepsilon_{j,t-1} + 0.807251Q_{i,j,t-1}$$

Fig. 4: Estimated correlations for Lithium and Tesla



Source: own calculations in Eviews from Investing.com data.

Regarding correlations, we affirm that the correlation is always positive, so that an increase in lithium value produces an increase in the company value. As can be seen in **Chyba! Nenašiel sa žiaden zdroj odkazov.**, the volatility of these is decreasing as time goes by. The lowest value is observed at the end of 2013 and the highest value in the third quarter of 2015.

The descriptive statistics of the dynamic conditional correlation are presented in Table 2. All the values of the DCC reached just positive values during the whole testing period, the mean is 0.336. The highest value (0.558) is reported at the beginning of February 2015 while the minimum (0.104) was reached in December 2013.

Tab. 2: Descriptive statistics of the estimated dynamic conditional correlations

Mean	St. Deviation	Min	Date	Max	Date
0.336	0.080	0.104	09/12/2013	0.558	09/02/2015

Source: own calculations in Eviews

In the next step, we estimated relationships among dynamic conditional correlations and particular volatilities (Syllignakis and Kouretas, 2011). Table 3 gives a brief summary of results according to equation (3), which explains the dynamic conditional correlations in terms of conditional volatilities of both time series. The volatility of Tesla is negative but not significant while the volatility of lithium is positive and significant at 5% significant level. The impact of Lithium volatility on the DCC is undeniable and essential. The coefficient of the lagged dependent variable (0.939) is significant at the 5% level as well. Time trend was insignificant as implied from Table 1. Based on the Ljung-Box test and Durbin-Watson tests, we clearly rejected the presence of autocorrelation in residuals. The same is true for heteroskedasticity in residual term according to White test.

Tab. 3: Results of estimated model according to equation (3)

Constant	Time	$\rho_{1,2,t-1}$	$\sigma_{1,t}$	$\sigma_{2,t}$	R^2_{adj}	Durbin - Watson
0.015*	5.18E-07	0.939	-2.271	126.042*	0.906	2.041

Source: own calculations in Eviews

3 Discussion and conclusions

Tesla company, dedicated to the manufacture and sale of electric vehicles, has a strong dependence on two metals that, in recent times, have experienced a high value due to the high demand and the shortage of availability: lithium and cobalt. Although, since 2013, the quote of the company has shown an increasing trend, as well as the values of these materials, which are basic in the manufacture of vehicle batteries; these trends have been reduced and even reversed in some periods of time since the beginning of 2018.

We have estimated models that allow us to study the relationship of the value of these metals and the quote of Tesla. After numerous attempts, we discarded the model that relates cobalt and Tesla, due to one of the coefficients' negativity. The second one, which relates the value of the lithium index with the company's valuation, has been estimated by obtaining a model that is stable and whose matrix is positively defined. This model allows us to conclude the existence of a direct and variable correlation in intensity between the value of lithium and that of the company in the market.

The high dependence of the Tesla company on these two metals, together with the strong demand they have, the shortage of generation and the instability of some of the supplier countries, which can generate an escalation in their value, is a risk factor for the stability of the production of electric vehicles and their subsequent commercialization.

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