- What relationship exists between oil prices, lithium prices and electric vehicle growth: Is lithium really becoming a substitute for oil? -

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Abstract

The world is continuously shifting from fossil fuel to more environmental friendly sources of energy. Many articles and recognized newspapers have questioned the prevalence of oil as the main source of energy, particularly for transportation purposes. In this sense the growth of electric vehicle (hereafter EV) consumption has increased and the demand for lithium as the main component of batteries has also been in the spotlight. Newspapers, such as the Financial Times, argue that lithium would be the future substitute for oil. In this thesis, we examine the link between EV sale, oil prices and lithium prices, with the intention of detecting if there is a relationship between these three variables and whether lithium is a possible substitute for oil.

We apply a VECM to all three target variables. We found fairly good models to explain oil prices and lithium prices when treating them as endogenous variables. However, when choosing EV sale as target equation the obtained results were not satisfying. The most robust model was found when the target equation was the lithium prices. Our results from this model show that there is a long run relationship between the variables; which confirm our believes. The causality is mostly from EV sale and oil prices towards lithium prices. Additionally, we have detected the impulse response and variance decomposition to see the reaction of the variables when introduces to shocks. Our results shows no evidence of oil being a substitute for lithium. According to our causality tests, we conclude the opposite. Both EV sale and lithium prices are influenced by the fluctuations in the oil price, meaning that shocks such as increased demand or price would not have a noteworthy effect on the oil prices.

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1 Introduction

1.1 Motivation

We want our research to be of interest and matter to a wide audience, not only wealthy investors. In this regard we believe that a popular topic from the news is required. As we acknowledge the importance of renewable energy and environmental friendly alternatives, we want to build our thesis around EVs and commodities that have or may have an impact on the world economy. Lithium caught our attention, as it is an important component in the batteries which represent the most expensive component of EVs, in addition to being a hot topic in media; many times referred to as “The new gasoline”. During a conversation with Jon Hykawy and Tom Chudnovsky from Stormcrow Canada, we were inspired to dig deeper into the relationship between oil, lithium and the adoption rate of EVs.

For some people, environmental reasons are the driver in order to move from common transportation to EVs. However, as people are becoming wealthier, the cost of consumption of fossil fuel itself loses its importance and people still demand this type of fuel despite the environmental cost. On the other hand, the current global dependence on fossil energy, having in mind that it one day will be exhausted, have encouraged the development of new technologies. Scientists all over the world are constantly trying to explore new possible sources of energy that are affordable and environmental friendly. Over the last years the world has experienced an exponential growth in sale EVs. The Financial Times, Goldman and Sachs and BBC among others, have argued that the importance of the oil is decreasing while commodities such as lithium will be more vital in the future. Lithium is one of the main components in long lasting batteries (Li.on batteries) which is found in EVs and portable devices such as laptops, cell phones and other rechargeable electric devices.

We hope that our thesis give the readers a better understanding of the future importance of lithium in the transition from fossil fuel to a more environmental friendly source of energy. We aim to confirm or deny the relationship between these variables, and if such a relationship is detected, we hope to provide a base for future research and forecasting.

1.2 Research Question

We are considering oil and lithium, two commodities related to both current and future expected energy supply. Our thesis has a particular focus on lithium as it is the fundamental metal in production of batteries for EVs. In this regard, we aim to create a model that enables us to map the relationship between oil, lithium and EV sale, to answer the following research question:

What relationship exists between oil prices, lithium prices and electric vehicle growth: Is lithium really becoming a substitute for oil?

As we want to determine whether fluctuations in oil prices, lithium prices and EV sale vary simultaneously and the impact they have on each other, this research is relying heavily on vector autoregressive models (VAR) and vector error correcting models (VECM). We will use global EV sale, accounting for both plug-in, hybrid and PEV. For lithium, we will look at the prices from the Asian market, as this is where the largest players in the industry operate today. Oil prices are represented by the West Texas Intermediate (WTI) spot price index.

In this regard, we have formulated our hypothesis test as the following:
H_0*: There is not a long-run relationship among the variables*
H_A*: There is at least one long-run relationship among the variables.*

The rest of this paper is structured as follow: In part 2 we discuss the current situation of oil prices, lithium prices and the EV industry and results from earlier research. Descriptive statistics of our data is discussed in part 3, along with a discussion of its features. We construct our model and analyse the results and findings in part 4. In the final part, we conclude based on the results from previous parts in the paper.

2 Background and Literature

2.1 Current Situation of the EV Industry

The EV industry has been facing rapid growth over the past few years. Despite this growth, worldwide sales figures are still quite small. Less than 1% of new cars registered in 2013 were EVs. However, experts seem to believe that we find ourselves in an early adoption phase. This can be seen both consumption wise and on the regulatory side. The directive from the European Commission shows initiative to develop the infrastructure to be more convenient for EV users. Directed towards the consumers, one can observe a noteworthy uptake rate in EV sales in several countries within Europe, with Norway and the Netherlands in the lead. Of total car sales in 2013, 6.2% and 4% of them were EVs in Norway and the Netherlands respectively (Amsterdam Round Tables, 2014). Currently, EVs are priced significantly higher than regular oil burners, but the prospects for future growth are looking good as new technologies are developing and batteries become cheaper. According to Bloomberg (2016, 25 Feb) 35% of all new cars by 2040 will be powered by electricity and will be priced lower than $22 000 per unit. Such a quick transformation from regular gasoline driven cars to EVs can be enough to cause the next oil crises, if one were to believe the analysts from Bloomberg. Even though there is a common perception of the rapid growth in the EV industry, experts are not necessarily agreeing on the effect this will have on the future prospects for the oil. According to the article in FORBES magazine from 25 Feb 2016, this is not necessarily all bad news for the oil. The analysts are confident in their believes, that even though we will see more EVs on the roads, it will still be a small fraction of total vehicles sale (FORBES Energy, 2016, 25 Feb). Put in perspective, Tesla is currently building a Gigafactory to produce and assemble its own batteries and vehicles to be able to meet the demand in the near future with a yearly production capacity by 2020 of 500 000 EVs. This is seemingly a large number of cars, but in comparison to the forecasted production of regular fossil fuel light cars by 2020 the EV production only amounts for 0,5% (Statista, 2016). The numbers are more convincing when including other large EV producers such as BMW, Nissan, Chevrolet and Ford, EVs accounts for 17% of all car production according to the forecast for 2020 made by Juniper Research (2016).

When consumers are deciding whether to buy an electric car, or a gasoline driven car there are three main factors that are considered according to the early adopters of EVs: (i) reduction in polluting emissions, (ii) driving and usage benefits and (iii) cost reductions, where the latter turns out to have the most influence (EV Obsession, 2016).

During the past decade there has been much focus on low-emission measures and more environmental friendly alternatives. This development can be seen in consumer behaviour as new products are starting to appear. Consumers want organic food, fair trade clothes and moreover they have a desire for EVs. Not solely motivated by the urge to save the environment, but owning an EV comes with certain benefits. Superior parking permits, the right to drive in taxi and bus lanes during rush hours and tax benefits to mention some. These benefits are country specific and are determined by the government. At last but not least, the cost is important. How much you save compared to driving a regular car will off course depend on the price of oil and electricity, but under normal times, it will cost less to drive an EV once you have obtained it.

As of today the average price of EVs are too high to compete with its counterparty, namely regular cars. Putting design and branding aside, the main reasons for its high price is the battery. The battery of EVs account for one-third of the total price of the car (The Wall Street Journal, 17 April 2012). Hence, for the price of EV to decrease one need to see a decline in the price of batteries. On the current market there are three common types of batteries for EVs: Lithium-ion (Li-ion), Lithium Polymer (Li-poly) and Lithium Iron Phosphate (LFP). What characterizes them all is that both their energy and power density are several times better than those of regular car batteries (Leas-Acid and Nickel-Metal-Hydride).[1] Due to its many desirable features, lithium is now a common component in many types of batteries, including batteries produced for EVs and 3C[2] devices (Electric Vehicles CAA, 2016). Being the preferred metal in batteries produced for use in EVs today, entail

[1] Energy density tells how much energy the battery can hold. If the density is high the battery will need fewer recharges. Power density measure how much energy the battery can deliver on demand.

[2] 3C stands for computer, communication and consumer electronics. The devices accounts for mobile phones, laptops, tablets, cameras and other electric devices in need of a high performance battery.

that there is a relationship between price and demand for lithium and price on EVs on the market. Although lithium does not represent an important cut of the total cost of the electric vehicle, a shortage of lithium would significantly increase the price of the battery making the EVs less affordable.

The cost of the gasoline in many countries is presuming a relevant factor when acquiring a new vehicle. Therefore, high prices of the oil, in addition to its volatility may reinforce consumers' willingness to try an EV when buying a new car. Based on this, there is an apparent relationship between EV sales and the current oil price.

2.2 The Oil Market

For decades, we have blamed the oil for low levels of real interest rates and productivity, and high unemployment rates. This commodity has also received credit for ensuring good performance in the U.S. economy when prices are high. In the absent of more suitable explanatory variables, the oil prices have gained a significant role in a great amount of macroeconomic models. According to Hooker (1996), this is a bit of a paradox: at the same time as oil price fluctuations keep increasing, the importance of oil's effect on the world economy has diminished. Even though he finds no clear relationship in the data after 1973, he still believes that there is a relationship. The implication is that the relationship is too complex to be explained by simple models. More recent research shows that there is indeed a relationship between oil prices and world economic growth, but scholars still struggle to find the exact. There is a reverse causality problem resulting in difficulties when it comes to conclude whether oil price affects economic growth or vice versa (Hamilton, 2008). Even though the causality is heavily debated there is no doubt that there is a relationship and if one were to believe Evans (2000) statement, oil shocks are the most influencing factor in triggering recessions.

The most recent oil crisis is still on going with oil prices as low as $35 per barrel resulting in a long list of inconvenient side effects. Rising interest rates, increased unemployment, default on derivatives and drop in stock market prices to mention some. For oil dependent countries such as Norway, such an oil crisis is more dangerous than a financial crisis. Norway is dealing with higher unemployment rate in these days than under the global financial crisis in 2008 (Oilprice.com, 08 Jan, 2015).

Modeling Oil Prices

Due to the unsolved mystery of oil prices, there have been many attempts to find suitable models and forecasts for the oil prices throughout the years. This have resulted in many different methods and forecasting techniques. In the literature the most traditional way to forecast real oil prices is through a random walk forecast or no-change forecast. Researchers are continuously aiming to improve the forecasting techniques to achieve more accurate results for even longer time horizons (Baumeister and Kilian, 2014).

According to Baumeister and Kilian (2014), central banks typically rely on the oil future markets when forecasting real oil prices. The forecast is based on oil future contracts representing nominal oil prices. Expected inflation is subtracted to convert the prices to real prices. This conversion from nominal to real prices is incorporated in the forecasting model:

$$R_{t+h|t} = R_t(1 + f_t^h - s_t - \pi_t^h), \qquad (2.1)$$

where R_t denotes todays level of real oil prices and f_t^hdenotes the current price for oil futures with maturity h. The current spot price of oil is represented by WTI spot price, which is denoted by s_t. Expected inflation rate is denoted by π_t^h.Baumeister and Kilian (2012) argue that the inflation forecast could be developed further, but they do not expect it to change the affluence of their findings. In their study they use the mean square predicting error (MSPE) to measure the accuracy of the model. The results show that their method reduces the recursive MSPE with a tendency to decline even more over the longer forecasting horizons. One main drawback is that none of the declines in MSPEs are statistically significant. Regardless of apparent advantages when it comes to usage and implementation Baumeister and Kilian (2012) do not recommend this model.

Alquist et al. (2011) exploit the relationship between industrial raw material prices and short term nominal WTI prices of oil. Their research suggests the following nonregression-based forecasting model:

$$R_{t+h|t} = R_t\left(1 + \pi_t^{h,industrial\ raw\ materials} - \pi_t^h\right), \tag{2.2}$$

where $\pi_t^{h,industrial\ raw\ materials}$ denotes the percentage price change of industrial raw materials other than oil over h months, represented by the CRB index. The model yields a reduction of MSPE in 1- and 3-months forecasting periods, but these declines are only statistically significant at a 10% significance level. When expanding the forecast horizon there are no significant reductions of the MSPE. The method appears to have an overall adequate explanatory power and this is not a coincidence. Both industrial raw materials and crude oil prices are driven by fluctuations in the same macroeconomic factors. Oil prices however, are in addition strongly influenced by geopolitical factors. Hence, a model purely based on industrial raw materials will not be able to fully absorb these effects. To develop a more robust method one has to rely on a richer set of variables.

Baumeister and Kilian (2012) aimed to develop a more accurate model for central banks, with a forecasting horizon up to one year. Their objective were to forecast real oil prices rather than log prices, as the former is what matters to policymakers. In their research they test both autoregressive moving average models (ARMA), autoregressive models (AR), Bayesian autoregressive models (BAR) and Bayesian vector autoregressive (BVAR) models for time horizons of 1, 3, 6, 9 and 12 months. The ARMA and AR models are based on U.S. refiner´s acquisition cost of crude oil imports and the VAR models are a four-variable method developed by Kilian and Murphy (2010). The four variables are: (i) percentage change in global crude oil production, (ii) global real activity that deviates from trends, (iii) inventory change in global crude oil and (iv) real U.S. refiners´ acquisition cost for crude oil imports, which is representing the global markets real price of crude oil. Forecasting accuracy is tested against real U.S. refiners´ acquisition cost for crude oil imports and real WTI prices, for both reduction in MSPEs and directional accuracy. They find that BVAR(24) and VAR(12) show very similar results: they perform reasonably under normal times, but in contrast to the no-change model, they increase their relative performance during the global financial crisis. The authors believe this is due to the characteristics of the VAR models, namely that they are forward looking. Overall Baumeister and Kilian (2012) found that all their models outperformed the no-change model and the future-based forecast. The VAR models performed best in the short run and BVAR(24) was the one that yield best results overall on both MSPE and directional accuracy. For longer horizons, the ARMA model yields larger MSPE reductions even though it suffers from absences of directional accuracy. Based on an overall judgement of the models, they conclude that BVAR (24) is the most accurate model.

In more recent times, artificial neural networks (ANN) have proven to be a more suitable method for analysis due to oil prices' nonlinearity characteristics. The advantage with the ANN is that it is less restrictive when it comes to assumptions about the underlying distribution. This implies that it allows non-parametric functional forms, which yields a higher degree of robustness. As a result, the ANN has achieved great popularity among engineers for its high level of flexibility and accuracy. Mirmirani and Li (2004) have compared VAR and ANN when forecasting oil prices. They argue that oil prices fluctuate based on supply and demand, in addition to intervention of government policy. Inflation and economic growth are constraint by monetary policy. As both these factors interact with oil price movements, Mirmirani and Li suggest money supply as a representative proxy for government policy. According to their VAR model, lagged oil prices were the best variable for forecasting future price movements. Surprisingly, money supply was not selected as a variable by the VAR model. Mirmirani and Li believe this might be a result of money supply being an inappropriate representation of government policy. Based on the forecast evaluation statistics, the neural networks with genetic algorithm clearly outperformed the VAR model. However, they are unable to prove that the ANN method always outperforms the VAR model.

Being aware of the challenge of finding suitable models to explain oil prices, this thesis aims to find out if there is a relevant relationship between oil, lithium and EV to detect whether other variables than those already discussed in existing literature can be considered in further studies to make a more complete or suitable model for oil forecasting. [3]

2.3 The Lithium Market

In the Huffington Post online edition on 13 April, 2016 it is stated that lithium is the only commodity in the world which has shown positive price development during 2015. Same year Australia, Chile and Argentina were the world's largest lithium producers. When it comes to reserves China is on the top next to Chile and Argentina (USGS, 2015). Beside the countries listed with the world's largest reserves, there is yet another country that needs some attention. Bolivia is holding 50% of the world's lithium reserves according to a post in Latin Correspondent from 01 February, 2016. However, these reserves are not jet extracted and for that reason, it is challenging to comment on both quality and amount. Investors have been reluctant to enter the Bolivian market due to its political issues. There have been some changes in this pattern with the Bolivian government signing the contract with the German company K-UTEC Ag Salt Technologies, as recently as August 2015, to design and develop a lithium carbonate plant in Bolivia (Bratlett, 2016).

There are two key markets that are developing which could have a significant impact on the future lithium demand and result in development of additional supply sources. With today's prospects for the future, such a development will have to happen despite the prevailing risk factors in the countries in possession of large reserves. First, through the development of technology and manufacturing advances in both the production of EVs and batteries, Tesla and GM have enabled themselves to launch models with significant lower costs. Second, with today's growth in renewable energy, one has seen the need for a more balanced energy supply through improving the energy storage systems (Roskil, 2014).

Lithium has faced an increase in demand of 18% yearly since 2010, as a result of the rapid growth in the rechargeable battery sector. The world has seen an increased

[3] If there is a significant relationship between our variables further research can be improved by including only lithium prices and EV sales in addition to including exogenous variables in a VARX model.

demand for smartphones and tablets in addition to the momentum in electric vehicles sales. Battery producers are not the only demanders of lithium as it is also widely used in glass production, lubricants, chemical and pharmaceuticals. Still, it is among battery producers we find the highest growth in demand. The demand for these batteries combined accounts for 22% of total lithium consumption (Roskill, 2014). For this reason, it is reasonable to believe that this demand will drive the production of lithium and hence be the most significant determinant for the lithium price (Stormcrow, 2015). It is expected to see an even larger demand for lithium in the near future as Tesla are launching its new Gigafactory to produce batteries. However, as stated in reports from both Stormcrow and Avicenne the lithium demand from the rechargeable battery market depends on end-user battery demand and not on the scale of factories being constructed. Some believe that Tesla's new Gigafactory will be large enough to have a significant impact on the demand of lithium in the future, but if one is to believe Joe Lowry, President of Global Lithium LLC this is not too convincing. In his opinion, Tesla is receiving a disproportionate amount of attention when it comes to the discussion of the lithium market. If Tesla were to buy the lithium currently used in all Tesla batteries themselves, it would still counts for less than 2% of the global lithium market. In contrast, in 2015 battery producers in China have consumed 20% of total lithium production. When it comes to production of lithium there are few, but large companies that are in the lead, namely SQM, Albemarle, FMC, Tianqi and Ganfeng. Combined, these producers control two-thirds of refined lithium (Lowry, 2015).

As of today, the price of lithium is a relative little piece of the total cost of the battery. The cathode chemicals in the battery represent only 23% of overall cost, and lithium represents only 33% of the metal in the battery, which implies that only 7.6% of the total battery cost is due to lithium. Meaning that even a dramatically rise in the lithium prices would not be a major problem for neither the battery producers nor the end-users. This implies that the lithium price can continue its strong growth without notable decrease in demand. Even during the global financial crisis with its recession, it followed that the lithium price remained strong, which also makes experts believing that it will continue its strong growth in the future. Despite being a valuable market, that has been developed and explored since the beginning of 2010, there has been limited entry of new suppliers. Experts believe that this is due to both technical and financial constraints. In the absent of a wide range of suppliers, market requirements have been met by high-cost Chinese producers. The spot prices in China have been observed to be twice as high as contract prices elsewhere in the world. According to Lowry (2015), it is rare to see such a spread between high and low prices in a market as the one which have been observed for the lithium.

Modeling Lithium Prices

As lithium and LCE[4] has gained high attention in more recent times, there are not yet established many models to explain lithium prices. Usually, lithium prices show up as an independent variable to forecast future battery prices or EV prices (e.g. Weiss et. al, 2012). However, there have been produced models where lithium prices are the exogenous variable, and these models are usually based on expected future supply and demand of the commodity. There is one drawback with this method of forecasting based purely on demand and supply. It can give inaccurate estimates as a big proportion of total demand comes from other sectors as shown in Figure 2.1 below.

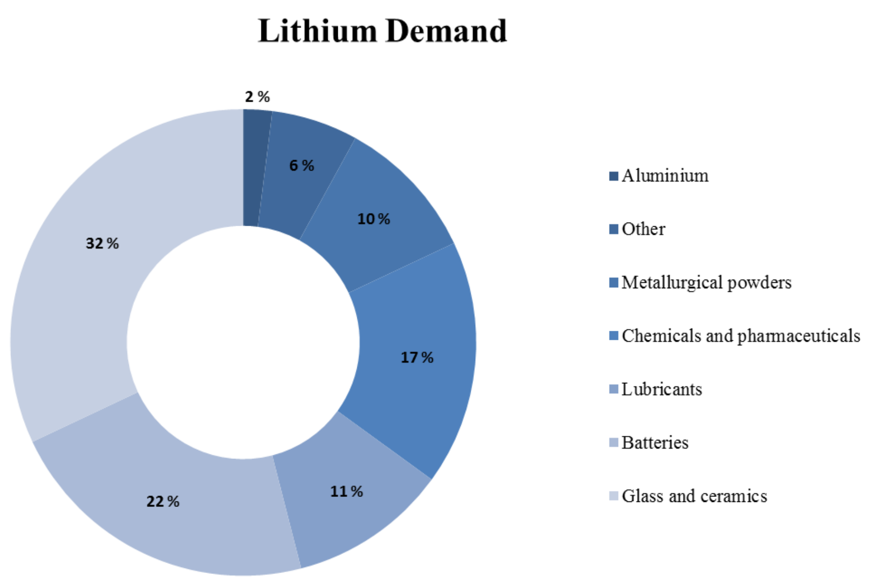


Figure 2.1: Lithium Demand by Products
Source: Roskill 2014

[4] LCE stands for Lithium Carbonate Equivalents, and this comprises 99,5% lithium battery grade and 99.9% refined lithium.

It is possible to separate some of the supply and demand, as there are different types of lithium used for different purposes. For the purpose of producing batteries for EVs the *battery grade* 99.5% LCE is required. The second type of lithium is the *pure technical grade* 99% which are more common in the production of glass and ceramics. In this study the focus is on the battery grade 99.5% lithium as we are interested in the connection to EVs. According to the three largest producers of lithium in the world, SQM, FMC and Rockwood, the lithium with 99,5 % pureness can also be used in the production of glass and ceramics, but with a significantly lower extend in heat resistance, this is not very common.

To model the future demand of lithium prices, future contracts have shown to be very useful. According to experts, there is a high correlation between current lithium prices and futures contracts implying that models to forecast could be based on the expected future contracts demand. Referring to Stormcrow's report, there are no apparent new technologies that will replace or disrupt lithium as a commodity for batteries production purposes in the near future. This makes their forecasts of future demand more certain for several decades.

As of today there are few, but large suppliers of lithium. To estimate future production and supply of lithium actual production capacity of the largest producers, expanded capacity and new possible producers need to be included. Stormcrow has used production capacity of the largest producers of lithium. In order to forecast total supply there has been made some assumptions. The first is that some of the companies will expand their capacity during the forecasting horizon. Furthermore, they assume that all the existing producers are fully utilizing total capacity throughout the forecasting period. Their last assumption is that after 5 years the smaller companies will start to contribute to the world's total capacity, but in a smaller extend.

	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	2025
SQM	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9	47,9
Tianqi	55,0	55,0	55,0	55,0	55,0	55,0	82,6	110,1	110,1	110,1	110,1	110,1	110,1	110,1	110,1	110,1	110,1	110,1	110,1
China	15,1	15,1	15,1	15,1	15,1	15,1	15,1	15,1	15,1	15,1	15,1	18,1	18,1	18,1	18,1	21,7	21,7	21,7	21,7
RB											5,0	10,0	20,0	20,0	20,0	20,0	20,0	20,0	20,0
Orocobre									4,0	8,3	16,6	16,6	16,6	16,6	16,6	16,6	16,6	16,6	16,6
FMC	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9	22,9
Albemarle	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2	39,2
Galaxy												5,0	10,0	20,0	20,0	20,0	20,0	25,0	30,0
LAC											3,0	15,0	40,0	40,0	40,0	40,0	40,0	80,0	80,0
Total (t LCE)	**180,1**	**180,1**	**180,1**	**180,1**	**180,1**	**180,1**	**207,7**	**235,2**	**239,2**	**243,5**	**259,8**	**284,8**	**324,8**	**334,8**	**334,8**	**338,4**	**338,4**	**383,4**	**388,4**

Table 2.1: Lithium Production Capacity in tons of LCE
Source: Stormcrow 2015

It is reasonable to believe that if the lithium price increases even more, some of the largest producers will expand their capacity as their output becomes more profitable. Hence, they can justify an investment of such a large scale.

Stormcrow (2015) find that they need two different models to forecast the two different types of lithium. The model suggested for the pure technical grade is the following linear model:

$$Price_y = -2{,}625x10^{-5}\ (Supply - Demand)_{y-1} + 6{,}99 \qquad (2.3)$$

For the 99,5% battery graded lithium they find that a power curve is better suited. Their suggested model is the following non-linear model:

$$Price_y = 24{,}035\ (Battery\ Demand_{y+1})^{\frac{1}{20}} - 34{,}86 \qquad (2.4)$$

There is no doubt that the booming EV industry will increase the demand for battery-graded lithium. According to PR Newswire (2016), every 100 000 new EVs involving demand of 5 000 to 8 000 tons of battery graded lithium carbonate. It is important to bear in mind that the EV industry is not the only driver for the growth in lithium demand. The world is also facing an increased demand for smartphones, tablets and other portable electronic devices, which are also going to affect the overall battery graded lithium demand. Stormcrow's result shows what is indeed stated in earlier theory, namely that the price of raw lithium will not have a significant impact on the price of batteries.

It is suggested at the end of this study further research in order to forecast future lithium prices not only based on the simultaneous changes in the variables that we consider in this study, but also other exogenous variables that cover general demand, supply, inventory and world activity. The suggested proxies are shown in the correlation matrix in Appendix 7.5.1

3 Data

Our dataset consists of daily data from 02 June 2011 to 25 April 2016. As lithium is not publicly traded, the length of the data set is limited due to difficulty of obtaining lithium prices back in time. In addition prices of lithium are determined based on negotiations between the trading partners, which make it even harder to obtain historical prices. Another important limitation in our data set is the data frequency. Both lithium prices and oil prices are obtainable in daily data while EV sale is only obtainable with monthly frequency. This force us to convert the EV sale into daily data, as using monthly data for all variables would result in too few observations. Seasonality of EV sale will not be an issue as the effect is only observable on a monthly basis. This matter will be elaborated in a later section.

We have excluded the weekends, so we are working with 5-days weeks. This gives us 1278 observations to work with. The variables are obtained in different currencies and have been converted into U.S. Dollar, by using the historical daily exchange rates. It is important to emphasize that during the period of our data set there has been two global economic crises. First the financial crisis in 2008 and secondly the more recent oil crisis. Presumably, these two crises will show up in our data set as outlying data points. In the following the sources and characteristics of each variable are explained in more detail before we move on to descriptive statistics.

As mentioned earlier EV sale is not accessible in daily data. Monthly data were obtained from www.ev-sales.blogspot.no. We have checked that these data are reliable by comparing them with the once reported at The Statistics Portal (2016). In addition we run background check on the author, Jose Pontes, of the www.ev-sales.blogspot.no. He is currently working for EV Obsession in addition to being a partner at EV Volumes, which are both recognized reliable sources (EV Obsession, 2016). Based on this we conclude that this source is reliable despite the fact that the information is extracted from a blog. There are some minor discrepancies between the two sources, but the authors do not believe these differences will have any significant impact on the results or the overall long term relationship that we are aiming to map. The data at The Statistics Portal are only reported on a yearly basis, and this is the reason why we picked the data from the former source, which is listed on a monthly basis, meaning that is also account for seasonality. To obtain daily data we have divided monthly sales on the number of days in each respective month. In this way, we are not ignoring the possibility of seasonality in EV sale on a monthly basis.

For the oil prices we use the WTI spot prices for crude oil (CRUDOIL), obtained from Datastream. Crude oil is a globally traded commodity, which gives this price index good credibility. The notation of the index is U.S. Dollars per barrels of oil. Datastream allowed us to obtain 5-days week data so no further adjustments of the data were needed.

Unfortunately, there is no similar price index for lithium. The only index for lithium is The Global X Lithium ETF (LIT), which covers the full lithium cycle, from mining and refining the metal, through battery production. From this index, it is not possible to isolate the prices of raw lithium or separate one quality from another. Both these features are important in our study and hence, The Global X lithium ETF (LIT) is an inappropriate proxy for global lithium prices. Instead, we use the 99.5% battery graded lithium prices from the Asian Metal Inc. One drawback is that these prices are not global prices but the prices that apply to the largest producers in China. As China is a very important supplier of all lithium chemicals, due to the purchase of Talison by Sichuan Tianqi Lithium, Chinese pricing for these materials ought to be regarded a good proxy.[5] These prices include a tariff, which we have extracted to obtain the real prices.

3.1 Descriptive Statistics

We can see from the descriptive statistics that we have high differences in volatility (relative std. dev.) across our variables. EV sale (EV_SALES) are the most volatile variable with a relative standard deviation of 84.83%. The least volatile variable is the oil prices (OIL_PRICE) with a relative standard deviation of 29.07%. In the middle we have the lithium prices (LI_PRICE) with a relative standard deviation of 56.24%.

[5] This market imports the most lithium produced in the world since the largest producers of Li-ion batteries are established here. Hence, prices reported on the Asian Metal are the best proxy for lithium carbonate prices, in our opinion.

We observe that none of the variables are symmetric around the mean, as they all have excessed skewness. Judging by kurtosis, we observe that the oil price is normally distributed while EV sales and lithium prices have a kurtosis higher than 3, meaning that they are not normally distributed. One should not rely on this solely when checking for normality. According to the Jarque-Bera test, none of the time series are normally distributed since all the test statistics are significant and exceeds the critical values at all levels.

	EV_SALES	LI_PRICE	OIL_PRICE
Mean	1145,824	7,757	81,401
Median	1005,065	6,419	92,565
Maximum	4321,700	25,288	110,530
Minimum	54,100	5,386	26,210
Std. Dev.	972,016	4,363	23,673
Relative Std. Dev. *	84,83 %	56,24 %	29,08 %
Skewness	1,207	3,107	-0,862
Kurtosis	4,333	11,425	2,212
Jarque-Bera	405,044	5835,530	191,438
Probability	0	0	0
Observations	1278	1278	1278

Table 3.1: Descriptive Statistics
Relative standard deviation = (Std.Dev/Mean)*100

EV sale

When looking at the accumulated sales of EVs (Figure 3.1) we can see that it is facing an exponential adoption rate. Today's accumulated sale is around 1.4 million and according to analysts, we should expect an increase of almost half a million new cars during 2016. In Figure 3.2 monthly sales of EVs are depicted from the original sample. We can see that sale vary largely from month to month. Based on this we believe to detect multiple breaks, in this time series.

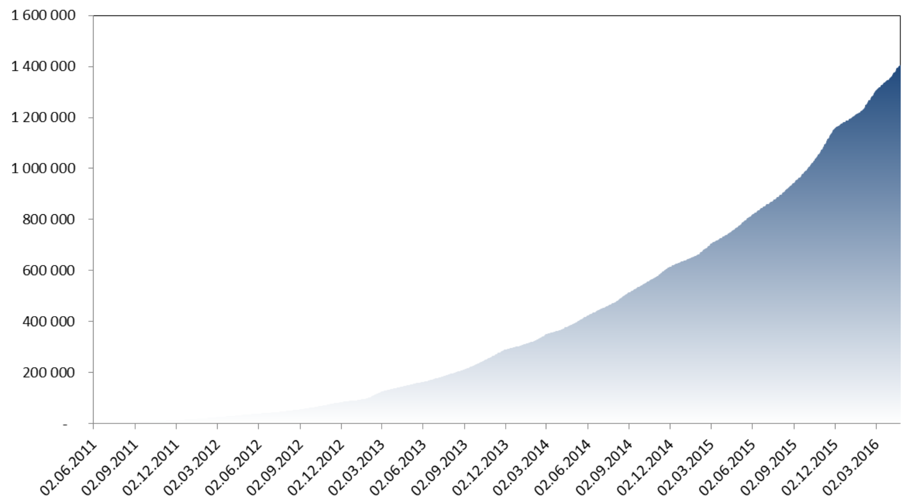


Figure 3.1: Global EV accumulated sales
Units of accumulated new registered EVs from 2011-2016

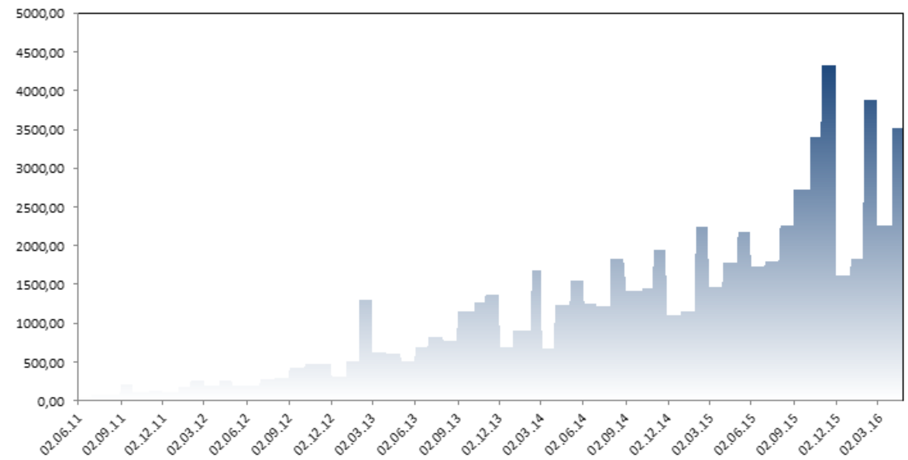


Figure 3.2: Global EV monthly sale
Units of new registered EVs per month from 2011-2016

We have also found some outliers in EV sale. As the outliers were detected on a monthly basis, we choose not to exclude these outlying data points as this will result in around 30 missing data points when converting to daily data. Instead we have smoothed out the data in the months where the outliers appeared. In the analysis we will use both the original and the smoothed data series in order to find the best possible model in addition to analyse the impact of outliers in our data set. When checking for outliers we analysed both monthly and daily data. When looking at monthly data we find that there is one outlying data point. However, when checking on a daily basis we find two outlying data point, which in this case represents two months, as the sales on the daily basis equally distributed over the whole month.

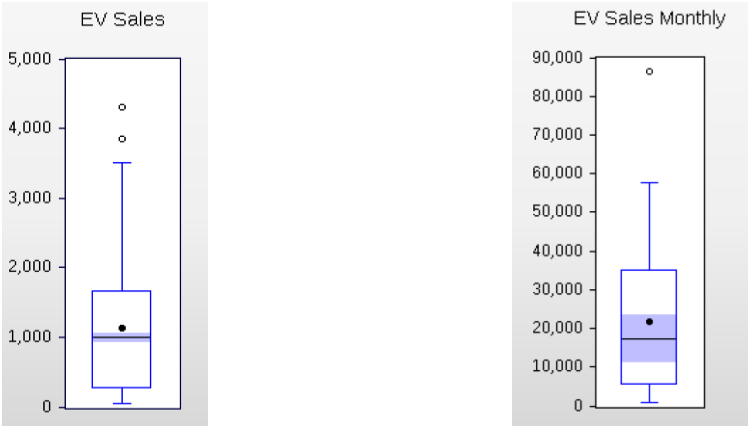
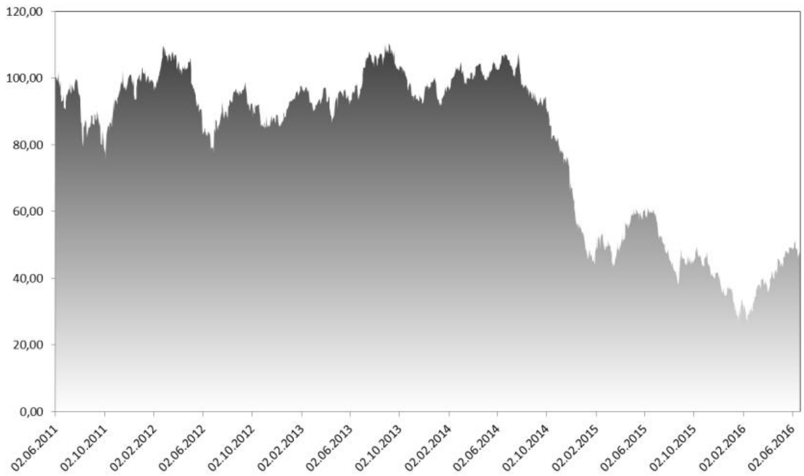


Figure 3.3: Outlying data points EVs
Then having daily data we see that there are two outlying data points. When working with monthly data there is only one outlying data point.

Oil prices

For the oil prices, we can see normal fluctuations up to the second quarter of 2014 with prices ranging from $80 to $108. During the second and third quarter of 2014, the world faced a dramatic decline in the oil prices because of the oil crisis, hitting a bottom price of $26.21 per barrel. When it comes to outliers in the oil prices, we can see from figure 3.5 that there are no outliers in the time series. We can also confirm from the boxplot that the oil prices are not normally distributed as the mean defers from the median. This is consistent with the Jarque –Bera test discussed earlier.



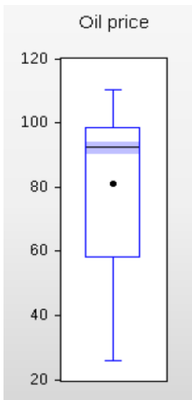
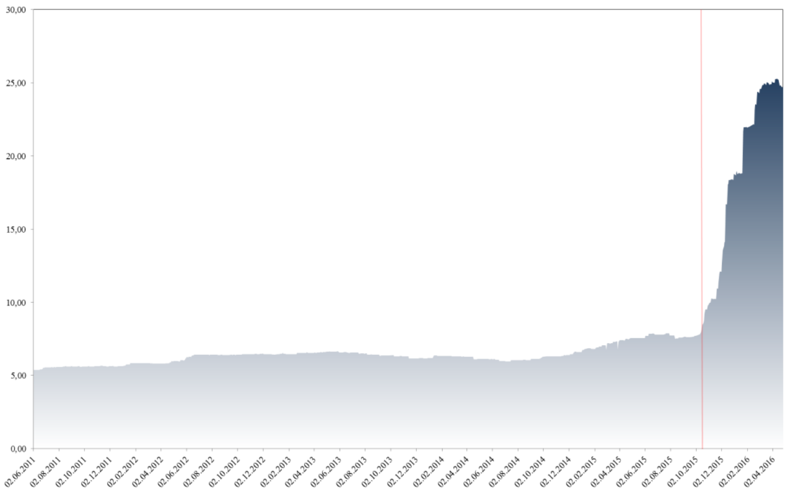


Figure 3.4 : Historical prices of crude oil
Oil prices in USD per barrel

Figure 3.5 : Outlying data points in Oil prices
The boxplot shows that there are no outlying data points in the oil price time series.

Lithium prices

Figure 3.6 depicts the historical prices of lithium in U.S. Dollars. Based on the graph there is an apparent break in the time series in the last quarter of 2015. Prior to the break, the price has been quite steady, increasing at a slow pace. According to the Figure 3.7 we there are seemingly many extreme outliers. These apparent outliers are actually caused by a trend/break in the time series, which can also be seen from the RHS graph. As the observations after the break constitutes for only a small part of the total sample, meaning that they do not have a large enough impact on the mean, the observations after the breaks shows up as outliers.



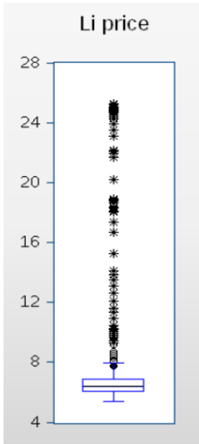


Figure 3.6: Historical prices of lithium
Lithium prices in USD per kilogram

Figure 3.7: Outlying data points lithium prices

There are quite high correlations for all three variables (Table 3.2). There is a negative relationship between EV sale and oil prices. According to the theory and market expectations discussed earlier one should expect an increase in EV sale when there is an increase in oil prices. Based purely on the former, one would expect a positive correlation between the two. There is a positive correlation between EV sale and lithium. Not surprisingly, when the demand for lithium increases because of increased demand for batteries and subsequently EVs, the price of lithium is expected to increase. There is a negative correlation between lithium and oil prices. As stated earlier, many experts believe that lithium will become the substitute for oil in the future, and this can justify the negative correlation in prices. However, one need to be careful about drawing conclusions based on correlations alone. One cannot interpret correlations such as a change in one variable would cause an opposite movement in the other. To elaborate regarding relationships between the variables and how they move together we will perform various causality tests.

	EV_SALES	LI_PRICE	OIL_PRICE
EV_SALES	1,0000	**0,5868**	**-0,7224**
LI_PRICE		1,0000	**-0,6691**
OIL_PRICE			1,0000

Table 3.2: Correlation Matrix
For EV sale, lithium prices and oil prices

3.2 Stationarity and Cointegration

In order to avoid spurious regression we need to make sure that our data is stationary. When a series is stationary it has constant mean, -variance and – autocorrelation for all set of lags (Brooks, 2014). If we have non-stationarity in one of the variables, shocks hitting this variable will never die away. Hence, non-stationarity is an undesirable feature for a time series. Unfortunately, they are quite common in financial time series (Bjørnland and Thorsrud, 2015). We perform the Agumented Dickey-Fuller (ADF) test for unit root, in order to check for stationarity and trends in our variables. In addition, we test for breaks by running the Bai-Perron test. The latter one allows to test for maximum five breaks. This means that there might be more than five breaks, even though the test results show five breaking points.

For EV sale we found a unit root, which means that the process is not stationary. When running the test with first difference we found no unit root, implying that the series has first difference stationarity. When taking first difference we lose valuable information about the long run relationship. For this reason, we apply the VECM as it incorporates and error correction term to bring the model back to the long run equilibrium. When it comes to breaks we expect multiple breaking points in the time series. Therefore, we allow for the maximum possible breaking points when running the test. [6] The most significant break appears on 5 May 2014. Additionally there are two more minor breaks both before and after the 5 May 2014.

[6] The Bai-Perrion test allows for 5 breaking points.

For oil prices we find at least one unit root meaning that there is non-stationarity or a trend. When testing for breaks, an additional test for stationarity, we find multiple breaks. The most important break occurs on the 28 November 2014. There are additionally three minor breaks before that date, and one after. In order to make the process stationary we take first difference, which results in no unit root. This entails that the process has first difference stationarity.

Similarly for lithium, we observe that there is no stationarity. In case of trends we find that there is at least one unit root. In fact to make the series stationary, we need to take the difference nine times. This is due to the structural break occurring on the 30 October 2015. Prior to this break, there are two other minor breaks: one on the 17 May 2012 and one on the 18 February 2015.

Since the main interest of this study is to see if there is a long run relationship between the three variables, we run tests to see if the variables are cointegrated. In order to check for cointegration we test for stationarity in the residuals through the Engle-Granger test (1987) and the Johansen test. We attach more focus to the Engle-Granger test since this is more robust compared to the Johansen test as we have a relative large sample. If there is cointegration among all pair of variables it means that the model itself is stationary. If we find that some of the pairs of variables are not cointegrated, we have to difference the variables until we obtain stationarity. In the cases where we have cointegration we will use the VECM, which is based on the number of cointegrated equations. Here the variables are differences to provide stationarity in addition to adding an error correcting term which recapture the long term equilibrium that the model were supposed to have before differencing.

4 Analysis

In our analysis we will examine the VAR model to map and understand the relationship between EV sale, oil prices and lithium prices when varying the target equation (endogenous variable) in our three-equation system without exogenous variables. Analysis will be performed based on the coefficient diagnostics and stability diagnostics. We expect to map the relationship through Granger causality tests, impulse response and variance decomposition. Additional analysis is performed based on the VECM, in which we evaluate the significance of the error correction terms when changing target equation. Analysis of jointly significance will be emphasised throughout the study. The forecasting evaluation of the VECMs will be analysed to check the accuracy of the model and as a measure of how good the model explain the variables simultaneously. Residual diagnostics, such as tests for normality, heteroscedasticity and serial correlations are also performed.

4.1 Model introduction

The companion form of an VAR(p) model with K endogenous variables is shown below, both in equation form and matrix form. We will apply the same method where we have three endogenous variables, namely EV_SALES, LI_PRICE and OIL_PRICE.

$$y_t = \alpha + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t \tag{4.1}$$

$$\begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{bmatrix} = \begin{bmatrix} \alpha \\ 0 \\ \vdots \\ 0 \end{bmatrix} + \begin{bmatrix} A_1 & A_2 & \cdots & A_{p-1} & A_p \\ I & 0 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & 0 \\ 0 & 0 & \cdots & I & 0 \end{bmatrix} \begin{bmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{bmatrix} + \begin{bmatrix} e_t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \tag{4.2}$$

Further in our analysis we will apply the VAR(p) model for the following set of equations:

$$EVsales_t = \alpha + \sum_{i=0}^{t} \theta_i * EVsales_{t-i} + \sum_{i=0}^{t} \beta_i * Li\,price_{t-i} + \sum_{i=0}^{t} \delta_i * Oil\,price_{t-i} + \varepsilon_t \tag{4.3}$$

$$Li\,price_t = \alpha + \sum_{i=0}^{t} \beta_i * Li\,price_{t-i} + \sum_{i=0}^{t} \beta_i * EVsales_{t-i} + \sum_{i=0}^{t} \delta_i * Oil\,price_{t-i} + \upsilon_t \quad (4.4)$$

$$Oil\,price_t = \alpha + \sum_{i=0}^{t} \delta_i * Oil\,price_{t-i} + \sum_{i=0}^{t} \beta_i * EVsales_{t-i} + \sum_{i=0}^{t} \delta_i * Li\,price_{t-i} + \varphi_t \quad (4.5)$$

In order to describe the relationship between oil prices, lithium prices and EV sale we will develop several VAR models. Both when it comes to length of data set, frequency and amount of lags.

The VECM has the following equation system where the first difference is taken of all variables and error correction terms are included to bring the model back to equilibrium in the long run:

$$EVsales_t = \alpha + \sum_{i=0}^{t} \theta_i * d(EVsales_{t-i}) + \sum_{i=0}^{t} \beta_i * d(Li\,price_{t-i}) + \sum_{i=0}^{t} \delta_i * d(Oil\,price_{t-i}) + \sum_{i=0}^{t} \gamma_i * ECT + \varepsilon_t \quad (4.6)$$

$$Li\,price_t = \alpha + \sum_{i=0}^{t} \beta_i * d(Li\,price_{t-i}) + \sum_{i=0}^{t} \theta_i * d(EVsales_{t-i}) + \sum_{i=0}^{t} \delta_i * d(Oil\,price_{t-i}) + \sum_{i=0}^{t} \gamma_i * ECT + \upsilon_t \quad (4.7)$$

$$Oil\,price_t = \alpha + \sum_{i=0}^{t} \delta_i * d(Oil\,price_{t-i}) + \upsilon_t + \sum_{i=0}^{t} \theta_i * d(EVsales_{t-i}) + \sum_{i=0}^{t} \delta_i * d(Li\,price_{t-i}) + \sum_{i=0}^{t} \gamma_i * ECT + \varphi_t \quad (4.8)$$

4.2 VAR and VECM modeling

We have tried different number of lags suggested by both the Hannan-Quinn (HQ) information criterion and the Akaike (AIC) information criterion in order to determine the model. When comparing the number of lags given by the HQ and AIC information criterion we find that including more lags not necessarily improves the model. On the contrary, it brings more noise to our model. As a rule of tomb, we have chosen those models whose number of lags improves the significance of the coefficients and the model as a whole. Initially we take the complete sample with all the 1278 observations without trimming to get an overview of the relationship where all coefficients are estimated, based on the complete data in both the VAR and VECM models. We have applied the VECM to forecast the last half of the data in order to have a first grasp of the movements and behavior of the model and its coefficients. We acknowledge that this yield a biased forecast, as the estimation of the coefficients are based on the whole data set. Meaning that the coefficients are based on the future information we are forecasting. For the models in later sections, we use trimmed samples and VECM estimates does not account for “future values” which represents a more realistic approach.

Figure 4.1 below shows the comparison of the forecast of different models where different amounts of lags are considered. EV sale is target equation for these models.

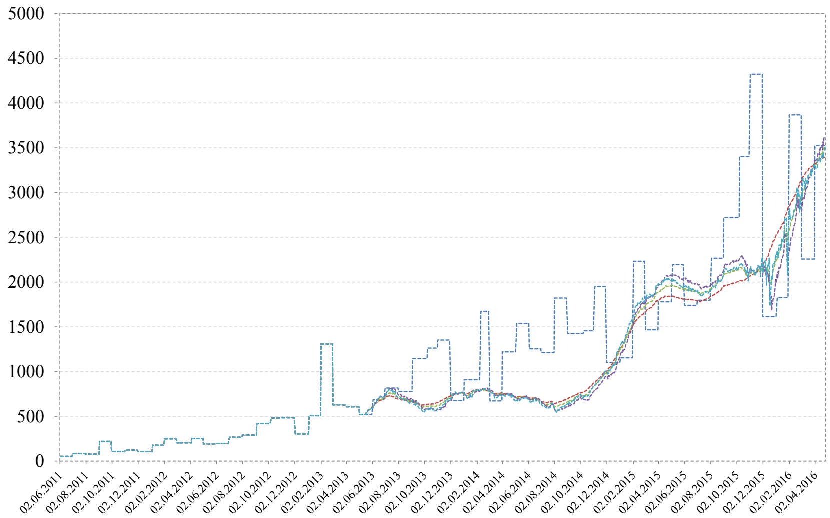


Figure 4.1: Forecast evaluation comparison
Blue line: Actual EV sales. Red line: EV forecast with 1 lag. Green line: EV forecast 2 lags. Turquois line: EV forecast 4 lags, Purple line: EV forecast 9 lags.

The model with 4 lags performed best when the target equation is EV sales. This model was superior to the other when comparing individual and jointly significance, in addition to forecast evaluation. The 4-lag model has the most significant coefficients and the lowest MAPE. However, this model is not superior if we aim to forecast lithium or oil prices as can be seen from the graph below.

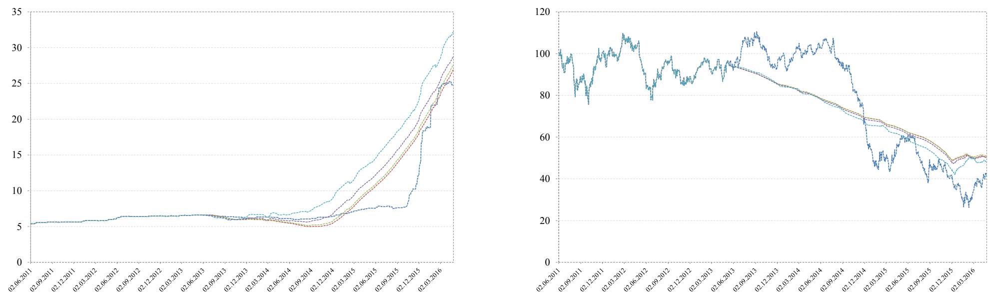


Figure 4.2: Forecast evaluation of lithium prices and oil prices
Left side: Lithium prices froecast. Right side, oil prices forecast. Same color code as in Figure 4.1.above

We are checking whether there are cointegration in our variables through the Johansen test and confirming the findings with the Engle Granger test, where the latter is more robust for large samples. Since neither of the variables are stationary, we estimate the VECM with the number of co-integrated equations and estimate the coefficients for the differenced lagged variables and the error correction terms.

The model accounts for two co-integrated equations, resulting in two error correcting terms as shown in Equation 4.9 below. The first error correcting term has a negative and significant coefficient meaning that there is a long run relationship, converging towards equilibrium. The second error correcting term has a positive and significant coefficient, implying that instead of converging towards equilibrium it is in fact diverging. This might be due to a structural change in the variable or due to autocorrelation. None of the coefficients for lagged variables of electric vehicles sale (EV_SALE) are significant. For the lagged variables of lithium prices (LI_PRICE) all the coefficients are significant: one at a 10% level and three at a 1% level. Only the fourth lag of oil prices (OIL_PRICE) are significant at a 10% level. However, all the coefficients are jointly significant as shown by the F-statistic in Appendix 7.1.1.

$$\begin{aligned} EVsales_t = {} & \alpha + \beta_1 * d(EV\ sale_{t-1}) + \beta_2 * d(EV\ sale_{t-2}) + \beta_3 * d(EV\ sale_{t-3}) \\ & + \beta_4 * d(EV\ sale_{t-4}) + \gamma_1 * d(Li\ price_{t-1}) + \gamma_2 * d(Li\ price_{t-2}) \\ & + \gamma_3 * d(Li\ price_{t-3}) + \gamma_4 * d(Li\ price_{t-4}) + \delta_1 * d(Oil\ price_{t-1}) \\ & + \delta_2 * d(Oil\ price_{t-2}) + \delta_3 * d(Oil\ price_{t-3}) + \delta_4 \\ & * d(Oil\ price_{t-4}) + \lambda_1 * ECT_1 + \lambda_1 * ECT_2 + \varepsilon_t \end{aligned} \tag{4.9}$$

Below is the representation of the modeling, accounting for the whole sample to estimate the coefficients. The model has a MAPE of 29.33%, which we consider as decent considering that the out-of-sample forecast accounts for almost 60% of the observations. [7] Additionally, that the original data for EV sale is monthly and has been modified from monthly to daily sale. It is not vital to have a good forecast for

[7] The MAPE forecast evaluation accounts for the difference between the forecasted out of sample data and the actual data. If the out of sample forecasted data is large it is likely that MAPE will be large, conversely the smaller the forecasted out of sample data the lower the MAPE for the same estimated coefficients.

daily EV sale, rather being able to address monthly or even yearly-accumulated sale.

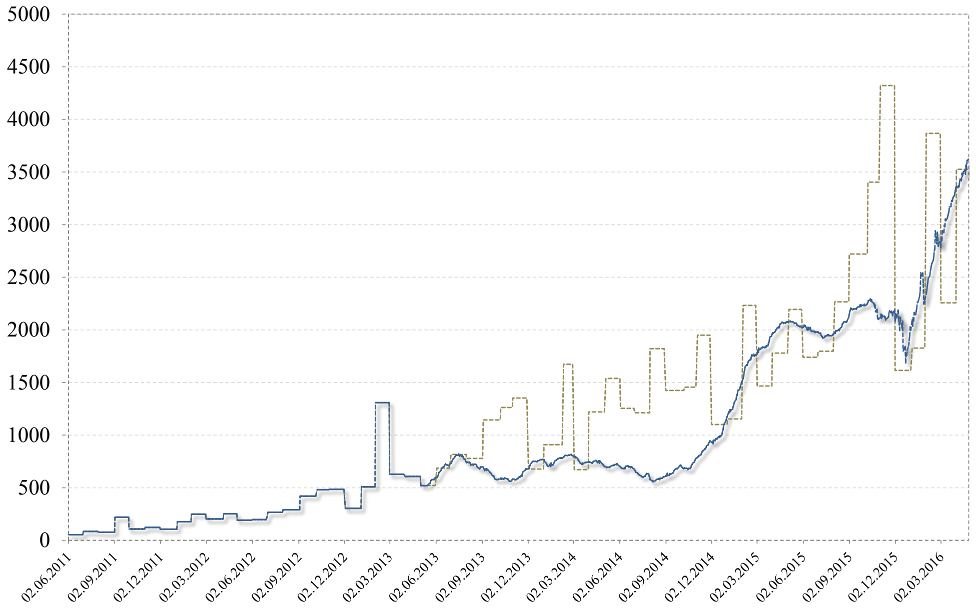


Figure 4.3: Forecast VAR(4)
The gold line is the actual time series and the blue is the out of sample forecasting.

In our attempt to improve the model, we took first difference of the variables to make them stationary before estimating the coefficient in the VAR model. As the VECM are taking the first difference of the variables when creating the model we are ending up with variables that are differenced twice. In this case the suggested number of lags is nine, resulting in quite comprehensive model without any noteworthy improvements in the significance of the coefficients or the forecast itself.

Further in the process we have trimmed the sample 15% to estimate the coefficients. This result in a data set ranging from 02 June 2011 to 27 July 2015 After our data is trimmed our forecasting sample does not include data of the apparent break, neither for lithium prices nor electric vehicles sale. For this VAR model, the suggested number of lags was 1 by all the criteria and we find one cointegrated equation. Based on the Wald causality test we observe that oil prices have Granger causality on lithium prices. This differs from the obtained results from the 4-lags model where we used the whole data set to estimate the parameters. Following the same procedure as before, we find no improvements in the results. In terms for forecasting power this model has an MAPE of 46.16%, which is an increase from the former model. When forecasting EV sale we find that monthly data yield better results as we are obtaining a better forecast evaluation in comparison to daily data. However, when we change the target equation, in order to forecast either lithium prices or oil prices, daily date gives results that are more accurate. For lithium, this is not very surprising given the break that occurs around October 30, 2015. Due to the significant break in this variable, we split the sample in two to make one model before and after the break. When using monthly date, there are not enough observations after the break for the VAR model to yield significant coefficients or a good out-of-sample forecast. When using daily data, there are enough observations in order to create a reliable model for lithium.

Residual Diagnostic:

To test for serial correlation in the residuals we perform the Breusch-Godfrey test. We reject the null hypothesis of no serial correlation, implying that we have serial correlation in our residuals. Furthermore, we find heteroscedasticity in our residuals, meaning that we do not have a constant variance. At last, we test for normality in the residuals by performing the Jarque-Bera test. The null hypothesis of normality is rejected, meaning that our residuals are not normally distributed.

Coefficient Diagnostic:

The causality tests, both Wald test and Engle Granger causality test, show that there are two significant causalities. However, the two tests disagree regarding the direction of the causality. The Wald test states that lithium prices have causality to EV sale, while the Engle Granger test does not support this. Both tests agree that EV sale has causality in lithium prices. Additionally we find that oil prices have causality on EV sale, which is supported by both tests. There is no causality the other way around for EV sale and oil prices.

We believe that the poor results in the model above are due to the apparent breaks that we believe have an impact not only on the forecasting evaluation, but also on the diagnostic evaluation in general. In the following, we will test for breaks and develop this theory further, by accounting for the presumable breaks.

4.2.1 Structural breaks

By observing the historical prices in Figure 3.1 and 3.2, we can see that there is an apparent shift in both lithium and oil. Since we are not able to tell exactly when the break occurs or even if they are significant, we run the Bai-Perron test for multiple breaking points. The test allows us to check for up to five breaking points. Below is depicted the three time series with their respective breaking points, where the most significant breaks is marked with a bold red line and the other breaking points are marked with the faded lines.

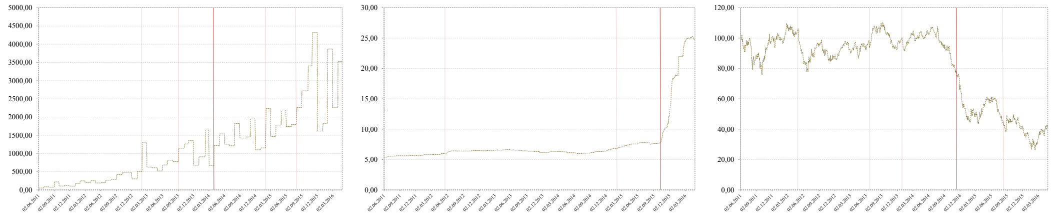


Figure 4.4: Breaking points EVs, Lithium and Oil
The bold red line marks the point with the most significant break. The faded lines mark other breaking points detected by the test. The graph shows EV sale, lithium prices and oil prices from left to right.

We believe that splitting the sample in two at the break point will improve the results compared to the model developed in the previous section. As the break in the lithium prices are seemingly more significant than the break in any of the other variables, we chose to split the sample based on the break in the lithium variable. The Bai-Perron test concludes that the break of lithium occurs at 08 October 2015. We will fit two models, one before and one after the break. The intuition is to see whether the same relationship holds both before and after the break. If this is the case, we can conclude that the relationship between the variables is consistent even when shocks hit one of the variables.

Until now, we have specified EV sale as our target equation. As mentioned earlier the Wald test and Engle Granger test do not agree on the direction of the causality. Therefore, we will estimate the model three times, each of which we change the target equation to see which model is most suitable to explain the relationship between the variables both before and after the break. Since the causality test yield different results, we will continue to test all three variables as target equations when developing further models.

4.2.2 Estimation Results

	Model Structure		Forecast Evaluation	Residual Diagnostic		
Target equation	# lags VECM	Cointegrated eqn.	MAPE	Serial correlation	Heteroscedasticity	Normality
EV_SALE	2	1	35,53 %	No	No	No
LI_PRICE	2	1	2,40 %	No	No	No
OIL_PRICE	2	1	11,64 %	No	Yes	No

Table 4.1: Estimation Characteristics of before break sample

	Model Structure		Forecast Evaluation	Residual Diagnostic		
Target equation	# lags VECM	Cointegrated eqn.	MAPE	Serial correlation	Heteroscedasticity	Normality
EV_SALE	1*	2*	37,55 %	No	No	No
LI_PRICE	1	2	4,99 %	No	No	No
OIL_PRICE	1	2	6,73 %	No	Yes	No

Table 4.2: Estimation Characteristics of after break sample
*After taking the first difference

Over all we can see the there are few lags included to estimate all target equations, both before and after the break. The lags for the VAR and VECM are chosen by the AIC information criteria as earlier. We can observe that the MAPE is lower in the period before the break for the variables EV sale and lithium prices. For oil prices, the opposite apply. As shown in Table 4.1 and 4.2 the MAPE is generally lowest when lithium prices is the dependent variable. None of the models suffers from serial correlation, neither before nor after the break. Oil prices is the only target model that suffers from heteroscedasticity.

Models were lithium prices is the target equation obtain most significant coefficients over all. Based on this we will continue our analysis of this specific model with lithium as target equation to further elaborate the relationship between the variables. As shown in the Table 4.3 below there are most significant coefficients in the sample after the break. Both models are jointly significant as can be seen form the F-Statistic.

Table 4.3 shows that the sample after the break yield significant coefficient for the first lag of EV sale. This implies that sales of EVs may be an important variable when explaining lithium prices, not the other way around. This result has support from the Granger causality test (See appendix 7.2.11 and 7.2.12).

01.06.2011-30.10.2015	CoinEq1	CoinEq2	D(LI_PRICE(-1))	D(EV_SALE(-1))	D(OIL_PRICE(-1))	C	F-Statistics
Coefficient	**-0,0200**	**-0,0167**	**0,2984**	0,2050	-0,0001	**0,1000**	
Prob.	0,0035	0,0164	0,0007	0,3275	0,3595	0,0004	**0,0001**

30.10.2015-25.04.2016	CoinEq1	D(LI_PRICE(-1))	D(LI_PRICE(-2))	D(EV_SALE(-1))	D(EV_SALE(-2))	D(OIL_PRICE(-1))	D(OIL_PRICE(-1))	C	F-Statistics
Coefficient	**-0,0040**	-0,0045	-0,0217	**0,0000**	0,0000	0,0004	0,0001	**0,0017**	
Prob.	0,0000	0,8909	0,5115	0,0583	0,5656	0,2805	0,8476	0,0043	**0,0000**

Table 4.3: Coefficient for LI_PRICE target model
Significant coefficents and f-statistics are highlighted.

More importantly, the error correcting terms have a significant negative sign. This means that there is a long run relationship and that the error correcting term succeeds in converging the model towards equilibrium.

4.2.3 Forecasting Accuracy

To obtain a realistic picture of the forecasting accuracy we trimmed the sample before estimating the coefficients. This way we are able to perform an out-of-sample test. This was done both for the sample before and after the break. According to Hansen and Timmerman (2011) there is no rule of tomb when it comes to splitting the sample. Where we chose to split the sample may influence the results of the forecasting. This is a bit of a trouble especially when dealing with structural breaks. We have chosen to trim the sample no more than 15%, as we know that the break is close to the end of our sample.

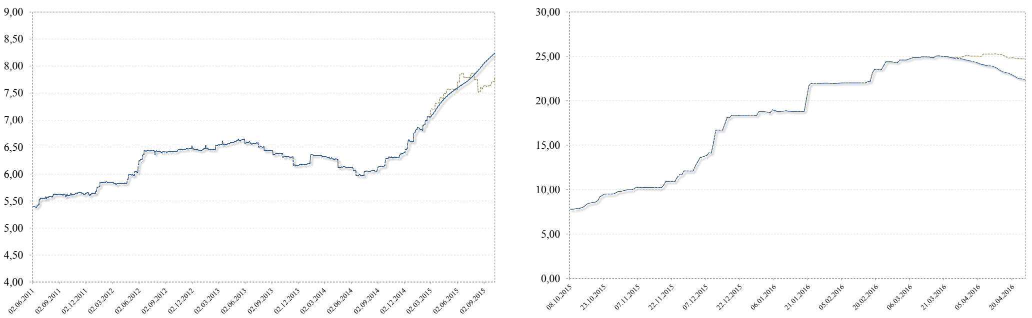


Figure 4.5: Out-of-Sample Forecasting – LI_PRICE
Left side: Out-of-sample forecast before the break. Right side: Out-of-sample forecast after the break. The gold line is the actual time series and the blue is the out-of-sample forecasting.

As shown in Figure 4.5 the out-of-sample forecast is quite accurate, compared to the model former model. This can be confirmed by the low MAPEs shown in Table 4.1 and 4.2.

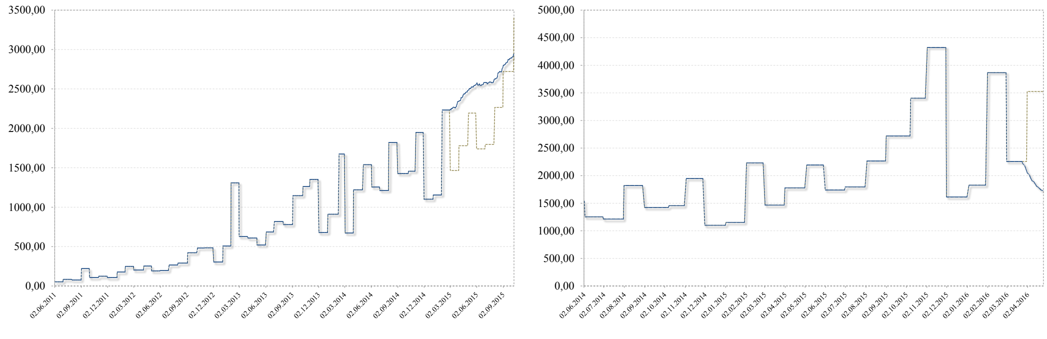


Figure 4.6: Out-of-Sample Forecasting – EV_SALE
Left side: Out-of-sample forecast before the break. Right side: Out-of-sample forecast after the break. The gold line is the actual time series and the blue is the out-of-sample forecasting.

We see that for the model before the breaks when the target equation is EV sale the model is neither very accurate nor jointly significant at any level. After the break, the forecasting accuracy show no sign of improvement. Neither this is jointly significant. It is important to note that we have examined different amount of lags, but independent of lag selection the model does not become significant.

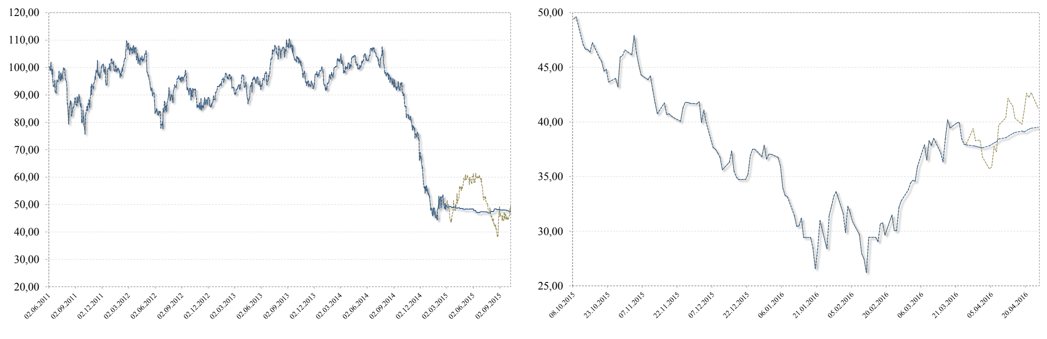


Figure 4.7: Out-of-Sample Forecasting – OIL_PRICE
Left side: Out-of-sample forecast before the break. Right side: Out-of-sample forecast after the break. The blue line is the actual time series and the red is the out-of-sample forecasting.

Regarding the models, both before and after the break where oil price is the target equation, we observe that the model improves its forecasting evaluation and that both models are jointly significant with a relatively high R^2.

4.2.4 Impulse response and Variance Decomposition

In the sample after the break, when there is a shock hitting the EV sale, lithium prices remain constant for the next 10 periods. This makes sense since the original data for EV sale is monthly and we have transformed it into daily data by dividing it equally on each day. On the other hand, when there is a shock in the oil prices, the response of lithium price is a linear decrease until the fourth day where it dies away. The variance decomposition shows that approximately 20% of the variance in lithium prices comes from oil prices and EV sale combined. Most of the variance however comes from oil prices.

As discussed in the literature review, there are many factors affecting the variables of investigation in this research. By including exogenous variables, we expect it is possible to obtain more robust models. We also believe that this will enable researchers to forecast EV sale as more information is included in the model and this will improve the significance of the coefficients. More elaborated inspiration for further research and development are to be found at the end of this study.

4.2.4 Outliers

As pointed out earlier in the descriptive statistics section we have detected some outliers in our sample. In the attempt of improving the model one could have simply removed the outliers. Instead, we have chosen to deal with the outlying data points by taken the average of the observation before and after the outlier. This way the authors hope to obtain more significant coefficients, and hence a better model, without losing any observations. The rest of our work is based on our adjusted sample without outliers.

4.3 VAR and VECM modeling with removed outliers

After removing the outliers and modeling the relationship with EV sale as target equation, we can see that the MAPE for EV sale is higher than the MAPE we found both before and after the break, before we removed the outliers. Respectively, 49.00% to 35.53% and 37.55%. We have run a stability test to see whether the model itself have any breaking points. We follow the same procedure as earlier by testing for multiple breaking points with the Bai-Perron test. Only this time we are testing for breaks in the model as a whole and not in the individual variables. The test detects one breaking point on 02 January 2014. However, the model is not significant at any level. When checking for causalities we find that only oil prices have a significant Granger causality on lithium prices.

With lithium as target equation, the suggested amount of lags is 1 which yields a VECM with one co-integrated equation. This suggests a long run relationship in one pair of the variables with a negative and significant coefficient at all levels. As earlier we have trimmed the sample 15% for modeling purposes. For lithium prices this entails that the break is outside the modeling period. The results yield a quite high MAPE of 35%, which is a significant aggravation compared to earlier models. When trimming the sample only 10% instead of 15% we see an increase in MAPE to 45%. This is surprising as the modeling horizon now include the breaking point, which we anticipated would have an improving effect on the model. There is an increase in the significance of the coefficients after including the breaking point, but the significance is still not satisfying. Only lagged values of lithium prices turns out to be significant. The other variables do not have any significant coefficients at any level. For the causality test we find that oil prices are the only variable that has Granger causality to lithium prices. When checking for breaks in the model we find the same result as earlier. There a no breaks found when the sample is trimmed 15%, but when we reduce the trimming to 10% we find a break in the model at the exact same date as the lithium variable breaks.

The MAPE of 18% with oil as target equation, is higher than the MAPE we have seen earlier. The model itself is jointly significant at a 10% level with a structural break on 30 September 2014. When running the causality test we find that oil prices has Granger causality on EV sale meaning that there is a short term relationship. Unfortunately, we find heteroscedasticity in the residuals which is an undesirable characteristic.

	Model Structure		Forecast Evaluation	Residual Diagnostic		
Target equation	# lags VECM	Cointegrated eqn.	MAPE	Serial correlation	Heteroscedasticity	Normality
EV_SALE	2	1	49,00 %	No	No	No
LI_PRICE	1	1	35,00 %	No	No	No
OIL_PRICE	3	1	18,00 %	No	Yes	No

Table 4.4: Estimation Characteristics from sample with removed outliers

The model where EV sale is the target equation is not significant at any level, meaning that lithium prices and oil prices with its lags and differences have no significant impact on the behavior of the EV sale. The results are slightly better when the target equation is lithium prices. The model has more significant coefficients in addition to being jointly significant. When treating oil prices as target equation we also find jointly significance, at a 10% level. In other words, the VAR model shows best results when having lithium prices or oil prices as target equation from a forecasting perspective. Rather looking at overall significance, lithium prices preformed best when treaded as endogenous variable. Not solely based on jointly significance, but also the amount of significant coefficients. This makes it reasonable to draw the conclusion that EV sale and oil prices have more impact on lithium prices than the other way around. This is consistent with the results of the Granger causality showing that oil prices has Granger causality on lithium prices and EV sale. The opposite causality receive no support from the test.

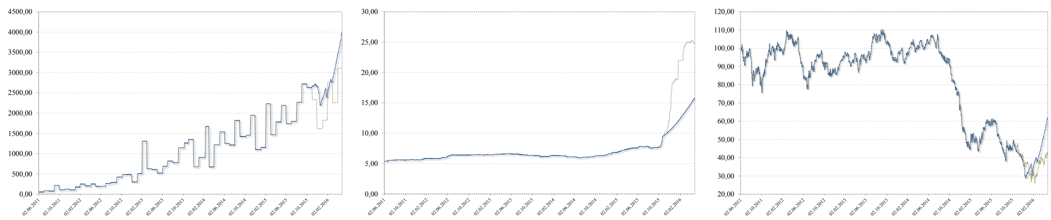


Figure 4.8: Forecasting accuracy – with removed outliers
The figures depict the forecasting accuracy with a 10% trimming. The gold line is the actual time series and the blue is the out-of-sample forecasting.

The sample without outliers shows no significant improvements in the results, neither when it comes to reduction in MAPE nor significant coefficients. As shown in the Figure 4.8 the forecast is seemingly decent until the breaking point. On the other hand, after the breaking point it looks quite arbitrary.

4.3.1 Impulse response and Variance Decomposition

The first thing to point out from the impulse response analysis is that neither oil prices nor EV sale are noteworthy affected by shocks in lithium prices. On the other hand, we observe that lithium prices are affected by both changes in oil prices and EV sale. When there is an increase in oil prices, lithium prices are declining. For EV sale we see the opposite effect. When EV sale increase, so does the lithium prices. After 360 days we can see from the variance decomposition that most of the variance in the oil price comes from its own shock. 22% of the change in variance comes from EV sale and only 4% from lithium prices. For EV sale the results are quite similar to those obtain for oil prices. Most of the variance in EV sale is due to its own shock. However, 40% of the variance is due to oil prices. For lithium prices the variance decomposition shows that in the first 50 days lithium prices itself counts for all the variance, but the longer horizon we analyze the less significant lithium prices are to explain its own variance. After around 200 days oil prices and EV sale accounts for close to all the variance in lithium prices. Oil prices accounts for 74% of the variance in lithium and EV sale accounts for 20%. These results are consistent with the causality test showing that lithium is affected by oil and electric vehicles sale, but not the other way around (See appendix 7.3.2, 7.3.4 and 7.3.6)

In our research so far, we have seen the importance of accounting for the breaking points in one or more variables. In the next section, we include dummy variables in our modeling to accounting for the breaks.

4.4 VAR and VECM modeling with dummy variables

Removing the outliers did not result in the desired improvements, and we believe that this has to do with the breaks in the variables. Recall that all our time series have at least one break. The next step to improve the model is to introduce dummy variables that accounts for the breaks. The dummy will have value zero for all observations before the break and 1 for all observations after the break. We have followed the same procedure as for the earlier model, namely create three models where all three variables are set as target equation. This time we have only trimmed the sample 5% in order for the dummy variable of lithium price to have any importance. If we trim the sample more than 5%, the break of lithium would not have an impact on the target equation and its values would have been zero always. [8] The latter is a result of the break occurring in the last 10% of the observations.

When EV sale is set as target equation, we find that there is one cointegrated equation, which results in one error correcting term in the VECM. The sign of the statistical significant coefficient is negative, which means that model is brought back to equilibrium in the long run. The amount of significant coefficients has increased and the model itself is jointly significant. When looking at the forecast evaluation we observe that the MAPE are somewhat higher than before we introduced dummy variables. Hence, the overall improvements are related to the significance and not the forecasting accuracy. The causality tests show that lithium and oil prices have Granger causality on EV sale at a 5% level. Additionally, oil prices have Granger causality on lithium prices at a 1% significance level.

The results obtained when lithium price is target equation, are quite similar to the results found for EVs. An important difference is that the R^2 has improved noteworthy compared with the results before dummy variables were introduces. It is important to note that this time, only the coefficient for the dummy accounting for the lithium break is statistically significant. Even though the target equation is changed, the results from the pairwise Granger causality test remain unchanged.

Oil price as target equation similarly show some improvements. The R^2 and the amount of significant coefficients have both increased. However, for the dummy variables, the only significant coefficient is the one accounting for the break in lithium prices.

	Model Structure		Forecast Evaluation	Residual Diagnostic		
Target equation	# lags VECM	Cointegrated eqn.	MAPE	Serial correlation	Heteroscedasticity	Normality
EV_SALE	2	2	19,73 %	No	No	No
LI_PRICE	2	1	20,28 %	No	No	No
OIL_PRICE	2	2	26,17 %	Yes	No	No

Table 4.5: Estimation Characteristics from VAR and VECM with dummy variables for individual breaks

[8] Even though it is usually recommended to use 15% trimming we feel conformable when drawing some conclusion despite the small out of sample forecasting which is only 5%, given the intuition developed through past models and forecasting evaluations.

In general when comparing the same model with and without dummy variables, there are some obvious improvements. First, the models with dummy variables all show jointly significance at 5% level while the model without dummy variables does not. Additionally, introducing dummy variables improve the forecasting accuracy. Based on these two desirable features we believe it is reasonable to state that accounting for the breaks is of high importance to understand the relationship between the variables.

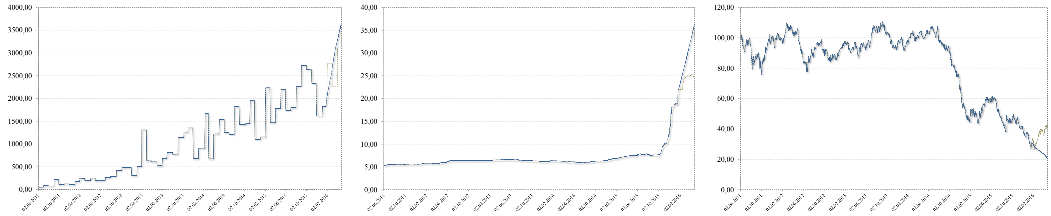


Figure 4.9: Forecasting accuracy – dummies accounting for breaks in the individual variables
The figures depict the forecasting accuracy with a 10% trimming. The gold line is the actual time series and the blue is the out-of-sample forecasting.

Until now we have used the dummy variables to account for the break in the individual variables. However, we know for a fact that the model itself breaks. In the following we have tested if the model improves if the dummy variables instead accounts for the breaks in the model rather than the breaks in the variables.

	Model Structure		Forecast Evaluation	Residual Diagnostic		
Target equation	#lags VECM	Cointegrated eqn.	MAPE	Serial correlation	Heteroscedasticity	Normality
EV_SALE	2	2	16,38 %	No	No	No
LI_PRICE	2	1	35,91 %	No	No	No
OIL_PRICE	2	2	39,55 %	Yes	No	No

Table 4.6: Estimation Characteristics from VAR and VECM with dummy variables for model breaks

In Table 4.6 above it is shown that the MAPE for EV sale is better when running the dummies for the break of the model instead of for the variables. This is the only improvement. For lithium prices and oil prices the MAPE has increased. When checking for Granger causalities for all target equations, we see that none of the results are significant at any level. This implies that there are no pair wise causalities when the dummies account for the breaks in the model.

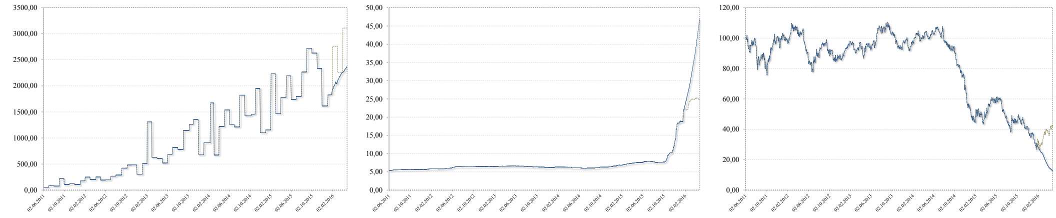


Figure 4.10: Forecasting accuracy – dummies accounting for breaks in the model
The figures depict the forecasting accuracy with a 10% trimming. The blue line is the actual time series and the red is the out of sample forecasting.

4.4.1 Impulse response and Variance Decomposition

After including dummy variables we observe that oil prices mostly respond to its own shocks. In addition, the shock dies away after close to 200 days. Neither EV sale nor lithium prices have any noteworthy effect on oil prices. For EV sale we see quite similar results with the difference that lithium price has a much higher impact on EV sale. When looking at the variance decomposition for both lithium prices and oil prices we observe that close to all change in variance is due to the shock in the variable itself. For EV sale the results are quite different. Oil prices have negligible impact on EV sale. Additionally, as the shock in EV sale dies away lithium prices increase its importance when it comes to influence the change in variance of EV sale. After 360 days, 60% of the variance in EV sale is due to lithium prices. This is also consistent with the Granger causality test. We see that regardless of target equation, lithium prices have causality on EV sale at a 10% significance level. The other variables show no results of pairwise causality. (See appendix 7.4.4 and 7.4.6)

4.5 Model summary

Throughout the analysis part, we have tries various models aiming to find the one best suited for explaining the relationship between oil prices, lithium prices and EV sale. In this section we give a summary of the main characteristics and diagnostics we have analyzed and detected for all models.

EV_SALE	Significance	Forecast Evaluation		Residual Diagnostic		
Model	Jointly	R Square	MAPE	Serial correlation	Heteroscedasticity	Normality
Optimal # lags	Yes***	3,61 %	29,33 %	No	No	No
Splitted sampel - *Before Break*	No	0,83 %	35,53 %	No	No	No
Splitted sampel - *After Break*	No	2,80 %	37,55 %	No	No	No
Without outliers	No	0,30 %	49,00 %	No	No	No
With dummies - Individual breaks	Yes***	1,89 %	19,73 %	No	No	No
With dummies - Model breaks	Yes***	1,80 %	**16,38 %**	No	No	No

Table 4.7: Summary of model characteristics when EV sale is target equation
***: Jointly significant at a 1% significance level.

As shown in Table 4.8 above, one can see a clear improvement after introducing dummy variables. In addition to being jointly significant at a 1% level we also see a reduction in MAPE. Overall we can see that the R^2 is quite low when EV sale is chosen as target equation.

LI_PRICE	Significance	Forecast Evaluation		Residual Diagnostic		
Model	Jointly	R Square	MAPE	Serial correlation	Heteroscedasticity	Normality
Splitted sampel - *Before Break*	Yes***	3,25 %	**2,40 %**	No	No	No
Splitted sampel - *After Break*	Yes***	20,60 %	**4,99 %**	No	No	No
Without outliers	Yes***	3,48 %	35,00 %	No	No	No
With dummies - Individual breaks	Yes***	**31,31 %**	20,28 %	No	No	No
With dummies - Model breaks	Yes***	29,97 %	35,91 %	No	No	No

Table 4.8: Summary of model characteristics when lithium price is target equation
***: Jointly significant at a 1% significance level.

When lithium price is set as target equation we see that all models are jointly significant at a 1% significance level. As lithium price has the most significant break it is not surprising that the models where lithium price is the target equation, shows overall more satisfying results. The R^2 is overall higher when lithium price is target equation compared to when EV sale is. Additionally, the table shows the high importance of accounting for the break either through splitting the sample or including dummy variables: MAPE decrease significantly and R^2 increase.

Oil_PRICE	Significance	Forecast Evaluation		Residual Diagnostic		
Model	Jointly	R Square	MAPE	Serial correlation	Heteroscedasticity	Normality
Splitted sampel - *Before Break*	Yes**	1,69 %	**11,64 %**	No	Yes	No
Splitted sampel - *After Break*	No	6,46 %	**6,73 %**	No	Yes	No
Without outliers	Yes*	1,49 %	18,00 %	No	Yes	No
With dummies - Individual breaks	Yes**	**1,59 %**	26,17 %	Yes	No	No
With dummies - Model breaks	Yes***	3,04 %	39,55 %	Yes	No	No

Table 4.9: Summary of model characteristics when oil price is target equation
*: Jointly significant at a 10% significance level.
**: Jointly significant at a 5% significance level.
***: Jointly significant at a 1% significance level.

Table 4.10 show that most of the models are jointly significant at 1%, 5% or 10% significance level. The lowest MAPE is found after the break in the split sample. However, this model is not significant at any level. Overall, we found low R^2, which is similar to the results for EV sale. For oil prices, there is another problem which did not occur for the other two variables. Depending on the model, we have detected both heteroscedasticity and serial correlation in the residuals which are undesirable characteristics.

	Lithium to EV	Lithium to Oil	EV to Lithium	EV to Oil	Oil to EV	Oil to Lithium
Accept 5% significance over all	1	-	1	-	2	2
Accept 5% signigicance in causality and 10% in model	2	-	1	-	3	2
Accept 10% significance over all	4	1	1	-	4	2

Table 4.10: Summary of Granger Causalities
The table shows the sum of pair wise causalities detected from all the models at different significant levels. When accepting for 10% significance in both the model and the significant test we find in total 12 pair wise causalities. When allowing the model to be significant at 10% and the causalities to be significant at 5%, we have detected 8 causalities. When the criteria for both model and causality results are 5% significance level we find 6 pair wise causalities.

When looking at the summary of the Granger causality tests (Table 4.11) we see that the most consistent result is the causality from oil prices to lithium prices, meaning that a change in oil prices will cause a change in lithium prices. Additionally, oil price has causality on EV sale. The number of causalities decreases as we are expanding the confidence interval. At last we see that lithium has causality on EV sale, which also decreases with increased confidence interval. Hence, oil prices affects lithium prices which subsequently affects EVs, in addition to oil prices having a direct influence on EV sale.

However, it is important to have in mind the fact that these relationships are extremely complex and that many factors are influencing the fluctuations in these variables. It is close to impossible to include all variables that have an impact on our three variables. However, we believe it is possible to develop the model further and see improvements by including additional variables that helps explain the fluctuations in the target variables in this study. Our ideas for further development are elaborated in the following section.

4.5.1 Recommendation for further research

Throughout our study we experienced what we expected from the very beginning. Namely, that these relationship are complex and hard to map with only three variables. We believe that the model could be improved by including more variables through a VARX model (vector autoregression model with exogenous variables). For this reason we will give a short introduction to the VARX model, by introducing possible exogenous variables for the commodities, to provide inspiration and ideas to further research. This section is inspired by the work of Kilian and Murphy (2010) with further development of Baumeister and Kilian (2012). In their research they forecast oil prices based on a four-variable VAR model. We believe that including these variables as exogenous variable for oil prices, and variables with similar characteristics for lithium prices, will enable the researcher to improve the results.

The four variables that are to be included should be good proxies for the following: supply, demand, change in inventory and change in global real activity. For oil prices Baumeister and Kilian (2012) used the following four variables: The four variables are: (i) percentage change in global crude oil production, (ii) global real activity that deviates from trends, (iii) inventory change in global crude oil and (iv) real U.S. refiners´ acquisition cost for crude oil imports which is representing the global markets real price of crude oil. According to Klovland (2004) there is no doubt that the factor with most influence on the demand of transport service is world economic activity. For this reason, it is believed that changes in freight rates are a good indicator of cumulative global demand. To construct the index of global real activity that deviates from trends one can follow the method from Kilian (2006), which is to deflate the fright rates with U.S. CIP. However, one should be careful when using such an index, as it is not free of drawbacks. The focus should be on the link between freight rate and real economic activity, but as the index also includes ship construction and scrapping cycle one may not be able to isolate the real area of interest. The variables discussed above for oil forecasting is broadly accepted as good proxies. When it comes to forecasting lithium prices based on the same method as used by Baumeister and Kilian (2012) there are no such common perception of good proxies. For this reason we have checked the correlation on several possible proxies (see appendix 7.5.1) with the same characteristics as those used in the oil price forecasting For demand the Japanese import price index shows high correlation with lithium prices. As Japan is one of the largest producers of lithium-ion batteries, in addition to not extracting of refining any lithium, it is reasonable to believe that their import is a good proxy for demand. Now a days this might change once the market is more developed and factories such as Tesla's Gigafactory start its production. For supply on the other hand, China is one of the largest producers of lithium and therefore their export is seemingly a good proxy. When it comes to inventory we are also direction our focus to Japan. Since they are a significant producer of batteries their inventories of refined battery-graded lithium should be an adequate measure. At last we are looking at the production capacity of lithium as this is an important constraint on the supply side. Forecasted worldwide production capacity is available through Stormcrow's report form 2012 "Initiating Sector Coverage: Lithium – Stronger Gets Stronger".

5 Conclusion

It this paper we have tried to map the relationship between electric vehicles sales, oil prices and lithium prices. Over 15 different models have been tested accounting for different samples and varying target equations. In general, we found that there is a long run relationship between the variables, meaning that we reject the null hypothesis stated at the beginning of this study. However, the forecasting accuracy and the significance of the models vary remarkably when the target equation changes.

We have found that throughout the great majority of the tested models, EV sale and oil prices along with its corresponding lags are more suited to explain lithium prices rather than vice versa. Meaning that the best results were obtained when lithium prices was chosen as target equation. In fact, we found that the least suitable models are those where EV sale are treated as endogenous variable. For the causality, we find that oil prices are the driver for changes in both EV sale and lithium prices. Oil prices have causality on lithium prices, which subsequently affects EV sale, in addition to oil prices having a direct influence on EV sale.

We acknowledge the great improvements of the models, either when split the sample (based on the break of lithium prices) or when introducing dummy variables. This suggests that breaks are the main disruptor of the variations in any of the models. Moreover, we have found that there is a consistent relationship between the variables when tested separately before and after the break where again the best models turned out to be those where lithium prices was the target equation. We find evidence of cointegration between the variables in both samples, which confirms our assumption of the variables moving together

The most suitable model is obtained from the split sample. Particularly for the lithium prices, which in line with the causality tests. Over all the results shows that EV sale and oil prices are two variables that are indeed relevant for the behavior of lithium prices. These results are confirmed once more when using dummy variables, which yields models with higher R^2 and jointly significant at all levels.

Our findings differ from the comments from newspapers and articles as the ones from the Financial Times and BBC, where they state that the oil price will be vastly affected by the expected increase in the EV industry and that EV sale might be the triggering factor for the next oil crisis. From the causality point of view, we disagree with these statements. According to our results, oil prices cause the change in EV sales, as well as the variations in the lithium prices and not the other way around. Hence, increased sale of EVs is unexpected to have a significant impact on the oil prices.

With respect to the statement, that lithium will be the future substitute for oil, we also disagree since oil is used in many other segments of the transportation industry such as shipping and aircrafts. Here we find low costs in the bunker prices (fuel) and therefore the high prices of lithium batteries would not fit this market segment. However, there are some limitations to our models as we are only including three variables. Including variables to account for fringes by driving an EV, such as tax benefits, would presumably show increase in demand of EVs which has a causality on lithium in the long run. The demand for batteries, which closely follows the EV sale, will increase. This does not necessarily mean that the price of lithium will increase, as there is evident that there is no causality from EV sale to lithium prices.

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7 Appendix

7.1 VAR and VECM with optimal amount of lags

	Coefficient	Std, Error	t-Statistic	Prob.
CointEq1	-0,0239	0,0060	-3,9775	**0,0001**
CointEq2	2,0646	0,5212	3,9614	**0,0001**
D(EV_SALES(-1))	0,0226	0,0280	0,8055	0,4207
D(EV_SALES(-2))	0,0042	0,0281	0,1494	0,8813
D(EV_SALES(-3))	0,0108	0,0281	0,3841	0,7009
D(EV_SALES(-4))	0,0141	0,0281	0,5027	0,6153
D(LI_PRICE(-1))	105,6121	44,8850	2,3530	**0,0188**
D(LI_PRICE(-2))	-157,8085	47,0714	-3,3525	**0,0008**
D(LI_PRICE(-3))	130,5837	47,2267	2,7650	**0,0058**
D(LI_PRICE(-4))	-192,9044	44,8733	-4,2989	**0,0000**
D(OIL_PRICE(-1))	3,1777	2,7787	1,1436	0,2530
D(OIL_PRICE(-2))	2,6680	2,7890	0,9566	0,3389
D(OIL_PRICE(-3))	1,0568	2,7904	0,3787	0,7050
D(OIL_PRICE(-4))	5,1390	2,7808	1,8481	**0,0648**
C	4,8839	4,0153	1,2163	0,2241
R-squared	0,0361	F-statistic		**3,3650**
Adjusted R-squared	0,0254	Prob(F-statistic)		**0,0000**

Appendix 7.1.1: Coefficient and significance for EVs as target equation – VAR(4) Model
Significant coefficients are highlighted. The model is jointly significant as shown by the F-Statistic. The coefficients refers to the following equation system:
D(EV_SALES) *= C(1)*(EV_SALES(-1) - 10.0574887997*OIL_PRICE(-1) -328.952226684)+C(2)*(LI_PRICE(-1)-0.439286891517*OIL_PRICE(-1)+27.9960371271)+C(3)*D(EV_SALES(-1))+C(4)*D(EV_SALES(-2)) + C(5)*D(EV_SALES(-3))+C(6)*D(EV_SALES(-4))+C(7)*D(LI_PRICE(-1))+C(8)*D(LI_PRICE(-2))+C(9)*D(LI_PRICE(-3))+C(10)*D(LI_PRICE(-4))+C(11)*D(OIL_PRICE(-1))+C(12)*D(OIL_PRICE(-2))+C(13)*D(OIL_PRICE(-3))+C(14)*D(OIL_PRICE(-4))+C(15)*

Dependent variable: EV_SALES			Dependent variable: LI_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
LI_PRICE	9.514453	**0.0495**	EV_SALES	11.51140	**0.0214**
OIL_PRICE	6.209665	0.1840	OIL_PRICE	6.784135	0.1477
All	20.03203	0.0102	All	23.04797	0.0033

Dependent variable: OIL_PRICE		
Excluded	Chi-sq	Prob.
EV_SALES	2.673736	0.6138
LI_PRICE	1.398952	0.8444
All	3.698503	0.8833

Appendix 7.1.2: Granger Causality for EVs – VAR(4) Model
The VEC Granger Causality/Black Exogeneity Wald Test shows that lithium prices has a causality on electric vehicles sale and that electric vehicles sales has a causality on lithium prices. These results are significant at a 5% level.

7.2 VAR and VECM before and after break

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	-0,0005	0,0005	-0,9630	0,3358
D(EV_SALES(-1))	0,0004	0,0324	0,0120	0,9904
D(EV_SALES(-2))	-0,0008	0,0323	-0,0237	0,9811
D(LI_PRICE(-1))	-154,8237	149,0751	-1,0386	0,2993
D(LI_PRICE(-2))	-10,3213	149,1474	-0,0692	0,9448
D(OIL_PRICE(-1))	4,9046	1,8888	2,5967	**0,0096**
D(OIL_PRICE(-2))	1,0007	1,8929	0,5286	0,5972
C	2,8312	2,7175	1,0418	0,2977
R-squared	0,0083	F-statistic		**1,1419**
Adjusted R-squared	0,0010	Prob(F-statistic)		**0,3343**

Appendix 7.2.1: Coefficient and significance for EVs – Before the Break
Significant coefficients are highlighted. The coefficients refers to the following equation system:
D(EV_SALES)*=C(1)*(EV_SALES(-1)+6333.10127837*LI_PRICE(-1) + 437.160835561*OIL_PRICE(-1) - 80728.4068535)+C(2)*D(EV_SALES(-1)) + C(3)*D(EV_SALES(-2)) + C(4)*D(LI_PRICE(-1)) + C(5)*D(LI_PRICE(-2))+C(6)*D(OIL_PRICE(-1)) + C(7)*D(OIL_PRICE(-2)) + C(8)*

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	-0,0444	0,0280	-1,5861	0,1154
CointEq2	-7,9635	9,0165	-0,8832	0,3789
D(EV_SALES(-1))	0,0229	0,0935	0,2448	0,8070
D(LI_PRICE(-1))	-2,3864	115,5013	-0,0207	0,9836
D(OIL_PRICE(-1))	2,4150	28,0654	0,0861	0,9316
C	-3,1752	36,5365	-0,0869	0,9309
R-squared	0,0220	F-statistic		0,5226
Adjusted R-squared	-0,0201	Prob(F-statistic)		0,7588

Appendix 7.2.2: Coefficient and significance for EVs – After the Break
The results show that there are no significant coefficients at even a 10% significance level. The coefficients refers to the following equation system:
D(EV_SALES)*=C(1)*(EV_SALES(-1)-249.147484438*OIL_PRICE(-1)+6462.77279231)+C(2)*(LI_PRICE(-1)+1.33772516609*OIL_PRICE(-1)-67.2941702523)+C(3)*D(EV_SALES(-1))+C(4)*D(LI_PRICE(-1))+C(5)*D(OIL_PRICE(-1))+C(6)*

Dependent variable: D(EV_SALE)			Dependent variable: D(LI_PRICE)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(LI_PRICE)	22.95395	**0.0001**	D(EV_SALE)	10.48395	**0.0330**
D(OIL_PRICE)	4.526317	0.3394	D(OIL_PRICE)	6.543448	0.1621
All	27.02773	0.0007	All	17.46462	0.0256

Dependent variable: D(OIL_PRIC)		
Excluded	Chi-sq	Prob.
D(EV_SALE)	1.092967	0.8954
D(LI_PRICE)	1.535988	0.8202
All	2.651676	0.9543

Appendix 7.2.3: Granger Causality for EVs – Before the Break
Significant coefficients are highlighted. The test results shows that lithium prices has a causality on electric vehicles sale and that electric vehicle sales has causality on lithium prices. These results are significant at a 5% level.

Dependent variable: D(EV_SALES)			Dependent variable: D(LI_PRICE)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(LI_PRICE)	0.047517	0.8274	D(EV_SALES)	0.576147	0.4478
D(OIL_PRICE)	0.000178	0.9894	D(OIL_PRICE)	1.125327	0.2888
All	0.047704	0.9764	All	2.035520	0.3614

Dependent variable: D(OIL_PRICE)		
Excluded	Chi-sq	Prob.
D(EV_SALES)	0.141513	0.7068
D(LI_PRICE)	1.693310	0.1932
All	1.848395	0.3968

Appendix 7.2.4: Granger Causality for EVs – After the Break
The test results show that there are no significant causalities on neither

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	**-0,0019**	0,0041	-0,4508	0,6522
D(OIL_PRICE(-1))	**-0,0834**	0,0326	-2,5598	**0,0106**
D(OIL_PRICE(-2))	0,0509	0,0327	1,5586	0,1194
D(EV_SALES(-1))	0,0004	0,0006	0,7417	0,4585
D(EV_SALES(-2))	-0,0003	0,0006	-0,4530	0,6506
D(LI_PRICE(-1))	-5,4965	2,5718	-2,1372	**0,0328**
D(LI_PRICE(-2))	-1,7440	2,5731	-0,6778	0,4981
C	-0,0429	0,0469	-0,9160	0,3599
R-squared	0,0169	F-statistic		2,3451
Adjusted R-squared	0,0097	Prob(F-statistic)		**0,0224**

Appendix 7.2.5: Coefficient and significance for Oil prices – Before the Break
Significant coefficients are highlighted. The coefficient for the error correcting term is also highlighted as it has the right sign . That it is negative means that is correct the relationship in the long run. However, this coefficient is not significant. More over, the model is jointly significant as shown by the F-statistic The coefficients refers to the following equation system:
D(OIL_PRICE)*=C(1)*(OIL_PRICE(-1)+0.00228748762161*EV_SALES(-1)+14.4868907807*LI_PRICE(-1)-184.66523139)+C(2)*D(OIL_PRICE(-1))+C(3)*D(OIL_PRICE(-2))+C(4)*D(EV_SALES(-1))+C(5)*D(EV_SALES(-2))+C(6)*D(LI_PRICE(-1))+C(7)*D(LI_PRICE(-2))+C(8)*

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	0,0215	0,0085	2,5403	**0,0124**
D(OIL_PRICE(-1))	-0,1336	0,0950	-1,4072	0,1620
D(OIL_PRICE(-2))	-0,0491	0,0912	-0,5377	0,5918
D(EV_SALES(-1))	-0,0001	0,0003	-0,3474	0,7289
D(EV_SALES(-2))	-0,0001	0,0003	-0,2036	0,8390
D(LI_PRICE(-1))	0,4365	0,4068	1,0732	0,2854
D(LI_PRICE(-2))	0,4349	0,4067	1,0695	0,2870
C	-0,1459	0,1212	-1,2035	0,2312
R-squared	0.0646	F-statistic		1.1747
Adjusted R-squared	0.0096	Prob(F-statistic)		0.3224

Appendix 7.2.6: Coefficient and significance for Oil prices – After the Break
Highlighted coefficients are significant at a 5% leve. The only cofficient that is significant is the error correcting term. However, the sign of the coefficient is posietive meaning that it does not correct the long run relationship. The coefficients referst to the following equation system:
D(OIL_PRICE01*)=C(1)*(OIL_PRICE01(-1)+0.0080451278582*EV_SALES01(-1)+2.73760315356*LI_PRICE01(-1)-113.349561532)+C(2)*D(OIL_PRICE01(-1))+C(3)*D(OIL_PRICE01(-2))+C(4)*D(EV_SALES01(-1))+C(5)*D(EV_SALES01(-2))+C(6)*D(LI_PRICE01(-1))+C(7)*D(LI_PRICE01(-2))+C(8)*

Dependent variable: OIL_PRICE			Dependent variable: EV_SALES		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
EV_SALES	5.291272	0.0710	OIL_PRICE	6.138621	**0.0465**
LI_PRICE	5.706835	0.0576	LI_PRICE	3.157054	0.2063
All	9.780724	0.0443	All	10.18127	0.0375

Dependent variable: LI_PRICE		
Excluded	Chi-sq	Prob.
OIL_PRICE	26.66673	0.0000
EV_SALES	3.596923	0.1656
All	30.52592	0.0000

Appendix 7.2.7: Granger Causality for Oil prices – Before the Break
Significant results on a 5% level are highlighted. The results show that oil prices has a causality on electric vehicles sales.

Dependent variable: D(OIL_PRICE)			Dependent variable: D(EV_SALES)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(EV_SALES)	0.157576	0.9242	D(OIL_PRICE)	0.205294	0.9024
D(LI_PRICE)	3.452075	0.1780	D(LI_PRICE)	1.014715	0.6021
All	3.585433	0.4650	All	1.178193	0.8817

Dependent variable: D(LI_PRICE)		
Excluded	Chi-sq	Prob.
D(OIL_PRICE)	1.382047	0.5011
D(EV_SALES)	0.343021	0.8424
All	1.968053	0.7416

Appendix 7.2.8: Granger Causality for Oil prices – After the Break
The test shows no result of any causalities. Not any of the results are significant at even a 10% significance level.

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	**0,6522**	0,0008	-5,2314	**0,0000**
D(LI_PRICE(-1))	-0,0045	0,0325	-0,1372	0,8909
D(LI_PRICE(-2))	-0,0214	0,0325	-0,6568	0,5115
D(EV_SALES(-1))	0,0000	0,0000	1,8958	**0,0583**
D(EV_SALES(-2))	0,0000	0,0000	-0,5747	0,5656
D(OIL_PRICE(-1))	0,0004	0,0004	0,8774	0,3805
D(OIL_PRICE(-2))	0,0001	0,0004	0,1922	0,8476
C	0,0017	0,0006	2,8656	**0,0043**
R-squared	0,0325	F-statistic		4,5727
Adjusted R-squared	0,0254	Prob(F-statistic)		**0,0000**

Appendix 7.2.9: Coefficient and significance for Lithium prices – Before the Break
Highlighted coefficients are significant at a 5% level. The error correcting term is negative and significant, meaning that it corrects the long run relationship. More over, the model is jointly significant as shown by the F-statistic. The coefficients refers to the following equation system:
D(LI_PRICE)*=C(1)*(LI_PRICE(-1)+0.000157900522358*EV_SALES(-1)+0.0690279242895*OIL_PRICE(-1)-12.7470576113)+C(2)*D(LI_PRICE(-1))+C(3)*D(LI_PRICE(-2))+C(4)*D(EV_SALES(-1))+C(5)*D(EV_SALES(-2))+C(6)*D(OIL_PRICE(-1))+C(7)*D(OIL_PRICE(-2))+C(8)*

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	**-0,020**	0,007	-2,984	**0,004**
CointEq2	**-0,017**	0,007	-2,435	**0,016**
D(EV_SALES(-1))	0,298	0,086	3,470	**0,001**
D(LI_PRICE(-1))	0,021	0,021	0,983	0,328
D(OIL_PRICE(-1))	0,000	0,000	-0,920	0,360
C	0,100	0,027	3,677	**0,000**
R-squared	0,206	F-statistic		**6,020**
Adjusted R-squared	0,172	Prob(F-statistic)		**0,000**

Appendix 7.2.10: Coefficient and significance for Lithium prices – After the Break
Highlighted coefficients are significant at a 5% level. The error correcting tersm are negative and significant, meaning that they corrects the long run relationship. More over, the model is jointly significant as shown by the F-statistic. The coefficients refers to the following equation system:
D(LI_PRICE)*=C(1)*(LI_PRICE(-1)+0.00536921000471*EV_SALES(-1)-32.5941859176)+C(2)*(OIL_PRICE(-1)-0.00401368692225*EV_SALES(-1)-25.939546638)+C(3)*D(LI_PRICE(-1))+C(4)*D(OIL_PRICE(-1))+C(5)*D(EV_SALES(-1))+C(6)*

Dependent variable: LI_PRICE			Dependent variable: EV_SALES		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
EV_SALES	3.596923	0.1656	LI_PRICE	3.157054	0.2063
OIL_PRICE	26.66673	**0.0000**	OIL_PRICE	6.138621	**0.0465**
All	30.52592	0.0000	All	10.18127	0.0375

Dependent variable: OIL_PRICE		
Excluded	Chi-sq	Prob.
LI_PRICE	5.706835	0.0576
EV_SALES	5.291272	0.0710
All	9.780724	0.0443

Appendix 7.2.11: Granger Causality for Lithium prices – Before the Break
The highlighted results are significant. The results show that oil price has causality on lithium price and electric vehicles sale. Both lithium brices and electric vehicle sales have causality on oil prices.

Dependent variable: LI_PRICE			Dependent variable: OIL_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
OIL_PRICE	6.442688	0.1684	LI_PRICE	1.947780	0.7454
EV_SALES	3.056485	0.5484	EV_SALES	1.362821	0.8506
All	8.968337	0.3450	All	3.080173	0.9292

Dependent variable: EV_SALES		
Excluded	Chi-sq	Prob.
LI_PRICE	1.960851	0.7430
OIL_PRICE	0.762793	0.9434
All	2.849792	0.9434

Appendix 7.2.12: Granger Causality for Lithium prices – After the Break
The test shows no result of any causalities. Not any of the results are significant at even a 10% significance level.

7.3 VAR and VECM model without outliers

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	0,0000	0,0001	-0,1199	0,9046
D(EV_SALES(-1))	-0,0014	0,0306	-0,0451	0,9641
D(EV_SALES(-2))	-0,0006	0,0305	-0,0186	0,9851
D(LI_PRICE(-1))	-86,7101	131,6403	-0,6587	0,5102
D(LI_PRICE(-2))	-6,7574	131,7439	-0,0513	0,9591
D(OIL_PRICE(-1))	3,0336	1,8260	1,6613	0,0969
D(OIL_PRICE(-2))	1,4790	1,8260	0,8100	0,4181
C	2,0470	2,6231	0,7804	0,4353
R-squared	0,0033	F-statistic		0,5048
Adjusted R-squared	-0,0032	Prob(F-statistic)		0,8314

Appendix 7.3.1: Coefficient and significance when EVs is target equation – sample without outliers
The table shows that there are no significant coefficiients at 5% level after removing outliers. The coefficients refers to the following equation system:
D(EV_SALES)*=C(1)*(EV_SALES(-1)+43404.1598245*LI_PRICE(-1)+2759.44209759*OIL_PRICE(-1)-521456.048195)+C(2)*D(EV_SALES(-1))+C(3)*D(EV_SALES(-2))+C(4)*D(LI_PRICE(-1))+C(5)*D(LI_PRICE(-2))+C(6)*D(OIL_PRICE(-1))+C(7)*D(OIL_PRICE(-2))+C(8)*

Dependent variable: D(EV_SALES)			Dependent variable: D(LI_PRICE)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(LI_PRICE)	0.435886	0.8042	D(EV_SALES)	0.531398	0.7667
D(OIL_PRICE)	3.183395	0.2036	D(OIL_PRICE)	1.544929	0.4619
All	3.481896	0.4806	All	2.036957	0.7290

Dependent variable: D(OIL_PRICE)		
Excluded	Chi-sq	Prob.
D(EV_SALES)	0.524761	0.7692
D(LI_PRICE)	4.108151	0.1282
All	4.747484	0.3142

Appendix 7.3.2: Granger Causality when EVs is the target equation – sample wothout outliers
The table shows that there are no significant coefficiients at 5% level after removing outliers.

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	-0,0047	0,0008	-6,1065	**0,0000**
D(LI_PRICE(-1))	-0,0146	0,0305	-0,4784	0,6325
D(LI_PRICE(-2))	-0,0284	0,0305	-0,9316	0,3518
D(OIL_PRICE(-1))	0,0005	0,0004	1,2414	0,2147
D(OIL_PRICE(-2))	0,0001	0,0004	0,1832	0,8547
D(EV_SALES(-1))	0,0000	0,0000	0,4809	0,6307
D(EV_SALES(-2))	0,0000	0,0000	-0,5484	0,5835
C	0,0024	0,0006	3,9818	**0,0001**
R-squared	0,0348	F-statistic		5,5260
Adjusted R-squared	0,0285	Prob(F-statistic)		**0,0000**

Appendix 7.3.3: Coefficient and significance when lithium prices is the target equation – sample without outliers
The table shows that there are two significant coefficiients at 5% level after removing outliers. In addition the model is jointly signnificant as shown by the F-statistic. The coefficients refers to the following equation system:
D(LI_PRICE)*=C(1)*(LI_PRICE(-1)+0.063575521534*OIL_PRICE(-1)+2.30392663754E-05*EV_SALES(-1)-12.0139647975)+C(2)*D(LI_PRICE(-1))+C(3)*D(LI_PRICE(-2))+C(4)*D(OIL_PRICE(-1))+C(5)*D(OIL_PRICE(-2))+C(6)*D(EV_SALES(-1))+C(7)*D(EV_SALES(-2))+C(8)*

Dependent variable: LI_PRICE			Dependent variable: OIL_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
OIL_PRICE	16.51209	**0.0003**	LI_PRICE	4.988896	0.0825
EV_SALES	1.407387	0.4948	EV_SALES	3.422670	0.1806
All	17.97145	0.0013	All	6.737670	0.1504
Dependent variable: EV_SALES					
Excluded	Chi-sq	Prob.			
LI_PRICE	4.748983	0.0931			
OIL_PRICE	4.439973	0.1086			
All	10.18185	0.0375			

Appendix 7.3.4: Granger Causality when lithium prices is the target equation – sample wothout outliers
The highlighted coefficients are those that are significant at 5%. There are additionally two coefficients that are significant at a 10% level. The results show that oil prices has a causality on lithium prices at a 5% significance level. Lithium prices has a causality on oil prices and electric vehicles sale on a 10% significance level.

	Coefficient	Std. Error	t-Statistic	Prob.
CointEq1	0,0012	0,0016	0,7933	0,4278
D(OIL_PRICE(-1))	-0,0873	0,0298	-2,9298	**0,0035**
D(OIL_PRICE(-2))	0,0355	0,0299	1,1862	0,2358
D(OIL_PRICE(-3))	-0,0211	0,0298	-0,7077	0,4793
D(LI_PRICE(-1))	-1,6055	1,6594	-0,9675	0,3335
D(LI_PRICE(-2))	-1,6260	1,6816	-0,9670	0,3338
D(LI_PRICE(-3))	1,2004	1,6811	0,7141	0,4753
D(EV_SALES(-1))	0,0003	0,0005	0,6953	0,4870
D(EV_SALES(-2))	-0,0002	0,0005	-0,4376	0,6617
D(EV_SALES(-3))	0,0006	0,0005	1,1663	0,2438
C	-0,0464	0,0430	-1,0796	0,2805
R-squared	0,014925	F-statistic		1,718156
Adjusted R-squared	0,006238	Prob(F-statistic)		0,071907

Appendix 7.3.5: Coefficient and significance when oil prices is the target equation – sample without outliers
There is only significant coefficiients at 5% level after removing outliers. However, the model is jointly significant at a 10% significance level. The coefficients refers to the following equation system:
D(OIL_PRICE)*=C(1)*(OIL_PRICE(-1)+34.5335827209*LI_PRICE(-1)-0.0394833274016*EV_SALES(-1)-271.125055454)+C(2)*D(OIL_PRICE(-1))+C(3)*D(OIL_PRICE(-2))+C(4)*D(OIL_PRICE(-3))+C(5)*D(LI_PRICE(-1))+C(6)*D(LI_PRICE(-2))+C(7)*D(LI_PRICE(-3))+C(8)*D(EV_SALES(-1))+C(9)*D(EV_SALES(-2))+C(10)*D(EV_SALES(-3))+C(11)*

Dependent variable: OIL_PRICE			Dependent variable: LI_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
LI_PRICE	4.078109	0.2532	OIL_PRICE	7.048401	0.0704
EV_SALES	3.233627	0.3570	EV_SALES	1.013574	0.7980
All	5.833163	0.4421	All	14.67059	0.0230

Dependent variable: EV_SALES		
Excluded	Chi-sq	Prob.
OIL_PRICE	9.287329	**0.0257**
LI_PRICE	7.987093	**0.0463**
All	13.79109	0.0321

Appendix 7.3.6: Granger Causality when oil price is the target equation – sample wothout outliers
The test results show that oil price and lithium price have Granger causality on EVs. We can also see that lithium prices has Granger causality on oil prices on a 10% significance level.

7.4 VAR and VECM model with Dummy variables

	Coefficient	Std.Error	t-Statistic	Prob.
CointEq1	-0,0173	0,0043	-4,0319	**0,0001**
D(EV_SALES(-1))	0,0028	0,0287	0,0979	0,9220
D(EV_SALES(-2))	0,0038	0,0287	0,1322	0,8949
D(LI_PRICE(-1))	-34,6764	30,3366	-1,1431	0,2532
D(LI_PRICE(-2))	0,6305	30,4412	0,0207	0,9835
D(OIL_PRICE(-1))	3,4699	1,7423	1,9916	**0,0466**
D(OIL_PRICE(-2))	2,1547	1,7469	1,2334	0,2177
C	4,4786	3,1745	1,4108	0,1586
DUMMYEV	20,6304	8,6591	2,3825	**0,0174**
DUMMYLI	-55,3943	17,2577	-3,2098	**0,0014**
DUMMYOIL	-28,3693	11,0106	-2,5765	**0,0101**
R-squared	0,0189	F-statistic		2,3106
AdjustedR-squared	0,0107	Prob(F-statistic)		**0,0109**

Appendix 7.4.1: Coefficient and significance when EVs is target equation – with dummy variables
The table shows that we have five significant coefficients, in addition to the model being jointly significant. The coefficients refers to the following equation system:
D(EV_SALES)*=C(1)*(EV_SALES(-1)-295.589197505*LI_PRICE(-1)+35.7128592651*OIL_PRICE(-1)-1960.23716282)+C(2)*D(EV_SALES(-1))+C(3)*D(EV_SALES(-2))+C(4)*D(LI_PRICE(-1))+C(5)*D(LI_PRICE(-2))+C(6)*D(OIL_PRICE(-1))+C(7)*D(OIL_PRICE(-2))+C(8)+C(9)*DUMMYEV+C(10)*DUMMYLI+C(11)*DUMMYOIL*

Dependent variable: D(EV_SALES)			Dependent variable: D(LI_PRICE)		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
D(LI_PRICE)	1.472520	0.4789	D(EV_SALES)	3.979222	0.1367
D(OIL_PRICE)	5.082396	0.0788	D(OIL_PRICE)	0.408879	0.8151
All	6.537651	0.1624	All	4.245198	0.3738
Dependent variable: D(OIL_PRICE)					
Excluded	Chi-sq	Prob.			
D(EV_SALES)	0.248282	0.8833			
D(LI_PRICE)	0.903332	0.6366			
All	1.141064	0.8877			

Appendix 7.4.2: Granger Causality when EVs is the target equation – with dummy variables
The table shows that none of the results are significant at a 5% significance level. However, oil price has a Granger causality on electric vehicles sale at a 10% significance level.

	Coefficient	Std.Error	t-Statistic	Prob.
CointEq1	0,0015	0,0012	1,2201	0,2227
D(LI_PRICE(-1))	0,3976	0,0289	13,7742	**0,0000**
D(LI_PRICE(-2))	-0,1068	0,0290	-3,6870	**0,0002**
D(OIL_PRICE(-1))	0,0000	0,0017	0,0201	0,9840
D(OIL_PRICE(-2))	-0,0011	0,0017	-0,6346	0,5258
D(EV_SALES(-1))	0,0000	0,0000	1,0237	0,3062
D(EV_SALES(-2))	0,0000	0,0000	-1,7112	0,0873
C	0,0016	0,0030	0,5145	0,6070
DUMMYLI	0,1144	0,0164	6,9654	**0,0000**
DUMMYOIL	0,0014	0,0105	0,1292	0,8972
DUMMYEV	0,0051	0,0082	0,6222	0,5339
R-squared	0,3100	F-statistic		53,8739
AdjustedR-squared	0,3043	Prob(F-statistic)		**0,0000**

Appendix 7.4.3: Coefficient and significance when lithium price is target equation – sample without outliers
From the table we can see that there are 3 significant coefficients at a 5% level. Also, the model is jointly significant. The coefficients refers to the following equation system:
D(LI_PRICE)*=C(1)*(LI_PRICE(-1)-0.120819230089*OIL_PRICE(-1)-0.00338307356439*EV_SALES(-1)+6.63162652547)+C(2)*D(LI_PRICE(-1))+C(3)*D(LI_PRICE(-2))+C(4)*D(OIL_PRICE(-1))+C(5)*D(OIL_PRICE(-2))+C(6)*D(EV_SALES(-1))+C(7)*D(EV_SALES(-2))+C(8)+C(9)*DUMMYLI+C(10)*DUMMYOIL+C(11)*DUMMYEV*

Dependentvariable:LI_PRICE			Dependentvariable:OIL_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
OIL_PRICE	1.494879	0.4736	LI_PRICE	0.872961	0.6463
EV_SALES	1.123202	0.5703	EV_SALES	1.005387	0.6049
All	2.796924	0.5924	All	1.827033	0.7675

Dependentvariable:EV_SALES		
Excluded	Chi-sq	Prob.
LI_PRICE	5.712561	0.0575
OIL_PRICE	3.209461	0.2009
All	9.681990	0.0461

Appendix 7.4.4: Granger Causality when lithium price is the target equation – with dummy variables
None of the results are significant at a 5%. However, the table shows that litthium prices has Granger causality on electric vehicles sale on a 10% significant level.

	Coefficient	Std.Error	t-Statistic	Prob.
CointEq1	-0,0030	0,0025	-1,1815	0,2376
D(OIL_PRICE(-1))	-0,0895	0,0289	-3,0959	**0,0020**
D(OIL_PRICE(-2))	0,0341	0,0290	1,1754	0,2401
D(LI_PRICE(-1))	0,4209	0,5035	0,8361	0,4033
D(LI_PRICE(-2))	0,0652	0,5052	0,1290	0,8974
D(EV_SALES(-1))	0,0002	0,0005	0,4577	0,6472
D(EV_SALES(-2))	-0,0001	0,0005	-0,1965	0,8443
C	0,0144	0,0527	0,2739	0,7842
DUMMYOIL	-0,0706	0,1827	-0,3861	0,6995
DUMMYLI	-0,4925	0,2864	-1,7194	**0,0858**
DUMMYEV	-0,1070	0,1437	-0,7443	0,4568
R-squared	0,0159	F-statistic		1,9329
AdjustedR-squared	0,0077	Prob(F-statistic)		**0,0373**

Appendix 7.4.5: Coefficient and significance when oil price is target equation – with dummy variables
The table shows that there are two significant coefficients in addition to the model being jointly significant at a 5% level. The coefficients refers to the following equation system:
D(OIL_PRICE)*=C(1)*(OIL_PRICE(-1)-8.27682811145*LI_PRICE(-1)+0.0280011183808*EV_SALES(-1)-54.8888328506)+C(2)*D(OIL_PRICE(-1))+C(3)*D(OIL_PRICE(-2))+C(4)*D(LI_PRICE(-1))+C(5)*D(LI_PRICE(-2))+C(6)*D(EV_SALES(-1))+C(7)*D(EV_SALES(-2))+C(8)+C(9)*DUMMYOIL+C(10)*DUMMYLI+C(11)*DUMMYEV*

Dependentvariable:OIL_PRICE			Dependentvariable:LI_PRICE		
Excluded	Chi-sq	Prob.	Excluded	Chi-sq	Prob.
LI_PRICE	0.872961	0.6463	OIL_PRICE	1.494879	0.4736
EV_SALES	1.005387	0.6049	EV_SALES	1.123202	0.5703
All	1.827033	0.7675	All	2.796924	0.5924

Dependentvariable:EV_SALES		
Excluded	Chi-sq	Prob.
OIL_PRICE	3.209461	0.2009
LI_PRICE	5.712561	0.0575
All	9.681990	0.0461

Appendix 7.4.6: Granger Causality when oil price is the target equation – with dummy variables
The table shows that none of the results are significant at a 5% level. However, lithium prices has a Granger causality on electriv vehicles sale on a 10% significace level.

7.5 For future research

Correlation matrix	Li 99,5% (USD /kg)	StormCrow Global production capacity	JP IND.PROD - LI BATT (volume)	JP PRODUCERS SHIPMENTS - LI BATT.(volume)	JP PROD.- LI BATT. (volume)	JP SALES: DRY CELLS - LI (thousands units)	JP PROD. INV. - LI. BATT. (volumne)	JP INV. - LI BATT. (volume)	JP EXPORT PRICE INDEX - LITHIUM ION BATTERIES NADJ (MILL USD)	JP EXPORT PRICE INDEX: CNTRCT CURR BASIS -LI-ION BATTERIES (USD)	Chile EXPORTS: MINERAL -LCE (Mill USD)	JP IMPORT PRICE INDEX -LCE NADJ (USD)	JP IMPORT PRICE INDEX: CNTRCT CURR BASIS-LCE NADJ (USD)
Li 99,5% (USD /kg)	1,000	0,458	0,204	0,171	0,093	-0,032	0,649	0,627	-0,637	-0,518	0,510	0,713	0,107
Storm Crow production capacity		1,000	-0,195	-0,168	-0,239	-0,255	0,610	0,598	-0,846	-0,955	0,234	0,853	-0,624
JP IND.PROD - LI BATT (volume)			1,000	0,754	0,848	0,546	0,126	0,108	-0,175	0,067	0,101	-0,132	0,066
JP PRODUCERS SHIPMENTS - LI BATT.(volume)				1,000	0,639	0,755	-0,109	-0,157	-0,057	0,087	0,058	-0,236	-0,066
JP PROD.- LI BATT. (volume)					1,000	0,765	0,160	0,160	-0,070	0,134	0,041	-0,194	0,085
JP SALES: DRY CELLS - LI (thousands units)						1,000	-0,149	-0,150	0,089	0,187	-0,046	-0,318	-0,011
JP PROD. INV. - LI. BATT. (volumne)							1,000	0,999999	-0,735	-0,699	0,325	0,759	-0,250
JP INV. - LI BATT. (volume)								1,000	-0,719	-0,690	0,244	0,741	-0,317
JP EXPORT PRICE INDEX - LITHIUM ION BATTERIES NADJ (MILL USD)									1,000	0,937	-0,295	-0,855	0,474
JP EXPORT PRICE INDEX: CNTRCT CURR BASIS-LITHIUM ION BATTERIES (USD)										1,000	-0,248	-0,877	0,657
CL EXPORTS: MINERAL - LITHIUM CARBONATES CURN (Mill USD)											1,000	0,434	0,160
JP IMPORT PRICE INDEX - LITHIUM CARBONATES NADJ (USD)												1,000	-0,253
JP IMPORT PRICE INDEX: CNTRCT CURR BASIS-LITHIUM CARBONATES NADJ (USD)													1,000

Appendix 7.5.1: Correlation matrix of proxies for forecasting lithium
The correlations marked in red are those higher than 0.40. The correlations in the black box are the once suggested to include in the VARX model.

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BI Norwegian Business School

Preliminary Thesis Report
GRA19003

-How do Lithium prices as a potential substitute of oil, affect the South American Region and investment choices?-

Programme:
Master of Science in Financial Economics

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Abstract

Aiming to find a good investment opportunity, we explore the lithium industry in South American. With the currently high focus, and need for more environmental friendly sources of energy, lithium has been a hot topic both in media and among scholars. Questions are not only raised to lithium as a new source of renewable energy, but attention is drawn to the political issues, both prevailing and those that may arise during the development of a stable lithium industry. Given the speculative relationship between oil as a source of energy and lithium, the authors have attempted to forecast the future price development in lithium based on historical information of oil. This is to achieve a better understanding of future growth in South America, taking into account the development of the lithium industry.

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Introduction

Throughout the last years, the world has experienced different economic situations based on the fluctuations of oil as a fundamental commodity for development. However, several aspects encourage the transition of oil to other commodities such as lithium, cobalt and graphite that are gaining importance in the industry due to their important properties for batteries; namely the technological advances that allow the exploration and exploitation of other sources of energy generation such as renewal energy.
This research aims to give a more detailed perspective about investing in emerging markets particularly in South America as one of the major regions with highest reserves of lithium. Since we are in an almost economically globalized world, shocks or news are affecting most of the markets and investors need to make informed choices before investing their money in a specific market regarding what influences the performance of these markets.
This study has a particular interest in South America as an emerging region. This is due to their access to unexploited resources and reserves in different sources of energy production. Venezuela with the highest oil reserves in the world, Chile, Argentina and Bolivia (the lithium triangle) with the highest deposits and supply of lithium in the world (over 70%) (USGS (United States Geological Service) 2015) and Colombia and its power sources of renewable energy.

According to the Financial Times and its article “Tesla in stand-off over lithium supply” from December 15, 2015; a high demand of lithium is expected since several projects around the world are being developed such as the Gigafactory of Tesla in the US, which is set to supply batteries for the 500,000 cars that Tesla hopes to produce by the end of the decade, as well as to power homes. At the same time, new battery factories in China are set to increase demand for lithium.

Projects like those mentioned above, guarantee a high future demand of lithium and a need for development in the South American region. In addition, the political situation in Colombia, Venezuela and Argentina presents a need to analyse different factors that influence market performance in this region.

According to market analysts, lithium has the potential to become the new main source of energy (storage) and thus a substitute for oil once the transition from fossil fuels to renewable fuels is made. By using historical information about oil, we hope to achieve a good understanding of how oil, as a part of the energy industry influences the markets economy and use this to predict future influence of lithium with focus on South America.

Theory and earlier research

How does Oil affect the growth in the world economy?

For decades, we have blamed the oil for low levels of real interest rates and productivity, and high unemployment rates. It has also received credit for ensuring good performance in the U.S. economy when prices are high. In the absent of more suitable explanatory variables oil prices have been commonly accepted as an instrument variable to explain labour supply and demand and return to scale, in addition to having a significant role in a great amount of macroeconomic models. According to Hooker (1996), this is a bit of a paradox: at the same time as oil prices fluctuations keep increasing the importance of oil's effect on the world economy has diminished. However, even though he finds no cleared relationship in the data after 1973, he still believes that there is a relationship. The implication is that the relationship is too complex to be explained by simple models. More recent research shows indeed that there is a relationship between oil prices and world economic growth. However, scholars still struggle to find the exact relationship between economic growth and oil prices. In addition, there is a reverse causality problem where the authors struggles to tell whether oil price affects economic growth or vice versa (Hamilton, 2008).

Oil is the World's largest traded commodity both in volume and in value. Crude oil is still the main supplier of the Worlds energy even after the number of renewable energy sources that have been introduced more recently. Prevailing theory states that there is a strong relationship between oil price fluctuations and countries economic growth rate. This relationship depends, however on whether the country is exporting or importing oil. If the country is an exporter of oil increasing oil prices is good news. If the country exports oil the opposite applies, ceteris paribus.

When not looking at the world as a whole, but analyse smaller parts separately it has been proven that out of G-7 countries[9], OPEC countries[10], Russia, China and India, the G-7 countries are the only countries that experienced an implied change

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[9] Canada, France, Germany, Italy, Japan, The United Kingdom and The United States

[10] Algerie, Angola, Ecuador, Indonesia, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates and Venezuela

in GDP when oil price changed (Ghalayini, 2011). As the G-7 countries all are oil-dependent countries both producers and consumers change their behaviour according to oil price changes.
The South American sub-region did almost not grow given the heavy reliance in commodities, especially in oil. In contrast, the Central and Caribbean sub-region had a robust expansion in 2014 compared to 2013. In fact, the whole region slowed down 0.9% in 2014 from 2.7% in 2013. However, oil was not the only aspect that influenced the slowing of the region in terms of economic growth; the downgraded rating of sovereign risk in Argentina dampened investors' confidence as well as the annual inflation in Venezuela reached 65% in the second half of 2014. (The World Bank 2015)

From Oil to Lithium

According to the Financial Times in its online edition on its "Comment / the big read Section" on December 8, 2015 " Commodities: Material revolution", it states that the world is turning into more high-tech solutions and new industries are experiencing high demand growth which is the case of commodities such as lithium, graphite and cobalt in relation to the energy industry. There is also high growth in other metals such as titanium, which would potentially be a substitute for aluminium given the technological advances to transform this material and lower costs such as 3D printers (The Financial Times 2015).According to the Financial Times and Goldman Sachs, "lithium is the new gasoline" given its potential demand for more than 300.000 tons by 2025. (The Financial Times 2015).

Lithium is the lightest of the metals and this feature makes it the most energy dense of battery materials - meaning it stores the most energy for a given weight. This is why lithium is so important in the battle against climate change. This could be the key factor for the World when reduce its reliance on fossil fuels (BBC News 2014).

There are, however some drawback in lithium batteries. As an alkali metal, lithium's high reactivity turns out to be a bit of an Achilles' heel, because unwanted chemical reactions inside the battery cause it to degrade over time. Hence, duration is not the best characteristic. In addition, these reactions might lead to safety problems due to overheating.

The cost of lithium is not necessarily low. However, since its demand started to increase the price has gone down significantly, in addition to new technologies that makes easier to extract and transform the commodity. (BBC News 2014) Another question that arises is whether it is enough lithium to cover the demand in the upcoming years given the high growth of this industry.

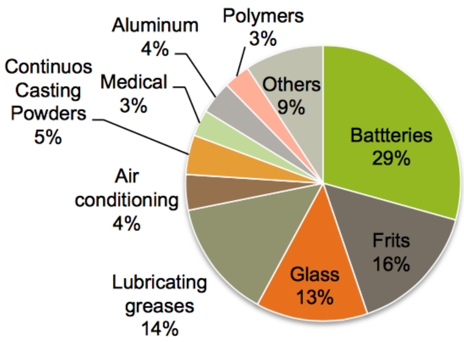
Lithium industry

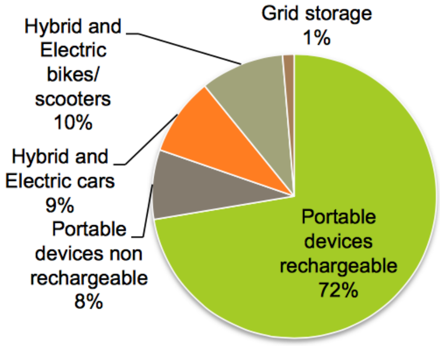
Worldwide lithium production increased by about 6% in 2014. Production from Argentina and Chile increased approximately 15% each in response to increased lithium demand for battery applications. In 2013, weather-related complications had reduced production for Argentina's major lithium producer. Lithium production in Australia and China also increased. Major lithium producers expected worldwide consumption of lithium in 2014 to be approximately 33,000 tons, an increase of 10% from that of 2013. Despite the increased lithium demand in 2014, worldwide lithium prices, on average, remained unchanged owing to the near balanced increase in worldwide lithium consumption and supply. Industrial Minerals reported a slight decrease in United States lithium carbonate prices. (USGS (United States Geological Service) 2015)

Use of lithium

As shown in the charts below, according to sugmunBOX the use of lithium was mostly for batteries , frits, glass and lubricating greases which accounts for almost 80 % of the total consumption of Lithium in which 72% of the batteries application is for mobility devices and 19 % electric transportation forms. The latter is expected to increase with a peak of 37.4% over the next years until 2020 accounting for 3% of the global vehicles sales.

Lithium consumption by application particularly in batteries 2011





SigmunBOX estimates, January 2011

Deposits

Bolivia's Salar de Uyuni is one corner of a "Lithium Triangle" that also takes in the northern ends of Chile and Argentina. These three countries dominate world lithium supplies thanks to the incredible geological forces shaped the South American continent.Lithium does not occur as a pure element in nature but is contained within mineral deposits or salts including brine lakes and seawater. This sources of lithium can be found in lithium triangle (Chile , Argentina and Bolivia) and can be recovered from three types of deposits: brines, pegmatites, and sedimentary rocks. The environmental conditions allows for the extraction of lithium from brines in the form of lithium chloride, which is the cheapest way to extract this mineral.

According to the latest geological survey available regarding the mineral commodity summary from 2015 from USGS, it has been identified approximately 39 million tons lithium resources worldwide: 9 millions are in Bolivia, 7.5 in Chile, and 5.5 in US. On the other hand the major producing countries are Argentina with 6.5 million tons, Australia with 1.7 million tons and China with 5.5 million tons. It is important to note that there is not unified information regarding these numbers. (USGS (United States Geological Service) 2015)

Extraction and Transformation

In the late 1990s, subsurface brines became the dominant raw material for lithium carbonate production worldwide due to lower production costs compared with the mining and processing of hard-rock ores. However, in 2014 mining of lithium accounted for almost 50% of the lithium supply in the world.

Two brines from Chile and extraction from pegmatite in Australia accounts for the major production of lithium; the latter is usually more pure than in brines but is more expensive. Argentina and China are also producers of Lithium in a smaller scale. (USGS (United States Geological Service) 2015)

World mine production and reserves 2015 USGS

	Mine production		Reserv
	2013	2014[e]	
United States	870	W	38,(
Argentina	2,500	2,900	850,(
Australia	12,700	13,000	1,500,(
Brazil	400	400	48,(
Chile	11,200	12,900	7,500,(
China	4,700	5,000	3,500,(
Portugal	570	570	60,(
Zimbabwe	1,000	1,000	23,(
World total (rounded)	34,000	[6]36,000	13,500,(

USGS 2015

How does Lithium contribute to the economy in South America?

Only fifteen to twenty years ago, lithium was not thought of a as source of energy and were solely used as a supplement in pharmaceuticals, ceramics and aluminum. This has changed dramatically over the last decade as now 90 percent of laptops and 60 percent of mobile phones are powered by lithium-ion batteries. This new way of utilizing lithium have resulted in an annually increase in demand of 10 percent in 2010 (Ghosh, 2008). In the lithium triangle, Bolivian soil holds over half of the world's reserves and Chile and Argentina are the two largest exporters to the United States, with 61 percent and 36 percent respectively. Even though Bolivia has the highest lithium reserves in the world, they still need to solve the issue when it comes to refining and processing the commodity. Many questions need an answer before they can start the processing of lithium. Should the government own the commodity and how will this affect national wealth, what is the equilibrium between optimal production and environmental permanence and who to ensure growth in the future when the reserves are exhausted. Arguably, this could be learned from Saudi Arabia from the way they have handled this with oil production (CHOA, 2009).

To be able to forecast the price of lithium in the future and to address its contribution to the South American continent we need to find data from previous periods. It turned out to be more challenging than first expected to find out how lithium production contributes to GDP growth and the economy in South America. However, this is crucial for our further analysis and will therefore be researched more in depth for our main Thesis.

Why invest in emerging markets?

In general, developed stock markets are assumed to be more liquid and efficient than emerging markets. Emerging markets are also more unstable and riskier than developed markets due to factors such as political risk, expropriation risk, corruption in government, exchange rate risk and liquidity risk among others. These risks are reflected in the stock prices and it is therefore reasonable to believe that investments in emerging markets would yield a higher return. The research of Kohers et al. (2006) looks at this relationship and finds indeed that emerging countries on average yield higher returns. Thus, investors are compensated for taking higher risk.

Until recently there has been an absence of available data for investors who have interest in entering emerging stock markets. This made it difficult to take well-informed decisions. In addition, international barriers such as regulations were high. However, on the contrary to the commonly held belief, barriers to transnational investments may provide investors with a unique opportunity to post superior performance (Errunza, 1983). As mentioned in the previous section investments in emerging economies tend to yield higher return on average. As theory suggests, research show that this is due to a handful of risk factors that are more prevailing in emerging markets than in developed markets (We will come back to these risk factors in more detail in a later section). In addition, emerging markets usually have elevated economic growth rates.

Stock Price Synchronous and Market Efficiency

Research has shown that stock prices tend to move more synchronous in emerging markets. According to Roll (1988) the level to stock price synchronous is influenced by the relative amount of market- and firm-level information that is captured in the stock prices. Morck et al. (2000) find that stock prices tend to move less together in economies with high GDP per capita. They conclude that this is due to less respect for private property and weaker legal protection against corporate insider in emerging markets. A more recent paper by Chan and Hameed (2006) emphasize important factors that explains why the level of firm-specific information incorporated in the stock prices is less in emerging countries than in developing countries. First, emerging countries have fewer regulations when it comes to information disclosure, and with little enforcement. In addition, very few companies release firm information voluntarily. Another noteworthy factor is that many companies are family owned which makes it hard to collect reliable information on these companies. Based on these factors, Chan and Hameed (2006) finds that the cost of finding reliable firm information is so high that most investors base their decisions on market information, which in turn may result in stock price synchronous.

As pointed out when it comes to stock price synchronous, they tend to move together as most investors lack firm specific information and base their decisions solely on market information. This might lead one to think that emerging markets are not efficient, even not to some extent. However, Urrutia (1995) makes it clear that there are emerging markets that are week-form efficient. In his paper he had to reject the hypothesis that stock prices in emerging markets follow a random walk and accept weak-form efficiency for all four Latin-American countries he studied. Fiedor (2014) compare the difference in efficiency between a developed and an emerging stock market, respectively the New York Stock Exchange (NYSE) and the Warsaw Stock Exchange (WSE). Based on financial theory it is reasonable to believe that the developed stock market is more efficient than the emerging one. Indeed this is what his research concludes. The NYSE is significantly more efficient than the WSE. Prevailing risk factors in emerging markets

Many risk factors are relevant for investors when placing their money in emerging markets. However, we have chosen those factors that, in our opinion have most influence in the geographical area of research, namely South America. We like to emphasize that by excluding some risk factors it does not mean that they are insignificant or not prevailing. Even though the focus is at emerging markets, it does not mean that the same risks do not exist in developed countries. Anyhow, theory has shown that these risk factors are not that prevailing in developed markets nor do they have influence to the same extent.

Political risk

Emerging stock markets tend to be located in emerging countries. Developing countries in turn experience more political instabilities and turmoil. Political and governmental actions may potentially change the value of a portfolio completely and unexpected (Bilson et al., 2002). This is an important factor for investors in the decision making process. However, it is hard to tell whether there is a direct relationship between stock return and political risk. Political risk is camouflaged as many factors and events such as civil strife, expropriation of property or resources, discriminatory taxation and loss of patents. Bilson et al. (2002) tried to address whether there is a relationship between these factors and stock return in their research. They found that political risk factors did indeed explain some of the variance in stock return in emerging markets. However, as pointed out by the authors: measuring the level of political risk can be challenging, as the factors are most of the time qualitative measures.

Change in political risk has a bigger impact on emerging market returns than in developed markets. Among the emerging market regions, Latin America has produced the highest standard deviation, largest monthly loss and largest monthly gains. The regions impressive volatilities are driven largely by Argentina and Brazil which even by emerging market standards, stand out as remarkably volatile (Diamonte, 1996).

Foreign Exchange rate risk

Investing in foreign markets will yield return in local currency. The investors then have to convert the return to domestic currency unless they want to re-invest it in the same local currency. As exchange rates fluctuate daily, this implies a potential risk for the investor. Even though the investment yields a positive rate of return, a weakening in local currency might offset the profit. Lack of governmental stability increase the volatility in risk-adjusted return on investments. This has an impact on the capital in- and outflow for the country, which in turn influence the exchange rate risk. However, many Latin America countries have pegged their currency to the U.S. Dollar, which makes the currency more stable. Then again, it is important to emphasize that governments are more likely to leave the fixed-rate commitment after government elections. This supports the belief that voters do not favour governments that do not hold their commitments to exchange rates. This was actually the case in Argentine where the government abandoned their decade-long agreement to peg the peso by a one-to-one exchange rate to the dollar, after the political turmoil in 2001 (Blomberg et al., 2005).

Liquidity risk

Generally speaking, emerging markets are less liquid than developed markets. In illiquid markets brokerage fees are usually higher as it requires higher effort from the broker to find counterparties to trade with. There is also a risk of price uncertainty in illiquid markets. The trader can never be sure that he will be able to sell/buy when he wants to nor at an admirable price (Bekaert et al., 2007). In a survey executed by Chuhan (1992), liquidity risk was arguable the main reason why foreign investors hesitated to invest their money in emerging markets.

Methodology

In order to answer our research question this study aims to forecast the lithium prices in order determine the impact on the GDP of the directly involved countries such as Chile, Argentina and Bolivia and consequently the indirect impact on the south American region economic growth considering the others characteristics of an emerging market.

Forecasting lithium prices

In order to forecast the growth in future GDP in South America given growth it lithium production we first need to find a suitable model to forecast the future price of lithium.

There are many different stochastic models to pick from when it comes to predicting commodity prices. However, scholars do not seem to agree on which the most is suited. Grosjean et al. (2012) used the Box&Jenkins method to forecast future lithium prices, in addition to ARIMA(1,1). In a research from 2008 the authors tried to find the best, suited stochastic model for forecasting commodity prices. They used the commodity aluminium in their forecasting. They found that mean-reverting models were the once best suited for the commodity metal as they are often subjects to shocks and have characteristics that set them apart from other commodities (Bernard et al., 2008).

According to pricing theory, commodity prices should be a stationary process and not have a unit root. Some researchers find evidence supporting this theory while other disagrees (Wang and Tomek, 2007). However, we need to consider this in our choice of model and find out whether lithium prices are a stationary process or have a unit root.

It could be tempting to use earlier models for forecasting aluminum, with some adjustments to forecast lithium prices, as both are metals. However, for our research and forecasting we will try to include the oil price as an explanatory variable. As one can read in the Financial Post on January 9 2012, the correlation between oil and lithium prices has been 89% over that last decade. This makes us believe that oil price will be an important independent variable in our forecasting. Anyhow, we will use both previous forecasting models of aluminum and oil in our forecasting model for future lithium prices.

Based on the research so far and financial theory we have addressed what we believe as the main drivers for changes in the lithium prices.

$$Lithium\ price = \alpha + \beta_1 GSUP + \beta_2 GEV + \beta_3 GMOB + \beta_4 GCER + \beta_5 OIL + \beta_6 RiskPol$$

Where ;$GSUP = Growth\ of\ suppliers$
$GEV = Growth\ of\ electric\ Vehicle\ Industry$
$GMOB = Growth\ of\ Mobile\ devices\ indusrty$
$GCER = Growth\ of\ Ceramic\ and\ Glass\ demand$
$Oil = Oil\ prices$
$Risk\ Pol = Political\ risk\ in\ producer\ countries$

Forecast of GDP growth

Forecasting GDP enables policy makers and the Central bank to determine whether the economy contracting or expanding. Measuring the GDP allows for analysing the impact of interventions in the monetary fiscal policy or economic shocks such as spikes in the oil prices as well as the taxation and the spending plans of each country.

We aim to forecast the GDP growth in South America considering the shocks in oil- and lithium prices given that there is a speculative relationship in between these two commodities. One can calculate GDP using the expenditure approach (most used), the income approach or the value added approach. The latter applies when calculating the GDP by industry and probably the most relevant in order to better understand the impact of shocks in the lithium commodity. However, one major drawback of this method is the difficulty to differentiate between intermediate and final goods. This is why some countries such as the United States and Japan prefer other methods, like the income or the expenditure approach. (Picardo 2013)

In the expenditure approach:

$$GDP = C + I + G + (X - M)$$

Where; $C = Consumer\ Spending, I = Bussines\ Spending, G = Government\ Spending, X = Exports, M = Imports$

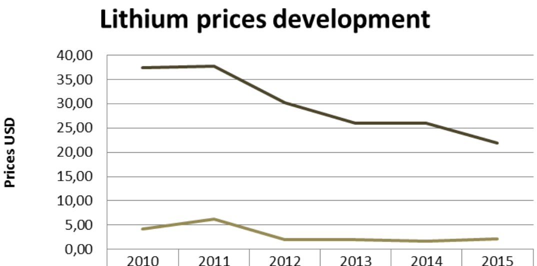
In order to forecast the GDP, the explanatory variables should be forecasted independently considering that they may have different characteristics and may require the use of different models.

It is important to mention that as this model is building on expenditures, we need to adjust for inflation for each individual country in order to arrive to a real GDP instead of the nominal GDP. One very important drawback is that this approach not necessarily accurate or perfect since there are other activities that are accounted for that influences the consumption in a country. This could be the case of illegal activities in the economy such as drug dealing, money laundry or even corruption in the in the governmental investments.

Data

Goldman Sachs is the biggest commodity trader in the world, and will be a useful source of information. Regarding current reserves and production of lithium, sources such as ***USGS (united states geological service)*** usually provide good data in terms of indexes by country.

In addition, sources as ***Bloomberg*** and ***Nasdaq*** offer good historical data.



	2010	2011	2012	2013	2014	2015
year avg.	37,48	37,78	30,19	26,00	25,93	21,83
std dev.	4,17	6,19	2,00	2,04	1,62	2,18

After doing some basic descriptive analysis regarding lithium prices we can see that the prices are more stable in more recent years and tends to decrease with time. This price development shows the potential in the industry and that demand clearly has increased.

By analyzing growth in EVS such as ***Tesla***, and other leading electric cars companies as GM could provide information regarding current end future demand. There are several sources in order to raise data related to the ***EVs Industry Growth*** as well as the ***Mobile Devices Industry***. However, industry specific reports are usually available on country level and will be useful to support our research. We will also search for relevant information from the worlds largest lithium producers, “the 3 big” namely: ***Rockwood Lithium*** which is listed in the NYSE as (ALB) , ***Chile’s Sociedad Quimica y Minera de Chile*** (NYSE:SQM), and ***FMC*** which is located in Argentina. China is also producing at a high growing rate and additional research needs to be done in order to identify the most relevant companies.

Governmental reports are also very important as the lithium industry is still under development and considered by the government as a source of growth. ***The Ministry of Mining*** in Chile, Bolivia, Argentina and Australia have annual reports with numerical data that can be of use. We expect to find already existing forecasts on how fast the world would shift its reliance of oil to other renewable sources of energies and how this affect the consumption of lithium.

We expect to have several meetings with the Norwegian firm ***Hydro*** which is the largest commodity related company in Norway with its main focus on aluminum. We believe that professional inputs regarding commodity trading would provide a great amount of data and insights that will contribute to the development of this thesis.

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