INSTITUTE
OF ECONOMIC STUDIES
Faculty of Social Sciences
Charles University

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Oleg Alekseev
Karel Janda
Mathieu Petit
David Zilberman

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Institute of Economic Studies,
Faculty of Social Sciences,
Charles University in Prague

[UK FSV – IES]

Opletalova 26
CZ-110 00, Prague
E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

Institut ekonomických studií
Fakulta sociálních věd
Univerzita Karlova v Praze

Opletalova 26
110 00 Praha 1

E-mail : ies@fsv.cuni.cz
http://ies.fsv.cuni.cz

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Impact of Raw Material Price Volatility on Returns in Electric Vehicles Supply Chain

Oleg Alekseev[a,*]
Karel Janda[a,b]
Mathieu Petit[a]
David Zilberman[c]

[a]Institute of Economic Studies, Faculty of Social Sciences, Charles University, Prague, Czech Republic
[b]Department of Banking and Insurance, Faculty of Finance and Accounting, Prague University of Economics and Business, Prague, Czech Republic
[c]Department of Agricultural and Resource Economics, Rausser College of Natural Resources, University of California, Berkeley, USA
*Corresponding author

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Abstract:
This paper investigates the impact of volatility in the upstream electric vehicles (EV) battery raw materials market on the downstream stock returns of individual EV producers. The study uses the daily stock returns of two lithium producers and the newly proposed EGARCH-EARJI model to capture the jump component of volatility in the EV battery raw materials market. The effect on individual stock returns of EV producers is studied via the adjusted Fama-French model with the jump factor. The results indicate that jumps exist in the EV battery raw materials market and ripple through stock returns of EV producers, having a stronger effect on those specializing in EVs solely.

JEL: C22, G14, L61, L62
Keywords: EVs, volatility, jump intensity, jump size, ARJI, EGARCH-EARJI

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1. Introduction

The electric vehicle (EV) industry has had rapid growth in recent years. By the end of 2024, the sales of electric vehicles in the United States are projected to increase nearly fourteen times from 2012 (Brooker and Manager, 2015). Although the efficiency of batteries used in EV production has also grown significantly, contributing to energy sustainability on a global scale (Zubi et al., 2018), the supply chain is still vulnerable to price changes occurring in the upstream battery raw materials market. In this light, it is worth studying how the volatility in the relevant commodity market affects the stock returns of individual EV producers.

Based on previous research for oil and stock returns (Li et al., 2022; Chen et al., 2019; Xiao and Zhao, 2021; John and Li, 2021), we hypothesize that there is a jump component in the EV battery raw materials market volatility. Traditional GARCH models aim to capture smooth volatility, whereas other specifications should be used to capture the jump component (Janda and Kourilek, 2020). Specifically, we construct the EGARCH-EARJI model, which uses mixture distribution to model the number of jumps occurring between two periods. Jump intensity and size are not assumed to be constant but rather have time-varying specifications that improve model fit. Also, we devote substantial care to the model estimation since many parameters and restrictions on them can cause the process to explode.

Our estimates of parameters related to jump intensity and size are used to predict the daily stock returns of individual EV manufacturers. Our results show both variables might have an effect when introduced into the mean equation of individual stock returns.

We expand the work of Maheu and McCurdy (2004) by applying a completely new specification with no restrictions on parameter coefficients to estimate a version of the GARCH-ARJI model, which we call EGARCH-EARJI, with daily data on the EV battery raw materials market. The obtained estimates of jumps in that returns are used in the models of individual stock returns of EV manufacturers. In this paper the work of Zhang and Shang (2023) is extended in the sense that the model estimation process is improved to avoid unnecessary shortcuts and jumps in the EV battery raw materials market are analyzed rather than in the oil returns.

The rest of this paper is structured as follows. In the second section, a brief review of the car manufacturing industry and relevant commodity markets is provided. In the third section, the methodology and data sources are described. In the fourth section, the results are presented. The last section concludes.

2. Energy Markets Supply Chain

2.1. Volatility in Energy Markets

Volatility in energy and commodity markets (Lyocsa et al., 2021; Yip et al., 2020), their interdependence (Hanif et al., 2021), its effects on stock returns (Baur and Dimpfl, 2018; Hernandez et al., 2022), the relationship between energy stocks, and the implications of these for portfolio management have been the objects of many studies. However, despite the increasing adoption of electric vehicles (EVs) across the globe and policy reforms intended to facilitate and smooth the transition from internal combustion cars, there is a lack of related literature studying the stock returns of EV manufacturers.

Analyzing sources of volatility, Lyocsa and Todorova (2021) showed that market volatility, stock volatility, and industry-level volatility are, in this order, the most driving factors of the day-ahead stock price volatility of firms in the Oil, Gas Exploration, and Production sub-industry. For volatility measurement, Lyocsa et al. (2021) found that while volatility models relying on high-frequency data are much more accurate for short-term forecasting, volatility models relying on daily ranges are comparable and, in some cases, even more accurate than their high-frequency counterparts for medium- and long-term forecasting.

Studying volatility effects on stock returns, Arouri et al. (2011b,a, 2012b) examined the volatility transmission between oil and stock markets in the Gulf Cooperation Council (GCC) countries, Europe and the United States at the sector level and concluded that volatility spillovers between oil and sector stock returns are significant. These spillovers are unidirectional from oil markets to stock markets in Europe and bidirectional in the United States. Spillovers are also present in emerging markets, as Raza et al. (2016) found that gold and oil volatilities have a negative impact on stock markets of all emerging economies in both the short- and long-run, and Aloui et al. (2012) concluded that oil price risk has a significant effect on emerging markets.

Investigating the effects of one group of energy stocks on another, Janda et al. (2022) found that past returns of the U.S. renewable energy companies significantly influence the current returns of Chinese renewable energy companies and support the already established findings that the stock returns of clean energy companies correlate more with technology companies rather than with oil prices. Baur and Todorova (2018) found evidence of the connectedness of EV stocks to oil prices. The authors analyzed how much oil price developments impact car manufacturers and included the U.S. electric car maker Tesla in the analysis. They hypothesized the positive exposure of Tesla to oil price shocks through the substitution effect between combustion-engine cars and electric cars. Their results indicate that Tesla has considerably higher oil price sensitivity than other companies examined.

2.2. Jumps in Energy Markets

The price of lithium has undergone a significant increase of 265% between 2014 and 2018. The Covid-19 pandemic brought significant changes in the structure and time-varying patterns of volatility connectedness among precious metals, energy and stocks (Farid et al., 2021; Shahzad et al., 2021). During the economic recovery after the Covid-19 pandemic, lithium prices achieved new record highs (TradingEconomics, 2023). The price volatility of precious metals and its relationship with returns, economic drivers, and other commodities have been widely studied (Arouri et al., 2012a; Dinh et al., 2022; Balli et al., 2019; Kang et al., 2023). We assert that abrupt price changes in the EV battery raw materials market can be modeled with a class of jump models, which have already been applied in the literature for oil and stock returns.

Gronwald (2016) defined the extremely sudden fluctuations in global crude oil prices caused by international emergencies as oil price jumps. Liu et al. (2023) concluded that jump dynamics account for a remarkable percentage of oil price volatility, especially during lower volatility periods. On the other hand, Dutta et al. (2022) revealed that the conditional expected number of jumps in oil futures prices increases significantly amid the depression periods. Zhang and Shang (2023) applied jump models to study oil prices and used the jump intensity estimates to study the stock returns of Chinese automobile manufacturers.

Chan and Maheu (2002) and Maheu and McCurdy (2004) significantly contributed to the literature on jumps in financial time series. They argued that news about anticipated cash flows and the appropriate discount rate is particularly relevant for stock prices. Then, instead of relating the volatility of stock returns to the flow of information to the market directly, they proposed models of the conditional variance of returns implied by the impact of different types of news.

Maheu and McCurdy (2004) viewed the latent news process to consist of two distinct components: normal news and unusual news events. They assumed that these components have different effects on returns and the expected volatility of individual stocks. They assumed that normal news innovations cause gradual changes in the conditional variance of returns, while the second component of the latent news process leads to infrequent moves in returns, which they referred to as jumps. Therefore, the news process induces two components in the equation for returns, which are identified by their volatility dynamics and higher-order moments.

This framework can be utilized to study jumps in the EV battery raw materials markets, and the estimates can be used in the models of individual stock returns of EV producers.

3. Hypotheses, Methodology and Estimation Procedure

3.1. Hypotheses and Methodology

We investigate these two major hypotheses related to returns and jumps in the EV supply chain:

1. Jumps in the EV battery raw materials market have varying intensity and size and explain the volatility in the time series of returns.
2. The intensity of jumps and the mean value of the jump size distribution in the EV battery raw materials market affect the mean value of EV manufacturers' stock returns.

Since the traditional GARCH and EGARCH models cannot describe jumps in financial time series, we include both smooth movements and jumps in the model in this paper. Further, we use the log link function to model jump intensity, which enables relaxing restrictions on parameters and prevents the estimation process explosion. We call the resulting model the EGARCH-EARJI model.

For the second hypothesis, this work does not assume any direction of the relationship since the results of previous studies show their unexpected nature that is possibly related to the behavior of market participants. It is important to note that the previously described studies did not investigate the possible effect of the jump size distribution on the mean value of stock returns.

The detailed setting of the EGARCH-EARJI model is as follows.

$$r_t = u + a_t \tag{1}$$

$$a_t = \epsilon_{1,t} + \epsilon_{2,t} \tag{2}$$

where r_t represents the returns of the EV battery raw materials market in period t. The disturbance term a_t is divided into two parts. The first component, $\epsilon_{1,t}$, is intended to capture the normal time-variation of volatility associated with the predictable decay of the impact from past news innovations to returns. The second component, $\epsilon_{2,t}$, captures events when significant news occurs that can cause an unusual change in returns. The former is assumed to be a standard EGARCH component:

$$\epsilon_{1,t} = \sqrt{h_t} Z_t;\ Z_t \sim NID(0,1) \tag{3}$$

$$\log h_t = \omega_0 + \alpha_1 |z_{t-1}| + \alpha_2 z_{t-1} + \beta \log h_{t-1} \tag{4}$$

where z_{t-1} is a standardized residual at time $t-1$ and ω_0, α_1, α_2, and β are parameters to be estimated.

Specifying $\epsilon_{2,t}$ refers to the works of Chan and Maheu (2002) and Maheu and McCurdy (2004). Firstly, information set at time $t-1$ consists of the history of returns $\Phi_{t-1} = \{r_{t-1}, ..., r_1\}$. Also, let $Y_{j,t}$ be jump size where j indicates a jump's number. Then, the sum of jump size from one to N_t and its conditional expectation given the information of the previous period define $\epsilon_{2,t}$:

$$\epsilon_{2,t} = J_t - E[J_t|\Phi_{t-1}] \tag{5}$$

$$J_t = \sum_{j=1}^{N_t} Y_{j,t};\ Y_{j,t} \sim NID(\theta_t, \delta) \tag{6}$$

$$\theta_t = \vartheta + \phi a_{t-1} \tag{7}$$

Thus, the conditional expectation of $\epsilon_{2,t}$ is zero and the first moment of the jump size distribution can respond to the last period's market unexpected return. This variant of mean specification follows the work of Zhang and Shang (2023).

Meanwhile, N_t, is a random variable and has a Poisson distribution:

$$P[N_t|\Phi_{t-1}] = \frac{e^{-\lambda_t}\lambda_t^j}{j!},\ j \in \mathbb{N} \tag{8}$$

$$\log \lambda_t = \lambda_0 + \rho \log \lambda_{t-1} + \gamma \xi_{t-1} \tag{9}$$

In words, $\log \lambda_t$ is a logarithm of jump intensity and follows an autoregressive process. The jump intensity is always positive by construction, so we do not have any restrictions on parameters. ξ_{t-1} is defined as the change in the conditional forecast of N_{t-1} as the information set is updated:

$$\xi_{t-1} = E[N_{t-1}|\Phi_{t-1}] - E[N_{t-2}|\Phi_{t-1}] = \sum_{j=0}^{\infty} jP[N_{t-1} = j|\Phi_{t-1}] - \lambda_{t-1} \tag{10}$$

That means that for each time $t-1$ one has to update its expectations based on new arrived information in order to use this to estimate λ_t. $P[N_{t-1}|\Phi_{t-1}]$ is often called filter or posterior probability of the current jump frequency j. Bayes rule is applied to get a formula:

$$P[N_t|\Phi_t] = \frac{f(r_t|N_t = j, \Phi_{t-1})P[N_t = j|\Phi_{t-1}]}{P[r_t|\Phi_{t-1}]} \tag{11}$$

Using the conditional density of returns given that a number of jumps occur, the denominator of (11) is obtained through the summation of the numerator term for $j \in \mathbb{N}$. In practice, one cannot sum up till infinity, so the summation has to be constrained at some reasonable j assuming that the probability of more jumps than that is zero. Following the work of Maheu and McCurdy (2004), where they used 20 jumps, the same bound is chosen.

The conditional density of returns given that a number of jumps occur requires the calculation of the mean and variance of returns given the same condition. For this, we need to take the expectation of $\epsilon_{2,t}$. In order to do that, the first two moments of its left-hand side should be calculated. Standard calculations show that:

$$E[J_t^i|\Phi_{t-1}] = \sum_{j=0}^{\infty} E[J_t^i|N_t = j, \Phi_{t-1}] \times P[N_t = j|\Phi_{t-1}],\ i > 0 \tag{12}$$

$$E[\epsilon_{2,t}|N_t = j, \Phi_{t-1}] = E[J_t|N_t = j, \Phi_{t-1}] - \theta_t\lambda_t = \theta_t(j - \lambda_t) \tag{13}$$

$$Var(\epsilon_{2,t}|N_t = j, \Phi_{t-1}) = Var(J_t|N_t = j, \Phi_{t-1}) = j\delta^2 \tag{14}$$

With these calculations at hand, one can integrate out the discrete-valued variable N_t, governing the number of jumps to get the denominator of (11):

$$P[r_t|\Phi_{t-1}] = \sum_{j=0}^{\infty} f(r_t|N_t = j, \Phi_{t-1})P[N_t = j|\Phi_{t-1}] \tag{15}$$

$$f(r_t|N_t = j, \Phi_{t-1}) = \frac{1}{\sqrt{2\pi(h_t + j\delta^2)}} exp\left(-\frac{(r_t - u + \lambda_t\theta_t - j\theta_t)^2}{2(h_t + j\delta^2)}\right) \tag{16}$$

Then, the log-likelihood function is:

$$L(\Psi) = \sum_{t=1}^{T} \log(P[r_t|\Phi_{t-1}, \Psi]) \tag{17}$$

where Ψ is a set of parameters to be estimated. This study adopts the MLE and emphasizes the model specification adopted, which relaxes restrictions on parameters compared with other studies.

For the second hypothesis, the estimated jump intensity and size in the EV battery raw materials market are introduced into EV producers' stock returns models. A potential dependence is investigated by means of the Fama-French three factors (the market risk premium, R_M - R_f, a capitalization factor of small to big firms, SMB, a stock valuation factor of high to low book value stocks, HML), short-term reversal, REV, momentum, MOM, and the proposed jump factor. The following six-factor regression model is estimated for the excess returns R_t of each automobile company:

$$R_t = \alpha_0 + \alpha_1(R_{M,t} - R_{f,t}) + \alpha_2 SMB_t + \alpha_3 HML_t + \\ \alpha_4 REV_t + \alpha_5 MOM_t + \beta JUMP_t + \epsilon_t$$

where $(\alpha_1, \alpha_2, \alpha_3, \alpha_4, \alpha_5)$ and β are regression coefficients. Based on the results obtained investigating the first hypothesis, we will consider several specifications with the jump factor constructed using jump intensity and size independently as well as their interaction.

3.2. Estimation Procedure

Maheu and McCurdy (2004) asserted that they used Maximum Likelihood (ML) method for the model estimation. Zhang and Shang (2023) also referred to ML after they specified the likelihood function. However, the attached code shows that when estimating parameters for volatility in the oil market, the authors applied two optimization procedures, working with two likelihood functions instead of the one discussed in the text. Firstly, they used the "rugarch" package to estimate the EGARCH model for the smooth volatility component. Then, they obtained residuals from this model, which they used in another model to estimate parameters for the jump component. Consequently, parameters estimated for smooth and jump parts were obtained under different likelihood functions and could be different if estimated simultaneously.

In practice, with the ML method, the negative likelihood function is minimized by using an optimizer and specifying the starting values of parameters. However, the optimizer might fail to find a reasonable solution, as discussed by Danielsson (2011). The algorithm may not be successful in finding the global minimum, especially in cases where there are restrictions on parameters to estimate or the likelihood function is not well-behaved. The two-step approach applied by Zhang and Shang (2023) might point out estimation problems encountered by the authors. In the model specification used, jump intensity is assumed to follow somewhat like an autoregressive process with restrictions on parameters ensuring that jump intensity is positive. However, these restrictions forbid the parameters to take negative values, which might cause estimation problems if the negative likelihood has its global minimum there. Hence, it makes sense to perform the sensitivity analysis on how the results change when changing starting values of the parameters or to adjust the model specification to relax restrictions. In our study, we follow the latter path.

4. Data and Empirical Results

4.1. Data description

4.1.1. Electric Vehicles Supply Chain

Baur and Todorova (2018) mentioned that the price of lithium-ion battery packs for EVs experienced a 65% decline from 2010 until 2016. More recent data shows battery costs drop 90% from 2010 to 2020 (Neil, 2021). A battery pack is the single most expensive component in EVs and the primary reason they typically cost more than traditional vehicles. According to a recent analysis, the cost of a battery pack for an electric vehicle increased by 6.9% in 2022 compared to the previous year (Mollica and Hiller, 2023). The increase was mainly attributed to the rising costs of essential components used in the batteries of most EVs, such as lithium, nickel, and cobalt.

Technological advances affect the production of battery packs. Iron-based batteries, known as LFP, do not use nickel and cobalt, which are increasingly supply-constrained and expensive. Experts estimate that iron-based batteries now represent nearly a third of all batteries in electric vehicles worldwide, and that share may continue to grow (Mollica and Hiller, 2023). Specifically, such batteries now power the majority of EVs in China and are an option on some Tesla Model 3s in the U.S.

We conclude that the key metal for the EV battery raw materials market is lithium. However, its prices are not easily available. Even Eikon database does not contain a sufficiently long history of lithium prices that could be used to model returns in the EV battery raw materials market. Also, lithium prices alone may not be enough to investigate the supply chain argument since the largest lithium producers are located in different parts of the world and can have special commitments to particular EV manufacturers.

Figure 1: ALB and SQM adjusted prices. Data are downloaded from the Yahoo Finance database.

We define the EV battery raw materials market more broadly than merely lithium prices. The largest lithium producers are Albemarle (NYSE: ALB), Sociedad Quimica y Minera de Chile (NYSE: SQM), and Ganfeng Lithium (OTC: GNENF). We hypothesize that jumps in their stock returns can affect the stock returns of EV producers. Since GNENF is traded over the counter and

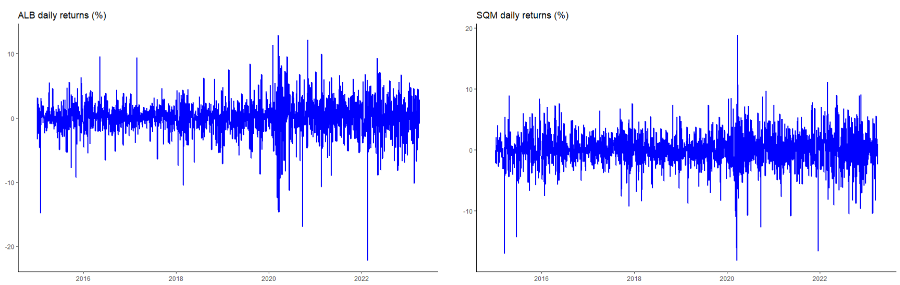


Figure 2: ALB and SQM daily returns.

does not have a sufficiently long price history, we apply the EGARCH-EARJI model on ALB and SQM.

	ALB	SQM
Mean	0.069	0.076
Median	0.161	0.075
Maximum	12.873	18.800
Minimum	-22.203	-18.106
Std.dev	2.660	2.838
Skewness	-0.724	-0.394
Kurtosis	9.246	7.524
Jarque-Bera	3552.171	1822.135
Shapiro-Wilk	0.934	0.955
ADF	-12.448	-12.921
PP	-44.667	-44.315
KPSS	0.065	0.066
Observations	2074	2074

Table 1: The descriptive statistics of ALB and SQM returns with unit root and stationary tests.

4.1.2. Electric Vehicles Producers

Until the mid of 2010s, the industry was in its infancy, with less than 2 million newly sold electric vehicles in 2015. For 2023, some experts project this number will be nearly 20 million. This growth in units sold is distributed in the sense that more EV producers have appeared since 2015. However, many of them do not leave the traditional car manufacturing business.

We do not restrict our analysis to stocks of those EV manufacturers which sell only electric vehicles and do not produce traditional ones. The transition from fuel-consuming cars is happening gradually, and we hypothesize that jumps in the EV battery raw materials market can affect the stock returns of those companies that produce non-EVs as well. Moreover, it will be beneficial to compare the strength of the effects between the two kinds of companies. The complete list of companies is presented in Table 2.

Full name	Ticker	Geography	Production
Tesla Inc	NASDAQ: TSLA	US	EVs
Toyota Motor Corp	NYSE: TM	Japan	Mix
Ford Motor Co	NYSE: F	US	Mix
General Motors Co	NYSE: GM	US	Mix
BYD Co. Ltd.	OTCMKTS: BYDDF	Chinese	EVs
Li Auto Inc.	NASDAQ: LI	Chinese	EVs
Rivian Automotive Inc	NASDAQ: RIVN	US	EVs
Lucid Group Inc	NASDAQ: LCID	US	EVs
Nio Inc	NYSE: NIO	Chinese	EVs
Xpeng Inc	NYSE: XPEV	Chinese	EVs
Niu Technologies	NASDAQ: NIU	Chinese	EVs

Table 2: List of EV stocks analyzed in the paper with corresponding names, tickers, main country of business, and production type.

The time range of the sample for the daily stock prices is every business day from January 1, 2015, to March 31, 2023 (i.e., 2075 observations). Data on stocks come from the Yahoo Finance database. All the data on risk factors used to study stock returns come from the Kenneth French database. The formula for stock returns is as follows:

$$r_t = 100 \times ln\left(\frac{p_t}{p_{t-1}}\right),$$

where p_t is the stock price.

4.2. Empirical Results

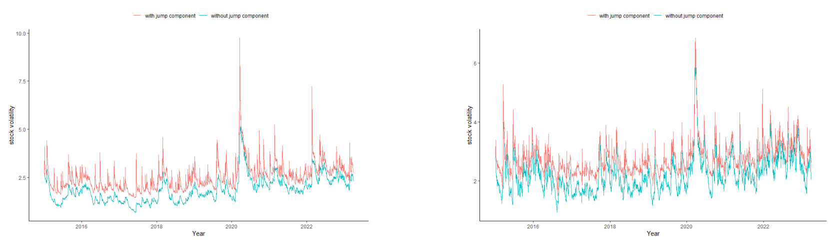
4.2.1. Volatility in the EV Battery Raw Materials Market

Table 1 shows the results of the EGARCH-EARJI model fitting. The benefits of the model specification with no restrictions on parameters can be seen immediately. ALB has jump intensity with ρ and γ positive, whereas SQM has negative sensitivities of jump intensity to the previous period components. Other studies (Maheu and McCurdy, 2004; Zhang and Shang, 2023) used model specifications that require restrictions forbidding negative sensitivities. Hence, the flexibility of the EGARCH-EARJI model allows us to get different results and can improve the model estimation procedure.

parameter	ALB	SQM
μ	0.068	0.083
	(0.048)	(0.057)
ω	-0.081^{***}	-0.107^{***}
	(0.015)	(0.031)
α_1	0.087^{***}	0.172^{***}
	(0.016)	(0.031)
α_2	-0.015	-0.012
	(0.011)	(0.015)
β	0.995^{***}	0.964^{***}
	(0.004)	(0.013)
λ_0	-0.321^{**}	-3.017^{***}
	(0.161)	(0.551)
ρ	0.803^{***}	-0.524^{***}
	(0.086)	(0.155)
γ	1.050^{***}	-1.945
	(0.263)	(1.236)
ϑ	-0.689^{***}	-0.193
	(0.262)	(0.365)
ϕ	-0.092	0.128
	(0.067)	(0.169)
δ	3.599^{***}	4.154^{***}
	(0.366)	(0.590)
N	2074	2074

Table 3: The results of the EGARCH-EARJI model fitting on returns of ALB and SQM. This table presents the estimated parameter coefficients with corresponding standard errors in parentheses. Note: ***, **, * indicate statistical significance at 1%, 5% and 10%.

We conclude that jumps exist in the EV battery raw materials market and have time-varying nature since parameters for λ_0 and ρ are statistically significant for both stocks. Different signs of parameter values imply that market participants can react differently to news about the EV battery raw materials market. For SQM, jump intensity is generally lower than for ALB because it has a more negative value of λ_0. Furthermore, for ALB, jump intensity reacts positively to the unexpected component, ξ_t. It means that when news affects ALB in the previous period, it translates into higher volatility in the current one. For SQM, the parameter for ξ_t is not statistically significant. Jump intensity tends to stay higher for longer for ALB, whereas it exhibits negative autocorrelation for SQM. The mean value of jump size, θ_t, also differs among stocks, generally being negative for ALB and around zero for SQM.



(a) ALB

(b) SQM

Figure 3: The estimated volatility of ALB and SQM with jump component included and excluded.

Overall, our results show that constituents of the EV battery raw materials market can have different volatility structures, and the EGARCH-EARJI model successfully uncovers it. Figure 3 shows the volatility of two stocks with and without the jump component. For ALB, jumps seem to explain a greater portion of volatility than for SQM.

These estimates are used for the construction of the jump factor. We assert that it makes sense to include the mean value of the jump size distribution, θ_t, only if its sensitivity to past returns, ϕ, is statistically significant at some reasonable level. Otherwise, we cannot conclude with some degree of confidence that the changes in θ_t are not simple noise, which would contaminate the jump factor. Hence, when we construct the jump factor based on ALB and SQM volatility estimates, we select λ_t only. Further, we note that, for ALB, θ_t is generally negative, whereas, for SQM, it is around zero; consequently, jumps in returns tend to be negative for ALB. We will use this fact when analyzing the sensitivities of EV producers' stock returns.

4.2.2. Expected Returns of Electric Vehicles Producers

Tables 4 and 5 show the results of the six-factor regression model estimation.

When the jump factor is formed using the jump intensity of ALB, stock returns of TSLA, BYDDF, LCID, and NIO have an estimate of the jump factor sensitivity, β, with a negative sign, and it is statistically significant at the 1% or 5% levels. It means that with increasing λ_t, the expected return decreases. We relate the observed direction to the fact that jumps tend to be negative for ALB. Hence, negative news regarding ALB has mainly unfavorable implications for companies specializing in EVs. For companies transitioning to EVs, like F and GM, the effect is on the edge of conventional 5% statistical significance. For TSLA, we found public information that it gets lithium from ALB (Scheyder, 2022), and the results shed light on how this supply chain manifests itself in the financial markets. ALB is an American lithium producer with a presence in China, and the relationship is also found with Chinese EV manufacturers BYDDF and NIO. For other Chinese companies in the sample, the estimate of β is not statistically significant, even at the 10% level.

Six-factor regression model - ALB jump intensity

	TSLA	TM	F	GM	BYDDF	LI	RIVN	LCID	NIO	XPEV	NIU
Intercept	0.289	-0.056	0.063	0.116	0.188	0.194	-0.575	0.576	0.326	0.078	0.039
	[0.021]	[0.251]	[0.302]	[0.164]	[0.015]	[0.448]	[0.096]	[0.081]	[0.133]	[0.788]	[0.820]
$R_{M,t} - R_{f,t}$	1.304	0.708	1.083	1.104	0.983	0.912	1.4	1.104	1.121	1.236	0.92
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SMB_t	0.534	-0.044	0.429	0.4	0.262	1.223	0.816	1.603	1.388	1.464	0.998
	[0.000]	[0.349]	[0.000]	[0.000]	[0.030]	[0.000]	[0.089]	[0.000]	[0.000]	[0.000]	[0.000]
HML_t	-0.744	0.154	0.557	0.561	-0.191	-0.71	-0.59	-0.663	-0.78	-0.96	-0.778
	[0.000]	[0.000]	[0.000]	[0.000]	[0.037]	[0.000]	[0.014]	[0.001]	[0.000]	[0.000]	[0.000]
MOM_t	0.067	-0.024	-0.2	-0.155	0.041	0.041	-0.652	-0.139	-0.29	-0.06	0.054
	[0.358]	[0.335]	[0.000]	[0.000]	[0.58]	[0.765]	[0.031]	[0.321]	[0.03]	[0.698]	[0.662]
REV_t	0.272	-0.007	0.071	0.22	0.114	0.163	0.576	0.437	0.221	0.199	0.222
	[0.093]	[0.860]	[0.368]	[0.007]	[0.145]	[0.456]	[0.016]	[0.053]	[0.103]	[0.383]	[0.170]
$Jump_{alb,t}$	-1.066	0.142	-0.446	-0.692	-0.645	-0.603	0.546	-2.769	-1.376	-0.755	-0.658
	[0.026]	[0.487]	[0.059]	[0.055]	[0.001]	[0.391]	[0.581]	[0.025]	[0.002]	[0.305]	[0.164]
N	2074	2074	2074	2074	2074	671	347	636	1144	651	1117
R-squared	0.303	0.403	0.484	0.518	0.17	0.187	0.431	0.215	0.193	0.252	0.191

Table 4: The estimation results of the six-factor asset pricing model for individual stock returns of EV producers. This table presents the estimated parameter coefficients, R-squared and corresponding number of observations. For each stock, its excess returns are regressed on six risk factors: market risk premium, capitalization factor of small to big firms, stock valuation factor of high to low book value stocks, short-term reversal, momentum, and jump factor. The jump factor is constructed as follows: $JUMP_t = \lambda_{alb,t}$, where $\lambda_{alb,t}$ is the estimated jump intensity of ALB. The p-value of each parameter is obtained using Newey and West (1987)-adjusted t-statistics.

Six-factor regression model - SQM jump intensity

	TSLA	TM	F	GM	BYDDF	LI	RIVN	LCID	NIO	XPEV	NIU
Intercept	0.118	-0.058	-0.297	-0.129	0.146	-0.095	-0.021	-0.263	-0.194	-0.248	0.139
	[0.550]	[0.414]	[0.020]	[0.282]	[0.440]	[0.798]	[0.964]	[0.559]	[0.673]	[0.527]	[0.725]
$R_{M,t} - R_{f,t}$	1.310	0.708	1.088	1.109	0.986	0.913	1.4043	1.110	1.136	1.2381	0.923
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
SMB_t	0.540	-0.045	0.434	0.404	0.265	1.221	0.819	1.602	1.399	1.462	1.004
	[0.000]	[0.336]	[0.000]	[0.000]	[0.029]	[0.000]	[0.087]	[0.000]	[0.000]	[0.000]	[0.000]
HML_t	-0.730	0.153	0.571	0.575	-0.184	-0.714	-0.610	-0.689	-0.752	-0.965	-0.775
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.013]	[0.001]	[0.000]	[0.000]	[0.000]
MOM_t	0.073	-0.024	-0.192	-0.149	0.044	0.046	-0.643	-0.126	-0.275	-0.054	0.054
	[0.325]	[0.330]	[0.000]	[0.000]	[0.553]	[0.736]	[0.035]	[0.379]	[0.035]	[0.731]	[0.664]
REV_t	0.276	-0.007	0.074	0.223	0.116	0.158	0.578	0.423	0.227	0.194	0.225
	[0.092]	[0.859]	[0.329]	[0.008]	[0.135]	[0.469]	[0.016]	[0.062]	[0.086]	[0.396]	[0.155]
$Jump_{sqm,t}$	-0.434	0.228	1.766	0.621	-0.681	1.025	-2.898	1.372	1.259	1.037	-1.771
	[0.730]	[0.622]	[0.036]	[0.415]	[0.552]	[0.651]	[0.337]	[0.636]	[0.666]	[0.638]	[0.479]
N	2074	2074	2074	2074	2074	671	347	636	1144	651	1117
R-squared	0.3	0.402	0.485	0.514	0.169	0.187	0.432	0.211	0.19	0.251	0.191

Table 5: The estimation results of the six-factor asset pricing model for individual stock returns of EV producers. This table presents the estimated parameter coefficients, R-squared and corresponding number of observations. For each stock, its excess returns are regressed on six risk factors: market risk premium, capitalization factor of small to big firms, stock valuation factor of high to low book value stocks, short-term reversal, momentum, and jump factor. The jump factor is constructed as follows: $JUMP_t = \lambda_{sqm,t}$, where $\lambda_{sqm,t}$ is the estimated jump intensity of SQM. The p-value of each parameter is obtained using Newey and West (1987)-adjusted t-statistics.

When the jump factor is formed using the jump intensity of SQM, only stock returns of F exhibit an estimate of β that is statistically significant at the 5% level. Interestingly, the sign is positive, meaning expected returns of F increase with higher jump intensity of SQM. After the period under investigation, SQM announced a long-term lithium supply agreement with F (Sociedad Quimica y Minera de Chile, 2023); consequently, SQM was not a part of the supply chain of F under our sample, and the estimated relationship might be reasonable. In the future, the relationship might get a negative direction since adverse news about SQM would affect the supply chain of F.

Overall, the results are that the returns of ALB are prone to jumps in response to negative news about the company, and it ripples through the stock returns of EV producers, affecting them without regard to their geography and being stronger for companies specializing in EVs. In terms of the statistical significance of the estimates, the effect on Chinese companies is the most solid. Jumps in returns of SQM seem to have minimum effect on EV producers. The results might be interesting for portfolio management if one wants to know how EV producers are interconnected with lithium manufacturers in case of bad news for the second.

5. Conclusions

We examined the volatility in the EV battery raw materials market via the EGARCH-EARJI model and used jump intensity estimated from the model to explain the daily returns of EV producers through the adjusted Fama-French model. The EV battery raw materials market was defined through the stock returns of the largest lithium producers in the world. We choose several EV producers to explain returns: 6 from China, 5 from the US, and 1 from Japan. Data regarding the daily prices of all companies were collected from January 1, 2015, to March 31, 2023.

The hypothesis of jumps' existence in the EV battery raw materials market was not rejected. In order to investigate the hypothesis, we presented a new model specification, that allows for relaxing restrictions on parameters and prevents the estimation process explosion. We called the resulting model the EGARCH-EARJI model. We concluded that jumps exist in the EV battery raw materials market and have different structures depending on underlying stocks and time-varying nature.

The hypothesis of a significant effect of jumps on individual EV producers' stock returns was not rejected completely. Jump intensity seems to affect the stock returns of EV producers specializing in EVs rather than those producing non-EVs as well. Moreover, underlying stock returns in the EV battery raw materials market matter: the jump intensity of only one lithium producer has an effect. The results are robust to the inclusion of short-term reversal and momentum risk factors in the adjusted Fama-French model.

Overall, our results show that the EGARCH-EARJI model can be used to model volatility in supply chains, and one can utilize the model to investigate how EV producers are interconnected with lithium manufacturers in case of bad news for the second.

CRediT authorship contribution statement

Oleg Alekseev: Conceptualization, Methodology, Software, Data Curation, Writing - Review & Editing. **Karel Janda:** Writing - Original Draft, Supervision. **Mathieu Petit:** Validation, Formal analysis, Writing - Review & Editing. **David Zilberman:** Conceptualization, Writing - Review & Editing.

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Appendix

Statistic	TSLA	TM	F	GM	BYDDF	LI	RIVN	LCID	NIO	XPEV	NIU
Observations	2074	2074	2074	2074	2074	671	347	636	1144	651	1117
Mean	0.125	0.008	0.009	0.013	0.095	0.064	−0.561	−0.041	0.040	−0.096	−0.069
Std.dev	3.594	1.356	2.264	2.289	3.172	5.079	5.832	6.116	5.874	5.839	4.751
Minimum	−23.652	−9.019	−13.152	−19.023	−12.222	−23.084	−23.415	−48.819	−23.777	−16.351	−21.146
Median	0.126	0.022	0.000	0.067	0.000	−0.158	−0.497	−0.101	−0.282	−0.602	−0.114
Maximum	18.145	9.145	21.060	18.185	20.484	27.686	19.966	35.767	56.394	38.713	24.211

Table 6: The descriptive statistics of the EVs stock returns

References

Aloui, C., Nguyen, D. K., and Njeh, H. (2012). Assessing the impacts of oil price fluctuations on stock returns in emerging markets. *Economic Modelling*, 29:2686–2695.

Arouri, M. E. H., Hammoudeh, S., Lahiani, A., and Nguyen, D. K. (2012a). Long memory and structural breaks in modeling the return and volatility dynamics of precious metals. *Quarterly Review of Economics and Finance*, 52.

Arouri, M. E. H., Jouini, J., and Nguyen, D. K. (2011a). Volatility spillovers between oil prices and stock sector returns: Implications for portfolio management. *Journal of International Money and Finance*, 30(7):1387–1405.

Arouri, M. E. H., Jouini, J., and Nguyen, D. K. (2012b). On the impacts of oil price fluctuations on european equity markets: Volatility spillover and hedging effectiveness. *Energy Economics*, 34.

Arouri, M. E. H., Lahiani, A., and Nguyen, D. K. (2011b). Return and volatility transmission between world oil prices and stock markets of the GCC countries. *Economic Modelling*, 28.

Balli, F., Naeem, M. A., Shahzad, S. J. H., and de Bruin, A. (2019). Spillover network of commodity uncertainties. *Energy Economics*, 81.

Baur, D. G. and Dimpfl, T. (2018). The asymmetric return-volatility relationship of commodity prices. *Energy Economics*, 76.

Baur, D. G. and Todorova, N. (2018). Automobile manufacturers, electric vehicles and the price of oil. *Energy Economics*, 74.

Brooker, D. B. J. H. P. and Manager, D. D. G. (2015). Electric vehicle sales for 2014 and future projections.

Chan, W. H. and Maheu, J. M. (2002). Conditional jump dynamics in stock market returns. *Journal of Business and Economic Statistics*, 20.

Chen, Y., Ma, F., and Zhang, Y. (2019). Good, bad cojumps and volatility forecasting: New evidence from crude oil and the U.S. stock markets. *Energy Economics*, 81.

Danielsson, J. (2011). *Financial Risk Forecasting*. Wiley.

Dinh, T., Goutte, S., Nguyen, D. K., and Walther, T. (2022). Economic drivers of volatility and correlation in precious metal markets. *Journal of Commodity Markets*, 28.

Dutta, A., Soytas, U., Das, D., and Bhattacharyya, A. (2022). In search of time-varying jumps during the turmoil periods: Evidence from crude oil futures markets. *Energy Economics*, 114:106275.

Farid, S., Kayani, G. M., Naeem, M. A., and Shahzad, S. J. H. (2021). Intraday volatility transmission among precious metals, energy and stocks during the COVID-19 pandemic. *Resources Policy*, 72.

Gronwald, M. (2016). Explosive oil prices. *Energy Economics*, 60.

Hanif, W., Hernandez, J. A., Shahzad, S. J. H., and Yoon, S. M. (2021). Tail dependence risk and spillovers between oil and food prices. *Quarterly Review of Economics and Finance*, 80.

Hernandez, J. A., Shahzad, S. J. H., Sadorsky, P., Uddin, G. S., Bouri, E., and Kang, S. H. (2022). Regime specific spillovers across US sectors and the role of oil price volatility. *Energy Economics*, 107.

Janda, K. and Kourilek, J. (2020). Residual shape risk on natural gas market with mixed jump diffusion price dynamics. *Energy Economics*, 85:104465.

Janda, K., Kristoufek, L., and Zhang, B. (2022). Return and volatility spillovers between Chinese and U.S. clean energy related stocks. *Energy Economics*, 108:105911.

John, K. and Li, J. (2021). COVID-19, volatility dynamics, and sentiment trading. *Journal of Banking and Finance*, 133.

Kang, S. H., Hernandez, J. A., Rehman, M. U., Shahzad, S. J. H., and Yoon, S. M. (2023). Spillovers and hedging between US equity sectors and gold, oil, islamic stocks and implied volatilities. *Resources Policy*, 81.

Li, X., Liao, Y., Lu, X., and Ma, F. (2022). An oil futures volatility forecast perspective on the selection of high-frequency jump tests. *Energy Economics*, 116.

Liu, F., Shao, S., Li, X., Pan, N., and Qi, Y. (2023). Economic policy uncertainty, jump dynamics, and oil price volatility. *Energy Economics*, 120:106635.

Lyocsa, S. and Todorova, N. (2021). What drives volatility of the U.S. oil and gas firms? *Energy Economics*, 100:105367.

Lyocsa, S., Todorova, N., and Vyrost, T. (2021). Predicting risk in energy markets: Low-frequency data still matter. *Applied Energy*, 282.

Maheu, J. M. and McCurdy, T. H. (2004). News arrival, jump dynamics, and volatility components for individual stock returns. *Journal of Finance*, 59.

Mollica, A. and Hiller, J. (2023). How Tesla opening its superchargers alters the EV charging map. https://www.wsj.com/articles/how-tesla-opening-its-superchargers-alters-the-ev-charging-map-c9398c90?mod=Searchresults_pos3&page=1.

Neil, D. (2021). Electric cars are struggling to meet two key needs: Speed and range. https://www.wsj.com/articles/evs-batteries-range-electric-vehicles-tesla-kia-porsche-mercedes-11671232024?mod=article_inline.

Raza, N., Shahzad, S. J. H., Tiwari, A. K., and Shahbaz, M. (2016). Asymmetric impact of gold, oil prices and their volatilities on stock prices of emerging markets. *Resources Policy*, 49:290–301.

Scheyder, E. (2022). Albemarle plans major U.S. lithium processing plant. https://www.reuters.com/business/energy/albemarle-plans-major-us-lithium-processing-plant-2022-06-27/.

Shahzad, S. J. H., Naeem, M. A., Peng, Z., and Bouri, E. (2021). Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis*, 75.

Sociedad Quimica y Minera de Chile, S. (2023). SQM announces long-term lithium supply agreement with Ford Motor Company. https://www.prnewswire.com/news-releases/sqm-announces-long-term-lithium-supply-agreement-with-ford-motor-company-301830885.html.

TradingEconomics (2023). Lithium 2010-2023 data — 2024-2025 forecast — price — quote — chart — historical. https://tradingeconomics.com/commodity/lithium. Accessed: 2023-04-16.

Xiao, Y. and Zhao, J. (2021). Price dynamics of individual stocks: Jumps and information. *Finance Research Letters*, 38.

Yip, P. S., Brooks, R., Do, H. X., and Nguyen, D. K. (2020). Dynamic volatility spillover effects between oil and agricultural products. *International Review of Financial Analysis*, 69.

Zhang, C. and Shang, H. (2023). Asymmetry effect of oil price shocks and the lagging effect of oil price jumps: Evidence from China's automobile markets. *Energy Policy*, 172.

Zubi, G., Dufo-Lopez, R., Carvalho, M., and Pasaoglu, G. (2018). The lithium-ion battery: State of the art and future perspectives. *Renewable and Sustainable Energy Reviews*, 89:292–308.

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