Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Return and Volatility Spillovers between the Raw Material and Electric Vehicles Markets

CAMA Working Paper 40/2024
June 2024

Oleg Alekseev
Charles University

Karel Janda
Charles University
Prague University of Economics and Business
Centre for Applied Macroeconomic Analysis, ANU

Mathieu Petit
Charles University

David Zilberman
University of California, Berkeley

Abstract

This paper investigates the return and volatility spillovers between the upstream electric vehicles (EV) battery raw materials market and the individual downstream EV producers. The study uses the daily stock returns of two lithium producers and a new model in the GARCH family to capture the jump component of volatility in the EV battery raw materials market. Return and volatility spillovers are studied using an EGARCH(1,1) model including the excess stock returns of lithium producers in the mean equation and their jump component intensity in the variance equation. The results indicate that jumps exist in the EV battery raw materials market and that there exist significant return spillovers between lithium and EV producers. However, this paper didn't find any strong evidence of the existence of volatility spillovers between these two markets through lithium unexpected news.

Keywords

EVs, return spillovers, volatility spillovers, jump component, jump intensity, EGARCH-EARJI

JEL Classification

C22, G14, L61, L62

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

The Centre for Applied Macroeconomic Analysis in the Crawford School of Public Policy has been established to build strong links between professional macroeconomists. It provides a forum for quality macroeconomic research and discussion of policy issues between academia, government and the private sector.

The Crawford School of Public Policy is the Australian National University's public policy school, serving and influencing Australia, Asia and the Pacific through advanced policy research, graduate and executive education, and policy impact.

Return and Volatility Spillovers between the Raw Material and Electric Vehicles Markets

Oleg Alekseev[1], Karel Janda[1,2,4], Mathieu Petit[1,*], and David Zilberman[3]

[1] *Institute of Economic Studies, Faculty of Social Sciences, Charles University, Opletalova 26, 110 00 Nove Mesto, Prague, Czech Republic*

[2] *Department of Banking and Insurance, Faculty of Finance and Accounting, Prague University of Economics and Business, Namesti Winstona Churchilla 4, 130 67 Prague 3 - Zizkov, Prague, Czech Republic*

[3] *Department of Agricultural and Resource Economics, Rausser College of Natural Resources, University of California, Berkeley, 207 Giannini Hall, CA 94720-3310, Berkeley, USA*

[4] *Centre for Applied Macroeconomic Analysis (CAMA), Crawford School of Public Policy, ANU College of Asia and the Pacific, J. G. Crawford Building 132 Lennox Crossing, Acton ACT 2601 Australia*

[*] *Corresponding author*

May 14, 2024

Abstract

This paper investigates the return and volatility spillovers between the upstream electric vehicles (EV) battery raw materials market and the individual downstream EV producers. The study uses the daily stock returns of two lithium producers and a new model in the GARCH family to capture the jump component of volatility in the EV battery raw materials market. Return and volatility spillovers are studied using an EGARCH(1,1) model including the excess stock returns of lithium producers in the mean equation and their jump component intensity in the variance equation. The results indicate that jumps exist in the EV battery raw materials market and that there exist significant return spillovers between lithium and EV producers. However, this paper didn't find any strong evidence of the existence of volatility spillovers between these two markets through lithium unexpected news.

Keywords— EVs ; return spillovers ; volatility spillovers ; jump component ; jump intensity ; EGARCH-EARJI
JEL: C 22 ; G14 ; L61 ; L62

1 Introduction

The electric vehicle (EV) industry has grown rapidly 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 (Block et al., 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), our intuition suggests that EV producers are vulnerable to price changes occurring in the upstream battery raw materials market.

First, identifying return spillovers is used in modern portfolio theory to include diversified assets that can help reduce the overall risk of a portfolio. In this light, it is worth studying how the price movements in the relevant commodity market affect the stock returns of individual EV producers. Second, understanding volatility spillovers between different stock markets is one piece of the puzzle for informed hedging decisions and it allows financial market participants to correctly estimate the volatility transmission mechanism across these markets (Malik, 2021). Therefore, this paper also investigates the relationship between the volatilities in the battery raw materials and the EV manufacturers' markets.

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 - Exponential AutoRegressive conditional Jump Intensity model, abbreviated EGARCH-EARJI, which uses mixture distribution to model the number of jumps occurring between two periods. Jump intensity is not assumed to be constant but rather have time-varying specification. 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 is used to explain the daily stock returns of individual EV manufacturers. Our results provide sufficient evidence that there exists a relationship between the excess returns of the two largest lithium producers' stock and those of the EV manufacturers' stocks and fail to find strong evidence that there exist volatility spillovers between lithium and EV stock returns when unexpected lithium news occur.

We expand the work of Maheu and McCurdy (2004) by applying a new specification with no restrictions on parameter coefficients to estimate a version of the GARCH-ARJI model 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 to study both return and volatility spillovers. The contribution of this paper is twofold. Firstly, to the best of the authors' knowledge, there is no existing literature on investigating the existence of jumps in the EV battery raw materials market. Secondly, the current literature on return and volatility spillovers from the lithium market to the EV market is scarce without consensus on the significance of these relationships.

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 The EV market and its relationship with the lithium market

2.1 The EV market

Sun et al. (2022) presents the evolution of EV sales in China from 2012 to 2022 in which the reader can perceive the rapid growth of EV sales from nearly zero to half a million sold units in that period. The authors also provide projected EV growth scenarios ranging from Non-battery uses to fast EV growth. The authors argue that, although lithium price spikes are currently observed, the EV market is expected to maintain steady growth in the short-term and lithium prices should come back to 2020 price levels. Similar, recent general detailed overviews of EV and EV batteries markets are provided by Mohammadi and Saif (2023) and by Rapson and Muehlegger (2023). Such a growth necessarily involve an increasing demand for EVs. Mo and Jeon (2018) examined the dynamics of Lithium-Ion Batteries (LIBs) with EV demand using a Vector Error Correction Model. Among other findings, their results indicate that EV demand is important in short-run dynamics of lithium prices from which the authors advocate that the recent increase in lithum prices has been caused by the increase in EV demand. Lastly, empirical results suggest that the EV demand shock to lithium prices is small.

Incentives may support EV market growth. Münzel et al. (2019) applied a panel data regression on 32 European countries from 2010 to 2017 to study the effect of policies on EV sales. The authors' findings indicate that financial incentives have an impact on EV sales. However, an EV market steady growth would imply growing retired batteries. Wu et al. (2020) investigate under which circumstances the re-use of retired batteries can be profitable using an operational optimization model. Results suggest that the share of EVs on the roads could be increased with a successful establishment of a second life market.

Studies recently emerged investigating the relationship between the EV market and other markets such as, but not limited to, energy metals. Zhang et al. (2023) examined return and volatility spillovers effects among the clean energy which includes EV, electricity, and energy metals such as nickel or copper using a quantile VAR model. Results suggest that clean energy markets are always transmitters and that both return and volatility spillovers among all three markets have time-varying structure and they increase drastically when extreme events occur.

2.2 Return spillovers from lithium markets to EV 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 (Trading Economics, 2024).

Sun et al. (2022) shed lights on the drivers of the lithium price spike observed in 2022. The authors argue that optimistic expectations on EV sales initiated a supply-chain-wide race in production capacity growth. Global production capacity of lithium-ion batteries scheduled by 2025 is five times higher than 2021 level. Then, suppliers of basic chemicals overproduced attempting to increase inventory levels, which in turn implied overproduction in the downstream of the supply chain until lithium producers.

Burney and Killins (2023) provide an overview of the EV and battery metals supply chain and shed light on how prices of battery materials may affect automobile manufacturer's equity prices using a panel estimation technique and data from January 2, 2017 to December 31, 2021. Their empirical don't provide robust evidence for either a "production-cost effect" or an "EV-demand effect". Similarly, Baur and Gan (2018) investigate the relationship between automobile manufacturers and lithium prices and the authors find significant corresponding regression coefficients for six Chinese manufacturers and one German producer. Interpreting these empirical results, the authors argue that there exist an "EV-demand effect" for Chinese manufacturers and a "production-cost effect" for the German manufacturer.

Other studies use different assumptions on the model specification. Plante (2023) decomposed EV and battery supply chain stock returns into systematic and idiosyncratic components using latent factors extracted from a large panel of stock returns. The author found that there are three main drivers of co-movement among EV stocks, namely, the market factor, the tech factor including technology stocks such as Apple (AAPL) or Microsoft (MSFT), and a risk factor given by a set of latent factors extracted from stocks on the S&P 500 and the Nasdaq 100 using high-frequency principal components.

2.3 Volatility spillovers from lithium markets to EV markets

The price volatility of precious metals and its relationship with returns, economic drivers, and other commodities have been widely studied (Arouri et al., 2012; Dinh et al., 2022; Balli et al., 2019; Kang et al., 2023).

Cagli (2023) examined the volatility connectedness between battery raw materials prices, including base metals such as copper or nickel and minor metals such as lithium or cobalt, and the Solactive Electric Vehicles and Future Mobility Index using a frequency connectedness framework (Baruník and Křehlík, 2018). The author found that future mobility equity market is a net volatility recipient, and copper and lithium are the main net volatility transmitters. On the other hand, Shi et al. (2023) used VAR and DCC-GARCH models to analyse the risk spillover effect, specifically the volatility spillover effect, of New Energy Vehicles (NEV) Chinese firms' stock markets, lithium battery suppliers' stock markets, and the raw materials' spot markets. Among other findings, the authors didn't find sufficient evidence of the significance of raw material price of lithium battery on NEV stock price.

3 Hypotheses, Methodology and Estimation Procedure

3.1 Hypotheses and Methodology

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. A promising alternative non-parametric approach consists of calculating the jump component from the realized volatility in the return of the raw materials' stocks using high-frequency data (Andersen et al., 2007; Giot et al., 2010; Busch et al., 2011). The authors follow the EGARCH-EARJI modelling approach and compare it with the realized volatility non-parametric approach.

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.

We investigate three main hypotheses:

1. Jumps in the EV battery raw materials market have varying intensity and size and explain part of the volatility in the time series of returns.

2. There exists a relationship between the excess returns in the battery raw materials market and those of EV manufacturers.

3. The above mentioned jump intensity is significant in explaining the volatility of EV manufacturers' stock returns.

Since the traditional GARCH and EGARCH models cannot describe jumps, such as extreme news or abnormal information, in financial time series (Dutta et al., 2017), 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 relaxes the positivity constraint on the model parameters. We call the resulting model the EGARCH - Exponential AutoRegressive conditional Jump Intensity (EGARCH-EARJI) model.

For the second hypothesis, stock intrinsic value have been historically determined by discounted future cash flows (Rutterford, 2004). Therefore, economic intuition suggests that there is a link between the price level of raw materials and EV stock returns.

For the third hypothesis, in addition, this paper tests the existence of volatility spillovers between the battery raw materials market returns and EV manufacturers' stock returns, specifically through jump intensity in the battery raw materials market. The authors expect a positive relationship.

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

$$r_t = \mu + \zeta r_{t-1} + a_t \tag{1}$$

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

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 $\epsilon_{2,t}$:

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

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

Thus, the conditional expectation of $\epsilon_{2,t}$ is zero and the first moment of the jump size distribution is constant.

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

$$P[N_t|\Phi_{t-1}] = \frac{e^{-\lambda_t}\lambda_t^j}{j!},\ j \in \mathbb{N} \tag{7}$$

$$\log \lambda_t = \lambda_0 + \rho \log \lambda_{t-1} + \gamma \xi_{t-1} \tag{8}$$

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:

$$\xi_{t-1} = E[N_{t-1}|\Phi_{t-1}] - E[N_{t-2}|\Phi_{t-1}] = \sum_{j=0}^{\infty} jP[N_{t-1} = j|\Phi_{t-1}] - \lambda_{t-1} \tag{9}$$

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:

$$P[N_t|\Phi_t] = \frac{f(r_t|N_t = j, \Phi_{t-1})P[N_t = j|\Phi_{t-1}]}{P[r_t|\Phi_{t-1}]} \tag{10}$$

Using the conditional density of returns given that a number of jumps occurs, the denominator of (10) 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:

$$E[J_t^i|\Phi_{t-1}] = \sum_{j=0}^{\infty} E[J_t^i|N_t = j, \Phi_{t-1}] \times P[N_t = j|\Phi_{t-1}],\ i > 0 \tag{11}$$

$$E[\epsilon_{2,t}|N_t = j, \Phi_{t-1}] = E[J_t|N_t = j, \Phi_{t-1}] - \theta_t\lambda_t = \theta_t(j - \lambda_t) \tag{12}$$

$$Var(\epsilon_{2,t}|N_t = j, \Phi_{t-1}) = Var(J_t|N_t = j, \Phi_{t-1}) = j\delta^2 \tag{13}$$

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 (10):

$$P[r_t|\Phi_{t-1}] = \sum_{j=0}^{\infty} f(r_t|N_t = j, \Phi_{t-1})P[N_t = j|\Phi_{t-1}] \tag{14}$$

$$f(r_t|N_t = j, \Phi_{t-1}) = \frac{1}{\sqrt{2\pi(h_t + j\delta^2)}} exp\left(-\frac{(r_t - u + \lambda_t\theta_t - j\theta_t)^2}{2(h_t + j\delta^2)}\right) \tag{15}$$

Then, the log-likelihood function is:

$$L(\Psi) = \sum_{t=1}^{T} \log(P[r_t|\Phi_{t-1}, \Psi]) \tag{16}$$

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 (Zhang et al., 2018; Dutta et al., 2021, 2022; Hu and Jiang, 2023).

For the second hypothesis, the excess returns and the estimated jump intensity in the EV battery raw materials market are introduced into EV producers' stock returns mean and variance equation, respectively, of an EGARCH(1,1) model. A potential dependence is investigated by introducing the Fama-French three factors (the market risk premium, R_M - R_f, a capitalization factor of small to big firms, SMB, and a stock valuation factor of high to low book value stocks, HML), the EV stock's Price-to-Book (P/B) ratio, PtB_t, and the excess return of a given EV battery raw material producer, $R_{raw,t}$, into the mean equation. Lastly, jump intensity and its lag, namely λ_t and λ_{t-1}, are introduced into the variance equation. The following EGARCH(1,1) model is estimated for the excess returns $R_{EV,t}$ of each automobile company:

$$R_{EV,t} = \delta_0 + \delta_1(R_{M,t} - R_{f,t}) + \delta_2 SMB_t + \delta_3 HML_t + \delta_4 PtB_t + \beta_1 R_{raw,t} + \sigma_t z_t,$$

where $ln(\sigma_t^2) = \gamma_0 + \gamma_1 z_{t-1} + \gamma_2 ln(\sigma_{t-1}^2) + \gamma_3(|z_{t-1}| - \mathbb{E}[|z_{t-1}|]) + \gamma_4\lambda_t + \gamma_5\lambda_{t-1}$ and $z_t \sim GED(0, 1, \nu)$.

3.2 Jump component: 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, their 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" R 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 and lithium

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 dropped 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 this 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. Lithium prices alone may not be enough to investigate the relationship between EV manufacturers and lithium producers which are located in different parts of the world and can have special commitments to particular EV manufacturers.

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). Since GNENF is traded over the counter and does not have a sufficiently long price history, we apply the EGARCH-EARJI model on ALB and SQM. Their adjusted stock prices and daily returns are shown in Figure 1 and 2, respectively. Descriptive statistics of daily returns in Table 1 don't give any indication of the presence of unit root in the two time series and although they seem leptokurtic, fat-tailed and not normally distributed, the EGARCH representation allows to capture such characteristics (Carnero et al., 2004). We hypothesize that jumps in their stock returns can affect the stock returns of EV producers.

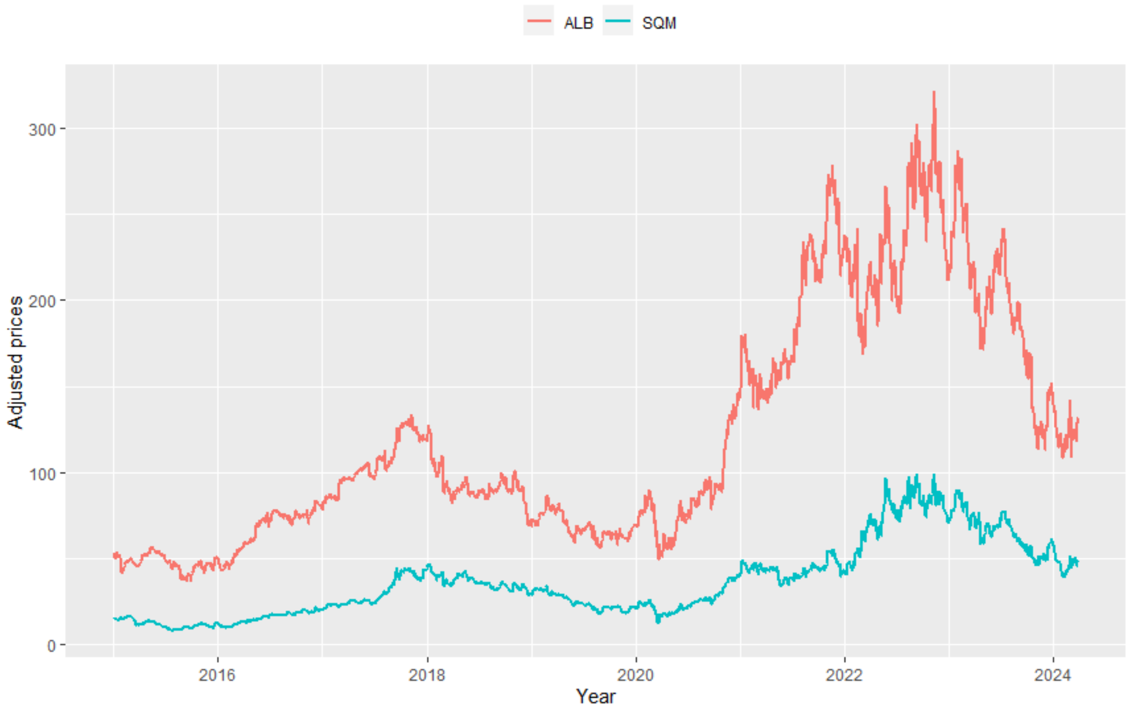


Figure 1: ALB and SQM adjusted prices. Data are downloaded from the Yahoo Finance database.

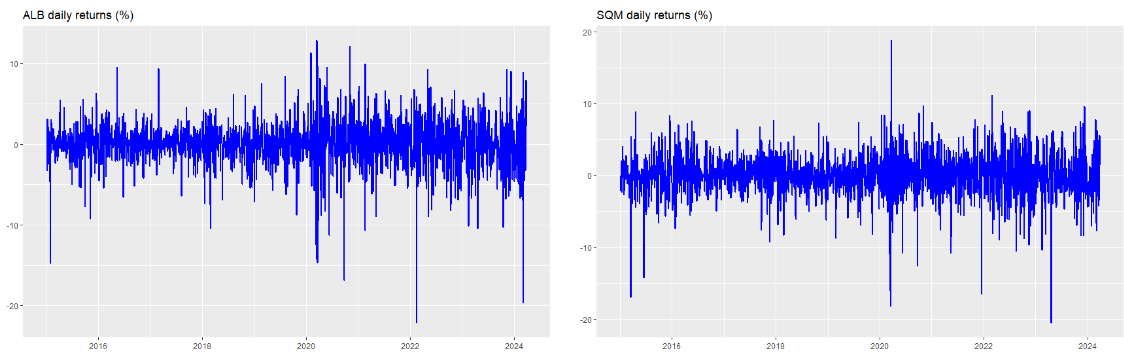


Figure 2: ALB and SQM daily returns.

	ALB	SQM
Mean	0.039	0.050
Median	0.143	0.040
Maximum	12.873	18.800
Minimum	-22.203	-20.546
Std.dev	2.745	2.881
Skewness	-0.756	-0.457
Kurtosis	9.070	7.844
Jarque-Bera	3788.689***	2352.487***
Shapiro-Wilk	0.937***	0.954***
ADF	-12.733***	-13.035***
PP	-47.371***	-47.140***
KPSS	0.087	0.069
Observations	2324	2324

Table 1: The descriptive statistics of ALB and SQM returns with unit root and stationary tests. Note: ***, **, * indicate statistical significance at 1%, 5% and 10%.

Lastly, high-frequency prices are required to apply the realized volatility approach. The authors have access to 5-minute time interval prices from May 8, 2023 to May 9, 2024, which covers a small portion of the studied period 2015-2024, from *Reuters Thomson* through the *eikon* python API.

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. According to the International Energy Agency (IEA), almost 14 million new electric cars were registered globally in 2023, bringing their total number on the roads to 40 million. Compared to 2022, electric car sales in 2023 were 3.5 million higher which represents a 35% year-on-year increase. This is more than six times higher than in 2018 (IEA, 2024). 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, 2024 (i.e., 2324 observations). Data on stocks come from the Yahoo Finance database. Descriptive statistics and standard test results are provided in Table 3. Similar to the two lithium stock returns, the eleven EV stock returns seem leptokurtic, fat-tailed and non-normally distributed with no indication of the presence of unit root. All the data on risk factors used to study stock returns come from the Kenneth French database. Lastly, the EV stocks' P/B ratios comes from *Reuters Thomson*. 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.

Statistic	TSLA	GM	TM	BYDDF	F	RIVN	NIO	LI	LCID	XPEV	NIU
Mean	0.107	0.022	0.033	0.079	0.014	-0.372	-0.027	0.066	-0.140	-0.113	-0.120
Median	0.126	0.078	0.044	-0.033	0	-0.391	-0.282	-0.133	-0.205	-0.477	-0.163
Maximum	18.145	18.185	9.145	20.484	21.060	19.966	56.394	27.686	35.767	38.713	24.211
Minimum	-23.652	-19.023	-9.019	-12.222	-13.152	-29.573	-23.777	-23.084	-48.819	-16.351	-21.146
Std.dev	3.539	2.251	1.381	3.081	2.250	5.426	5.610	4.722	5.740	5.590	4.599
Skewness	-0.172	-0.138	0.020	0.532	0.076	-0.355	1.330	0.354	0.199	1.076	0.358
Kurtosis	7.512	10.779	6.863	6.570	10.357	6.265	14.173	7.443	13.232	8.349	5.399
Jarque-Bera	1983.2***	5866.4***	1445.3***	1343.6***	5243.6***	277.7***	7662.3***	776.6***	3870.6***	1247.9***	356.9***
Shapiro-Wilk	0.944***	0.931***	0.962***	0.958***	0.924***	0.962***	0.923***	0.944***	0.898***	0.941***	0.973***
ADF	−11.7***	−12.2***	−13.9***	−11.9***	−11.4***	−7.9***	−10.1***	−9.9***	−8.8***	−9.5***	−11.3***
PP	−48.5***	−47.7***	−48.8***	−47.8***	−47.0***	−23.5***	−37.3***	−31.0***	−28.3***	−29.7***	−38.2***
KPSS	0.150	0.036	0.054	0.090	0.038	0.015	0.092	0.016	0.016	0.029	0.053
Observations	2324	2324	2324	2324	2324	597	1394	921	886	901	1367

Table 3: The descriptive statistics of EV stock returns with unit root and stationary tests. Note: ***, **, * indicate statistical significance at 1%, 5% and 10%.

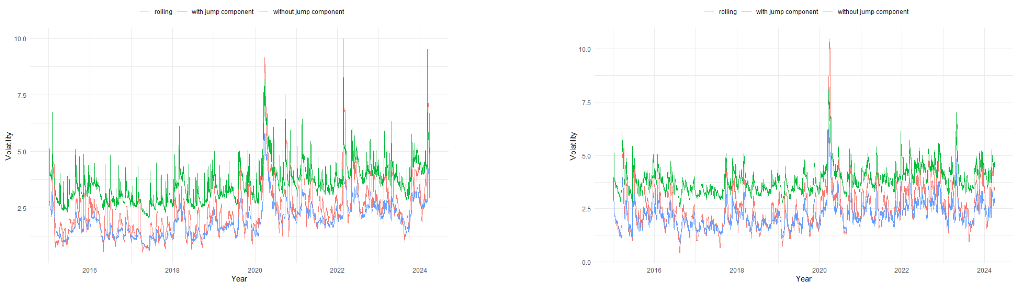
4.2 Empirical Results

4.2.1 Volatility in the EV Battery Raw Materials Market

Table 4 shows the results of the EGARCH-EARJI model fitting. EGARCH-EARJI exhibits flexibility by extending jump intensity sensitivity to the set of real numbers, resulting in the possibility of a better fit to the data compared to other studies (Maheu and McCurdy, 2004; Zhang and Shang, 2023) which used model specifications that require restrictions forbidding negative sensitivities. Results show that both ALB and SQM have positive ρ and γ coefficients, which means that they have positive sensitivities of jump intensity to the previous period components. This findings are consistent with the sign restrictions used in previous studies.

As a price jump reflects an abrupt price change over a very short time that cannot be part of a Gaussian distribution (Lahaye et al., 2011; Lee, 2011), the estimates of the jump intensity, λ_t, shown in Figure A.1a in Appendix A, and the estimate for the jump size, θ, in Table 4 indicate that on average about 0.2 abrupt price change occur daily and that a single jump tend to be negative with magnitude of about 0.73% for ALB, respectively. Furthermore, Figure A.1a would indicate that most of the jumps happened in the post-COVID period and that there was on (daily) average more than one jump some day in about February 2022 and in about March 2024. Therefore, a sudden, unexpected, and infrequent news shock to the Albemarle company would likely create one or more abrupt price declines of a magnitude of 0.73% during a given trading day. The same interpretation can be applied to SQM.

We conclude that jumps exist in the EV battery raw materials market. All estimated parameters have the same signs when comparing estimation results for ALB and SQM, which imply that market participants react in the same manner to news. For SQM, jump intensity is generally lower than for ALB because it has a more negative value of λ_0. Furthermore, for both ALB and SQM, jump intensity reacts positively to the unexpected component, ξ_t. It means that when news affects these stocks in the previous period, it translates into higher volatility in the current one. Although ρ is not significant for ALB, jump intensity tends to stay higher for longer for ALB, whereas it exhibits a lower autocorrelation for SQM. The jump size, θ, 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.

Figure 3 shows the volatility of the two lithium stock returns with and without the jump component, $\epsilon_{2,t}$, alongside their 14-days rolling standard deviation. Assuming the rolling volatility is representative of the true volatility, the estimated volatility with jump component, a_t, seems to overestimate the true volatility compared to the first component capturing only the normal time-variation of volatility. However, when a jump occur, a_t better approximates the true volatility. For

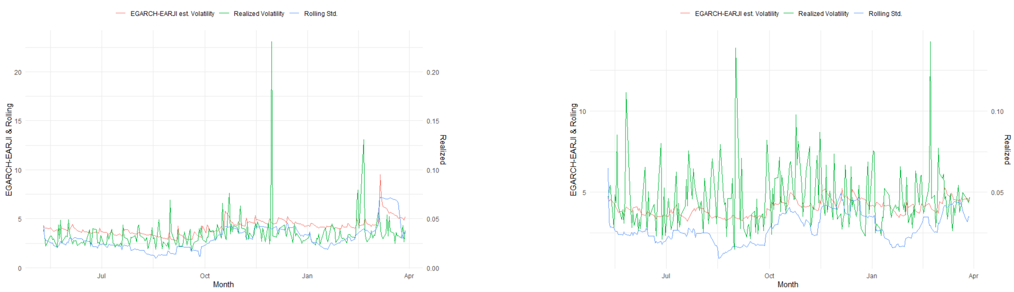
	ALB	SQM
ω_0	-0.098^{***}	-0.112^{***}
	(0.025)	(0.028)
α_1	0.106^{***}	0.171^{***}
	(0.025)	(0.024)
α_2	-0.022^{**}	-0.016
	(0.011)	(0.015)
β	0.996^{***}	0.967^{***}
	(0.004)	(0.013)
λ_0	-0.944	-1.075^{***}
	(0.921)	(0.000)
ρ	0.442	0.369^{***}
	(0.527)	(0.000)
γ	1.166^{***}	0.266^{***}
	(0.297)	(0.000)
θ	-0.733^{***}	-0.108
	(0.263)	(0.314)
δ	3.695^{***}	3.916^{***}
	(0.345)	(0.551)
μ	0.035	0.036
	(0.044)	(0.055)
ζ	0.018	0.029
	(0.020)	(0.021)

Table 4: 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%.

completeness, the estimated variance explained by the jump component is shown in the Appendix B in Figure B.2 for both ALB and SQM.

Given the uncertainty of the results from the estimation of the jump component due to the difficulty of estimating GARCH model parameters, the authors repeated the estimation using fixed initial parameter values and didn't find any difference in the jump intensity (λ_t) estimates. These findings advocate that the Broyden–Fletcher–Goldfarb–Shanno (BFGS) optimization algorithm, always converges to the same set of jump intensity parameters. For completeness, statistics of repeated jump intensity estimations using varying initial parameter values are provided in the Appendix A.

Lastly, the authors used a promising alternative non-parametric approach as a benchmark which consist of calculating the jump component from the realized volatility in the returns of the lithium's stocks using high frequency data (Andersen et al., 2007; Giot et al., 2010; Busch et al., 2011). The resulting realized volatility, realized bi-power variation, and estimated jump components for both ALB and SQM are provided in Figure C.3 in the Appendix C. Figure 4 is intended to compare both jump estimation approaches. For ALB, the realized volatility seems to be the closest to the 14-days rolling standard deviation. For SQM, it is difficult to judge which of the two approaches is superior. Overall, the realized volatility approach seems promising but it requires access to high-frequency prices and only one year history of 5-minute time intervals is at the author's disposal. Therefore, the EGARCH-EARJI estimated jump component is preferred.



(a) ALB (b) SQM

Figure 4: Comparison between the realized volatility and the estimated volatility from the EGARCH-EARJI model for both ALB and SQM. For visualization purposes and limited access to high-frequency data, the estimates range from May 2023 to May 2024. The 14-days rolling standard deviation of ALB and SQM stock returns is also provided.

In the next section, jump intensity estimates, λ_t, are used to analyze their effect on the EV manufacturer' stock returns.

4.2.2 Expectation and Volatility of Electric Vehicles Producers' Stock Returns

Table 5 presents the contemporaneous correlations between the two lithium stock returns and the eleven EV manufacturers' stock returns. First, we observe that for any pair of lithium/EV stock returns, the contemporaneous correlation is positive which gives indications that the stock return of lithium producers and EV manufacturers tend to move in the same direction. Such results may indicate that the expected discounted future cash flows of lithium and EV producers increase or decrease together. Second, correlations of EV manufacturers' stock returns with ALB are greater than those for SQM, except for BYDDF and LI. Such differences can be attributed to differences in partnership between lithium and EV producers.

	ALB	SQM
TSLA	0.450	0.380
GM	0.473	0.367
TM	0.306	0.228
BYDDF	0.332	0.340
F	0.453	0.350
RIVN	0.423	0.355
NIO	0.394	0.367
LI	0.269	0.301
LCID	0.404	0.305
XPEV	0.308	0.302
NIU	0.322	0.235

Table 5: Correlation matrix between returns of the two largest lithium producers and those of the eleven EV manufacturers.

Tables 6 and 7 show the results of the EGARCH(1,1) model estimation. First, obtaining positive estimates of β_1 for most of the lithium/EV manufacturers pairs is consistent with the simple contemporaneous correlations shown in Table 5. Intuitively, an increase of lithium prices would increase costs of production reflecting an even greater demand for EVs, named as an "EV demand effect" (Baur and Todorova, 2018). Second, the excess returns of ALB and SQM are all significant in explaining those of EV producers and mostly insignificant for traditional car manufacturers at 1%, providing no evidence to reject the hypothesis of the existence of a relationship between excess returns of lithium and those of EV producers, at the 5% significance level.

EGARCH(1,1) model - ALB jump intensity

	TSLA	GM	TM	BYDDF	F	RIVN	NIO	LI	LCID	XPEV	NIU
δ_0	0	-0.11^{**}	-0.732^{***}	-0.296^{**}	-0.212^{***}	-0.495^{***}	-0.438^{***}	-0.724	-0.52^{***}	-0.747	-0.373^{***}
	(0.001)	(0.046)	(0.028)	(0.14)	(0.016)	(0.162)	(0.065)	(2.048)	(0.099)	(0.934)	(0.069)
δ_1	1.294^{***}	1.102^{***}	0.625^{***}	0.773^{***}	1.061^{***}	1.361^{***}	1.052^{***}	0.552^{***}	1.006^{***}	1.042^{***}	0.745^{***}
	(0.034)	(0.066)	(0.028)	(0.094)	(0.054)	(0.283)	(0.089)	(0.185)	(0.117)	(0.261)	(0.105)
δ_2	0.454^{***}	0.483	-0.017	0.202	0.502^{***}	1.355^{***}	1.333^{***}	0.754^{***}	1.478^{***}	1.136^{***}	1.051^{***}
	(0.031)	(0.307)	(0.075)	(0.135)	(0.072)	(0.415)	(0.109)	(0.293)	(0.251)	(0.422)	(0.147)
δ_3	-0.684^{***}	0.627^{***}	0.125^{***}	-0.188^{*}	0.62^{***}	-0.886^{**}	-0.649^{***}	-0.72^{***}	-0.422^{***}	-0.93^{***}	-0.55^{***}
	(0.049)	(0.078)	(0.041)	(0.107)	(0.058)	(0.395)	(0.081)	(0.167)	(0.045)	(0.167)	(0.091)
δ_4	0^{***}	0.021	0.694^{***}	0.057	0.195^{***}	0.151^{***}	0.022^{***}	0.092	0.01^{***}	0.079	0.01^{***}
	(0)	(0.021)	(0.028)	(0.037)	(0.017)	(0.038)	(0.004)	(0.239)	(0.004)	(0.12)	(0.003)
β_1	0.103^{***}	0.054^{***}	0.006	0.123^{***}	0.037^{***}	0.257^{***}	0.177^{***}	0.154^{**}	0.146^{***}	0.127^{***}	0.164^{***}
	(0.015)	(0.005)	(0.012)	(0.044)	(0.004)	(0.048)	(0.036)	(0.063)	(0.032)	(0.041)	(0.049)
γ_0	0.099^{***}	0.011	-0.046	-0.015	0.007	0.202^{*}	0.115^{***}	0.094^{*}	0.099	0.122^{***}	0.041
	(0.036)	(2.729)	(0.034)	(0.019)	(0.078)	(0.108)	(0.035)	(0.05)	(0.325)	(0.039)	(0.036)
γ_1	0.015	-0.046	0.003	0.017	0.098^{***}	0.098^{*}	0.014	0.012	0.12	0.059^{**}	0.004
	(0.02)	(0.812)	(0.022)	(0.014)	(0.034)	(0.058)	(0.029)	(0.032)	(0.103)	(0.027)	(0.027)
γ_2	0.961^{***}	0.843	0.966^{***}	0.991^{***}	0.879^{***}	0.873^{***}	0.956^{***}	0.944^{***}	0.934^{***}	0.941^{***}	0.951^{***}
	(0.001)	(4.197)	(0.026)	(0)	(0.042)	(0.047)	(0.003)	(0.01)	(0.171)	(0.006)	(0.009)
γ_3	0.146^{***}	0.242	0.156^{***}	0.08^{***}	0.22^{***}	0.163^{**}	0.165^{**}	0.192^{***}	0.211^{**}	0.148^{***}	0.23^{***}
	(0.033)	(3.263)	(0.046)	(0.018)	(0.051)	(0.065)	(0.065)	(0.052)	(0.096)	(0.03)	(0.035)
γ_4	-0.34	-0.115	0.457	-0.412^{*}	0.757	-0.038	-0.316	-0.368	-0.64	-0.725^{**}	0.407
	(0.734)	(4.001)	(0.659)	(0.231)	(0.497)	(0.299)	(0.393)	(0.281)	(0.523)	(0.304)	(0.548)
γ_5	0.292	0.863	-0.185	0.576^{**}	-0.121	0.731	0.4	0.652^{*}	1.059	1.011^{***}	0.057
	(0.698)	(11.752)	(0.703)	(0.234)	(0.566)	(0.585)	(0.332)	(0.336)	(1.297)	(0.359)	(0.507)
ν	1.056^{***}	1.155^{***}	1.185^{***}	1.333^{***}	0.962^{***}	1.251^{***}	1.053^{***}	1.281^{***}	1.013^{***}	1.292^{***}	1.243^{***}
	(0.051)	(0.084)	(0.075)	(0.102)	(0.048)	(0.094)	(0.075)	(0.07)	(0.083)	(0.094)	(0.068)
obs	1509	1509	1319	1509	1509	536	1333	860	825	840	1306
neg Log Lik.	-3766	-2846	-1991	-3613	-2850	-1475	-3850	-2376	-2313	-2460	-3605
AIC	5.008	3.789	3.038	4.806	3.794	5.553	5.795	5.555	5.639	5.888	5.54
BIC	5.054	3.835	3.089	4.852	3.84	5.657	5.846	5.627	5.713	5.961	5.592

Table 6: The estimation results of the EGARCH(1,1) model for individual stock returns of EV producers. This table presents the estimated parameter coefficients, the corresponding number of observations, the logarithm of the likelihood at the last iteration, the Akaike Information Criterion (AIC), and the Bayes Information Criterion (BIC). For each stock, an EGARCH(1,1) is fitted including the market risk premium, capitalization factor of small to big firms, stock valuation factor of high to low book value stocks, the EV stock's Price-to-Book (P/B) ratio, the excess returns of ALB as regressors into the mean equation and the ALB jump intensity and its 1-day lag as regressors in the variance equation. Robust standard errors are provided in parenthesis. Note: ***, **, * indicate statistical significance at 1%, 5% and 10%.

EGARCH(1,1) model - SQM jump intensity

	TSLA	GM	TM	BYDDF	F	RIVN	NIO	LI	LCID	XPEV	NIU
δ_0	−0.052***	−0.118	−0.739***	−0.317*	−0.331***	−0.532***	−0.504	−0.704***	−0.484***	−0.666	−0.41***
	(0.003)	(0.13)	(0.051)	(0.162)	(0.029)	(0.062)	(0.421)	(0.089)	(0.052)	(0.538)	(0.074)
δ_1	1.289***	1.103***	0.629***	0.723***	1.097***	1.418***	1.068***	0.5***	1.034***	1.076***	0.842***
	(0.032)	(0.218)	(0.027)	(0.05)	(0.039)	(0.073)	(0.086)	(0.123)	(0.077)	(0.127)	(0.075)
δ_2	0.414***	0.462*	−0.018	0.171*	0.531***	1.409***	1.425***	0.814***	1.434**	1.117***	1.133***
	(0.024)	(0.238)	(0.032)	(0.099)	(0.068)	(0.157)	(0.075)	(0.143)	(0.569)	(0.254)	(0.169)
δ_3	−0.718***	0.629***	0.125***	−0.222***	0.633***	−0.946***	−0.684***	−0.774***	−0.416***	−0.913***	−0.554***
	(0.02)	(0.044)	(0.036)	(0.078)	(0.065)	(0.123)	(0.055)	(0.113)	(0.031)	(0.165)	(0.083)
δ_4	0.002***	0.03	0.697***	0.066	0.312***	0.14***	0.028	0.094***	0.008***	0.07	0.013***
	(0)	(0.059)	(0.058)	(0.041)	(0.025)	(0.019)	(0.043)	(0.017)	(0.002)	(0.066)	(0.002)
β_1	0.128***	0.053	0.005*	0.161***	0.016***	0.197***	0.171***	0.214***	0.11***	0.121***	0.105***
	(0.004)	(0.082)	(0.003)	(0.028)	(0.004)	(0.021)	(0.026)	(0.057)	(0.022)	(0.046)	(0.015)
γ_0	0.327	−0.538*	−0.649**	−0.29**	−0.728	0.964*	−0.166	0.337**	−0.045	−0.421	−0.901***
	(0.224)	(0.278)	(0.32)	(0.137)	(0.525)	(0.493)	(0.272)	(0.147)	(0.468)	(0.358)	(0.3)
γ_1	0.016	−0.028	0.006	0.017	0.091***	0.074	0.017	0.01	0.113***	0.058**	0.004
	(0.02)	(0.02)	(0.026)	(0.015)	(0.033)	(0.059)	(0.027)	(0.035)	(0.034)	(0.027)	(0.027)
γ_2	0.961***	0.966***	0.934***	0.99***	0.863***	0.882***	0.957***	0.933***	0.948***	0.938***	0.951***
	(0)	(0)	(0.002)	(0)	(0.047)	(0.071)	(0.001)	(0.009)	(0.002)	(0.004)	(0)
γ_3	0.142***	0.111***	0.209***	0.074***	0.241***	0.182**	0.159***	0.218***	0.188***	0.142***	0.209***
	(0.03)	(0.031)	(0.039)	(0.027)	(0.05)	(0.083)	(0.037)	(0.053)	(0.059)	(0.041)	(0.044)
γ_4	4.492	5.296***	0.754	0.161	7.746	−0.355	3.746***	−11.533***	0.089	−1.131	4.992***
	(3.999)	(0.602)	(0.544)	(0.14)	(5.689)	(7.242)	(1.327)	(3.47)	(2.93)	(1.742)	(1.61)
γ_5	−5.8**	−2.164**	2.881	1.525**	−2.931	−3.132	−2.14	10.694***	0.958	4.461***	0.651***
	(2.773)	(1.029)	(1.962)	(0.761)	(5.801)	(7.628)	(2.775)	(3.847)	(1.753)	(1.533)	(0.07)
ν	1.057***	1.147***	1.181***	1.338***	0.966***	1.186***	1.07***	1.29***	1.003***	1.283***	1.228***
	(0.052)	(0.075)	(0.072)	(0.1)	(0.046)	(0.1)	(0.073)	(0.071)	(0.095)	(0.095)	(0.072)
obs	1509	1509	1319	1509	1509	536	1333	860	825	840	1306
neg Log Lik.	-3759	-2844	-1990	-3604	-2853	-1480	-3850	-2370	-2319	-2460	-3606
AIC	4.999	3.787	3.038	4.793	3.798	5.572	5.796	5.541	5.654	5.887	5.541
BIC	5.045	3.833	3.089	4.839	3.844	5.676	5.847	5.613	5.729	5.96	5.593

Table 7: The estimation results of the EGARCH(1,1) model for individual stock returns of EV producers. This table presents the estimated parameter coefficients, the corresponding number of observations, the logarithm of the likelihood at the last iteration, the Akaike Information Criterion (AIC), and the Bayes Information Criterion (BIC). For each stock, an EGARCH(1,1) is fitted including the market risk premium, capitalization factor of small to big firms, stock valuation factor of high to low book value stocks, the EV stock's Price-to-Book (P/B) ratio, the excess returns of SQM as regressors into the mean equation and the ALB jump intensity and its 1-day lag as regressors in the variance equation. Robust standard errors are provided in parenthesis. Note: ***, **, * indicate statistical significance at 1%, 5% and 10%.

However, the hypothesis of the existence of volatility spillovers between the lithium and EV stock returns through the jump component is fairly rejected at any conventional level. As can be seen from Tables 6 and 7, the lithium jump intensity as well as its 1-day lagged value is mostly insignificant across EV companies for both ALB and SQM. Such a result suggests that the volatility of EV stock returns is not affected by unexpected news about lithium producers. The authors tested the robustness of the results obtained in Tables 6 and 7 by repeating the jump component and the second step estimations many times. Table 8 provides sample mean of the γ_4 and γ_5 estimates as well as 95% confidence interval for their mean. Results for both ALB and SQM are consistent with the conclusions drawn earlier about the existence of volatility spillovers through unexpected news about lithium producers.

	$\gamma_{4,l}$	$\gamma_{4,m}$	$\gamma_{4,h}$	$p_{\gamma_4,l}$	$p_{\gamma_4,m}$	$p_{\gamma_4,h}$	$\gamma_{5,l}$	$\gamma_{5,m}$	$\gamma_{5,h}$	$p_{\gamma_5,l}$	$p_{\gamma_5,m}$	$p_{\gamma_5,h}$
ALB-BYDDF	−0.567	−0.330	−0.093	−0.231	0.234	0.700	−0.334	0.341	1.015	−0.361	0.212	0.785
ALB-F	0.565	0.565	0.565	0.257	0.257	0.257	−0.019	−0.019	−0.019	0.973	0.973	0.973
ALB-GM	0.263	0.263	0.263	0.713	0.713	0.713	0.171	0.171	0.171	0.785	0.785	0.785
ALB-LCID	−1.019	−0.431	0.157	−0.069	0.278	0.625	−0.294	0.704	1.702	0.127	0.463	0.798
ALB-LI	−0.368	−0.368	−0.368	0.186	0.186	0.186	0.653	0.653	0.653	0.050	0.050	0.050
ALB-NIO	−0.446	−0.298	−0.150	0.308	0.429	0.549	0.189	0.377	0.564	0.079	0.241	0.403
ALB-NIU	0.407	0.407	0.407	0.457	0.457	0.457	0.057	0.057	0.057	0.910	0.910	0.910
ALB-RIVN	−0.038	−0.038	−0.038	0.899	0.899	0.899	0.731	0.731	0.731	0.212	0.212	0.212
ALB-TM	0.457	0.457	0.457	0.486	0.486	0.486	−0.184	−0.184	−0.184	0.792	0.792	0.792
ALB-TSLA	−0.406	−0.338	−0.269	0.574	0.647	0.719	0.231	0.289	0.348	0.615	0.679	0.743
ALB-XPEV	−0.725	−0.725	−0.725	0.017	0.017	0.017	1.011	1.011	1.011	0.005	0.005	0.005
SQM-BYDDF	−2.963	1.961	6.885	0.173	0.222	0.272	−0.273	1.041	2.355	−0.505	0.363	1.231
SQM-F	7.834	7.834	7.834	0.167	0.167	0.167	−3.018	−3.018	−3.018	0.602	0.602	0.602
SQM-GM	5.299	5.299	5.299	0	0	0	−2.169	−2.169	−2.169	0.040	0.040	0.040
SQM-LCID	−1.009	−0.004	1.000	0.713	0.953	1.192	−0.536	0.594	1.724	0.289	0.653	1.016
SQM-LI	−11.534	−11.534	−11.534	0.001	0.001	0.001	10.695	10.695	10.695	0.005	0.005	0.005
SQM-NIO	3.745	3.745	3.745	0.005	0.005	0.005	−2.140	−2.140	−2.140	0.441	0.441	0.441
SQM-NIU	4.985	4.985	4.985	0.002	0.002	0.002	0.657	0.657	0.657	0	0	0
SQM-RIVN	−0.355	−0.355	−0.355	0.961	0.961	0.961	−3.132	−3.132	−3.132	0.681	0.681	0.681
SQM-TM	0.748	0.748	0.748	0.163	0.163	0.163	2.886	2.886	2.886	0.140	0.140	0.140
SQM-TSLA	3.589	4.448	5.307	0.127	0.269	0.411	−6.907	−5.742	−4.578	−0.140	0.046	0.232
SQM-XPEV	−1.136	−1.136	−1.136	0.536	0.536	0.536	4.463	4.463	4.463	0.004	0.004	0.004

Table 8: The EGARCH-EARJI estimation at the first step and the EGARCH(1,1) estimation at the second step was repeated 100 times. Despite the low number of repeated estimations, the authors invoke the Central Limit Theorem to construct the confidence intervals. $\gamma_{4,m}$ is the sample mean for γ_4, $\gamma_{4,l}$, and $\gamma_{4,h}$ are the sample lower and higher bound of the 95% confidence interval, respectively. The same description goes for γ_5. Similarly, $p_{\gamma_4,m}$ is the sample mean for the p-value of γ_4, $p_{\gamma_4,l}$, and $p_{\gamma_4,h}$ are the sample lower and higher bound of the 95% confidence interval, respectively. The same description goes for p_{γ_5}.

5 Conclusion

We examined the volatility in the EV battery raw materials market and specifically for the largest lithium producers, namely Albemarle (ALB) and Sociedad Quimica y Minera de Chile (SQM) 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: 5 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, 2024.

The hypothesis of jumps' existence in the EV battery raw materials market was not rejected at conventional significance levels. In order to investigate the hypothesis, we presented a new model specification, which relaxes restrictions on parameters and might prevent 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.

There is no evidence that the hypothesis of the existence of a relationship between the ALB and SQM excess returns and those of the EV manufacturers can be rejected. Both using simple contemporaneous correlation and the EGARCH(1,1) model, the authors find that excess returns of lithium producers and EV manufacturers go in the same direction. This findings have implications for portfolio managers who seek qualitative portfolio diversification.

The hypothesis of a significant effect of jumps on the volatility of individual EV producers' stock returns was mostly rejected for both ALB and SQM at conventional significance levels.

Overall, our results show that the EGARCH-EARJI model can be used to model volatility in stock returns of lithium producing companies, and one can utilize the proposed two-step approach to examine the co-movements between lithium and EV manufacturers excess stock returns and the impact of unexpected extreme news concerning lithium manufacturers on EV producers' stock returns.

The authors leave three suggestions for future research. First, applying the realized volatility approach on a larger time range should be considered for future improvement to reduce uncertainty in the estimation of the jump component. Second, the use of the Fama-French five factor asset pricing model by Fama and French (2015) instead of the three factor model would be an additional robustness check. Third, the inclusion of other fundamental factors specific for each automobile manufacturer, such as earnings yield, size or cash flow yield (Chan et al., 1991; Muhammad and Scrimgeour, 2014), into the model specification of EV stock returns may reduce the bias in the estimated coefficients.

Acknowledgements

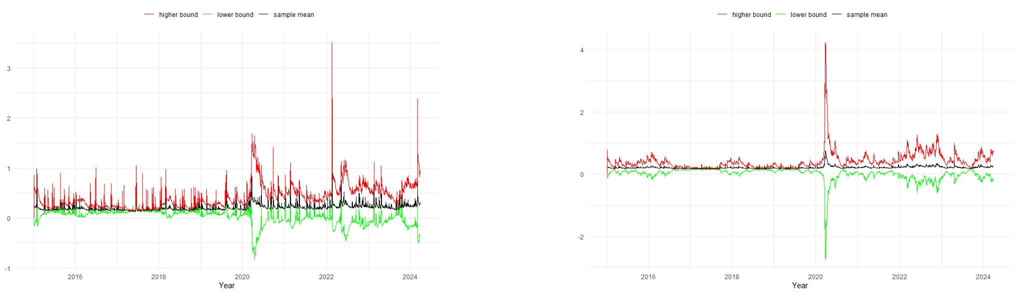
This paper is part of a project GEOCEP that has received funding from the European Union's Horizon 2020 research and innovation program under the Marie Skłodowska-Curie grant agreement No. 870245. Karel Janda acknowledges financial support from the Czech Science Foundation (grant no.24-10008S) and the research support provided during his long-term visit to the Department of Agricultural and Resource Economics, University of California, Berkeley. The authors express their gratitude to Binyi Zhang, who offered insightful feedback during several research seminar presentations of this paper. The views expressed here are those of the authors and not necessarily those of our institutions. All remaining errors are solely our responsibility.

Appendix A Jump intensity robustness check

GARCH model is hard to estimate. As a robustness check, the authors repeated the estimation of the jump component using the EGARCH-EARJI model and varying initial values. Initial values were generated as follows:

$$
\begin{aligned}
\omega_0, \alpha_1, \alpha_2 &\sim \mathcal{U}[0.01, 0.10]; \\
\beta &\sim \mathcal{U}[0.6, 1]; \\
\lambda_0 &\sim \mathcal{U}[-0.7, -0.3]; \\
\rho, \gamma, \theta, \mu, \zeta &\sim \mathcal{U}[-0.2, 0.2]; \\
\delta &\sim \mathcal{U}[2, 3].
\end{aligned}
$$

Figure A.1 depicts the uncertainty of jump intensity estimates over time.

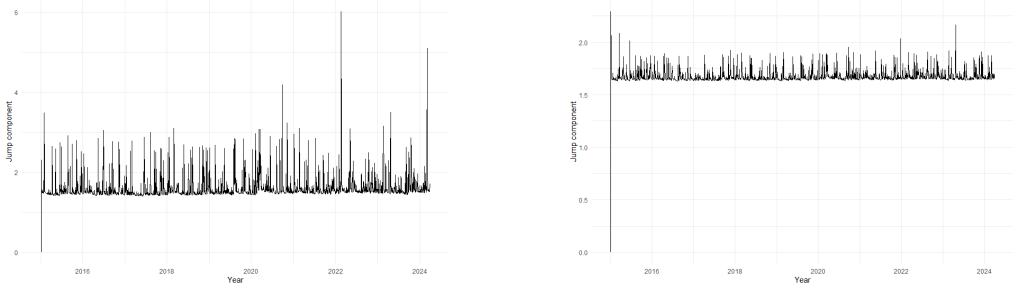


(a) ALB (b) SQM

Figure A.1: The jump intensity estimation procedure from the first step was repeated 100 times. Despite the low number of repeated estimations, the authors invoke the Central Limit Theorem to construct the confidence intervals. For both ALB and SQM, the black line is the jump intensity sample mean, the green and red lines are the lower and higher bound of the 95% confidence interval, respectively, from the 100 repeated estimations.

Appendix B Jump component

Figure B.2 shows the estimated variance explained by the jump component for both ALB and SQM.



(a) ALB (b) SQM

Figure B.2: The estimated variance explained by the jump component of ALB and SQM. The initial jump component spike is due to the starting values arbitrarily set to zero.

Appendix C Realized Volatility approach

(a) ALB (b) SQM

Figure C.3: The volatility estimates from the realized volatility approach for both ALB and SQM. Estimates range from May 2023 to May 2024 due to limited access to high-frequency data.

References

Andersen, T. G., Bollerslev, T., and Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. The Review of Economics and Statistics, 89(4):701–720.

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

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

Baruník, J. and Křehlík, T. (2018). Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk*. Journal of Financial Econometrics, 16(2):271–296.

Baur, D. G. and Gan, D. (2018). Electric vehicle production and the price of lithium. SSRN Electronic Journal.

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

Block, D., Harrison, J., and Brooker, P. (2015). Electric vehicle sales for 2014 and future projections.

Burney, R. B. and Killins, R. N. (2023). Sustainability and electrification of the automobile industry: Battery metals and equity returns. The Journal of Investing, 32:63–78.

Busch, T., Christensen, B. J., and Ørregaard Nielsen, M. (2011). The role of implied volatility in forecasting future realized volatility and jumps in foreign exchange, stock, and bond markets. Journal of Econometrics, 160(1):48–57. Realized Volatility.

Cagli, E. C. (2023). The volatility spillover between battery metals and future mobility stocks: Evidence from the time-varying frequency connectedness approach. Resources Policy, 86:104144.

Carnero, M. A., Peña, D., and Ruiz, E. (2004). Persistence and kurtosis in GARCH and stochastic volatility models. Journal of Financial Econometrics, 2(2):319–342.

Chan, L. K. C., HAMAO, Y., and LAKONISHOK, J. (1991). Fundamentals and stock returns in Japan. The Journal of Finance, 46(5):1739–1764.

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., Bouri, E., and Roubaud, D. (2021). Modelling the volatility of crude oil returns: Jumps and volatility forecasts. International Journal of Finance & Economics, 26(1):889–897.

Dutta, A., Nikkinen, J., and Rothovius, T. (2017). Impact of oil price uncertainty on Middle East and African stock markets. Energy, 123:189–197.

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.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. Journal of Financial Economics, 116(1):1–22.

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.

Giot, P., Laurent, S., and Petitjean, M. (2010). Trading activity, realized volatility and jumps. Journal of Empirical Finance, 17(1):168–175.

Hu, G. and Jiang, H. (2023). Time-varying jumps in China crude oil futures market impacted by COVID-19 pandemic. Resources Policy, 82:103510.

IEA (2024). Trends in electric cars. https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars. Accessed: 2024-05-06.

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

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.

Lahaye, J., Laurent, S., and Neely, C. J. (2011). Jumps, cojumps and macro announcements. Journal of Applied Econometrics, 26(6):893–921.

Lee, S. S. (2011). Jumps and information flow in financial markets. The Review of Financial Studies, 25(2):439–479.

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.

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

Malik, F. (2021). Volatility spillover between exchange rate and stock returns under volatility shifts. The Quarterly Review of Economics and Finance, 80:605–613.

Mo, J. Y. and Jeon, W. (2018). The impact of electric vehicle demand and battery recycling on price dynamics of lithium-ion battery cathode materials: A vector error correction model (VECM) analysis. Sustainability, 10(8).

Mohammadi, F. and Saif, M. (2023). A comprehensive overview of electric vehicle batteries market. e-Prime - Advances in Electrical Engineering, Electronics and Energy, 3:100127.

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.

Muhammad, N. and Scrimgeour, F. (2014). Stock returns and fundamentals in the Australian market. Asian Journal of Finance & Accounting, 6(1):271–290.

Münzel, C., Plötz, P., Sprei, F., and Gnann, T. (2019). How large is the effect of financial incentives on electric vehicle sales? – A global review and European analysis. Energy Economics, 84:104493.

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.

Plante, M. (2023). Investing in the batteries and vehicles of the future: A view through the stock market. FRB of Dallas, (2314).

Rapson, D. S. and Muehlegger, E. (2023). The economics of electric vehicles. Review of Environmental Economics and Policy, 17(2):274–294.

Rutterford, J. (2004). From dividend yield to discounted cash flow: a history of UK and US equity valuation techniques. Accounting, Business & Financial History, 14(2):115–149.

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.

Shi, Y., Feng, Y., Zhang, Q., Shuai, J., and Niu, J. (2023). Does China's new energy vehicles supply chain stock market have risk spillovers? Evidence from raw material price effect on lithium batteries. Energy, 262:125420.

Sun, X., Ouyang, M., and Hao, H. (2022). Surging lithium price will not impede the electric vehicle boom. Joule, 6(8):1738–1742.

Trading Economics (2024). Lithium - Price - Chart - Historical Data - News. https://tradingeconomics.com/commodity/lithium. Accessed: 2024-05-11.

Wu, W., Lin, B., Xie, C., Elliott, R. J., and Radcliffe, J. (2020). Does energy storage provide a profitable second life for electric vehicle batteries? Energy Economics, 92:105010.

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

Zhang, C., Liu, F., and Yu, D. (2018). Dynamic jumps in global oil price and its impacts on China's bulk commodities. Energy Economics, 70:297–306.

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.

Zhang, H., Zhang, Y., Gao, W., and Li, Y. (2023). Extreme quantile spillovers and drivers among clean energy, electricity and energy metals markets. International Review of Financial Analysis, 86:102474.

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.