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RESEARCH FINAL REPORT:
"Spillover Effects of Energy Transition Commodities on Electric Vehicle Indices"

GROUP 9

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Abstract

This study investigates the dynamic connectedness and spillover effects between energy transition commodities and electric vehicle (EV) indices across global markets from March 2012 to September 2024, where events such as COVID-19 and the Paris Climate Agreement are the most studied. It takes into consideration some of the primary EV battery components: aluminum, copper, lithium hydroxide, nickel, cobalt, and some popular EV indices, which include S&P Kensho Electric Vehicles Index (KEV Index), Solactive China Electric Vehicle and Battery Index (SOLCEVIN Index), S&P Eurozone Automotive & Electric Vehicles Index (SPEAEVUT Index) and Solactive Electric Vehicles and Future Mobility Index (SOLKARSN Index). Using DCC-GARCH, VAR, and TVP-VAR models, it is found that Aluminum and nickel are key net transmitters of return shocks, while lithium and cobalt act as net receivers due to their concentrated EV exposure. In the EV index market, the SOLCEVIN Index demonstrates the strongest volatility transmission effects, highlighting China's influential role in the EV supply chain. The SPEAEVUT Index, by contrast, consistently acts as a net volatility receiver, reflecting its sensitivity to external shocks. The research also came up with hedging strategies in which certain market pairs achieve up to 42% risk reduction, particularly involving the SOLKARSN Index and KEV Index.

Keywords: Spillover Effects, Volatility, DCC-GARCH, TVP-VAR, Electric Vehicle Indices, Energy Transition Commodities, Portfolio Diversification, Hedging Strategies, Financial Market Integration.

1. Introduction

The implementation of the Paris Climate Agreement of setting the limit on global warming to below 2°C in 2016 has significantly reshaped the automobile industry. The effort to reduce carbon dioxide emissions and attain net-zero emissions by 2050 has given rise to electric vehicles (EVs). The governments also gave subsidies for both consumers and producers to accelerate the growth. However, even without government subsidies, the projection of EVs will account for more than half of the global passenger car sales by 2035, according to BloombergNEF (BNEF) consultancy in London (Castelvecchi, 2021). This led some of the major automobile companies like General Motors and Audi to announce cease of production of petrol-powered and diesel models by 2035.

Indeed, this change has significantly increased the demand for the new transition materials, like lithium, cobalt, and manganese, needed for EV batteries (IEA, 2021). On the supply side, the new transition material is constantly facing challenges of scarcity, mining technology availability, and environmental regulations. The constant changing in supply and demand, it causes volatility in the price of those minerals. Moreover, since the cost of those EV battery minerals exceeds 50% of the battery pack's manufacturing cost, the price volatility risk is a serious concern for investors, governments, and manufacturers regarding the production of EV batteries and EVs. (Castelvecchi, 2021).

With the need to understand more about how the price volatility of the raw materials in making EVs would affect the stock returns of those manufacturing and selling companies, it is essential to explore the interconnectedness of the market. By understanding the interrelationship between EV battery minerals and automotive markets, investors can make informed decisions and mitigate potential risks. Furthermore, policymakers can gain a better understanding of the potential implications of price fluctuations on the overall stability and sustainability of the automotive industry.

2. Literature Review

There are many research studies about volatility spillovers among different financial markets or assets within the same market. In our research, we will categorize related studies into three areas. The first strand of the study focuses on the volatility spillover effect among metal commodities One of the early studies on various asset commodities by Chevallier and Ielpo (2013) found that gold, aluminum, and WTI are the net transmitters of volatilities spillover when comparing some other commodity silver, platinum, copper, nickel, zinc, lead, WTI, brent, gas oil and natural gas for the period 1995 to 2012 using Time-Varying Vector Autoregressive (TVP-VAR) model. Similarly, Ciner et al. (2020) studied volatility spillover on non-ferrous metals, including aluminium, aluminium alloy, copper, lead, nickel, tin, and zinc. They found that aluminum, copper, and zinc are the net volatility transmitters among those metals, and the remainder are net receivers. It also concluded that this non-ferrous metal can be considered a separate investment class due to its high degree of financial integration. Chen and Tongurai (2022) have researched the spillover effect over the base metal covering aluminum, copper, zinc, lead, nickel, and tin using data from spot and futures markets. They found that copper and zinc are the net transmitters, which can be explained by larger trading volumes from the copper and zinc due to high demand from industrial manufacturing, which transmits information flow from copper and zinc to other base metals futures on the Shanghai Futures Exchange.

The second strand of the study focuses on the study of the volatility spillover effect between metal commodities and other markets such as fixed income, currency, stock, and index. Mensi et al. (2017) investigated the interrelations of volatility spillover effects between precious metals and the major stock market indices. They concluded that most stock markets operate as net transmitters of volatility and precious metals as net receivers of volatility and thus gave a great hedge in the case of the global financial crisis. Using the Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model, Kirkpinar and Evrim (2023) found that there are negative relationships in volatility spillover between the bond markets of Brazil, Russia, and Turkey and the gold market, as well as between the bond markets of Russia, China, and Turkey and the oil market. They also concluded that investing in oil and gold might not offer diversification benefits for investors in certain markets. Yoon et al. (2019) studied the returns spillover shock transmission among stocks, bonds, currency, and commodities. Their finding suggested that the US stock, bond, and currency markets are the net transmitters, and Asian stock markets and gold are the main spillover receivers. They also found the total returns spillover effect across commodity and financial markets is stronger during economic and financial crises. They suggested that increasing the variety of asset classes would diminish the overall spillover effect and offer diversification advantages within a stock nexus portfolio.

The third strand of the study focuses on the study of the spillover effect of metal commodities related to electric vehicle production and the index or stock market. We will explore how the metal commodities used as raw materials in electric vehicle production interact with the stock market of companies that manufacture these EVs. Mo and Jeon (2018) have researched the interrelationship between EV demand and the price of lithium-ion metals, lithium, cobalt, manganese, and nickel.

They concluded that lithium and cobalt prices are the most sensitive to the impact of changes in EV demand. In a more recent study, Zang et al. (2023) conducted research on both return and volatility spillover effects between clean energy (electric vehicle index, solar index, and wind index) and the commodity market (silver, tin, nickel, cobalt, lead, zinc, aluminum and copper). They conclude that the clean energy market is the market net transmitter. They suggested that investors in clean energy, electricity, and energy metals markets should focus on increasing their investments during the positive phases of the COVID-19 pandemic and in high-tech indices. Conversely, they should reduce their investments during negative periods to avoid incurring unnecessary economic losses. Shi et al. (2023) researched the interconnectedness between the stock prices of EV and lithium battery manufacturers and minerals in China using TVP-VAR and DCC-GARCH models. They concluded that there were spillover effects between the stock price of EV manufacturers and lithium battery manufacturers. However, there was a limited impact of those mineral prices on those EV companies.

In conclusion, many researchers have studied the interconnectedness between the metal commodities market and other financial markets, but there are still not a lot of studies focusing on EV commodities and other markets. Therefore, this study contributes to the literature by considering the spillover effects of EV raw materials over the stocks of EV manufacturing companies across different markets. We believe the interconnectedness also be affected by the importer and exporter of those EV materials to those manufacturing EV car companies. We expect our study results will be useful for investors, portfolio managers, manufacturers, and governments in improving their risk management and other investment choices.

3. Hypothesis

Based on the literature review, our research will study the following hypothesis:

H1: There is a dynamic connectedness pattern and volatility spillover from the commodity price of EV-related minerals and the price of EV-related indices.

Some research shows that prices of metals transmit significant volatility to the EV index in both the short- and long term. The EV index is a net pairwise volatility recipient, especially in the short run. The impact of base metals' volatilities on EV volatility is more prominent than minor metals in the short term; however, lithium and manganese spill sizable volatility over the EV index in the long run (Cagli, 2023).

H2: There is a dynamic connectedness pattern and return spillover of the commodity price of EV-related minerals and the price of EV-related indices.

Taking reference from other research papers, it is shown that by using TVP-VAR analysis, rare earth metals act as leading return transmitters, and hence, we came out with our hypothesis that commodity return will have a spillover effect on the EV indices return (Haq et al., 2022).

H3: There is significant potential for hedging among EV-related commodity and EV-related indices.

Research conducted (Maitra et al., 2021) explored the potential of hedging strategies to manage the supply chains of shipping companies effectively. The study highlights the possibility of utilizing hedging to balance upstream resources and end-product demands, particularly in managing long or short positions involving transportation companies and gasoline prices. These findings provide a foundation for applying similar hedging strategies to the EV industry, focusing on EV-related minerals critical to the supply chain.

Previous research conducted by (Cagli, 2023) found that there is an effective hedging strategy between battery commodities and the Solactive Future Mobility Index, which is based on minimal portfolio connectedness. Consequently, this study aims to determine whether there is a viable hedging potential at a higher level among the EV-related metals and EV-related indices.

4. Data and Methodology

4.1. Data and Sources

This study will employ historical data from 20 March 2012 to 27 September 2024. We have selected five commodities that are essential components in making electric vehicles: aluminium (Al), copper (Cu), lithium Hydroxide (LiOH), nickel (Ni), and Cobalt (Co). We also included Brent Oil (Brent) as one of the benchmarks for commodity. For indices, we have selected some of the major EV indices covering the US, China, Euro and Asia markets including S&P Kensho Electric Vehicles Index (KEV Index), Global X China Electric Vehicle and Battery ETF (GSXAELEV Index), Solactive China Electric Vehicle and Battery Index (SOLCEVIN Index), S&P Eurozone Automotive & Electric Vehicles Index (SPEAEVUT Index), and Solactive Electric Vehicles and Future Mobility Index (SOLKARSN Index). These data are collected from Bloomberg and in terms of US Dollars.

To obtain the daily return, we use the following equation:

$$\boldsymbol{R_t = \frac{P_t - P_{t-1}}{P_{t-1}} * 100}$$

Where R_t is the asset daily return in time t, P_t is the asset price in time t, and P_{t-1} is the asset price in time t -1

To obtain the daily volatility, we use the following equation:

$$\boldsymbol{V_t = \left| log\left(\frac{P_t - P_{t-1}}{P_{t-1}}\right)\right|}$$

, where:

1. I_t is the asset's daily volatility in time t
2. P_t is the asset price in time t, and
3. P_{t-1} is the asset price in time t -1

We notice that the returns of the EV index market might contain the market returns. Therefore, to remove the market returns from the EV index market, we will have the residual returns from the EV index market. These residual returns should contain the information due to unexplained factors such as the risk from the commodities market. We will run a simple regression of index returns against the three major market indices including The Standard and Poor's 500, EURO STOXX 50 , and CSI 300. Then, based on the regressed question, we will obtain the daily EV index return residuals. The specification as follow:

$$EV\_returns = \beta_0 + \beta_1 S\&P500 + \beta_2 STOXX50 + \beta_3 CSI300 + \varepsilon$$

4.2. Methodology

4.2.1. DCC-GARCH

The Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (DCC-GARCH) model was proposed by Robert Engle (2002). This model is designed to study the spillover effect of volatilities across different assets. DCC-GARCH will give a correlation matrix and the computation of the conditional covariance matrix $\mathbf{H_t}$ at time t is computed as follows:

$$\boldsymbol{H_t} = D_t R D_t$$

, where:

1. R is the constant correlation matrix.
2. D_t = diag$(h_{commodity}^{\frac{1}{2}}, h_{EV\ index}^{\frac{1}{2}})$, i.e., is the diagonal matrix containing $h_{commodity}^{\frac{1}{2}}\ or$ $h_{EV\ index}^{\frac{1}{2}}$ of the fitted univariate GARCH models for each asset.

Therefore, we need to run the GARCH model first to obtain the fitted univariate GARCH models for each asset. The specification is as follows.

$$h_i = \omega_t + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{t-1}$$

Where ω_t is the constant term, i = commodity, or index, α_i and β_i are ARCH and GARCH coefficients, respectively.

The structure of $\mathbf{H_t}$ can be extended as follows:

$$\mathrm{H_t} = (1 - \alpha - \beta)\mathrm{S} + \alpha\sigma_{\mathrm{C},t-1}\sigma_{\mathrm{E},t-1} + \beta\mathrm{H}_{t-1}$$

, where:

1. $\mathbf{H_t}$ represents time-varying conditional correlation between commodity and EV index, markets; α shows positive and β, and shows a non-negative scalar parameter under the condition of $\alpha + \beta < 1$.

2. S shows an unconditional correlation matrix of standardized residuals is the unconditional correlation matrix of the epsilons.

4.2.2. VAR

Vector Autoregression (VAR) model captures the linear interdependencies among multiple time series. We will use VAR to run for daily returns of metal commodities against the EV index returns to see if there are any returns spillover effects between the two markets. The VAR model of order p is expressed as follow:

$$Y_t = c + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \varepsilon_t$$

, where:

1. Yt is a k×1 vector of endogenous variables at time t.
2. c is a k×1 vector of constants (intercepts).
3. A_i (for i=1, 2,…, p) are k×k matrices of coefficients that represent the impact of the previous pp periods of each variable on the current period.
4. εt is a k×1 vector of error terms, which are assumed to be white noise and uncorrelated across equations.

To simplify our research, we will implement a VAR (1) model, which means we will analyze each pair of a commodity and an index to see how their t-1 variables affect themselves and each other, Therefore, we have the equation as follows:

$$\text{VAR(1)} \begin{cases} Y_t = c_1 + a_{11} Y_{t-1} + \ a_{12} X_{t-1} + \ \varepsilon_{1,t} \\ X_t = c_2 + a_{21} Y_{t-1} + \ a_{22} X_{t-1} + \ \varepsilon_{2.t} \end{cases}$$

, where:

1. $\mathrm{Y_t}$: Commodity returns as time t
2. $\mathrm{c_1, c_2}$: Constant terms
3. $\mathrm{X_t}$: Index returns at time t
4. $\mathrm{a_{11}, a_{12}, a_{21}, a_{22}}$: Coefficents of the lagged variables
5. $\varepsilon_{1,t}$,$\varepsilon_{2,t}$: Error terms

4.2.3. TVP-VAR

In our research, we will apply the Time-Varying Vector Autoregression (TVP-VAR) developed by Antonakakis et al. (2020). This methodology is further extended by Diebold and Yılmaz (2014), who initially proposed the framework for the connectedness approach. We further TVP-VAR model to analyze how the commodities and EV index affect each other. Different from the DCC-GARCH model in which it can only obtain the correlation of spillover effect but not the overall direction of effect, the TVP-VAR will allow us to determine which assets are net volatility or returns transmitters or receivers. The specification of TVP-VAR(p) as follow:

$$Z_t = A_t Z_{t-1} + \varepsilon_t \qquad \varepsilon_t|\Omega_{t-1} \sim N(0, S_t)$$

$$vec(A_t) = vec(A_{t-1}) + v_t \qquad v_t|\Omega_{t-1} \sim N(0, R_t)$$

With

$$z_{t-1} = \begin{pmatrix} y_{t-1} \\ y_{t-2} \\ \vdots \\ y_{t-p} \end{pmatrix} \qquad A'_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \cdots \\ A_{pt} \end{pmatrix}$$

, where:

1. Ω_{t-1} represents all information available until t-1,
2. y_t and z_{t-1} are m x 1 and mp x 1 vectors, respectively.
3. A_t and A_{it} are m x mp and m x m are dimensional matrices, respectively.
4. $\varepsilon_t$and v_t are the error terms. ε_t is a m x 1 vector and v_t is a m^2p x 1 dimensional vector.

5. S_t and R_t are the variance-covariance matrices that vary over time. S_t and R_t are m x m and m^2p x m^2p dimensional matrices, respectively.

The next step involves calculating the scaled generalized forecast error variance decomposition (GFEVD) for an H-step ahead forecast. To achieve this, the TVP-VAR model is converted into its corresponding vector moving average representation, TVP-VMA based on the Wold representation theorem, which involves the following transformation:

$$Z_t = \sum_{i=1}^{p} A_{it} Z_{t-i} + u_t = \sum_{j=0}^{\infty} B_{jt} u_{t-j}$$

We further compute the GFEVD $\widetilde{\varphi_{ij,t}^{g}}(H)$ which represents the pairwise directional connectedness from j to i and illustrates the influence variable j has on variable i in terms of its forecast error variance share.

$$\widetilde{\varphi_{ij,t}^{g}}(H) = \frac{\varphi_{ij,t}^{g}(H)}{\sum_{j=1}^{k} \varphi_{ij,t}^{g}(H)}$$

From equation above we can have

1. The total directional connectedness from variable j TO all other variables in the network:

$$TO_{jt} = \sum_{i=1, i \neq j}^{k} \widetilde{\varphi_{ij,t}^{g}}(H)$$

2. The total directional connectedness to variable j FROM all other variables in the network:

$$FROM_{jt} = \sum_{i=1, i \neq j}^{k} \widetilde{\varphi_{ji,t}^{g}}(H)$$

3. The net total direction of connectedness associated with variable j:

$$NET_{jt} = TO_{jt} - FROM_{jt}$$

4. The total connectedness index:

$$TCI_t = k^{-1} \sum_{j=1}^{k} TO_{jt} \equiv k^{-1} \sum_{j=1}^{k} FROM_{jt}$$

4.2.4. Hedging Effectiveness

By highlighting which hedging strategies effectively reduce portfolio volatility, this report aims to produce output that goes beyond theoretical conclusions and instead translates these insights into practical applications for market participants. For example, it offers helpful guidance to investors and portfolio managers in the EV industry. These hedging techniques, which have also previously been used for some previous studies (Howard & D'Antonio, 1984; Maitra et al., 2020; Cagli, 2023), can help enhance decision-making and build stronger portfolios that better reflect the risk tolerance and investment goals of stakeholders.

To determine the optimal hedging ratio ($\hat{\beta}$), we first calculated the risk of the asset without any hedging in terms of the variance of the returns of the underlying asset (σ^2_{asset}):

$$\hat{\beta} = \frac{\sigma_{asset,hedge}}{\sigma^2_{hedge}}$$

Where $\sigma_{asset,hedge}$ is the return covariance between the underlying and hedging asset, while σ^2_{hedge} is the variance of the returns of the hedging assets.

As a result, we can determine the net variance of the portfolio ($\sigma^2_{portfolio}$) as follows:

$$\sigma^2_{portfolio} = \sigma^2_{asset} + \hat{\beta}^2 \sigma^2_{hedge} - 2\hat{\beta}\sigma_{asset,hedge}$$

Lastly, the hedging effectiveness is measured by comparing the hedge's reduction in variance to the asset's original variance:

$$Hedging\ Effectiveness = \left(1 - \frac{\sigma^2_{portfolio}}{\sigma^2_{asset}}\right) X\ 100\%$$

Where the hedging effectiveness essentially gives a direct measure of how much the hedged portfolio combinations mitigate the original risk.

5. Result and Discussion

5.1. DCC-GARCH

We first used a DCC-GARCH model to examine the volatility dynamics among the equity indices and commodities, focusing on two main parameter coefficients – α (Arch) and β (Garch). The α (Arch) term quantifies the squares of the prior period's shocks impact the volatility of the present. In other words, it measures the extent to which historical "surprises" impact present volatility, while β (Garch) and represents how persistent the volatility of the current period is compared to that of the past. Thus, it does not only reflect the shock but also the impact of the volatility of the preceding period.

	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	CO1	LA1	LFA1	LN1	LCO1	LOCADY
Arch (α)	0.0613***	0.0949***	0.0513***	0.1058*	0.0800	0.1248***	0.0453	0.0406***	0.3473**	0.1680***	0.1291***
p-value	0.0059	0.0000	0.0000	0.0669	0.2668	0.0007	0.5818	0.0002	0.0447	0.0021	0.0000
Garch (β)	0.9334***	0.8669***	0.9277***	0.8744***	0.9088***	0.8624***	0.9418***	0.9500***	0.4884***	0.6895***	0.7715***
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0014	0.0000	0.0000

***) *significant at 1%*
**) *significant at 5%*
*) *significant at 10%*

To illustrate, at the 1% level, the α the (Arch) coefficient for GSXAELEV (Goldman Sachs Asia EV Index) is 0.0949, suggesting a relatively high initial responsiveness to market shocks. This implies that following market news or events, GSXAELEV investors may see frequent and notable shifts in price volatility. Meanwhile, the β (Garch) coefficient for LA1 (Aluminum) was 0.9418, implying a high level of volatility persistence, requiring investors or traders with long exposure to LA1 to carefully evaluate their risk because changes in volatility are likely to have long-term consequences.

DCC-α	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN
CO1	0.0836***	0.0141**	0.0000	0.0064	0.0173**
LA1	0.0065**	0.0115**	0.0155	0.0059*	0.0071**
LFA1	0.0112	0.0000	0.0067*	0.0348*	0.011
LN1	0.0021	0.0342*	0.0492***	0.0028*	0.0036*
LCO1	0.0097	0.0416***	0.0072	0.0881***	0.016
LOCADY	0.0266*	0.0211	0.0105	0.0178**	0.0058

DCC-β	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN
CO1	0.5747***	0.9619***	0.9484**	0.9844***	0.9639***
LA1	0.9884***	0.9813***	0.6781***	0.9889***	0.9887***
LFA1	0.9620***	0.9179***	0.9861***	0.9241***	0.9653***
LN1	0.9929***	0.6821**	0.7902***	0.9911***	0.9924***
LCO1	0.0000	0.2471	0.9033***	0.0545	0.7656***
LOCADY	0.6204***	0.9035***	0.9683***	0.8934***	0.9859***

****) significant at 1%*

***) significant at 5%*

**) significant at 10%*

We further examined the dynamic conditional correlations between the equity and commodity indices, still using the DCC-GARCH model. As a result, two important variables were derived as the output of the model: DCC-α, which showed how shocks affected the correlations between the two asset pairs immediately (short-term spillover effects), and DCC-β, which indicated how persistent these correlations were over time.

For instance, the DCC-α for the pair KEV and CO1 was considerably high at 0.0836, suggesting a strong initial response to market shocks. The relationship between the KEV index and CO1 is extremely sensitive to new market shocks, and it may change dramatically in the short term. Other commodities, such as LFA1 and LCO1, on the other hand, had statistically insignificant and lower DCC-α values with their respective pairs, suggesting that they are less susceptible to sudden shifts in the market. Moving on to DCC-β, we can see that most of these pairs have a strong long-term correlation persistence, with DCC-β values getting close to 1, indicating remarkably stable correlations. This persistence (between KEV and CO1 pairs; 0.5747) implies that, after being impacted by shocks, the correlation between KEV and CO1 tends to be steady. The significant level of this volatility spillover effect is consistent with previous research by Maitra et al. (2020), who examined the relationships between shipping companies' supply chains.

5.2. TVP-VAR Volatilities

The global transition toward renewable energy and electric vehicles (EVs) has significantly influenced financial markets, especially commodities and EV-related indices. Understanding the interconnectedness and spillover effects between these two asset classes becomes critical when identifying market risks and opportunities during the global trend of energy transition. Here, the research adopted the Time-Varying Parameter Vector Autoregression (TVP-VAR) Model to capture the direction and intensity of the spillover effect between the commodities and EV indices volatilities and determine which assets are the net volatilities transmitters and receivers.

Bloomberg symbol	Full name of symbol
CO1	Brent Crude Oil
LA1	Aluminium
LFA1	Lithium Hydroxide
LN1	LME Nickel
LCO1	LME Cobalt
LOCADY	LME Copper
KEV Index	S&P Kensho EV
GSXAELEV Index	GS Asia EV
SOLCEVIN Index	Solactive China EV and Battery
SPEAEVUT Index	S&P Eurozone Automotive & EV
SOLKARSN Index	Solactive EV and Future Mobility

Table 5.2.1: List of Bloomberg symbols and its full name

Volatility Spillover Matrix *(Whole Timeframe)*	CO1	LA1	LFA1	LN1	LCO1	LOCADY	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	FROM
CO1	72.94	2.24	0.97	2.23	1.66	2.19	4.72	1.44	0.88	5.87	4.87	27.06
LA1	1.91	75.41	0.86	4.37	1.36	4.26	3.69	1.55	1.44	2.09	3.07	24.60
LFA1	0.93	1.10	90.17	0.93	0.64	1.18	1.10	0.71	1.00	1.06	1.16	9.81
LN1	1.87	4.49	0.77	79.96	1.30	3.53	1.47	1.03	2.15	1.65	1.78	20.04
LCO1	1.30	1.31	0.73	1.21	87.55	1.69	1.49	0.79	1.55	1.08	1.31	12.46
LOCADY	2.04	3.80	0.86	4.15	1.89	74.97	2.55	3.06	0.91	2.66	3.10	25.03
KEV	3.09	1.49	1.37	0.88	1.14	2.03	51.87	2.84	0.80	7.98	26.49	48.11
GSXAELEV	1.61	1.61	0.59	0.98	0.61	2.37	5.04	47.53	28.78	2.78	8.09	52.47
SOLCEVIN	1.06	1.45	0.79	1.18	0.80	0.95	0.92	30.06	57.71	1.57	3.50	42.28
SPEAEVUT	3.77	1.78	0.78	1.08	1.30	2.12	11.15	2.50	0.94	60.00	14.58	40.01
SOLKARSN	3.07	1.67	0.78	1.17	1.23	2.57	24.20	5.75	2.56	10.54	46.46	53.55
TO	20.66	20.94	8.50	18.18	11.93	22.89	56.33	49.74	41.01	37.28	67.96	355.42
Including own	93.60	96.36	98.67	98.13	99.47	97.86	108.20	97.26	98.72	97.28	114.42	cTCI/TCI
NET	-6.40	-3.64	-1.33	-1.87	-0.53	-2.14	8.20	-2.74	-1.28	-2.72	14.42	33.85/30.09

Table 5.2.2: Volatility Spillover Matrix (Whole Timeframe)

Volatility Spillover Matrix *(After Paris Agreement)*	CO1	LA1	LFA1	LN1	LCO1	LOCADY	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	FROM
CO1	72.80	2.69	0.97	2.31	1.15	2.16	5.18	1.54	0.88	4.95	5.38	27.20
LA1	1.87	73.28	0.86	4.38	1.66	4.94	3.36	2.27	1.44	2.56	3.39	26.73
LFA1	0.93	1.10	90.17	0.93	0.64	1.18	1.10	0.71	1.00	1.06	1.16	9.81
LN1	1.28	4.81	0.77	75.95	1.51	4.11	2.38	1.38	2.15	2.16	3.52	24.06
LCO1	0.96	1.81	0.73	1.71	86.45	1.39	1.84	1.03	1.55	0.81	1.72	13.54
LOCADY	2.23	4.82	0.86	5.39	1.83	70.31	2.83	3.05	0.91	3.83	3.93	29.69
KEV	3.07	1.67	1.37	1.69	1.01	2.15	50.47	3.77	0.80	8.74	25.26	49.53
GSXAELEV	1.53	1.88	0.59	1.26	0.57	2.39	5.00	47.17	28.78	2.63	8.22	52.84
SOLCEVIN	1.06	1.45	0.79	1.18	0.80	0.95	0.92	30.06	57.71	1.57	3.50	42.28
SPEAEVUT	3.63	2.01	0.78	1.69	1.14	2.75	11.57	2.73	0.94	57.30	15.44	42.68
SOLKARSN	3.00	1.92	0.78	2.16	1.03	2.58	23.09	6.45	2.56	11.56	44.88	55.13
TO	19.55	24.17	8.50	22.69	11.34	24.61	57.27	52.98	41.01	39.86	71.52	373.49
Inc.Own	92.34	97.44	98.67	98.64	97.79	94.92	107.74	100.15	98.72	97.16	116.40	cTCI/TCI
NET	-7.66	-2.56	-1.33	-1.36	-2.21	-5.08	7.74	0.15	-1.28	-2.84	16.40	36.18/32.16

Table 5.2.3: Volatility Spillover Matrix (After Paris Agreement)

The TVP-VAR model outputs "Volatility Spillover Matrix", with 2 major timeframes being classified, namely "whole timeframe" and "after Paris Agreement" timeframe, as shown in Table 5.2.2 and Table 5.2.3.

In both Table 5.2.2 and Table 5.2.3, the left-hand side (CO1, [LA1, LFA1, LN1, LCO1, LOCADY]) is commodities, with CO1 being "Traditional Combustion Cars Commodity" and [LA1, LFA1, LN1, LCO1, LOCADY] being the list of "EV-related Commodities". And CO1 is used as a benchmark of all commodities. While the right-hand side ([KEV, GSXAELEV, SOLCEVIN, SPEAEVUT, SOLKARSN]) is the list of EV Indices.

5.2.1. Volatility Spillover Matrix analysis for commodities

From Table 5.2.2 and Table 5.2.3, since in both timeframes CO1 has negative NET (-6.40 & -7.66), the benchmark of all commodities is a volatility shock “receiver”.

Among all “EV-related Commodities” ([LA1, LFA1, LN1, LCO1, LOCADY]), since all of them have negative values in both timeframes, they are all volatility shock “receiver”.

The strongest volatility shock “receiver” is LA1 (Aluminum), in both "whole" timeframe (-3.64%), and “after Paris Agreement” timeframe (-2.56%). The first potential reason and its characteristic is that Aluminum is easily impacted by countries' trade relations and tariffs. Aluminum is an asset subject to international trade agreements and tariffs, changes in countries' trade policies will directly influence the price. Trade disputes or shifts in trade patterns may trigger sudden price movements, such as US-China trade war, causing aluminum easily being influenced by "trade policy uncertainty shocks" (Boer et al., 2022). The second potential reason and its characteristic are the high market concentration of aluminum. The global aluminum market is dominated by a few key players, (Alcoa Corporation, UC Rusal, Rusal, Rio Tinto, China Hongqiao Group, Norsk Hydro) (Barjot et al., 2022), which may enlarge the effects of supply disruptions or changes in production capacities towards prices, causing aluminum particularly easy to be influenced by supply shocks.

5.2.2. Volatility Spillover Matrix analysis for EV indices

Regarding “transmitter”, among all “EV Indices”, SOLKARSN index (Solactive China EV and Battery Index) has the highest volatility shock “transmitter” in both timeframes (+14.42% & +16.40%). The first potential reason and its characteristic is the centralized regulatory environment of China. Since China has a centralized governance structure (Ahlers & Schubert, 2014), the fast changes in new regulations and policy actions cascaded down from national level to local governments, such as subsidies and developments in power battery technology, can have significantly sudden impact on EV and battery-related industries (Li et al., 2024). And since SOLKARSN index (Solactive China EV and Battery Index) is one of the top EV indices in China, it may easily influence the volatility of other assets, acting as a strong volatility shock "transmitter". The second potential reason and its characteristic are the emerging market dynamics of China. Compared to developed countries, emerging countries like China often experience higher market volatility due to the potential rapid economic growth ("Emerging Markets Finance," 2003). And when SOLKARSN Index experience high volatility due to emerging market dynamics, it may spillover the volatility to other smaller related assets, acting as a strong volatility shock "transmitter".

Regarding "receiver", among all "EV Indices", SPEAEVUT index (S&P Eurozone Automotive & EV Index) is a strong and significant volatility shock "receiver" in both the "whole" timeframe (-2.72%) & "after Paris Agreement" timeframe (-2.84%). It is the most significant "receiver" for both negative "NET" in both timeframes. The first potential reason and its characteristic is the high market sensitivity due to quite low market adoption. From Table 5.2.2.1, the SPEAEVUT index constituent "Country Breakdown", Germany has the largest index weight (52.7%) as of 29 Nov 2024 (*S&P Eurozone Automotive & Electric Vehicles Index*, n.d.), indicating this index is significantly influenced by Germany economy. Currently, there is quite low market adoption of EV across the globe, including Germany (Erber, 2016). And German Energiewende has been launched to foster the transition of German automotive industry from traditional combustion engine vehicles to electric vehicles (EV) (Erber, 2016). So, German EV market is sensitive to potentially more continuous changes in EV adoption rates, new regulatory policies and technological advancements, all of which may cause sudden volatility changes of SPEAEVUT index, the volatility shock "receiver". The second potential reason and its characteristic are its relatively smaller market size among global EV markets. Since Europe market size is relatively smaller than that of other regions (eg. US and China), SPEAEVUT index's volatility spillover effect towards other markets may be more limited, weakening SPEAEVUT index "transmitter" effect, thereby reinforcing its role as a volatility shock "receiver".

Country Breakdown

COUNTRY/REGION	NUMBER OF CONSTITUENTS	TOTAL MARKET CAP	INDEX WEIGHT
Germany	7	170,151.83	52.7%
France	3	35,890.95	23.1%
Italy	2	117,744.70	20.4%
Belgium	1	10,838.48	3.8%

As of Nov 29, 2024

Table 5.2.2.1: SPEAEVUT index constituent "Country Breakdown"

Overall, from the above result analysis, for commodities, both the benchmark CO1 (Brent crude oil) and all other commodities are volatility shock "receiver", with LA1 (aluminum) being the strongest. For EV indices, SOLKARSN index (Solactive China EV and Battery Index) has the highest volatility shock "transmitter" in both timeframes. While SPEAEVUT index (S&P Eurozone Automotive & EV Index) is a strong and significant volatility shock "receiver" in both timeframes. The analysis underscores the asymmetric nature of volatility spillovers between commodities and EV indices, revealing distinct roles as either volatility shock "transmitters" or "receivers" and the varying degrees of transmission and reception across asset classes. The distinct roles of commodities and EV indices as either transmitters or receivers underscore the need for targeted strategies to address vulnerabilities and enhance resilience in both sectors. Not only will this support smoother market functioning, but it also ensures the transition to sustainable energy systems is underpinned by robust financial systems capable of managing the associated risks effectively.

5.3.VAR Returns

IV / DV	S&P Kensho EV	GS Asia EV	Solactive China	S&P Eurozone
Oil (CO1)	0.30370	0.18470	0.02527	0.41330
Aluminium (LA1)	0.00221	0.05740	0.03805	0.26540
Lithium (LFA1)	0.00043	0.00024	0.00040	0.00022
Nickel (LN1)	0.00077	0.00054	0.00016	0.00094
Cobalt (LCO1)	0.00013	0.00137	0.00110	0.00014
Copper (LOCADY)	0.00023	0.06208	0.01193	0.02104

DV / IV	S&P Kensho EV	GS Asia EV	Solactive China	S&P Eurozone
Oil (CO1)	0.42580	0.02387	0.33450	0.03558
Aluminium (LA1)	0.55420	0.40210	0.11250	0.15550
Lithium (LFA1)	0.63580	0.98570	0.40820	0.81680
Nickel (LN1)	0.31020	0.00022	0.35540	0.47140
Cobalt (LCO1)	0.58130	0.35420	0.77350	0.31750
Copper (LOCADY)	0.51870	0.14400	0.07722	0.06182

Figure 1&2: VAR for EV indexes return against commodities return and vice versa.

From the basic Vector Auto Regression model result, it can be noticed that there is a one-sided relationship between EV indexes' return and commodities' return namely EV index returns are the return shock transmitter rather than receiver which is against the common knowledge that saying another way around. This can be observed through the two tables above where when the commodity return is being run as dependent variable, the P-Value is low which means that the independent variables (EV related indexes) have significant impacts on the commodities' returns. Secondly, it is found that Lithium, Nickel and Cobalt are most impacted by the EV index residuals. Thirdly, Lithium appears to be the metal that is most influenced by the EV index return residuals. The results shown here are roughly in line with the TVP VAR model that will be carried out below with explanations provided below.

5.4. TVP VAR Returns

Return Spillover Matrix *(Whole Timeframe)*	CO1	LA1	LFA1	LN1	LCO1	LOCADY	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	FROM
CO1	81.41	5.32	1.25	4.27	0.57	3.62	0.72	0.77	0.32	0.90	0.86	**18.59**
LA1	4.49	69.79	1.01	10.16	0.90	8.73	1.12	0.86	0.30	1.07	1.59	**30.21**
LFA1	1.28	1.83	88.23	1.46	1.41	0.72	0.81	1.39	1.02	1.00	0.85	**11.77**
LN1	3.78	9.92	1.10	71.88	0.77	7.91	0.67	0.78	0.17	1.37	1.65	**28.13**
LCO1	0.65	0.99	0.82	1.55	91.24	0.85	0.87	0.72	0.46	1.16	0.67	**8.74**
LOCADY	3.51	10.24	0.56	9.99	0.82	66.87	1.40	1.22	0.75	1.71	2.92	**33.13**
KEV	0.58	0.74	0.39	0.63	0.67	0.98	64.64	1.03	0.82	5.53	23.98	**35.35**
GSXAELEV	1.69	0.88	0.44	0.89	0.69	1.26	1.64	54.53	28.08	1.64	8.29	**45.48**
SOLCEVIN	1.00	0.62	0.68	0.28	0.31	0.86	0.52	32.22	56.28	1.26	5.97	**43.72**
SPEAEVUT	1.04	1.16	0.90	1.67	1.04	1.53	6.32	1.68	0.82	71.72	12.11	**28.27**
SOLKARSN	0.53	1.13	0.50	1.26	0.59	1.83	20.16	6.63	5.07	9.34	52.95	**47.04**
TO	**18.57**	**32.83**	**7.65**	**32.15**	**7.77**	**28.29**	**34.22**	**47.29**	**37.81**	**24.98**	**58.88**	330.44
Inc.Own	99.98	102.61	95.89	104.04	99.01	95.16	98.85	101.82	94.09	96.70	111.83	**cTCI/TCI**
NET	**-0.02**	**2.61**	**-4.11**	**4.04**	**-0.99**	**-4.84**	**-1.15**	**1.82**	**-5.91**	**-3.30**	**11.83**	**30.36/26.98**

To take into account dynamic relationships among those EV related indexes and commodities, TVP VAR model is applied as we believe across the period of more than 10 years of data being tested here, various events including the Covid 19, Paris Accord Agreement, US-China Trade war will impact the dynamics. This figure indicates that there is 26.98% (TCI) dependency resulting from the entire network with 73.02% coming from outside the variable itself.

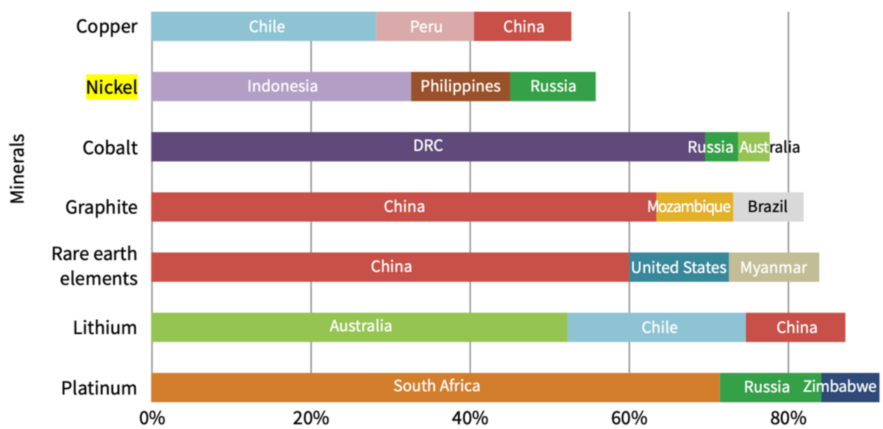
5.4.1. TVP VAR Returns - Commodity Analysis

Firstly, from the perspective of commodity, it is found that only aluminum (LA1) and Nickel (LN1) are net return shock transmitters while the rest are receivers in this model. For aluminum, it is used across various industries including automotive, construction and aerospace. Hence, its widespread use is subjected to both technological advancements and economic growth outside of our model, amplifying its potential to transmit return shocks into other variables in our model when market conditions change. Meanwhile for Lithium and Cobalt, their usages are concentrated in EV industry and hence lead to a more constrained impact by EV index residuals. This however is inconsistent with Cagli's findings stated that Lithium is dominant net shock transmitter in the commodity system for Electric vehicles (Cagli, 2023).

Secondly, despite Nickel's key role in increasing the energy density of lithium-ion batteries, which is the heart of EV technology revolution, its return is still not largely impacted by the performance of EV indexes. This is mainly due to the supply chain vulnerabilities overplay its importance and act as a transmitter of return shocks to other variables. Nickel mining is concentrated in only a few regions and hence its production is highly susceptible to geopolitical and operational risks in the regions. From figure 1 below, nickel production is concentrated in Indonesia, Russia and Philippines, region where subjected to high geopolitical risks (Andreoni & Roberts, 2022). Indonesia has been launching series of policies to restrict the export of nickel ore to promote domestic processing which creates havoc for EV industry which has triggered dissatisfaction from EU (Mitrania et al., 2021).

Figure 1: Production and processing of critical minerals, 2019

1a: Share of top three producing countries in total production for selected critical minerals, 2019



5.4.2. TVP VAR Returns – EV Indices Analysis

Return Spillover Matrix *(Whole Timeframe)*	CO1	LA1	LFA1	LN1	LCO1	LOCADY	KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	FROM
CO1	81.41	5.32	1.25	4.27	0.57	3.62	0.72	0.77	0.32	0.90	0.86	**18.59**
LA1	4.49	69.79	1.01	10.16	0.90	8.73	1.12	0.86	0.30	1.07	1.59	**30.21**
LFA1	1.28	1.83	88.23	1.46	1.41	0.72	0.81	1.39	1.02	1.00	0.85	**11.77**
LN1	3.78	9.92	1.10	71.88	0.77	7.91	0.67	0.78	0.17	1.37	1.65	**28.13**
LCO1	0.65	0.99	0.82	1.55	91.24	0.85	0.87	0.72	0.46	1.16	0.67	**8.74**
LOCADY	3.51	10.24	0.56	9.99	0.82	66.87	1.40	1.22	0.75	1.71	2.92	**33.13**
KEV	0.58	0.74	0.39	0.63	0.67	0.98	64.64	1.03	0.82	5.53	23.98	**35.35**
GSXAELEV	1.69	0.88	0.44	0.89	0.69	1.26	1.64	54.53	28.08	1.64	8.29	**45.48**
SOLCEVIN	1.00	0.62	0.68	0.28	0.31	0.86	0.52	32.22	56.28	1.26	5.97	**43.72**
SPEAEVUT	1.04	1.16	0.90	1.67	1.04	1.53	6.32	1.68	0.82	71.72	12.11	**28.27**
SOLKARSN	0.53	1.13	0.50	1.26	0.59	1.83	20.16	6.63	5.07	9.34	52.95	**47.04**
TO	**18.57**	**32.83**	**7.65**	**32.15**	**7.77**	**28.29**	**34.22**	**47.29**	**37.81**	**24.98**	**58.88**	330.44
Inc.Own	99.98	102.61	95.89	104.04	99.01	95.16	98.85	101.82	94.09	96.70	111.83	**cTCI/TCI**
NET	**-0.02**	**2.61**	**-4.11**	**4.04**	**-0.99**	**-4.84**	**-1.15**	**1.82**	**-5.91**	**-3.30**	**11.83**	**30.36/26.98**

In term of index return, Only GSXAELEV (GS Asia EV) and SOLKARSN (SOLACTIVE & Future mobility GLOBAL) are return shock transmitters.

For GS Asia EV, since its coverage is in Asia, with Asia strong position in raw metals for EV from South East Asia along with China, Korea and Taiwan being the main producers for EV components serves as a bell weather for the EV index performance and hence tend to act as key shock transmitter in the global EV ecosystem. The National Bureau of Economic Research (Diebold & Yilmaz, 2011) emphasizes that supply chain nodes with high concentration (e.g., Asia in EV battery production) act as primary transmitters in global markets.

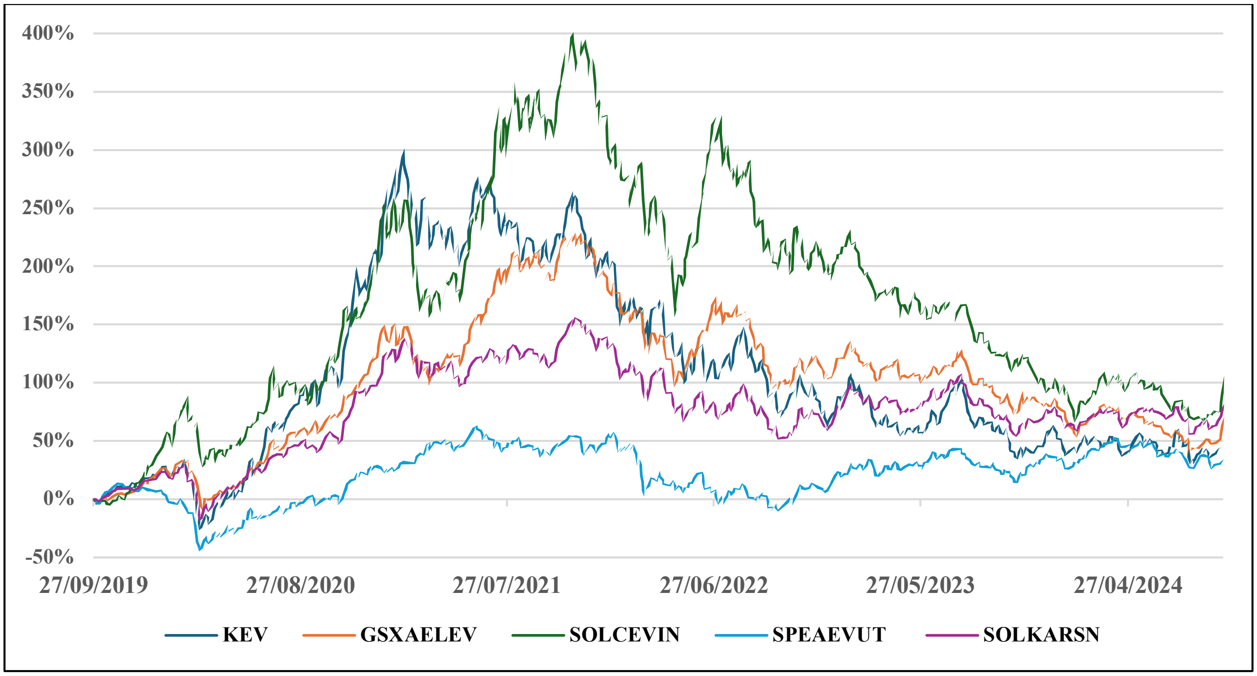
For SOLKARSN (SOLACTIVE & Future mobility GLOBAL), since this index is focusing on representing the companies for innovation in EV industry ecosystem. Breakthroughs in autonomous systems or battery efficiency create significant upstream and downstream spillovers. This is aligned with the study of return spillover around the globe stating that innovation driven indexes are return shock transmitter in financial market (Lyócsa et al., 2019).

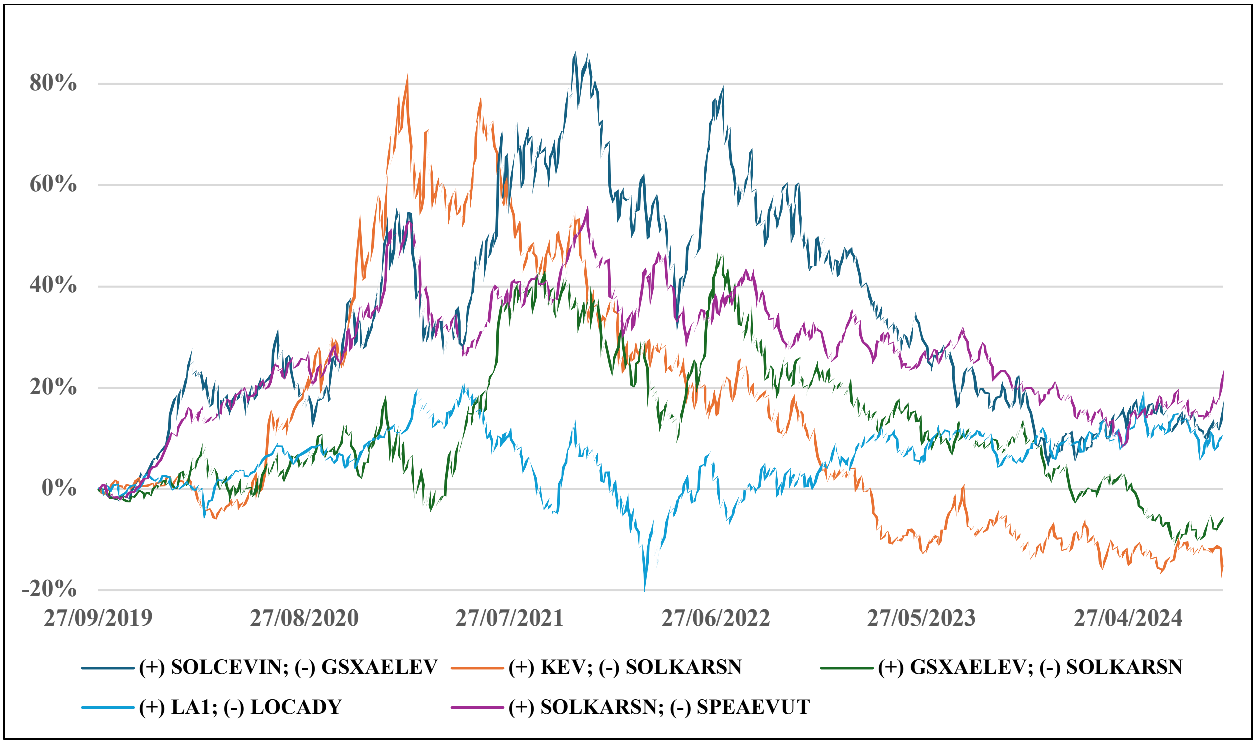
5.5. Hedging Effectiveness

Hedging Effectiveness		Short										
		KEV	GSXAELEV	SOLCEVIN	SPEAEVUT	SOLKARSN	CO1	LA1	LFA1	LN1	LCO1	LOCADY
Long	KEV	100.0%	1.2%	0.3%	6.0%	42.0%	0.3%	0.6%	0.1%	0.1%	0.0%	0.2%
	GSXAELEV	1.2%	100.0%	55.2%	4.2%	22.2%	0.3%	1.1%	0.1%	0.2%	0.2%	1.6%
	SOLCEVIN	0.3%	55.2%	100.0%	0.5%	9.4%	0.0%	0.0%	0.1%	0.1%	0.2%	0.0%
	SPEAEVUT	6.0%	4.2%	0.5%	100.0%	14.2%	0.2%	0.4%	0.1%	0.1%	0.4%	1.5%
	SOLKARSN	42.0%	22.2%	9.4%	14.2%	100.0%	1.2%	4.2%	0.1%	1.1%	0.3%	6.7%
	CO1	0.3%	0.3%	0.0%	0.2%	1.2%	100.0%	10.5%	0.5%	2.9%	0.0%	6.0%
	LA1	0.6%	1.1%	0.0%	0.4%	4.2%	10.5%	100.0%	0.3%	4.8%	0.1%	22.1%
	LFA1	0.1%	0.1%	0.1%	0.1%	0.1%	0.5%	0.3%	100.0%	0.8%	0.3%	0.0%
	LN1	0.1%	0.2%	0.1%	0.1%	1.1%	2.9%	4.8%	0.8%	100.0%	1.4%	8.1%
	LCO1	0.0%	0.2%	0.2%	0.4%	0.3%	0.0%	0.1%	0.3%	1.4%	100.0%	0.0%
	LOCADY	0.2%	1.6%	0.0%	1.5%	6.7%	6.0%	22.1%	0.0%	8.1%	0.0%	100.0%

The pair of SOLKARSN as the long position and KEV as the short position had a significant 42.0% hedging effectiveness, according to the table above. Given that a short position in KEV may offset 42.0% of the variation in SOLKARSN, this indicates that KEV is a reasonably good hedge. This hedge's efficacy shows that, despite both indices' exposure to the electric vehicle sector, they move independently enough to offer a sizable amount of risk compensation. This high degree of effectiveness implies that not all risks are linked and that resisting KEV movements can effectively mitigate some risks in SOLKARSN.

Additionally, we conducted a back-test to examine the returns of the unhedged EV indices and the five pair hedging techniques that, based on the above table, had the highest hedging effectiveness. The outcome was as follows:





The performance of the five hedged asset pairs was relatively inferior to having a single long position in the EV indices, as shown in the two figures above. This is because the hedging strategies were not aimed to generate a higher return, instead its objective is to reduce the risk exposure of traders or investors in EV industries (as indicated by smaller variance), which is shown to be effective, as shown in the table below.

Unhedged Portfolio	Variance	Hedged Portfolio	Variance
KEV	0.000564	(+) SOLCEVIN; (-) GSXAELEV	0.000379
GSXAELEV	0.000253	(+) KEV; (-) SOLKARSN	0.000166
SOLCEVIN	0.000470	(+) GSXAELEV; (-) SOLKARSN	0.000234
SPEAEVUT	0.000385	(+) LA1; (-) LOCADY	0.000118
SOLKARSN	0.000269	(+) SOLKARSN; (-) SPEAEVUT	0.000123

6. Conclusion

This research focuses on studying the financial interconnectedness within the electric vehicle (EV) sector by investigating volatility and return spillovers among EV-related commodities and indices. The findings reveal that EV indices, especially the Solactive China EV and Battery Index (SOLKARSN index), dominate as transmitters of volatility and return shocks, against the traditional assumptions of commodity-driven dynamics. The analysis shows a moderate degree of interdependence within the sector, driven by the sensitivity of indices to regulatory changes, technological breakthroughs, and shifts in investor sentiment.

Hedging strategies, such as pairing Solactive EV and Future Mobility (SOLKARSN Index) with the S&P Kensho EV (KEV index), substantially lower portfolio variance, providing practical tools for mitigating risks in this volatile yet high-growth market. These insights highlight the pivotal role of EV indices in market transmission and portfolio optimization, presenting applicable guidance for policymakers, investors, and industry participants.

Despite its contributions, the study acknowledges limitations, including the comparatively short history of EV indices and the exclusion of more macroeconomic metrics and technology-related indices. Future research may extend these findings by combining broader parameters, including geopolitical shocks and green bond markets, to strengthen the understanding of financial dynamics in this rapidly evolving ecosystem. With the rapid global shift toward sustainable transportation, this study lays a more crucial groundwork for understanding and managing the risks and rewards of the electrification age.

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