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Fossil Fuel-Based versus Electric Vehicles: A Volatility Spillover Perspective Regarding the Environment

Shailesh Rastogi [1], Jagjeevan Kanoujiya [1], Satyendra Pratap Singh [2], Adesh Doifode [3], Neha Parashar [3] and Pracheta Tejasmayee [1,*]

1 Symbiosis Institute of Business Management Nagpur, Symbiosis International (Deemed) University, Pune 440008, India; krishnasgdas@gmail.com (S.R.); jagjeevan24288@yahoo.co.in (J.K.)
2 Alliance School of Business, Alliance University, Bengaluru 562106, India; satyendras.14@gmail.com
3 Symbiosis School of Banking & Finance, Symbiosis International (Deemed) University, Pune 412115, India; equity.adesh@gmail.com (A.D.); nehaparashar10@gmail.com (N.P.)
* Correspondence: prachetatejasmayee1998@gmail.com

Abstract: Due to environmental concerns, electric vehicles (EVs) are gaining traction over fossil fuel-based vehicles. For electronic devices, including vehicles, copper is the key material used for building. This situation draws attention to the impact of copper prices, crude oil prices, and exchange rates on the economic viability of using EVs over fossil fuels. We use the volatility spillover effect (VSE) to determine the financial viability of these two types of vehicles in the context of environmental issues. Daily data on copper prices, crude oil, exchange rate, and the BSE100 ESG ("Bombay Stock Exchange 100 Environmental, Social and Governance") index are taken from 1 November 2017 to 20 September 2022. Two popular multivariate GARCH ("Multivariate Generalized Autoregressive Conditional Heteroscedasticity") family models, i.e., the BEKK ("Baba–Engle–Kraft–Kroner")-GARCH (BG) and DCC ("Dynamic Conditional Correlation")-GARCH (DG) models, are utilized to find volatility connections between these variables. These are appropriate GARCH models to observe the volatility dependence of one market on another market. It is found that there exist volatility effects of copper and exchange rate on the S&P BSE100 ESG Equity Index Price, which we will refer to here as ESG. However, crude oil is found to be insignificant for ESG. The novelty of this study is in the use of volatility spillover to determine economic viability. The volatility effects of copper prices are positive for ESG in the short run and negative for long-term volatility. The exchange rate has a positive volatility effect on ESG in the long run. Surprisingly, we find that EVs are technologically better than fossil fuel-based vehicles as a possible sustainable energy source. We observe studies that have raised similar concerns about EVs' lack of business sense compared to fossil fuels. However, using VSE to explore financial viability offers a fresh perspective. Based on the findings of the current study, it is recommended that policymakers and researchers revisit their support for EVs as an alternate and sustainable source of energy.

Keywords: electric vehicle; energy; environment; fossil fuel; volatility spillover effect

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1. Introduction

The quintessential role of logistics in the growth and development of any economy is abundantly evident in the literature. In a multi-country panel data study, D'Aleo and Sergi (2017) present positive and significant interactions between the logistics and competitiveness of the economic growth of nations. Similarly, Lean et al. (2014) find evidence of a significant bidirectional positive association between logistics growth and China's economic growth. Having logistics as an essential contributor to economic growth represents the brighter side of the situation. The darker side is related to pollution. Herndon (2018) presents air pollution as the leading cause of global warming. In addition, Popova et al. (2021) also posit vehicular pollution as the leading cause of environmental pollution and, eventually, global warming. Evidence of vehicular pollution as one of the leading causes of environmental concern is witnessed by other studies in different geographical locations (Inumaru et al. 2021; Ghimire and Shrestha 2014).

All over the world, electric energy is presented as an alternate energy source for logistics, assuming EVs to be environmentally better than fossil fuel-based vehicles. This situation is mainly in the nascent stage across the world. The documentary evidence of EVs' superiority to fossil fuel-based vehicles as a business proposition is more of an expectation than based on hard facts, as the future is always uncertain (Mutter 2021; Malik et al. 2018). In other words, whether EVs can successfully replace fossil fuels without hampering economic growth is not certain. The positive role of EVs over fossil fuels regarding the environment may be decisive (Abas et al. 2015). However, their economic viability is still uncertain (Bonilla et al. 2022). This situation raises two main questions, which are not unanimously answered in the literature: (1) Will the implementation of EVs be economically viable? (2) Will EVs be able to solve environmental concerns in the long run?

Malik et al. (2018) demonstrate people's support in a conceptual study on electric mobility in New Delhi, India, from 2016 to 2017. In addition, Mutter (2021) posits that the government in Sweden considers EVs as revolutionary and expects them to change the landscape and improve the environment. However, both are descriptive studies and lack empirical scrutiny or vetting of their findings. In a study in Mexico, Bonilla et al. (2022) found evidence that EVs are not commercially viable and may reduce the government's tax revenue by more than 20 per cent in 25–30 years. Young (2022) presents a US study that states that the success or failure of EVs depends upon the acceptance or rejection of the policies on EVs by different interest groups.

Moreover, Schade et al. (2012) present various approaches for improving the commercial success of EVs in other countries, especially between 25 developing and developed countries. The abovementioned studies are testimonies to the fact that EVs' commercial or economic success is contingent. Hence, a fresh perspective would surely add value to the contemporary debate on the financial success of EVs worldwide. Therefore, this study fills the above-mentioned research gaps by investigating the environmental viability of EVs and fossil fuel vehicles. It determines the volatility effects of crude oil, copper prices, and exchange rates on the ESG index.

The concerns raised in the current study could have been addressed using different research methodologies and approaches. The lack of empirical data is the biggest hurdle in reaching a consensus. There is a lack of a common viewpoint not only on the technological superiority of EVs over fossil fuel-based vehicles to improve environmental concerns. It is the financial viability of EVs that needs evidence of its success in the future, for which there are no data. The technological advancements in EVs and their related costs in the future cannot be ascertained to accurately establish EVs' financial viability. Hence, the use of indirect methods is the solution to the problem. This is attempted in the current study. The present study uses copper prices (a proxy for electric vehicles), crude oil prices (a proxy for fossil fuel), and the ESG indices of firms in India (a proxy for the environment). The bivariate GARCH family of models (BG and DG) is applied to assess the volatility spillover effect (VSE) among the time series used in this study. Daily data from 1 November 2017 to 20 September 2022 are taken. The lack of direct methods to determine EVs' commercial viability justifies using the VSE method to answer the questions raised in this study. The study's primary motivation is the presence of many alternative fuels competing with EVs (Astbury 2008; Salvi et al. 2013) and the lack of unanimity on EVs' economic viability.

No other study uses the VSE to address EVs versus fossil fuel-based vehicles. This study is a novel attempt to use the VSE to address this topic. It is found that there exist volatility effects of copper and exchange rate on ESG. However, crude oil has no significant volatility effect on ESG. This study's findings show that EVs can potentially improve environmental concerns. However, fossil fuels are not losing their (negative) influence on the environment. This represents a significant contribution of this study, which the authors do not witness in any other research. In addition, this study has several important and groundbreaking implications for policymakers and other stakeholders regarding EVs as an alternative to fossil fuels-based vehicles. Policymakers may be correct in attempting to have EVs as an alternate fuel for logistics of all kinds. However, the execution of the EV-based policy should be implemented with a grain of salt, as the commercial and economic viability of EVs is not certain. Hence, a phase-wise execution of EV-based policy may be a better bet alongside waiting for other technologies to come up in full swing. This way, the policymakers may have a few more options as an alternative to fossil fuel and EVs.

The rest of the study is presented in six sections. The second section contains a relevant review of the literature. The data and methodology used in the study are elaborated on in the third section. The fourth section presents the main findings of the study. The fifth section compares the current study with the earlier findings and discusses the results' main implications. The study is concluded in the sixth and last sections.

2. Literature Review

2.1. Theoretical Background

The spillover effect is defined as things in one platform flowing into another and the other way around (Ahluwalia et al. 2001; Liu 2008; Raufeisen et al. 2019). Several kinds of spillover effects are defined in the literature: behavioral, temporal, favorable, and hostile. The behavioral spillover effect sees the transfer of behavioral attributes from one platform to another (Poortinga et al. 2013). The temporal spillover effect is witnessed in a context from one platform to another (Van Rookhuijzen et al. 2021). The positive and negative VSE are self-explanatory and carry their literal meanings (Truelove et al. 2014). However, the volatility spillover effect can be classified as temporal, positive, or negative (Xiong and Han 2015; Sahoo et al. 2018). The volatility effect can be short term and long term. The short-term effect is caused by any shock in one market that can influence another. However, the long-term VSE is driven by price changes in one market affecting another market or variable (Rastogi and Kanoujiya 2022; Rastogi et al. 2021). The VSE from copper price to ESG means the price changes in copper result in changes in the ESG index. Similarly, oil price and exchange rate changes influence the ESG index (Rastogi and Kanoujiya 2022; Rastogi et al. 2021).

The spillover effect is researched well across the board (Ahluwalia et al. 2001; Bruhn et al. 2017; Raufeisen et al. 2019), including in environmental studies (Nilsson et al. 2017; Lanzini and Thøgersen 2014; Verfuerth et al. 2019). Ahluwalia et al. (2001) find that there exist spillover effects between markets due to consumer behavior. They utilize "analysis of variance" (ANOVA) models. Bruhn et al. (2017) and Raufeisen et al. (2019) have conducted a systematic literature review and indicate that spillover effects exist due to consumer-centric issues such as goods' prices. Nilsson et al. (2017), Lanzini and Thøgersen (2014) and Verfuerth et al. (2019), in their review study, have suggested the research agenda of determining spillover effects on environmental behavior. Hence, using the VSE related to the environmental studies in the current study is not out of context. Moreover, spatial spillover is also witnessed in the volatility spillover effect-based studies (Baumöhl et al. 2018; Yu et al. 2013).

A few theories prevail to explain spillover effects, mainly the volatility spillover effect: (1) the market contagion hypothesis and (2) the market integration hypothesis. In a seminal paper, King and Wadhwani (1990) present the contagion effect to explain the co-movement of the markets, especially volatility in the two markets, including money and capital markets. It assumes that an event occurring in one market influences other markets. These events might be economic shocks. Furthermore, Connolly and Wang (2003) aptly explain the difference between the economic fundamentals and contagion hypothesis as the cause of the co-movement between the markets. They posit that co-movement is the contagion hypothesis even after controlling for the economic fundamentals between the markets. The existence of the market contagion hypothesis is endorsed by other studies, too (Paas and Kuusk 2012; Sohel Azad 2009).

In addition, the market integration hypothesis explains the long-term association irrespective of the short-run aberrations (Philip 2008). The feedback is internalized in the market integration. Market integration goes beyond contagion (Bekaert et al. 2005; Tai 2007). Market integration is increased or reinforced due to crisis (Jebran et al. 2017). Market integration theory is based on price transmission from one market to another due to economic events. It means that price changes in one market influence the long-term volatility in other markets (Jebran et al. 2017; Tai 2007).

The paper theorizes that the volatility spillover effect between copper prices to ESG, crude oil prices to ESG, and exchange rates to ESG reveals the underlying market dynamics regarding EVs and fossil fuels. The existence of the VSE, from copper prices to ESG, ensures the technical superiority of EVs over fossil fuels. Similarly, the presence of the VSE from crude oil to ESG signifies the influence provided by fossil fuels on the environment. In addition, a significant VSE from the exchange rate to ESG provides evidence of international trade's impact on the nation's environment.

The extant literature on EVs versus fossil fuels is primarily descriptive. The quantitative studies on the topic are mainly on the technical side of establishing the superiority of EVs over fossil fuels. The literature is scarce on demonstrating the economic sanctity of EVs over fossil fuel. This section presents a thematic analysis of the relevant literature.

2.2. Copper Prices and ESG

Undoubtedly, the world is looking for sustainable sources of energy. It is not a new phenomenon (Ruckelshaus 1989). However, clamor for it has increased recently (Teske et al. 2011). One essential metal affected most due to this transition is copper (Fuentes et al. 2021). This situation is more demanding regarding copper due to population growth and economic development. However, the maximum impact on copper is witnessed due to considering the power sector (electric power) as a sustainable energy source (Fuentes et al. 2021). Valenta et al. (2019) and Lèbre et al. (2022) unanimously admit the deficit of copper in the future. Moreover, they also present that using unutilized orebodies for copper will have adverse environmental consequences.

However, the literature is insufficient to address the concern. Rangel (2021) identifies the association of the four stages of the supply chain of copper production with the environment. Fuentes et al. (2021) recognize the increase in the usage of copper due to electric power being a sustainable energy source and classify how copper is linked to other industries regarding the environment. However, both studies limit their discussion to the descriptive level and expect future research to take up the matter further and conduct the empirical analysis. A few studies present efforts to link copper with ESG as well. Hatayama (2022) relates metals, including copper, to sustainable development goals (SDG). Knizhnikov et al. (2021) find evidence of an increase in transparency of manufacturing copper in Russia regarding reporting for the ESG index.

However, we do not observe many studies that link the volatility or volatility spillover effect from copper to ESG and present evidence of the association between copper and the environment. Only Cagli et al. (2022) show the volatility spillover effect from metal to the ESG index. They report that copper is the net transmitter of volatility to the ESG portfolios. This scarcity of studies between copper and ESG justifies future studies, including the current study on volatility transfer. Thus, the following hypothesis is framed in an alternate form for empirical scrutiny.

Hypothesis 1 (H_1). *There exists a volatility spillover effect from copper prices to the ESG index.*

2.3. Crude Oil Prices and ESG

The literature is replete with instances indicating that shock or crude oil fluctuations impact ESG worldwide. Liu et al. (2021) find that US and European ESG indices are affected by the volatility of stocks, gold, and crude oil. The shares and gold volatilities see the maximum impact. Cagli et al. (2022) also report (similar to the copper prices) that crude oil price volatility impacts the ESG index in US markets. De Liz (2020) in Brazil says oil shocks significantly affected the ESG stocks from 2008–2015.

In addition, some sideways evidence is also observed related to crude oil and ESG. Lei et al. (2023), while exploring the haven for ESG shares, find gold as the best bet. However, the uncertainty involving commodities, including oil prices, also significantly influences the shelter of gold for ESG stocks. Similarly, corporate ESG performance in China is adversely impacted by the fear of low carbon policy-related crude oil policies. Güngör and Şeker (2022) find evidence that board structure may also significantly affect the global ESG performance in oil and gas companies.

However, the volatility spillover effect using bivariate GARCH models is rarely applied between crude oil and ESG indices. Therefore, a fresh perspective is justified to determine the VSE from crude oil prices to ESG. Hence, the following hypothesis is framed in the alternative form for the testing:

Hypothesis 2 (H_2). *There exists a volatility spillover effect from crude oil prices to the ESG index.*

3. Data and Methodology

3.1. Data Collection

This study uses the time-series data of copper prices, crude oil prices, the exchange rate (USD/INR), and the BSE100 ESG index daily from 1 November 2017 to 20 September 2022. While keeping a risk and performance profile akin to the standard and poor (S&P) BSE 100, the S&P BSE 100 ESG index evaluates equities that adhere to sustainable investment standards. The period is chosen to treat an extensive observation for consistent and reliable outcomes by the selected GARCH models (Sardar and Sharma 2022). Initially, we had a total of 1500 observations. However, after data filtration, we have a total of 1284 observations because we have skipped the data of all variables if a variable lacks data on a particular day. This way, we have found, authenticated, and synchronized all variables if a variable lacks data on a specific day. This way, we have discovered authenticated and synchronized data. The data are sourced from kaggle.com (accessed on 21 September 2023), yahoofinance.com (accessed on 21 September 2023), and bseindia.com (accessed on 21 September 2023). The returns of variables are used for data analysis. Returns are calculated as (PCD-PPD)/PPD, where 'PCD' is priced at the current day, and 'PPD' is the price at the previous day. Table 1 enlists the variables used in the study.

Table 1. Variable.

Name	Description
COP	Copper Spot Price
CRUDE	WTI Crude Oil Spot Price
EXR	USD/INR Currency Spot Price
ESG	S&P BSE 100 ESG Equity Index Price

Note: All prices are taken in INR ("Indian National Rupee") as the Indian economy is taken for study.

3.2. Methodology

This paper looks for the short-term and long-term volatility effects between pairs of markets, for example, from copper, crude oil, and exchange rate (USD/INR) to ESG. Following Nortey et al. (2015), Kazemizadeh et al. (2021), Rastogi et al. (2021), and Rastogi and Kanoujiya (2022), this study applies multivariate GARCH models (BG model and DG model) to test VSE. Firstly, the paper assesses the descriptive statistics as demonstrated in Table 2. Various diagnostics tests are also employed to ensure the M-GARCH models' validity. The Jarque–Bera test establishes the data's normality (Jarque and Bera 1987). The Phillip–Perron (PP) (Phillips and Perron 1988) and Augmented Dickey–Fuller (ADF) tests (Dickey and Fuller 1981) investigate the stationarity of the data (Rastogi and Kanoujiya 2022; Rastogi et al. 2021). The ARCH test identifies the Arch effect existence (volatility clustering in the data). Finally, the bivariate GARCH models are undertaken to estimate volatility effects. The diagnostic tests are essential to be performed before the application of GARCH models. Hence, all necessary tests are performed to ensure the applicability of GARCH models. The results of all tests are discussed in the Results section. The log-likelihood verifies the model's complexity and accuracy (model diagnostics for good fit model) (Rastogi and Kanoujiya 2022; Rastogi et al. 2021). R programming tools are used to perform the analysis. Figure 1 gives the flowchart of the methodology performed.

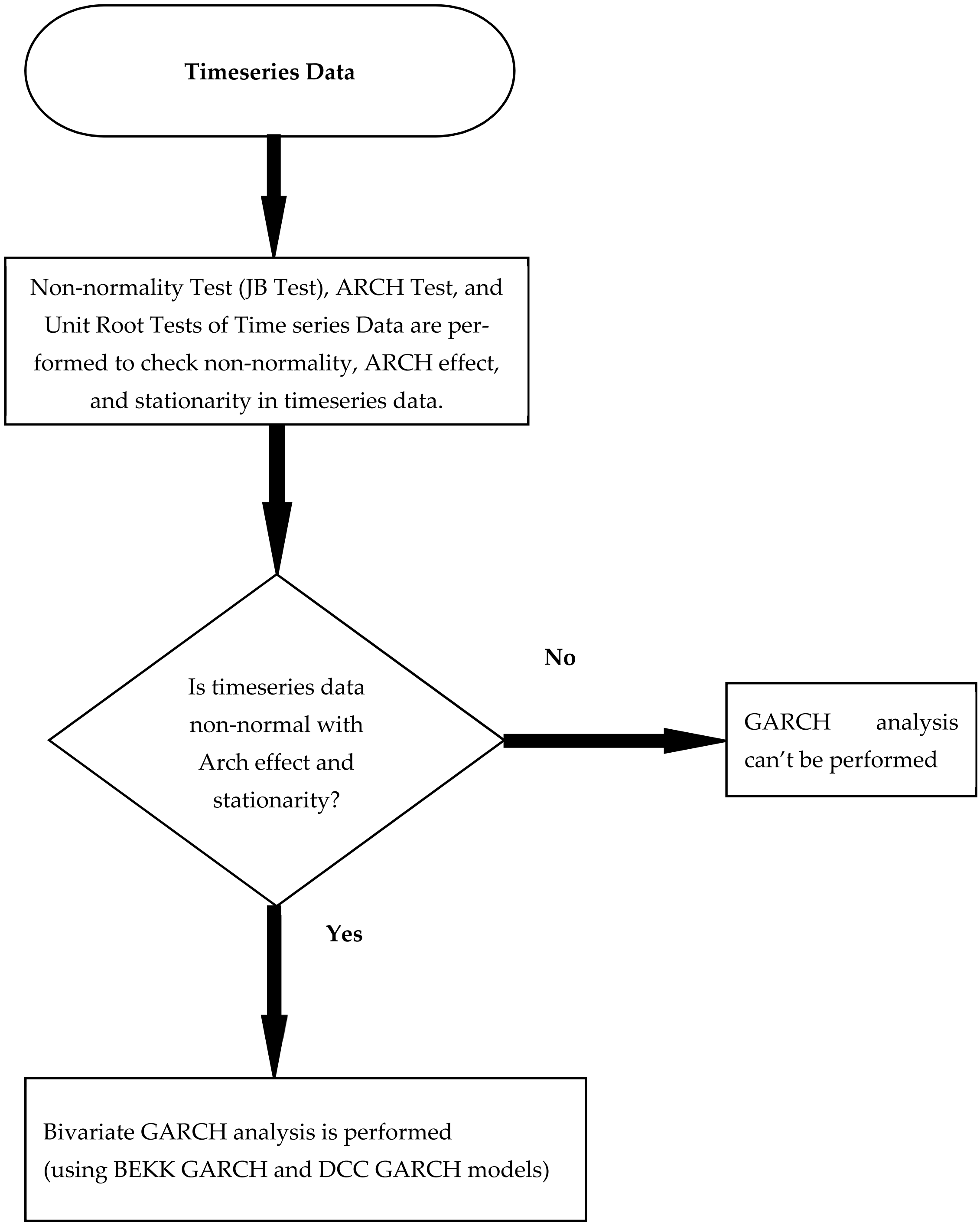

Figure 1. Flowchart of methodology.

Table 2. Descriptive statistics.

	1 November 2017 to 20 September 2022			
	COP	**CRU**	**EXR**	**ESG**
Mean	0.0001	−0.0020	0.0001	0.0005
Maximum	0.0617	0.3766	0.0234	0.0864
Minimum	−0.0659	−3.0590	−0.0195	−0.1272
Standard Deviation	0.0136	0.0983	0.0035	0.0122
Skewness	−0.1522	−25.007	0.3640	−1.1069
Kurtosis	1.869	751.213	3.959	16.014
Jarque–Bera	189.21 ***	300.43 ***	857.4 ***	138.47 ***
Observation	1284	1284	1284	1284
ARCH (LM) Test	37.288 ***	36.561 ***	70.44 **	454.88 ***
Unit Root Tests				
Augmented Dickey–Fucker	−10.104 ***	−12.426 ***	−10.494 ***	−10.481 ***
Philips–Perron	−1312.3	−797.59 ***	−1294 ***	−1369 ***

Note: *** & ** denotes the significance level at 1%, 5%, and 10%, respectively. It means the given values of the tests are significant at these levels (1%, 5%, and 10). The Unit Root Test is used considering constraint and trend to confirm data stationarity. The ARCH test signifies serial correlation of the heteroscedasticity in the data at one lag to identify the ARCH effect.

3.3. M-GARCH Models

M-GARCH stands for "Multivariate Generalized Autoregressive Conditional Heteroscedasticity" (Bauwens et al. 2006; Bollerslev 1990). Bauwens et al. (2006) advocate that the M-GARCH models are the most valuable tools to examine the connection between the market pairs considering volatilities and co-volatilities. As per the nature of the data, GARCH models are the appropriate fit for volatility connection between variables of time-series data (Rastogi and Kanoujiya 2022; Rastogi et al. 2021). It provides unbiased results by providing comprehensive information regarding volatilities and co-volatilities between markets (Bauwens et al. 2006). This study utilizes two popular M-GARCH models. One is the bivariate BG model, and the other is the DG model. The BG model estimates the volatility transmission from one market to another. The DG is then applied to ensure the results' robustness. These two models are considered in this paper because both models are advanced and reliable M-GARCH models and have comparable features to justify the results' robustness (Rastogi and Kanoujiya 2022; Rastogi et al. 2021). As per the time-series data observations, these models are well suited. Their results are unbiased due to semidefinite variance, a covariance matrix, and fewer parameters (Siddiqui and Khan 2018; Rastogi and Kanoujiya 2022).

3.4. Bivariate BEKK GARCH (BG) Model

Engle and Kroner (1995) have developed the BEKK ("Baba–Engle–Kraft–Kroner")-GARCH (BG) model. It is one of the advanced M-GARCH models and estimates unbiased results on volatility connections between the market pairs. It can deliver consistent results even for small samples (Engle and Kroner 1995; Rastogi et al. 2021). It explores both shock spillovers (for short-term volatility) and price volatility spillovers (for long-term volatility) (Campbell and Hentschel 1992). It identifies time-series variables' conditional variances and covariances (Campbell and Hentschel 1992). The specification of the BG model is as follows:

H_t symbolizes the variance–covariance matrix

$$H_t = \begin{bmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{bmatrix} \text{ For i} = 1, 2 \quad (1)$$

(a) The H_t shows the variance of the error term in the BG model.

$$H_t = C_0' C_0 + \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} + \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}$$

is specified as:

$$H_t = C_0' C_0 + E_{11}' \varepsilon_{t-1} \varepsilon_{t-1}' E_{11} + F_{11}' H_{t-1} F_{11} \tag{2}$$

(b) Where C_0 is the N × N matrix (upper triangular), and E and F are the N × N parameter matrix having elements of shock effects and price effects, respectively. ε_t is the residual vector at time t. The diagonal terms of the H_t matrix are conditional variance represented by *hii*,*t*. Here, *i* = *j* showing the same markets. However, off-diagonal terms are represented by *hij*,*t* Similarly, the diagonal elements in matrix *E* show the connection among shock effects in the same market (*eii*), and the off-diagonal elements show cross-market shock effects (*eij*). Similarly, diagonal elements in matrix *F* show the VSE connection in the same market (*fii*) and off-diagonal elements show cross-market VSE (*fij*) (Campbell and Hentschel 1992). The bivariate BEKK (1,1) model is implemented using the following equation:

$$H_t = C_0' C_0 + \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\,\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\,\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{bmatrix} e_{11} & e_{12} \\ e_{21} & e_{22} \end{bmatrix} + \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{bmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{bmatrix} \tag{3}$$

e_{ij} and f_{ij} are the elements of the parameter matrixes E and F, respectively. These elements indicate the shock spillover effect (short-term effects) and price volatility spillover (long-term effects), e_{ij} represents shock spillover effects, and f_{ij} represents price spillover effects. e_{ij} and f_{ij} observe volatility effects in the identical market if $i = j$; else, they show volatility effects transferring from market i to j (cross-market). 'i' is a representation of the market as it observes the relationship between two markets; hence, it has values of 1 and 2. The conditional variance and covariance matrix H_t has the elements $h_{ij,t}$. These elements are derived by Equation (4).

Equation (4) arrives at the following conditional variance and covariance equations.

$$h_{11,t} = c_1 + e_{11}^2 \varepsilon_{1,t-1}^2 + 2 e_{11} e_{21} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + e_{21}^2 \varepsilon_{2,t-1}^2 + f_{11}^2 h_{11,t-1} + 2 f_{12} f_{21} h_{12,t-1} + f_{21}^2 h_{22,t-1} \tag{4}$$

$$h_{22,t} = c_3 + e_{12}^2 \varepsilon_{1,t-1}^2 + 2 e_{12} e_{22} \varepsilon_{1,t-1} \varepsilon_{2,t-1} + e_{22}^2 \varepsilon_{2,t-1}^2 + f_{12}^2 h_{11,t-1} + 2 f_{12} f_{22} h_{12,t-1} + f_{22}^2 h_{22,t-1} \tag{5}$$

$$h_{12,t} = c_2 + e_{11} e_{12} \varepsilon_{1,t-1}^2 + (e_{21} e_{12} + e_{11} e_{22}) \varepsilon_{1,t-1} \varepsilon_{2,t-1} + e_{21} e_{22} \varepsilon_{2,t-1}^2 + f_{11} f_{12} h_{11,t-1}^2 + (f_{21} f_{12} + f_{11} f_{22}) h_{12,t-1} \tag{6}$$

3.5. DCC-GARCH (DG) Model

This study also applies the DCC ("Dynamic Conditional Correlation")-GARCH (DG) model to confirm the robustness of the results. The DG model is chosen to have comparable attributes to BEKK-GARCH. DG is also a strong M-GARCH approach to estimate variables related to short-term and long-term volatility effects. It also determines the volatility effects by permitting the interaction of variances and covariances. It is advanced to overcome the subjectivity of constant conditional correlation in earlier models (Engle 2002a, 2002b). It breaks down the variable's variance and means estimates.

$$d_t = \mu_t + \omega d_{t-1} + r_t \tag{7}$$

where the d_t vector shows the residuals of returns, and the returns are daily percentage changes of the variables. Terms μ_t, and r_t are vectors representing the conditional mean and residuals, respectively. The variant equation is specified as follows:

$$k_t = c + xe_{t-1}^2 + yk_{t-1} \tag{8}$$

where k_t is conditional covariance at time t, while c is a constant term in Equation (8). The ARCH effect (x) is for the short-term shock transmission to conditional variance between the markets (variables). The GARCH effect (y) is for the long-run volatility spillover to the conditional variance between the markets (variables).

4. Empirical Results

4.1. Descriptive Statistics and Correlation

Table 2 presents the descriptive statistics of the time-series data of the variables. The mean values of copper price returns and crude oil price returns are 0.0001 (0.01%) and −0.0020 (0.20%), respectively. The daily returns or changes are quite small, which is evident for daily data. The average exchange rate return is 0.0001 (0.01%), and the average value of EGG index returns is 0.0005 (0.05%). Here, again, daily returns or changes are small. The values are closer to the maximum; hence, daily returns are quite important for further analysis. The significant values by the Jarque–Bera test confirm the non-normality of the time series. The skewness and kurtosis values also show the non-normality of the time series. Standard deviation is also found to be substantial as it is much different than mean values. Moreover, the ARCH (LM) test checks volatility clustering in the time-series data. It is bunching in the variance or volatility of a specific variable, forming a pattern influenced by some cause. The ARCH test's significant values ensure the ARCH effect's existence in data. Time-series data should be stationary for applying GARCH models. The PP and ADF tests are the unit root tests to confirm the stationarity. Data stationarity is also confirmed by the significant values released by PP and ADF tests. Hence, all the criteria are met to perform M-GARCH models. Table 3 shows that the correlation matrix has no significant correlation coefficient of more than 0.800. Therefore, multicollinearity does not exist between the market pairs.

Table 3. Correlation matrix.

	COP	**CRU**	**EXR**	**ESG**
COP	1.000			
CRUDE	0.0052	1.000		
EXR	−0.0470	−0.0390	1.000	
ESG	0.0475	−0.0778 *	−0.0022	1.000

Note: * shows value is significant at 5%.

4.2. BEKK GARCH Outcomes

This study primarily employs the bivariate BG model to estimate the volatility effect transmission from one market to another (from the copper market, crude oil market, and exchange rate to the ESG equity market). Table 4 presents the results of the BG model. The log-likelihood ratio is mentioned to show the goodness of the model's fit. The higher log-likelihood indicates a better fit of the model.

The outputs are mainly focused on three parameters. The Eij for ARCH effects shows the shock spillover (short-term volatility effect) from the market '*i*' to '*j*'. It implies that any undesirable news from the market '*i*' influences market '*j*' returns (Engle and Kroner 1995;

Rastogi and Kanoujiya 2022; Lee and Yoder 2007). The Fij for GARCH effects (long-term volatility effect) indicates the effect of price changes of the market '*i*' on market '*j*' (Engle and Kroner 1995; Rastogi and Kanoujiya 2022; Lee and Yoder 2007). D*ij* is a constant term (elements in upper triangular matrix *C* as mentioned in Equation (2)).

Table 4. Bivariate BEKK-GARCH (1,1) estimation.

	COP (1) ESG (2)	CRUD (1) ESG (2)	EXR (1) ESG (2)
Variance Equation:			
D_{11}	0.0060 **	0.0983 ***	0.0352 ***
D_{21}	0.0001	−0.0009	−0.0271
D_{22}	0.0024 ***	0.0121 ***	0.0122
E_{11}	0.2283 ***	0.1000 ***	0.0010 ***
E_{12}	0.1122 **	0.0200	0.0020
E_{21}	−0.0039	0.0200 **	0.0020
E_{22}	0.3622	0.1000 **	0.0010
F_{11}	0.8606 **	0.9000 ***	0.0900 ***
F_{12}	−0.0636 **	0.0100	0.0010 ***
F_{21}	0.0139	0.0510 ***	0.0510 ***
F_{22}	0.9062 ***	0.9000 ***	0.0900 ***
Model Diagnostics:			
log-likelihood	7788.671	2805.558	8105.918

Note: ***, ** denotes the significance level at 10%, and 5%, respectively.

Table 4 exhibits that the E_{12} and F_{12} parameters for the market pair copper and ESG have significant coefficients. However, E_{12} is positive (0.1122), and F_{12} is negative (−0.0636). Hence, both short-term and long-term volatility effects exist from copper to ESG. This result implies that shock spillover (short-term volatility effect) is transmitted from copper to ESG. Furthermore, any undesirable news in the copper market positively influences ESG. Additionally, the long-term volatility spillover effect transmits from copper to ESG. It implies that price changes in the copper market negatively affect ESG due to a negative F_{12}. Additionally, reverse volatility effects (from ESG to copper) are not found, as both E_{21} and F_{21} are insignificant (Table 4).

Unlike earlier market pairs (copper and ESG), the crude oil and ESG market pair have insignificant estimates of E_{12} and F_{12} (Table 4). Hence, no significant volatility effects were transmitted from the crude oil market to ESG. However, the reverse volatility effects (VSE from ESG to crude oil) are observed because both E_{21} and F_{21} are significant and positive (Table 4). It implies that both short-term and long-term volatility effects from ESG positively influence crude oil returns.

In Table 4, no significant estimates exist for E_{12} and E_{21} between the exchange rate and ESG. Hence, shock spillover (short-term volatility effects) does not exist between the exchange rate and ESG. However, F_{12} and F_{21} parameters have optimistic estimates (0.010 and 0.0510, respectively). Hence, bidirectionally, a long-term VSE exists between the exchange rate and ESG market pair. It means changes in exchange rates positively influence ESG and vice versa. It means exchange rate fluctuation increases ESG volatility.

4.3. DCC-GARCH Outcomes

In DCC-GARCH estimates (see Table 5), we are only concerned with joint estimates JDCCA1 ("joint dynamic conditional correlation coefficient A1") and JDCCB1 ("joint dynamic conditional correlation coefficient B1"). The A1 coefficient is for shock effects from one market to other. B1 is the price volatility effect from one market to other. JDCCA1 indicates the joint ARCH effect (short-term shock effect), and JDCCB1 signals the joint GARCH effect (long-term price volatility effect) between the market pairs. JDCCA1 for the copper and ESG market pair is insignificant; hence, no effect exists between this market pair. However, JDCCB1 for this market pair is positive and significant; hence, a long-term volatility spillover effect exists between copper and ESG. Similar results are also found for the market pair of the crude oil and ESG (JDCCA1 is insignificant, and JDCCB1 is significant and positive). For the market pair exchange rate and ESG, both JDCCA1 and JDCCB1 parameters are significant and positive (0.0291 and 0.9005, respectively).

Table 5. Bivariate DCC GARCH (1,1) estimation.

	COP (1) ESG (2)	CRUDE (1) ESG (2)	EXR (1) ESG (2)
Optimal Parameters:			
$one\mu(1)$	0.0001	0.0013 **	0.0001
$\omega(1)$	0.0000 ***	0.0000 ***	0.0000
$one\alpha_1(1)$	0.0348 ***	0.2774 ***	0.0872 ***
$\beta_1(1)$	0.9377 ***	0.7038 ***	0.8588 ***
$\mu(2)$	0.0008	0.0008	0.0008
$\omega(2)$	0.0000	0.0000	0.0000
$\alpha_1(2)$	0.1420 *	0.1420 *	0.1420 *
$\beta_1(2)$	0.8267 **	0.8267 **	0.8267 **
$JDCCA_1$	0.0147	0.0000	0.0291 *
$JDCCB_1$	0.8160 ***	0.9112 ***	0.9005 ***
Model Diagnostics:			
Log-likelihood	7803.865	7046.464	9581.053

Note: ***, **, * denotes the significance level at 10%, 5% and 1%, respectively.

Moreover, the sum of JDCCA1 and JDCCB1 is less than '1'. Hence, this condition satisfies the validity of the DCC GARCH model in each case. In a nutshell, it is found that there exists a volatility connection of copper, crude, and exchange rate with ESG. Additionally, the plots of conditional correlation estimated by the DCC GARCH over time (daily basis) are demonstrated in Figure 2, Figure 3, and Figure 4, respectively, for market pairs copper and ESG, crude oil and ESG, and exchange rate and ESG. The X-axis in the figure shows time on a daily basis. The Y-axis is the conditional correlation between two markets (represented by cor_x). In Figure 2, it is between copper and ESG. The conditional correlation over time between crude oil and ESG is shown in Figure 3. Figure 4 shows conditional correlation over time between the exchange rate and ESG. The conditional correlation over time (in Figures 2–4) observed from the DCC model indicates the volatility connectivity between the variables.

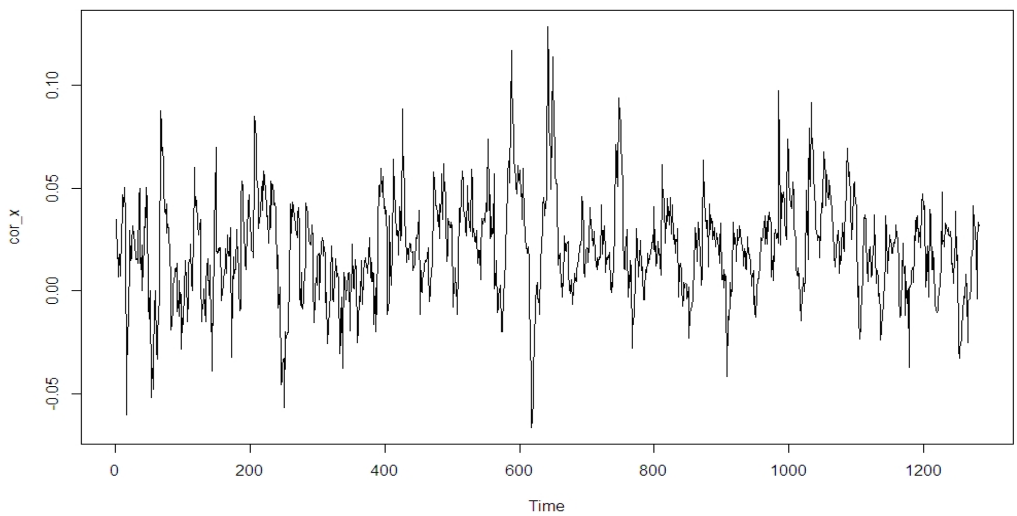

Figure 2. Conditional correlation between copper and ESG. Note: cor-x represents the conditional correlation between copper and ESG derived from the DG model.

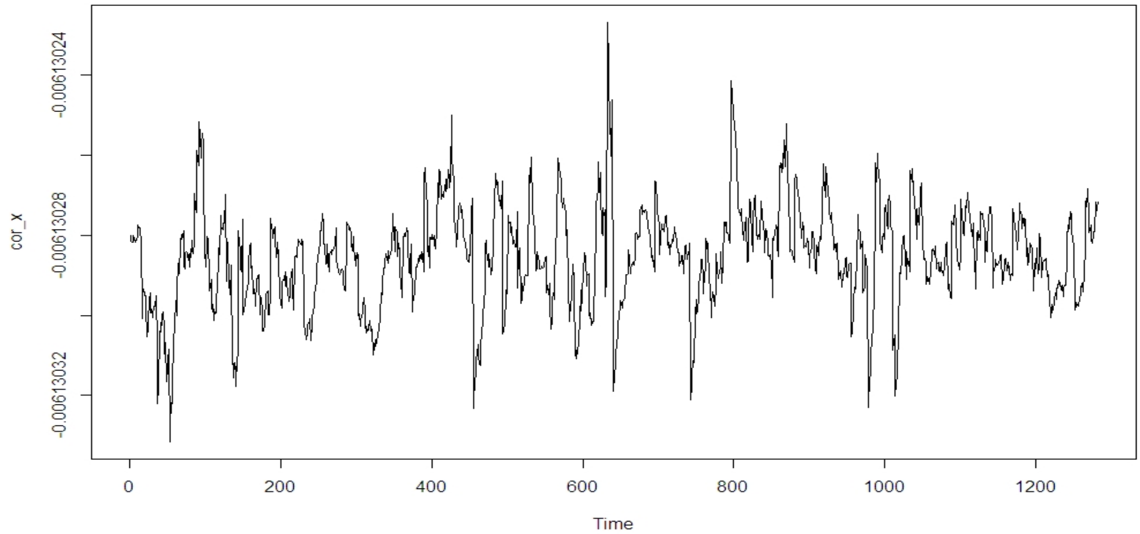

Figure 3. Conditional correlation between crude oil and ESG. Note: cor-x represents the conditional correlation between crude oil and ESG derived from the DG model.

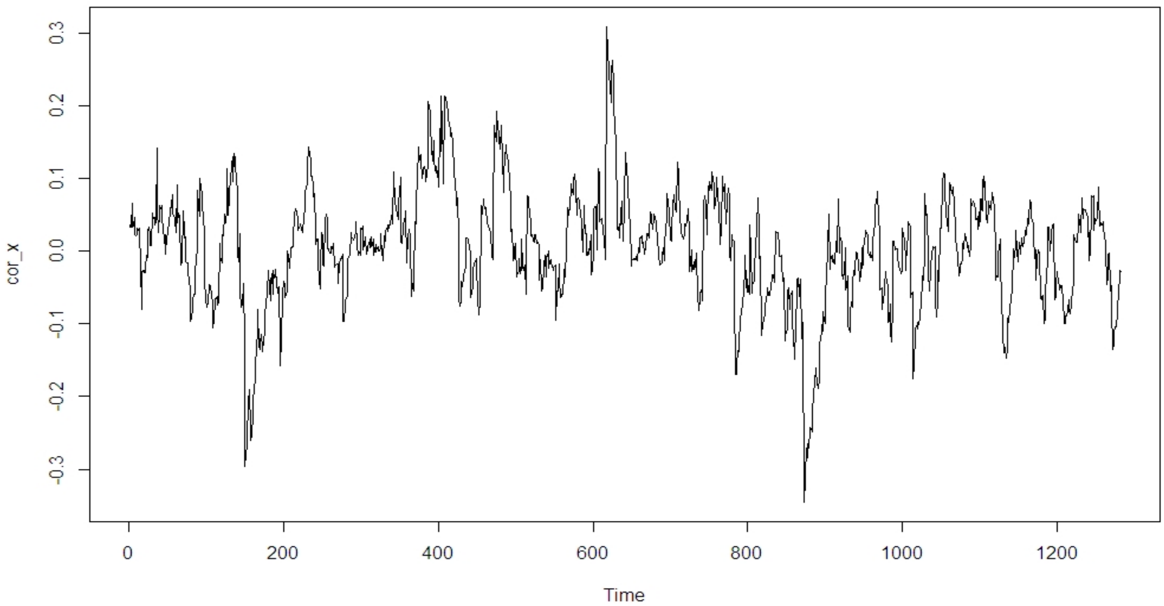

Figure 4. Conditional correlation between exchange rate and ESG. Note: cor-x represents the conditional correlation between the exchange rate and ESG derived from the DG model.

4.4. Results Robustness

The current study validates the robustness of the results by applying the multi-method approach (Baker et al. 2008). This approach applies more than one method to the same data, and the results are compared (Rastogi and Kanoujiya 2022). Results are robust if similar outcomes are observed in different approaches on the same data. This study employs two powerful multivariate GARCH models (BEKK-GARCH and DCC-GARCH) to observe the volatility connection between the three market pairs, i.e., copper and ESG, crude oil and ESG, and exchange rate and ESG. The BEKK-GARCH estimations find volatility effects from copper, crude oil, and exchange rate to ESG (Table 4). Almost similar results are also exhibited by the DCC-GARCH (Table 5), indicating significant volatility connections from copper, oil and exchange rate to ESG. Hence, the volatility effects are observed from three market pairs. Thus, the robustness of the results is ensured.

5. Discussion

Hypothesis one, that copper prices have a VSE on the ESG index, cannot be rejected (Tables 4 and 5). Hypothesis two, that crude oil prices have a volatility spillover effect on the ESG index, is rejected due to insufficient evidence in its support. The analysis found that the significant impact of copper volatility on ESG implies that EVs are technically superior to fossil fuel-based vehicles as they better support ESG. It encourages sustainable energy utilization. However, the insignificant effect of the volatility of crude oil on the ESG index suggests that the markets are indifferent to this aspect. This result can also be construed that irrespective of the policies on fossil fuel (over EV), the market believes there is no influence on ESG. In addition, a significant bidirectional VSE from the exchange rate and ESG index provides a controlling aspect that exports and imports (primary sources of transactions in exchange rates) have a considerable impact on ESG and vice versa regarding volatility spillover.

Due to a lack of studies to compare the findings, which are conducted on similar lines as the current study, we have considered some studies on a similar topic for comparison. Only Cagli et al. (2022) find evidence that copper prices have a volatility spillover effect on the ESG index. However, the current paper finds an insignificant VSE from crude oil price to the ESG index, which is the opposite of what was reported by Cagli et al. (2022). The contradiction regarding the insignificance of VSE from crude oil to ESG in the current study can be explained from an Indian perspective that the crude oil volatility does not make a mark during the study period. However, the significant VSE between the two reported by Cagli et al. (2022) is seen in the US markets. The difference in the markets might have caused a difference in the outcomes.

The current study's findings are novel and significantly contribute to the scarce literature on the topic. The simultaneous significance of copper with ESG and the insignificance of crude oil with ESG regarding the VSE posits acceptance of the technical superiority of EV over fossil fuel. However, the economic consequences of the execution of EVs over fossil fuels cannot be established. Replacing EVs with fossil fuel may be technically correct but may be a poor decision regarding financial viability in the long run. It may lead to higher electric fuel prices, resulting in higher costs for sustainable energy consumption. Hence, a balance between electric fuel and other fuels should be maintained to have a reasonable cost for sustainable energy consumption.

The findings of the current study have some startling and path-breaking implications. The implication for policymakers is the most important. They need to cross-check their policy-level decision regarding the implementation of EVs by replacing fossil fuels, as the financial and economic viability of the latter is bleak. The managers need to explore newer alternative sources. The literature supporting green hydrogen (Gondal et al. 2018; Clark and Rifkin 2006) alludes to other options which may be explored as a sustainable energy source (other than electricity). The ultimate consumer and customers also may wait for the finalization of the execution of EVs before rushing to join the herd for EVs.

6. Conclusions

The study aimed to determine the economic viability of EVs over fossil fuels. The study's findings support the EV's technical superiority over fossil fuels regarding the environment. However, the study's findings do not find evidence or support for EVs' economic viability over fossil fuels in the long run. These findings are significant as the governments are investing in the technology and its commercialization despite being fully confident of its long-run financial viability. Therefore, the findings are significant, including giving the government feedback for rethinking the policy regarding EVs over fossil fuel. The impact of the study's implications would also be a major one following its contribution, importance, and significance. Similar analyses can also be conducted for another alternate energy source to provide some feedback on their economic viability through market movements (volatility spillover).

The current study has two main limitations. First, the measures used and the theory applied to determine the financial viability are indirect and can always be questioned. However, a fresh perspective may be beneficial on vague and uncertain issues similar to the issues raised in the current study. The approach adopted in the present study can provide insight into the issue, which is an achievement. Second, the other alternative fuel attracting the attention of policymakers worldwide is green hydrogen. Despite having input regarding this, the current study could not incorporate that. This study's limitation in providing a comparative picture can be future scope. Based on the present study's findings, the authors would recommend rethinking the EV policy to have a reasonable cost for sustainable energy consumption. They may also consider other possibilities as an alternate energy source, for example, green hydrogen.

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