International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(4), 481-489.

Assessing the Influence of Geopolitical Risks and Indian Uncertainty Index on Energy Sector with VECM

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Received: 12 January 2025 **Accepted:** 08 May 2025 **DOI:** https://doi.org/10.32479/ijeep.19170

ABSTRACT

The energy industry is susceptible to geopolitical challenges, like armed conflicts, international disputes, and diplomatic tensions. These factors can result in disruptions to energy supplies, instability in energy prices, and shifts in energy-related policies and strategies. This study explores the impact of Geopolitical Risk (GPR) and India News-Based Policy Uncertainty Index on India's Energy Sector. To achieve this, several GPR indices and the India News-Based Uncertainty Index is employed as explanatory variables. Response variables to develop a Vector Error Correction Model (VECM) comprised monthly values of the energy index, prices of energy commodities, and stock prices of the top three companies. The analysis encompassed data from February 2011 to August 2023, totaling 151 data points. Contrary to the established theory that suggests that GPR significantly affects crude oil prices, this study finds no supportive evidence, indicating that neither the GPR indices nor the India News-Based Policy Uncertainty Index are statistically significant within the VECM framework. This nuanced analysis highlights the complex interrelationship between geopolitical risks, uncertainty, and different segments of India's energy market.

Keywords: Geopolitical Risk, Policy Uncertainty Index, VECM, MCX, NIFTY Energy, Crude Oil, Natural Gas
JEL Classifications: C43, D81, Q43

1. INTRODUCTION

Geopolitical risk (GPR) indicates the uncertainty and instability resulting from political events and decisions on a global scale (Jha et al., 2024), substantially influence the Indian economy (Balcilar et al., 2018). Factors such as conflicts, trade disputes, sanctions, and political instability in major economies disrupt global trade and investment flows, thus affecting India's exports and foreign direct investment (Liu et al., 2024). India News-based Policy Uncertainty Index (Ramesh, 2024) measures the level of uncertainty surrounding government policies based on news articles (Perić and Sorić, 2018). Policy uncertainty arises because of factors such as changes in regulations, tax policies, and trade policies (Al-Thaqeb and Algharabali, 2019). These factors lead to a slowdown in economic activity and hinder the country's growth prospects. The combination of GPR and India News-based Policy Uncertainty has a compounding effect on the Indian economy.

The stock market and the commodity market is highly sensitive to various factors that can impact investor sentiment and market performance (Griffith et al., 2020; Haritha and Rishad, 2020). In India, geopolitical risks and India News-based Policy Uncertainty significantly impact on both the stock market and commodity market, especially in energy sectors (Li et al., 2022; Doğan et al., 2023) as it is heavily influenced by global oil prices, geopolitical tensions in oil-producing regions, policy decisions, such as changes in taxation, subsidies and regulations (Dhingra et al., 2023). Higher levels of geopolitical risk and the uncertainty surrounding government policies can lead to increased spillovers and fluctuations in stock and commodity prices, thus, influencing investor sentiment and decision-making, leading to buying or selling pressure in the energy sector.

The study attempts to cross-validate these observations through available data related to GPR Indices, India News-Based Policy Uncertainty Index, Energy Commodities, Energy Index India, and the stock prices of top energy companies in India. This study intends to scrutinize the existence of the impact of GPR Indices, Indian Uncertainty Index on Energy Sector of India using the VECM mode.

2. LITERATURE REVIEW

The key GPR indices used in India include the Nifty 50 Index (NSEI) and, BSE GREENEX, and CARBONEX indices. These indices measure the performance of the Indian stock market and sustainability of companies in terms of their environmental impact (Sharma et al., 2023) (Akbulaev et al., 2022). The impact of GPR indices on the energy commodities market (Sinha et al., 2022; Gong and Xu, 2022) in India can be seen through their correlation with energy prices, such as Brent oil, crude oil, and natural gas. Brent and crude oil prices have a considerable influence on the indexes; however, natural gas prices have no meaningful impact (Guliyeva, 2023). The correlation between GPR indices and the energy commodities market in India is complex and multi-faceted (Hoque and Zaidi, 2020; Wang et al., 2023). The Granger causality test shows that changes in energy prices can disturb the performance of the indices, and the performance of the indices influence energy prices (Sharma et al., 2023). This interplay between the indices and the energy commodities market highlights the interconnectedness of these two sectors in the Indian economy. The calculation of GPR indices in India involves the use of various factors such as wholesale price index, money supply, industrial production, and crude oil prices (Akbulaev et al., 2022).

Energy market sentiments, such as crude oil and gasoline sentiments, have a substantial influence on stock returns and ESG investments (Bai et al., 2024) in the U.S and Gulf Cooperation Council (GCC) economies (Verma and Mohnot, 2023). Geopolitical uncertainty, as measured by the GPR index, affects the volatility of renewable energy exchange-traded funds (ETFs) (Dutta and Dutta, 2022). Changes in energy prices, such as Brent and crude oil prices, have significant effects on stock market indices in Turkey, Brazil, and India (Akbulaev et al., 2022). GPR positively influences oil price fluctuations and oil demand, while exerting a significant negative impact on oil supply (Wu et al., 2023). An upsurge in the GPR index reduces the likelihood of high volatility in renewable-energy ETFs, indicating a lower risk for these assets (Dutta and Dutta, 2022). Based on these findings, GPR indices provide insights into the impact of GPR on commodity markets, including the Indian energy market (Dehghanzadeh Shahabad and Balcilar, 2022). They can help investors make informed decisions by considering the influence of energy market sentiment and geopolitical uncertainty on their investment outcomes.

Risk considerably transmits from crude oil, gold, and silver markets to various Indian green stock indices during periods of high uncertainty (Dutta et al., 2021). The factors contributing to the volatility of energy prices in India include environmental fluctuations, global oil prices, exchange rate depreciation, and energy-efficient investments (Sharma and Khanna, 2024). The Indian Uncertainty Index is calculated using text analysis of monthly country reports with studies highlighting its relationship with energy price volatility in India (Gupta et al., 2022; Dakey and Bicchal, 2024). The VECM, a multivariate time-series model used in time-series analyses, is particularly useful for analyzing the relationship between non-stationary variables and long-term cointegration relationships. In the context of the energy market, the VECM has been applied to forecast energy prices and analyze the connection between energy use, environmental quality, and economic growth (Fahria and Sulistiana, 2021).

The Energy Index measures trends through five summary dimensions and provides insights into the condensed form of the energy sector (Sreenivas and Iyer, 2015). Studies have not focused on the specific calculation methodology for Energy Index in India. To forecast energy prices using the VECM model, researchers have used various input factors, such as previous prices, demand, gas, coal, and nuclear energy. These factors have been found to be significant in influencing electricity prices (McHugh et al., 2018). The VECM model, along with other forecasting methods such as the Grey Verhulst Model (GVM), Nonlinear Regression, Feedforward Neural Network, and Support Vector Regression (SVR), has been applied to both short-term and long-term electricity price forecasting. These findings suggest that the SVR method accurately captures trends and turning points in electricity prices for long-term forecasting (Abroun et al., 2024). However, there are limitations to using the VECM to forecast energy prices. One limitation is the unsatisfactory error rate associated with long-term forecasting using SVR. To address this issue, a modified version of SVR (MSVR) was proposed to mitigate errors. Additionally, the accuracy of energy price forecasts using data-driven models depends on the characteristic of the input data and the choice of the model structure (Abroun et al., 2024; Lu et al., 2021).

2.1. Research Gap

The study observed a noticeable gap in the existing literature, emphasizing the limited exploration of the interplay between geopolitical risk, the India News-Based Policy Uncertainty Index, energy commodities, and the performance of top energy companies in India. While prior studies may have touched upon individual elements of this intricate relationship, a comprehensive investigation integrating these factors is lacking. This study aims to bridge this gap by employing VECM, allowing for a dynamic analysis of the long-term and short-term relationships among the specified variables. By filling this void, this study contributes significantly to the academic discourse surrounding the intersection of geopolitical dynamics, economic uncertainty, and the energy sector in India, offering valuable insights for policymakers, investors, and scholars.

2.2. Objectives of the Study

This study aims to achieve several significant objectives pertaining to the impact of geopolitical risk and the India News-Based Policy

Uncertainty Index onside the energy sector. First, this analysis aims to investigate the influence of GPR and the India news-based uncertainty risk on the NIFTY Energy Index of India through VECM analysis. Second, it assesses the effects of these risk factors on the prices of key Energy Commodities in India, specifically examining the dynamics of Crude Oil and Natural Gas prices using the VECM methodology. Finally, this study endeavors to scrutinize the repercussions of GPR and news-based uncertainty risk on the stock prices of the top three Energy Companies operating in India, employing VECM to analyze the relationships between these variables. Through these objectives, this study seeks to deliver valuable insights into the interplay of geopolitical and news-driven uncertainties in India's energy sector.

3. METHODOLOGY AND DATA

The study targets to explore the cointegration connection between geopolitical risk indices, the Indian uncertainty index on energy commodities, the energy index, and energy companies in India using the VECM. This section outlines the research design, data collection methods, variable selection, model specifications, and the statistical techniques employed in the analysis.

3.1. Research Design

This study adopts an empirical approach to analyze the connection between GPR, uncertainty in energy commodities, the energy index, and energy companies in India. It utilizes a time-series analysis framework to scrutinise the long- and short-term dynamics of variables. The VECM was employed to capture the cointegration and dynamic adjustments in the system.

3.2. Data Collection

The study utilizes secondary data sourced related to the Indices of Geopolitical Risk, India News-Based Policy Uncertainty Index. The data related to GPR Indices are extracted from the website www.matteoiacoviello.com, India News-Based Uncertainty Index from the website https://www.policyuncertainty.com/india_monthly.html and the monthly prices of NIFTYENERGY, Crude Oil, Natural Gas, NTPC, PowerGrid and Adani Power were obtained from www.investing.com. The dataset comprises monthly time-series data spanning the period April 2011-August 2023 to capture the dynamics of the variables under investigation. The data include geopolitical risk indices, the Indian uncertainty index, prices of energy commodities (crude oil and natural gas), the energy index, and stock prices of the top three energy companies in India (NTPC, Powergrid and Adani Power). The time series data at monthly frequency are used for the period from February 2011 to August 2023, which comprises 151 data points for the analysis. Table 1 depicts the abbreviations used to input the command in the E-views software.

3.3. Variables Selection

3.3.1. Independent variables

8 indices of Geopolitical Risk and India News-Based Policy Uncertainty Index. Total 9 independent variables.

3.3.2. Dependent variables

One index related to energy sector i.e. NIFTY Energy, two energy commodities prices i.e. price of crude oil and natural gas and three stock prices of top three companies India i.e. NTPC, PowerGrid and adani power.

3.4. Model Specification

The study employs the VECM to explore the cointegration connection among the variables. The VECM is a suitable framework for analyzing the dynamic interactions and long-term equilibrium relationships among multiple time-series variables. The model captures both short-term dynamics and long-term equilibrium relationships, thus providing insights into the adjustment process following shocks in the system.

3.5. Statistical Techniques

3.5.1. Pre-test for stationarity (unit root tests)

Before estimating the VECM, unit root tests i.e. Augmented Dickey-Fuller (ADF) will be conducted to assess the stationarity of the variables.

3.5.2. Pre-test for lag-length criteria

As earliest exercise, it is mandatory to pre-test all variables to assess their order of integration. Cointegration requires that the variables be integrated in the same order. We apply the ADF test to check the stationarity of the selected variables. Cointegration Analysis Johansen's cointegration test was employed to examine the existence of long-term equilibrium relationships among the variables.

Table 1: Data and variables input in EVIEWS

Abbreviations	Construction of variables	Data source
LNGPRC_IND	Country GPR: Percent of articles (India)	www.matteoiacoviello.com
LNGPRHV_IND	Country GPR Historical: Percent of articles (India)	www.matteoiacoviello.com
LNGPRM	Natural logarithm of the monthly average of GPR Monthly	www.matteoiacoviello.com
LNGPRH	Natural Log of Historical GPR	www.matteoiacoviello.com
LNGPRM_ACT	Natural Log of Geo Political Risk Monthly Acts	www.matteoiacoviello.com
LNGPRH_ACT	Natural Log of Geo Political Risk Historical Acts	www.matteoiacoviello.com
LNGPRM_THREATS	Natural Log of Geo Political Risk Monthly Threats	www.matteoiacoviello.com
LNGPRH_THREATS	Natural Log of Geo Political Risk Historical Threats	www.matteoiacoviello.com
LNNBPU_IND	Natural Log of India News Based Uncertainty Index	https://www.policyuncertainty.com/india_monthly.html
LNNIFTYENERGY	Monthly Natural Log Returns of NIFTY Energy Index	www.investing.com
RCRUDEOILP	Monthly Natural Log Returns of Crude Oil	www.investing.com
RNTPC	Monthly Natural Log Returns of NTPC	www.investing.com
RADANIPOWER	Monthly Natural Log Returns of Adani Power	www.investing.com
RPOWERGRID	Monthly Natural Log Returns of PowerGrid	www.investing.com

3.5.3. VECM estimation

The VECM is estimated to analyze the short-term dynamics and long-term equilibrium connections among the variables. The model captures the speed of adjustment and the direction of causality among the variables.

3.5.4. Diagnostic tests

Various diagnostic tests will be conducted to assess the validity of the model assumptions, including residual diagnostics, stability tests, and Granger causality tests.

The research methodology outlined above provides a systematic framework for investigating the cointegration relationship between geopolitical risk indices, the Indian uncertainty index on energy commodities, the energy index, and energy companies in India using the VECM. By employing rigorous statistical techniques and reliable data sources, this analysis contributes to the understanding of complex dynamics within the energy sector in the context of geopolitical risks and uncertainties.

4. RESULTS AND DISCUSSION

The vector error correction model (VECM) has emerged as a highly apt analytical tool for exploring the intricate dynamics between various economic variables, particularly in the context of examining the cointegration of geopolitical risk (GPR) indices, the India News-Based Policy Uncertainty Index, energy commodities, the Energy Index in India, and the stock performance of the top three energy companies in the country. The VECM is well suited for this multifaceted analysis owing to its ability to capture both short-term fluctuations and long-term equilibrium relationships among interconnected time-series variables. As energy markets are inherently influenced by a confluence of factors, including geopolitical events, economic uncertainties, and market trends, the inclusion of GPR indices and uncertainty measures adds a layer of complexity that demands a robust modeling approach. The VECM's incorporation of an error correction term (ECT) is particularly advantageous in this scenario, allowing for an understanding of how the system corrects itself over time when deviations from the long-term equilibrium occur. Moreover, the model's capacity to handle endogeneity and facilitate Granger causality testing is crucial when exploring the bidirectional relationships among energy commodities, market indices, and company stock prices. By employing VECM, researchers can gain insights into the interplay between these variables, discerning not only the immediate impacts, but also the enduring relationships that shape the energy landscape in India. In essence, the VECM is a comprehensive and powerful tool that offers a nuanced understanding of the cointegration dynamics within the complex interdependencies of GPR indices, the India News-Based Policy Uncertainty Index, energy commodities, the Energy Index in India, and the stock performance of the nation's top three energy companies. The VECM models formulated in this study are described in the conceptual framework section.

A long-run linkage with short-run dynamics is established using the VECM. One of the main characteristics of the cointegrated variables is that the degree of any deviation from the long-run equilibrium affects their time trajectories. The degree of the disequilibrium must be considered by the movements of at least some of the variables if the system is to return to long-run equilibrium.

$x_{t.}$ $(x_{1t,}\ x_{2t},\ x_{3t},\ldots,\ x_{nt})$ has an error correction demonstration; if, it can be articulated in the form.

$$\Delta x_t = \pi_0 + \pi_1\, x_{t-1} + \pi_1\, \Delta x_{t-1} + \ldots\ldots + \pi_p\, \Delta x_{t-p} + \varepsilon_t \tag{1}$$

Where-

- π_0 = an (n. 1) Vector of intercept terms with elements π_{i0}
- π_0 = (n. n) Coefficient matrices with elements $\pi_{jk}(i)$
- π = matrix with elements π_{jk} such that one or more of $\pi_{jk} \neq 0$
- ε_t = an (n. 1) vector with elements ε_{it}

The disturbance terms are such that ε_{it} may be correlated with ε_{jt}. and all variables in x_t are I (1). If there is an error-correction representation of these variables, as in the above equation, there is necessarily a linear combination of the I (1) variables that are stationary. Solving the above equation for πx_{t-1} yields

$$\pi\, x_{t-1} = \Delta x_{t-1} - \pi_0 - \sum \pi_i\, \Delta x_{t-i} - \varepsilon_t \tag{2}$$

Since each expression on the right-hand side is stationary, πx_{t-1} must also be stationary.

4.1. Conceptual Framework

To frame the VECM, the eight indices of the GPR and India News-Based Policy Uncertainty Index are considered as independent variables. As dependent variables, we consider one index related to the energy sector (i.e., NIFTY Energy), two energy commodities prices (i.e., price of natural gas and crude oil), and three stock prices of the top three companies, NTPC, PowerGrid, and Adani Power. A detailed list of independent and dependent variables can be seen in the Figure 1. Figure 1 also represents the list of independent variables and their abbreviations that are regressed on each dependent variable related to the energy sector.

VECM model is formulated by imported the data into EVIEWS 10 using suitable abbreviations that will be appropriate and easy for drafting the command to formulate and analyze the outcomes or results of the various models. A detailed list of the abbreviations used is mentioned in the Data Description section.

For the application of VECM, it is necessary for the data to be stationary. To verify if the chosen variables had stationarity, the ADF test was utilised. Based on this test, all variables are found to be stationary at 1 per cent level after calculating the log returns of the variables. The order of integration for all the selected variables used in this analysis is listed in Table 2.

Correctly determining the lag structure to be employed in the Johansen cointegration process is crucial to preventing autocorrelation in the estimated model's residuals. To select the appropriate lag length, we apply the VAR prototype to the level data. VAR lag order selection criteria selects one lag based on the

Figure 1: Conceptual framework representing independent and dependent variables

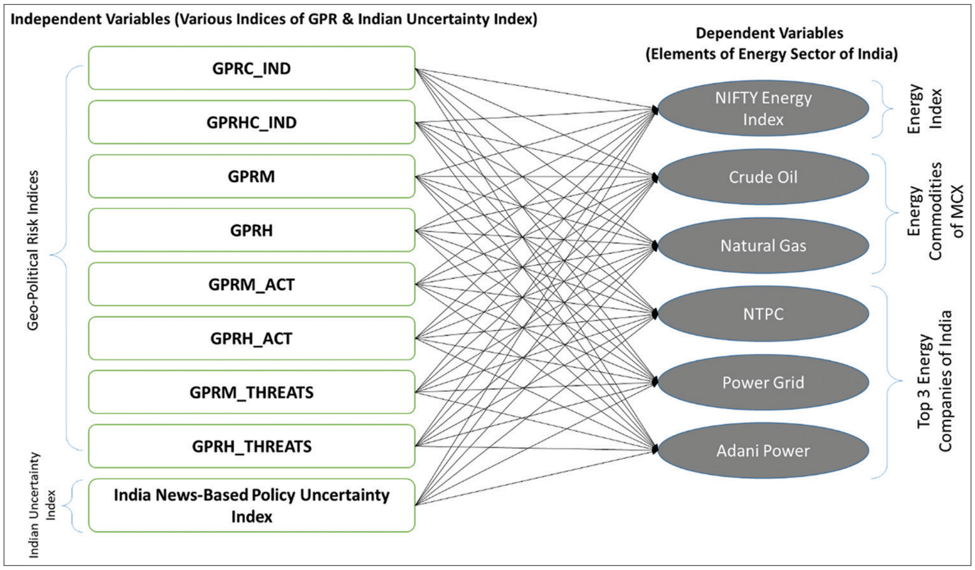

Table 2: Unit root test for stationarity of variables

Variables	Order of integration (when data is non-stationary)	Order of integration (when data is stationary)
LNGPRC_IND	I (1)	I (0)
LNGPRHV_IND	I (1)	I (0)
LNNBPU_IND	I (1)	I (0)
LNGPRM	I (1)	I (0)
LNGPRH	I (1)	I (0)
LNGPRM_ACT	I (1)	I (0)
LNGPRH_ACT	I (1)	I (0)
LNGPRM_THREATS	I (1)	I (0)
LNGPRH_THREATS	I (1)	I (0)
RNIFTYENERGY	I (1)	I (0)
RCRUDEOILP	I (1)	I (0)
RNATURALGAS	I (1)	I (0)
RNTPC	I (1)	I (0)
RPOWERGRID	I (1)	I (0)
RADANIPOWER	I (1)	I (0)

FPE, AIC, SC, and HQ criteria. Therefore, we establish a relation at lag 1 for all selected variables.

Table 3 shows the values of the different criteria for lag orders, ranging from 0 to 8. Certain terms used in the table are Lag: The number of lags considered in the VAR model, LogL: the value of the log-likelihood function for the given lag order, LR: The sequential modified LR test statistic used for lag order selection. Each test was performed at a 5% level of significance, and FPE: Final prediction error, a criterion used for model selection. The selection of lag length criteria is based on values of Akaike information criterion (AIC), Schwarz information criterion (SC) and Hannan-Quinn Information Criterion (HQ) which are the criteria used for model selection. Lower values of AIC, SC and HQ indicate a better fit. Typically, one would choose the lag order that minimizes one of these criteria (AIC, SC, or HQ), as it suggests a more parsimonious model without sacrificing too much explanatory power. In this specific analysis, it appears that lag order 1 was selected by all three criteria (AIC, SC, HQ), as indicated by asterisks. This suggests that a VAR model with one lag may provide the best balance between the model complexity and explanatory power for the given data.

From the results listed in Table 4, the cointegration relationships between RNIFTYENERGY, RCRUDEOILP, RNATURALGAS, RNTPC, RPOWERGRID, RADANIPOWER, and the nine selected explanatory variables can be re-expressed in the following equation:

RNIFTYENERGY = 0.102 LNGPRC_IND − 0.099LNGPRHV_IND − 0.006LNNBPU_IND − 0.636LNGPRM +0.888LNGPRH +0.066LNGPRM_ACT−0.168LNGPRH_ACT+0.395LNGPRM_THREATS − 0.473LNGPRH_THREATS

RCRUDEOILP = 0.025LNGPRC_IND +0.068LNGPRHV_IND − 0.043LNNBPU_IND + 0.312LNGPRM −0.069LNGPRH +0.086LNGPRM_ACT−0.187LNGPRH_ACT−0.290LNGPRM_THREATS +0.031LNGPRH_THREATS

RNATURALGAS = 0.248LNGPRC_IND − 0.251LNGPRHV_IND − 0.041LNNBPU_IND − 5.034LNGPRM +3.984LNGPRH +2.428LNGPRM_ACT−2.009LNGPRH_ACT+3.032LNGPRM_THREATS − 2.399LNGPRH_THREATS

RNTPC = 0.114LNGPRC_IND − 0.077LNGPRHV_IND − 0.032LNNBPU_IND − 0.531LNGPRM +0.179LNGPRH +0.220LNGPRM_ − 0.077LNGPRH_ACT +0.172LNGPRM_THREATS +0.007LNGPRH_THREATS

RPOWERGRID = 0.056LNGPRC_IND − 0.038LNGPRHV_IND − 0.015LNNBPU_IND − 0.585LNGPRM +0.440LNGPRH +0.201LNGPRM_ACT−0.151LNGPRH_ACT+0.306LNGPRM_THREATS − 0.223LNGPRH_THREATS

RADANIPOWER = 0.014LNGPRC_IND + 0.154LNGPRHV_IND − 0.045LNNBPU_IND − 1.120LNGPRM +2.016LNGPRH +0.336LNGPRM_ACT−0.680LNGPRH_ACT+1.188LNGPRM_THREATS − 1742LNGPRH_THREATS

Table 3: Pre-test for lag-length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	721.9884	NA	2.24e-17	−9.957880	−9.750688	−9.873687
1	1002.497	517.8611	1.80e-18*	−12.48247*	−10.20336*	−11.55635*
2	1093.425	155.1505*	2.08e-18	−12.35559	−8.004562	−10.58754
3	1156.358	98.58031	3.67e-18	−11.83717	−5.414223	−9.227193
4	1234.116	110.9279	5.51e-18	−11.52610	−3.031231	−8.074192
5	1320.478	111.1234	7.85e-18	−11.33536	−0.768573	−7.041525
6	1382.438	71.05807	1.72e-17	−10.80332	1.835386	−5.667557
7	1489.896	108.2094	2.27e-17	−10.90763	3.802997	−4.929935
8	1627.446	119.2745	2.34e-17	−11.43281	5.349736	−4.613187

*indicates lag order selected by the criterion

Table 4: Vector error correction estimates (long-run relationship)

Variables	LNGPRC_IND	LNGPRHV_IND	LNNBPU_IND	LNGPRM	LNGPRH	LNGPRM_ACT	LNGPRH_ACT	LNGPRM_THREATS	LNGPRH_THREATS
RNIFTYENERGY	−0.102	0.099	0.006	0.636	−0.888	−0.066	0.168	−0.395	0.473
	(0.024)	(0.021)	(0.009)	(0.248)	(0.228)	(0.093)	(0.082)	(0.173)	(0.154)
	[−4.21]	[4.83]	[0.62]	[2.56]	[−3.88]	[−0.71]	[2.056]	[−2.29]	[3.08]
RCRUDEOILP	−0.025	−0.068	0.043	−0.312	0.069	−0.086	0.187	0.290	−0.031
	(0.058)	(0.049)	(0.022)	(0.602)	(0.554)	(0.227)	(0.200)	(0.419)	(0.372)
	[−0.441]	[−1.383]	[1.90]	[−0.52]	[0.13]	[−0.38]	[0.93]	[0.69]	[−0.083]
RNATURALGAS	−0.248	0.251	0.041	5.034	−3.984	−2.428	2.009	−3.032	2.399
	(0.096)	(0.081)	(0.038)	(0.994)	(0.912)	(0.371)	(0.325)	(0.694)	(0.616)
	[−2.57]	[3.09]	[1.09]	[5.06]	[−4.37]	[−6.54]	[6.18]	[−4.37]	[3.89]
RNTPC	−0.114	0.077	0.032	0.531	−0.179	−0.220	0.077	−0.172	−0.007
	(0.028)	(0.023)	(0.011)	(0.284)	(0.261)	(0.107)	(0.094)	(0.198)	(0.176)
	[−4.11]	[3.31]	[2.98]	[1.86]	[−0.69]	[−2.065]	[0.82]	[−0.87]	[−0.04]
RPOWERGRID	−0.056	0.038	0.015	0.585	−0.440	−0.201	0.151	−0.306	0.223
	(0.022)	(0.018)	(0.008)	(0.223)	(0.204)	(0.083)	(0.073)	(0.155)	(0.138)
	[−2.58]	[2.09]	[1.71]	[2.63]	[−2.15]	[−2.41]	[2.07]	[−1.97]	[1.62]
RADANIPOWER	−0.014	−0.154	0.045	1.120	−2.016	−0.336	0.680	−1.188	1.742
	(0.082)	(0.069)	(0.032)	(0.845)	(0.77)	(0.317)	(0.277)	(0.589)	(0.523)
	[−0.17]	[−2.21]	[1.38]	1.32]	[−2.60]	[−1.06]	[2.45]	[−2.01]	[3.33]

It is observed that the Energy Index Return is cointegrated with the nine selected explanatory variables, of which seven variables are significant. The directions of LNGPRC_IND, LNGPRH, and LNGPRM_THREATS are positive, whereas those of LNGPRHV_IND, LNGPRM, LNGPRH_ACT, and LNGPRH_THREATS are negative. The Crude Oil Index Return was cointegrated with the nine selected explanatory variables; however, none of the variables were significant. The natural gas return is cointegrated with the nine selected explanatory variables, of which eight variables are significant. The directions of LNGPRC_IND, LNGPRH, LNGPRM_ACT, and LNGPRM_THREATS were positive, whereas the directions of LNGPRHV_IND, LNGPRM, LNGPRH_ACT, and LNGPRH_THREATS were negative.

NTPC Return is cointegrated with the nine selected explanatory variables, out of which four variables are significant. The directions of LNGPRC_IND and LNGPRM_ACT are positive, whereas the directions of LNGPRHV_IND and LNNBPU_IND are negative. The Power Grid Index Return was cointegrated with the nine selected explanatory variables, out of which six variables were significant. The directions of LNGPRC_IND, LNGPRH, and LNGPRM_THREATS are positive, whereas the directions of LNGPRHV_IND, LNGPRM, and LNGPRH_ACT are negative. The Adani Power Index Return is cointegrated with the nine selected explanatory variables, out of which six variables are significant. The directions of LNGPRHV_IND, LNGPRH, and LNGPRM_ACT are positive, whereas those of LNGPRM, LNGPRH_ACT, and LNGPRH_THREATS are negative.

In this study, nine explanatory variables are considered, of which some variables are significant and some are insignificant. Further, we drop insignificant variables, establish the VECM relationship with significant variables, and find the optimized results to be more robust. A Summary of the optimized models with significant variables is presented in Table 5.

From the results listed in Table 5, the cointegration relationships between Log Returns of NIFTY Energy Index, Log Returns of Natural Gas price, Log Returns of NTPC stock price, Log Returns of ADANIPOWER, and the nine selected explanatory variables can be re-expressed in the equation form with only significant variables, as given below. However, in the case of Log Returns of Crude Oil prices, none of the independent variables were considered significant in the case of crude oil; hence, the model could not be formulated.

RNIFTYENERGY = 0.118 LNGPRC_IND − 0.132 LNGPRHV_IND + 0.386 LNGPRH −0.168 LNGPRM_ACT + 0.0193 LNGPRH_ACT −0.066LNGPRM_THREATS − 0.085LNGPRH_THREATS

RNATURALGAS = 0.319 LNGPRC_IND − 0.339LNGPRHV_IND − 4.032LNGPRM + 3.862 LNGPRH +1.622LNGPRM_ACT

Table 5: Vector error correction estimates (long-run relationship) of optimized model

Variables	LNGPRC_IND	LNGPRHV_IND	LNNBPU_IND	LNGPRM	LNGPRH	LNGPRM_ACT	LNGPRH_ACT	LNGPRM_THREATS	LNGPRH_THREATS
RNIFTYENERGY	−0.118 (0.026) [−4.49]	0.132 (0.022) [5.99]	Insignificant hence dropped	Insignificant hence dropped	−0.386 (0.149) [−2.58]	0.168 (0.053) [3.14]	−0.0193 (0.064) [−0.30]	0.066 (0.041) [1.60]	0.085 (0.102) [0.83]
RCRUDEOILP	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped
RNATURALGAS	−0.319 (0.083) [−3.82]	0.339 (0.069) [4.86]	Insignificant hence dropped	4.032 (0.869) [4.64]	−3.862 (0.795) [−4.86]	−1.622 (0.325) [−4.99]	1.528 (0.285) [5.36]	−2.519 (0.604) [−4.170]	2.295 (0.536) [4.28]
RNTPC	−0.046 (0.022) [−2.12]	0.018 (0.019) [0.96]	0.017 (0.010) [1.68]	Insignificant hence dropped	Insignificant hence dropped	−0.014 (0.014) [−1.02]	Insignificant hence dropped	Insignificant hence dropped	Insignificant hence dropped
RPOWERGRID	−0.079 (0.021) [−3.65]	0.071 (0.018) [3.83]	Insignificant hence dropped	0.132 (0.047) [2.80]	−0.158 (0.059) [−2.65]	0.003 (0.051) [0.07]	0.007 (0.051) [0.14]	Insignificant hence dropped	Insignificant hence dropped
RADANIPOWER	Insignificant hence dropped	−0.118 (0.033) [−3.57]	Insignificant hence dropped	Insignificant hence dropped	−1.101 (0.407) [−2.70]	Insignificant hence dropped	0.418 (0.147) [2.84]	−0.434 (0.098) [−4.44]	1.052 (0.276) [3.81]

− 1.528 LNGPRH_ACT +2.519LNGPRM_THREATS − 2.295 LNGPRH_THREATS

RNTPC = 0.046 LNGPRC_IND − 0.018 LNGPRHV_IND − 0.017 LNNBPU_IND + 0.014 LNGPRM_ACT

RPOWERGRID = 0.079 LNGPRC_IND − 0.071 LNGPRHV_IND − 0.132 + 0.158LNGPRH − 0.0031LNGPRM_ACT − 0.007LNGPRH_ACT

RADANIPOWER = 0.118LNGPRHV_IND +1.1016LNGPRH − 0.418LNGPRH_ACT +0.434 LNGPRM_THREATS − 1.052 LNGPRH_THREATS

The above five optimized model can be used to examine the cointegration between GPR Indices, Indian Uncertainty Index and Energy Index, Commodities and Energy Companies of India. It is observed from the above results that the NIFTY Energy is cointegrated with the seven selected explanatory variables, out of which four variables turn out to be significant. The directions of LNGPRC_IND and LNGPRH are positive while direction of LNGPRHV_IND and LNGPRH_ACT are negative. Natural gas returns are cointegrated with eight selected explanatory variables, out of which all eight variables are significant. The directions of LNGPRC_IND, LNGPRH, LNGPRM_ACT and LNGPRM_THREATS are positive while direction of LNGPRHV_IND, LNGPRM, LNGPRH_ACT and LNGPRH_THREATS are negative. NTPC return is cointegrated with the four selected explanatory variables, out of which only one variable was found to be significant. Only the direction of LNGPRC_IND is positive only. The Power Grid Index Return is cointegrated with the six selected explanatory variables, out of which four variables are significant. The directions of LNGPRC_IND and LNGPRH are positive while direction of LNGPRHV_IND and LNGPRM are negative. The Adani Power Index Return is cointegrated with the five selected explanatory variables, out of which all five variables are significant. The directions of LNGPRHV_IND and LNGPRH are positive while direction of LNGPRH_ACT, LNGPRM_THREATS and LNGPRH_THREATS are negative.

The results of the study depict that the presence of impact of GPR elements on energy stocks, commodities and index which is well connected with the established economic model discussed in the literature review. But, it is also noted that the impact of variable, India News-Based Policy Uncertainty Index is not present in the data related to energy sector which is completely adverse to established economic model. The reasons of such fluctuations in results of modelling may be due to lack of reflection of uncertainties in Indian economy in the formulated India News-Based Policy Uncertainty Index or due to considering monthly data points instead of daily data points.

5. CONCLUSION

This study examined the cointegration of different variables related to Geopolitical Risks and India News-Based Policy Uncertainty Index on Energy Sector of India with VECM from February 2011 to August 2023 using 151 data points. The study employed

VECM using the closing prices of Crude Oil and Natural Gas, closing values of NIFTYENERGY Index and closing prices of top three energy company stocks in India as target variables. The results report that NIFTY Energy is cointegrated with the four significant explanatory variables in which the directions of Country GPR: Percent of articles of India and Historical GPR are positive while direction of Country GPR Historical: Percent of articles of India and Geopolitical Risk Historical Acts are negative. Natural gas returns are cointegrated with eight significant explanatory variables in which the directions of Country GPR: Percent of articles (India), Historical GPR, Geopolitical Risk Monthly Acts and Geo Political Risk Monthly Threats are positive while direction of Country GPR Historical: Percent of articles (India), monthly average of GPR, Geo Political Risk Historical Acts and Geo Political Risk Historical Threats are inversely related. NTPC Return is cointegrated with one significant variable in which the direction of Country GPR: Percent of articles (India) is positive. The Power Grid Index Return is cointegrated with the six selected explanatory variables, out of which four variables are significant. The directions of Country GPR: Percent of articles (India) and Historical GPR are positive while direction of Country GPR Historical: Percent of articles (India) and monthly average of GPR are negative. The Adani Power Index Return is cointegrated with the five significant explanatory variables. The directions of Country GPR Historical: Percent of articles (India) and Historical GPR are positive while direction of Geopolitical Risk Historical Acts, Geo Political Risk Monthly Threat and Geo Political Risk Historical Threats are negative.

The variables concerned with GPR Act index, which measures geopolitical actions like conflicts and terrorism, is directly proportional to the stock prices of Indian energy companies, closing prices of energy commodities, and the NIFTYENERGY index due to its impact on global energy supply. There is possibility that geopolitical tensions, especially in oil-rich regions, heighten fears of supply disruptions, driving up global energy prices. This may boost revenues for energy firms and lead investors to view energy assets as safe havens, raising their stock prices. Consequently, higher energy prices increase the profitability of energy companies, positively influencing indices like NIFTTYENERGY that track their performance. The variables associated with GPR Threat index, reflecting potential geopolitical threats, is inversely related to the stock prices of Indian energy companies, closing prices of energy commodities, and the NIFTY ENERGY index. It might be possible that potential threats create uncertainty and fear of future instability, prompting concerns about decreased demand and economic downturn. Investors, anticipating economic slowdowns and lower energy consumption, may sell off energy stocks, causing their prices to drop. Additionally, the prospect of prolonged geopolitical instability may lead to volatility in energy markets, suppressing commodity prices and negatively impacting indices like NIFTY ENERGY, which track the performance of the energy sector.

The utilization of VECM in this research provides a robust framework for examining the cointegration of different variables concerned with GPR and India News Based Policy Uncertainty Index on the Indian energy sector, offering valuable insights for policymakers, investors, and industry stakeholders. Further investigation could explore the factors influencing these relationships and explore additional variables to enhance the predictive power and applicability of the model in real-world scenarios. The study has also certain limitations which are highlighted below:

- Exogeneity assumption: The VECM model assumes that the explanatory variables are exogenous, meaning that they are not influenced by the error term in the model. However, geopolitical events and new-based uncertainties may have endogenous effects on energy markets, potentially violating this assumption.
- Variable selection bias: The study's focus on specific variables, such as GPR indices, India News-Based Policy Uncertainty Index, and selected energy commodities and companies, may overlook other relevant factors that could influence the energy sector. Omitting important variables could lead to biased estimates and incomplete understanding of the relationships under investigation.
- Generalizability: The outcomes of this analysis may be specific to the context of the Indian energy sector and may not be readily generalizable to other countries or regions with different geopolitical dynamics, regulatory environments, and market structures. Caution should be exercised when extrapolating the results beyond the scope of this study.

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