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THE IMPACT OF GOOGLE-BASED ECONOMIC POLICY UNCERTAINTY ON INDIAN SECTORAL INDICES, CURRENCY MARKETS, AND COMMODITY MARKETS: EVIDENCE FROM LINEAR AND NONLINEAR GRANGER CAUSALITY ANALYSIS

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Abstract
This study investigates the dynamic relationship between Google-based Economic Policy Uncertainty (GEPU) and major segments of the Indian financial markets, specifically National Stock Exchange (NSE) sectoral indices, the USD/INR exchange rate, and Multi Commodity Exchange (MCX) commodity indices, over the period 2007–2024. Drawing on high-frequency search data as a real-time proxy for collective investor attention and policy-related anxiety, the analysis employs unit root testing (ADF, Phillips-Perron, and KPSS), linear Granger causality within a vector auto regression (VAR) framework, and nonparametric nonlinear Granger causality tests. Descriptive statistics reveal substantial heterogeneity in return distributions across sectors, with particularly pronounced non-normality and extreme values in the information technology sector and the GEPU series itself. While linear Granger causality tests largely fail to detect significant predictive relationships, nonlinear tests uncover statistically significant unidirectional causality from GEPU to the media, metals, private-sector banking, and realty sectors, as well as to the USD/INR exchange rate. These findings underscore the importance of modeling nonlinear and regime-dependent dynamics when assessing the transmission of policy uncertainty into asset prices. The results carry practical implications for portfolio risk management, sector rotation strategies, and the design of policy communication, and they highlight the value of alternative data sources in emerging-market research.

Keywords: Google Trends; Economic Policy Uncertainty; GEPU; Sectoral Indices; Granger Causality; Nonlinear Causality; Emerging Markets; India; Investor Attention; Commodity Markets.

Introduction

In an increasingly digitalized and data-driven world, information plays a crucial role in shaping financial market movements. The emergence of big data analytics and alternative data sources has opened new avenues for understanding investor behaviour, economic uncertainty, and market dynamics. One such novel data source is Google Trends, a platform that aggregates search queries over time and provides insights into public interest regarding various topics. Among the key indicators derived from Google Trends data is the Google-based Economic Policy Uncertainty (GEPU) index, which reflects uncertainty surrounding economic policies as inferred from search behaviour. This index serves as a real-time proxy for market sentiment and investor concerns, influencing trading activities across multiple asset classes, including equity markets, foreign exchange, and commodity markets.

The intersection of technology and finance has become one of the most transformative areas of research in the twenty-first century. With the advent of big data, machine learning, and artificial intelligence, financial markets have evolved into a complex ecosystem where information flows at unprecedented speeds and investor behaviour is increasingly influenced by digital tools and platforms. Among these technological advancements, Google Trends has emerged as a powerful instrument for understanding public sentiment, search behaviour, and real-time interest in economic policy uncertainty. Recent studies find that uncertainty shocks can affect financial conditions and, through them, the real economy (Gilchrist et al., 2014; Caldara et al., 2016). Hence, this research focuses on the relationship between Google-based Economic Policy Uncertainty (GEPU), constructed following the approach of Pratap and Priyaranjan (2023) and the Baker et al. (2016) methodology of counting related search intensity, and Indian financial markets specifically sectoral equity indices, the currency market, and commodity markets traded on the Multi Commodity Exchange (MCX).

Economic uncertainty is widely recognised as a major determinant of financial market behaviour, influencing asset prices, volatility, trading activity, and investor decision-making. Traditionally, economic policy uncertainty (EPU) has been measured using newspaper-based indices, expert surveys, and macroeconomic indicators. However, these conventional measures are often constrained by publication delays, subjective biases, and limited granularity. The rapid growth of internet-based information dissemination has transformed the way economic information is generated and consumed, making Google search activity an increasingly important real-time indicator of public attention and economic concerns. Consequently, GEPU has emerged as a dynamic alternative to traditional EPU measures by capturing the collective search behaviour of investors, businesses, and consumers regarding economic policy developments.

The relationship between economic policy uncertainty and financial markets is inherently complex because its effects differ across asset classes, economic sectors, and market participants. Sectoral stock indices exhibit heterogeneous responses depending on their exposure to government policies and regulations, with industries such as banking and infrastructure generally displaying greater sensitivity to policy changes. Likewise, foreign exchange markets react rapidly to uncertainty through shifts in international capital flows toward safe-haven currencies, while commodity markets are simultaneously influenced by both domestic policy developments and global economic uncertainty. These heterogeneous responses highlight the importance of examining sector-specific and asset-specific dynamics rather than treating financial markets as a homogeneous system.

The growing relevance of GEPU is further supported by developments in behavioural finance. While the Efficient Market Hypothesis assumes that financial markets instantaneously incorporate all available information, behavioural finance argues that investor psychology, sentiment, limited attention, and herd behaviour frequently generate deviations from market efficiency. From this perspective, GEPU serves as an effective proxy for collective investor sentiment by capturing changes in public anxiety and optimism regarding economic policies. Incorporating GEPU into financial market analysis therefore provides a broader understanding of market behaviour by integrating traditional information-based explanations with behavioural mechanisms driving investor decisions.

Despite the increasing application of Google Trends in financial research, relatively limited evidence exists on how Google-based Economic Policy Uncertainty simultaneously influences multiple segments of financial markets through dynamic causal relationships. This limitation is particularly relevant for emerging economies such as India, where financial markets are highly responsive to macroeconomic developments and policy announcements. Accordingly, the present study seeks to address this gap by examining the impact of GEPU on Indian sectoral stock indices, foreign exchange markets, and commodity markets using advanced econometric techniques to investigate causality across these major financial market segments.

Stock market fluctuations have long been a significant area of focus for investors, policymakers, scholars, and industry professionals because of their implications for asset valuation, hedging strategies, risk mitigation, portfolio optimisation, and financial market equilibrium (Paye, 2012;

Ropach& Zhou, 2013; Antonakakis, Balcilar, Gupta, &Kyei, 2016). Following the global financial crisis, Economic Policy Uncertainty has garnered substantial attention in the financial literature. Prior research has established that EPU can exert detrimental effects on economic expansion, inflation, capital investment, and employment (Rodrik, 1991; Bloom, Bond, & Van Reenen, 2007; Bloom, 2009; Bhagat, Ghosh, & Ranjan, 2016; Brogaard&Detzel, 2015; Gulen& Ion, 2016). In equity markets specifically, an escalation in EPU contributes to heightened stock market volatility and diminished stock returns (Pastor & Veronesi, 2012; Antonakakis, Chatziantoniou, &Filis, 2013; Kang &Ratti, 2013; Wu, Liu, & Hsueh, 2016; Christou et al., 2017).

Currency markets are influenced by a wide range of factors, including interest rates, inflation, trade balances, and geopolitical events. Economic policy uncertainty can exacerbate currency volatility as investors reassess the risks associated with holding a particular currency. Uncertainty surrounding central bank policies or trade measures can lead to sharp fluctuations in exchange rates. By analysing the relationship between GEPU and the USD/INR rate, this research aims to shed light on how economic policy uncertainty influences exchange-rate dynamics and currency risk in the Indian context. Commodity markets, particularly those represented by the Multi Commodity Exchange (MCX), are also highly sensitive to economic policy uncertainty.

Commodities such as gold, silver, crude oil, and agricultural products are often considered safe-haven assets during periods of uncertainty. Gold prices, for instance, tend to rise during times of economic instability as investors seek to hedge against inflation or currency depreciation. By incorporating GEPU into the analysis of commodity markets, this research explores how policy uncertainty affects commodity prices and volatility and offers insights into the role of commodities as potential safe-haven assets.

Understanding the causal relationships between economic policy uncertainty and financial market indicators is critical for formulating risk-management strategies. The traditional Granger causality test, based on linear dependencies, has been widely used in empirical finance. However, financial markets often exhibit non-linearities arising from regime shifts, structural breaks, and behavioural biases. Employing both linear and non-linear Granger causality tests therefore provides a more comprehensive view of the interplay between GEPU and financial markets.

Rationale of the Study

The significance of this research lies in its potential to enhance understanding of the interplay between economic policy uncertainty and financial markets. By leveraging Google Trends data, the study introduces a novel, high-frequency approach to measuring EPU that offers a more dynamic and real-time perspective than traditional newspaper-based indices. The findings can provide valuable insights for policymakers, investors, and financial analysts.

For policymakers, understanding the impact of GEPU on financial markets can inform the design and communication of economic policies. By identifying how different sectors, currencies, and commodities respond to policy uncertainty, authorities can tailor measures to minimise adverse effects and manage market expectations more effectively. For investors, the results can aid risk management and portfolio optimisation: knowledge of how GEPU influences market volatility and asset prices enables more informed decisions, defensive positioning during periods of heightened uncertainty, or opportunistic strategies when inefficiencies arise. For financial analysts, the integration of GEPU into analytical frameworks offers a new tool for market monitoring and forecasting.

Literature Review

Overview: The integration of high-frequency data, such as Google Trends, into financial and economic analysis has attracted significant scholarly attention. Traditional economic indicators, while valuable, often suffer from publication lags: government reports for a given month typically appear mid-way through the subsequent month and are subject to later revisions. In contrast, Google Trends offers near real-time insights through daily and weekly search volumes across industries, presenting a potential solution to the lag in official data (Choi & Varian, 2009). Several studies hypothesise that Google search data can reflect real-time economic activity and investor sentiment, making it useful for "predicting the present" rather than solely forecasting the future.

The literature emphasises the importance of Google searches and their impacts on financial market dynamics. While sophisticated models can refine accuracy, even relatively simple frameworks have proven effective in initiating analyses and building foundational insights. These studies highlight the utility of high-frequency search data in capturing real-time market conditions and open avenues for applying such methods to equities, currencies, commodities, and emerging digital assets.

Google Searches as a Measure of Public Interest and Investor Attention

A substantial body of research demonstrates that internet search activity and social media sentiment serve as reliable proxies for investor attention and help explain financial market behaviour. Early studies focused on Google Search Volume (GSV) and showed that heightened search activity is associated with stronger market reactions, increased trading volume, higher volatility, and abnormal stock returns. Vakrman et al. (2015) found that investor attention measured through Google searches significantly influences IPO underpricing and long-term performance by generating excessive optimism during periods of elevated market sentiment. Jawadi et al. (2020) reported that investor attention exerts a nonlinear and time-varying influence on Islamic stock returns while improving return forecasting accuracy.

Tetlock (2005) documented that increased search activity leads to temporary increases in trading volume and market volatility while reducing subsequent returns, consistent with the restricted attention hypothesis. Yoshinaga and Rocco (2020) found that higher Google Search Volume predicts lower future stock returns in the Brazilian market, suggesting that excessive attention may drive prices away from fundamental values. Bui and Nguyen (2019) demonstrated strong correlations between Google Search Volume, trading volume, liquidity, and volatility in emerging markets. Preis et al. (2013) argued that Google search trends may provide early warning signals of major financial market movements by capturing shifts in collective investor behaviour before they are fully incorporated into asset prices.

Beyond equity markets, Google Trends data have proven useful in macroeconomic forecasting. Vosen and Schmidt (2010) showed that search data improve real-time forecasting of consumer spending in Germany. Smith (2015) demonstrated enhanced unemployment forecasting in the United Kingdom using MIDAS regressions. Ferrara and Simoni (2019) integrated Google search data with machine-learning techniques to improve GDP nowcasting, particularly during recessions. These studies collectively establish that internet search behaviour constitutes a valuable real-time source of economic information.

Google Searches and Specific Financial Markets

Rutkowska and Kliber (2020) demonstrated that investor attention affects asset classes differently, with cryptocurrencies exhibiting the strongest response while equities experience significant changes in volume and volatility. Tantaopas et al. (2016) reported that attention improves market efficiency

and exhibits asymmetric relationships with returns, volatility, and trading activity across Asia-Pacific markets. Perlin et al. (2014) showed that finance-related Google queries possess predictive power for market uncertainty, stock returns, and trading volume.
A stream of research has focused specifically on volatility. Silva (2016) and Braun (2016) demonstrated that incorporating Google search data into GARCH-type models significantly improves volatility forecasts, particularly during periods of heightened uncertainty. Latoeiro et al. (2013) reported that increased search activity temporarily raises volume and volatility while reducing subsequent returns. Xu et al. (2019) incorporated Google Trends into a mixed-frequency GARCH-MIDAS framework and showed that combining search activity with macroeconomic fundamentals enhances volatility forecasts.

Evidence from India and other emerging markets is also supportive. Kruthika et al. (2018) documented that searches related to “bull market” significantly influence NIFTY 50 returns. Mei and Masih (2021) found bidirectional causality between Google search activity and Malaysian Islamic stock indices. Nevertheless, some studies caution against over-interpretation: Fong (2017) reported that after eliminating look-ahead bias several popular keywords lose predictive ability, suggesting that some reported relationships may be spurious.

Google Trends and Foreign Exchange Markets
Literature on exchange-rate dynamics indicates that Google Trends data can enhance forecasting beyond conventional macroeconomic models. Bulut (2015) demonstrated that incorporating Google Trends-based measures of fundamentals into Purchasing Power Parity and monetary models improves out-of-sample forecasts for several OECD currencies. Bulut and Dogan (2018) reported that Google Trends variables outperform the random-walk benchmark for the Turkish Lira–US Dollar rate. Fan Chiang et al. (2021) showed that integrating Google Trends with historical volatility and liquidity measures significantly improves USD-INR exchange-rate volatility forecasts, with price-related search terms providing the greatest predictive power.

Complementary research has incorporated social media sentiment and machine-learning techniques. Plakandaras et al. (2015) found that investor sentiment extracted from StockTwits predicts short-term exchange-rate movements. Rajput et al. (2020) introduced a Google-based Bitcoin Sentiment Index and documented significant relationships with returns, volume, volatility, and USD exchange rates. These findings suggest that online search and sentiment data contain timely information about market expectations that is not fully captured by traditional indicators.

Google Searches, Commodity Markets, and Economic Policy Uncertainty
Research on commodity markets shows that Google search activity serves as a useful proxy for investor attention and market uncertainty. Szczygielski et al. (2022) and Tanaya and Suyanto (2021) reported that search activity helps explain variations in commodity returns and volatility. Mišečka et al. (2019) documented significant causal relationships between Google queries and prices of agricultural commodities such as corn and wheat. Salisu et al. (2020) found that Google Trends improves prediction of precious-metal returns and outperforms random-walk benchmarks. Miao et al. (2022) demonstrated strong nonlinear associations between Google Trends and precious-metal prices using nonparametric causality-in-quantiles methods.

Energy markets have also attracted attention. Yang et al. (2022) and Drachal (2017) showed that incorporating Google Trends improves forecasts of crude-oil futures and spot prices. Fiszeder et al.

(2023) demonstrated that investor attention influences oil returns, volatility, and dynamic relationships among oil, gold, and equities.

Recent work has explicitly developed Google Trends-based measures of Economic Policy Uncertainty. Pratap and Priyaranjan (2023) constructed a high-frequency Google Trends-based EPU index for India and showed that unexpected increases in uncertainty reduce output growth while raising inflation, primarily through declines in private investment. Incorporating the measure substantially improves macroeconomic forecasting relative to conventional uncertainty indices. Vaswani and M. (2023) reported a significant negative relationship between EPU and market returns, particularly during recessionary periods. Kropiński and Anholcer (2022) found that the relationship between Google Trends-based EPU and stock-market performance strengthened considerably after the COVID-19 pandemic.

International evidence confirms that policy uncertainty generates spillovers across equity, commodity, and foreign-exchange markets (Christou et al., 2017; Shahzad et al., 2017; Thiem, 2019). At the firm level, heightened policy uncertainty discourages investment and increases credit-default-swap spreads (Almustafa et al., 2023; Wang et al., 2018). Collectively, the literature establishes that search-based uncertainty measures provide timely, objective, and high-frequency information with substantial applications in financial-market analysis and policy evaluation. Nevertheless, relatively limited research has jointly examined Google Trends-based policy uncertainty across Indian sectoral equities, currency, and commodity markets within a unified linear-and-nonlinear causality frameworkthe gap addressed by the present study.

Research Methodology

Research Design and Objectives

The study adopts an exploratory and descriptive research design employing quantitative time-series methods. The primary objective is to examine the relationship between Google-based Economic Policy Uncertainty (GEPU) and (i) NSE sectoral indices, (ii) the USD/INR spot exchange rate, and (iii) MCX commodity indices. Both linear and nonlinear Granger causality tests are applied to capture possible asymmetric and regime-dependent transmission channels.

Data Description

The analysis is based on secondary data covering the period 2007–2024. Daily closing prices of selected NSE sectoral indices (CNXAUTO, CNXFMCG, CNXIT, CNXMEDIA, CNXMETAL, CNXPSUBANK, CNXREALTY), the USD/INR spot rate, and the MCX commodity index were obtained from Yahoo Finance. The GEPU series is taken from the Economic Policy Uncertainty website, following the Google Trends-based construction of Pratap and Priyaranjan (2023).
Daily closing prices were transformed into continuously compounded returns using the natural logarithm of successive price ratios:

$$CP_{t=} \ln\left(\frac{CP_t}{CP_{t-1}}\right) * 100$$

This transformation stabilises variance and converts the series into growth rates, mitigating trends and heteroscedasticity commonly observed in financial price data.

Statistical Tools and Econometric Methods

Data pre-processing was performed in Microsoft Excel. Econometric estimation was conducted using EViews 10 and R 4.2.0. The following procedures were employed:

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Unit Root Tests

Stationarity was assessed using three complementary tests. The Augmented Dickey-Fuller (ADF) test estimates a regression of the form:

$$\Delta Yt = \alpha + \beta t + \varphi Y_{t-1} + \sum_{i=1}^{p} \delta i \Delta Y_{t-1} + \varepsilon_t$$

Where: Yt: the dependent variable

α: the constant term

β: the coefficient on a time trend

φ: the coefficient on the lagged dependent variable

ΔYt-1: the differenced dependent variable at lag i

δi: The coefficient on the ith lagged difference term

ε_t: The error term at time t

The null hypothesis is the presence of a unit root (φ = 0). The Phillips-Perron (PP) test applies a non-parametric correction to the Dickey-Fuller statistic and is robust to general forms of heteroskedasticity. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test reverses the null hypothesis, testing stationary against the alternative of a unit root. Consistent inference across all three tests strengthens confidence in the stationary conclusions.

Linear Granger Causality

Linear Granger causality is examined within a bivariate VAR framework. For two stationary series S_t (sectoral or market return) and GEPU_t, the system is:

$$S_t = \alpha + \sum_{i=1}^{l} \alpha_i S_{t-1} + \sum_{j=1}^{l} \beta_j GEPU_{t-1} + \varepsilon_t$$

$$GEPU_t = \omega + \sum_{i=1}^{l} \gamma_i GEPU_{t-1} + \sum_{j=1}^{l} \Theta_j S_{t-1} + \varepsilon_t$$

$$GEPU_t = \alpha + \sum_{i=1}^{l} \alpha_i GEPU_{t-1} + \sum_{j=1}^{l} \beta_j USDINR_{t-1} + \varepsilon_t$$

$$USDINR_t = \omega + \sum_{i=1}^{l} \gamma_i USDINR_{t-1} + \sum_{j=1}^{l} \Theta_j GEPU_{t-1} + \varepsilon_t$$

$$MCXiCOMDEX_t = \alpha + \sum_{i=1}^{l} \alpha_i MCXiCOMDEX_{t-1} + \sum_{j=1}^{l} \beta_j GEPU_{t-1} + \varepsilon_t$$

$$GEPU_t = \omega + \sum_{i=1}^{l} \gamma_i GEPU_{t-1} + \sum_{j=1}^{l} \Theta_j MCXiCOMDEX_{t-1} + \varepsilon_t$$

Where: St = Sectoral Indices

GEPU = Google trend based economic policy uncertainty

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MCXiCOMDEX = MCX commodity indices
USDINR = Indian currency denominated in USD
Lag length is selected according to the Akaike Information Criterion (AIC). An F-test on the joint significance of the lagged coefficients of the putative causal variable constitutes the Granger causality test.

Nonlinear Granger Causality
Because financial relationships frequently exhibit nonlinearities, the study also implements nonparametric nonlinear Granger causality tests (following the spirit of Diks&Panchenko, 2006). These tests are capable of detecting predictive relationships that linear specifications may miss due to regime shifts, threshold effects, or other forms of nonlinearity. Rejection of the null of non-causality in the nonlinear framework, while the linear test fails to reject, indicates the presence of important nonlinear transmission channels.

Results and Discussion
Descriptive Statistics
Table 1 presents descriptive statistics for the daily return series of the sectoral indices, the USD/INR rate, the MCX index, and the GEPU series. Mean returns are positive across all variables. The information-technology sector (CNXIT) records the highest mean return (0.073), followed by the automobile sector (0.015) and the MCX index (0.015). Median returns are generally lower than means, indicating right-skewed distributions. CNXIT exhibits extreme skewness (11.21) and kurtosis (129.67), reflecting the presence of large positive outliers. GEPU itself displays high positive skewness (6.95) and kurtosis (65.98), consistent with occasional sharp spikes in policy-related search intensity.

Volatility, measured by standard deviation, is highest for CNXIT (0.738), followed by MCX (0.119) and the realty sector (0.102). The exchange rate (INR_X) and the FMCG sector display comparatively low volatility. Jarque-Bera tests reject normality for most series at conventional significance levels; only CNXFMCG and CNXPSUBANK fail to reject the null of normality. These distributional features underscore the heterogeneity of risk profiles across Indian financial market segments and motivate the use of methods robust to non-normality and potential nonlinear dependence.

Table 1: Descriptive Statistics of Daily Return Series

Statistic	AUTO	FMCG	IT	MEDIA	METAL	PSUBNK	REALTY	INR	MCX	GEPU
Mean	0.0154	0.0126	0.0731	0.0068	0.0126	0.0116	0.0163	0.0038	0.0152	1.8672
Median	0.0231	0.0085	0.0185	0.0013	0.0130	-0.0002	0.0007	0.0029	0.0057	-0.2447
Maximum	0.2473	0.1280	8.5581	0.3351	0.3055	0.3188	0.3557	0.1115	0.3709	172.95
Minimum	-0.3147	-0.0990	-0.9273	-0.3775	-0.2939	-0.3191	-0.3744	-0.0714	-0.4140	-50.654
Std. Dev.	0.0663	0.0416	0.7377	0.0806	0.0907	0.1101	0.1016	0.0205	0.1189	17.884
Skewness	-0.882	0.104	11.210	0.012	0.219	0.227	0.155	0.840	0.248	6.954
Kurtosis	7.369	2.908	129.67	7.673	4.079	3.221	4.595	9.549	4.324	65.980
Jarque-	126.77	0.293	94464	124.68	7.735	1.457	15.076	260.91	11.420	23746

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Probability	0.000	0.864	0.000	0.000	0.021	0.483	0.001	0.000	0.003	0.000

Note: AUTO = CNXAUTO; FMCG = CNXFMCG; IT = CNXIT; MEDIA = CNXMEDIA; METAL = CNXMETAL; PSUBNK = CNXPSUBANK; REALTY = CNXREALTY; INR = USD/INR; MCX = MCX Commodity Index; GEPU = Google-based Economic Policy Uncertainty.

Unit Root Test Results

Table 2 summarises the results of the ADF, Phillips-Perron, and KPSS tests. For every seriessectoral returns, the exchange-rate return, the MCX return, and the change in GEPU the ADF and PP statistics are significantly negative, with p-values well below 0.01, leading to rejection of the unit-root null. The KPSS test statistics lie below the 10 percent critical values, so the null of stationary is not rejected. Collectively, the three tests provide strong evidence that all return series and the GEPU change series are stationary at levels and are therefore suitable for subsequent Granger causality analysis without further differencing.

Table 2: Unit Root Test Results

Variable	ADF (p-val)	PP (p-val)	KPSS Stat.	Conclusion
CNXAUTO	< 0.01	< 0.01	0.181	Stationary at level
CNXFMCG	< 0.01	< 0.01	0.102	Stationary at level
CNXIT	< 0.01	< 0.01	0.105	Stationary at level
CNXMEDIA	< 0.01	< 0.01	0.148	Stationary at level
CNXMETAL	< 0.01	< 0.01	0.222	Stationary at level
CNXPSUBANK	< 0.01	< 0.01	0.253	Stationary at level
CNXREALTY	< 0.01	< 0.01	0.250	Stationary at level
USD/INR	< 0.01	< 0.01	0.093	Stationary at level
MCX	< 0.01	< 0.01	0.220	Stationary at level
GEPU	< 0.01	< 0.01	0.128	Stationary at level

Note: ADF and PP null = unit root; KPSS null = stationarity. Critical values for KPSS (approx.): 0.347 (10%), 0.463 (5%). All series are stationary at conventional significance levels.

Linear Granger Causality Results

Table 3 reports the results of the linear Granger causality tests. For the great majority of pairwise relationships, the null hypothesis of no Granger causality cannot be rejected at the 5 percent level in either direction. Past values of GEPU do not linearly predict the returns of the automobile, FMCG, IT, media, private-sector banking, or realty sectors, nor do they predict the USD/INR rate or the MCX index. Conversely, none of these market variables Granger-cause GEPU in a linear sense. The sole marginal exception is the relationship running from GEPU to the metals sector ($p = 0.0606$), which is significant only at the 10 percent level and therefore constitutes weak evidence at best.

The absence of widespread linear causality does not imply the absence of economic relationships. Financial markets frequently exhibit nonlinear, threshold, or state-dependent responses to uncertainty shocks. Linear tests average across regimes and may therefore lack power to detect such dynamics. This consideration motivates the application of nonlinear causality tests.

Table 3: Linear Granger Causality Tests

Direction	F-Statistic	p-value	Conclusion
CNXAUTO → GEPU	0.0784	0.9246	No causality
GEPU → CNXAUTO	0.2548	0.7754	No causality
CNXFMCG → GEPU	2.1367	0.1222	No causality
GEPU → CNXFMCG	0.7416	0.4784	No causality
CNXIT → GEPU	0.0835	0.92	No causality
GEPU → CNXIT	0.985	0.3762	No causality
CNXMEDIA → GEPU	0.4707	0.6257	No causality
GEPU → CNXMEDIA	2.1844	0.1167	No causality
CNXMETAL → GEPU	1.3259	0.2691	No causality
GEPU → CNXMETAL	2.8644	0.0606	Weak causality ($p < 0.10$)
CNXPSUBANK → GEPU	1.3758	0.2563	No causality
GEPU → CNXPSUBANK	0.4021	0.6697	No causality
CNXREALTY → GEPU	1.4829	0.2308	No causality
GEPU → CNXREALTY	0.8364	0.4356	No causality
INR=X → GEPU	0.2399	0.7871	No causality
GEPU → INR=X	0.1867	0.8299	No causality
MCX → GEPU	0.2865	0.7514	No causality
GEPU → MCX	0.1571	0.8548	No causality

Note: Reverse directions (market variable → GEPU) are similarly insignificant in all cases and are omitted for brevity.

Nonlinear Granger Causality Results

Table 4 presents the nonlinear Granger causality results. In contrast to the linear findings, several statistically significant unidirectional relationships from GEPU to market variables emerge. GEPU nonlinearly Granger-causes returns in the media sector ($p = 0.0086$), the metals sector ($p = 0.0001$), the private-sector banking sector ($p < 0.001$), and the realty sector ($p = 0.0302$). In addition, GEPU significantly predicts the USD/INR exchange rate in a nonlinear fashion ($p = 0.0056$). No significant nonlinear causality is detected running from the market variables back to GEPU, nor is there evidence of nonlinear causality from GEPU to the automobile, FMCG, IT, or MCX series.

These results indicate that the transmission of Google-based policy uncertainty into Indian financial markets is predominantly nonlinear and sector-specific. Sectors with high policy sensitivity banking, real estate, metals (which are influenced by infrastructure and industrial policy), and media (sensitive to regulatory and advertising-cycle uncertainty) exhibit clear nonlinear responses. The significant effect on the exchange rate is consistent with the role of policy uncertainty in driving capital-flow volatility and currency risk premia. The absence of linear causality alongside the presence of nonlinear causality underscores the methodological importance of employing tests capable of detecting non-linear dependence structures.

Table 4: Nonlinear Granger Causality Tests (Selected Results)

Direction	GCI	F-Statistic	p-value	CV	Conclusion
CNXAUTO → GEPU	0.0119766	0.0828342	0.999999	1.746	No causality
GEPU → CNXAUTO	0.167885	1.25675	0.238252	1.746	No causality
CNXFMCG → GEPU	0	-0.123377	1	1.746	No causality
GEPU → CNXFMCG	0.138791	1.02358	0.438067	1.746	No causality
CNXIT → GEPU	0	-0.337042	1	1.746	No causality
GEPU → CNXIT	0.154704	0.408438	0.997748	1.698	No causality
CNXMEDIA → GEPU	0.0274567	0.0679554	1	1.698	No causality
GEPU → CNXMEDIA	0.278399	2.20696	0.00859587	1.746	Significant causality ($p < 0.01$)
CNXMETAL → GEPU	0.0271061	0.188903	0.999756	1.746	No causality
GEPU → CNXMETAL	0.393385	3.31367	0.00010087	1.746	Significant causality ($p < 0.001$)
CNXPSUBANK → GEPU	0	-0.026747	1	1.698	No causality
GEPU → CNXPSUBANK	0.871323	9.55674	1.87E-14	1.746	Significant causality ($p < 0.001$)
CNXREALTY → GEPU	0.102236	0.262779	0.999979	1.698	No causality
GEPU → CNXREALTY	0.241265	1.8759	0.0301524	1.746	Significant causality ($p < 0.05$)
INR=X → GEPU	0.0930681	0.670563	0.817101	1.746	No causality
GEPU → INR=X	0.598919	2.00213	0.00556572	1.698	Significant causality ($p < 0.01$)
MCX → GEPU	0	-0.112986	1	1.698	No causality
GEPU → MCX	0.198849	1.51248	0.107866	1.746	No causality

Note: Results for reverse causality (market → GEPU) are insignificant in all cases.

Discussion

The empirical findings carry several implications. First, the clear contrast between linear and nonlinear results demonstrates that conventional linear Granger tests can understate the influence of policy uncertainty on asset prices. Investors and risk managers who rely solely on linear models may underestimate the impact of rising Google-based uncertainty on specific sectors and on the exchange rate.Second, the sectoral pattern of nonlinear causality is economically intuitive. Private-sector banks are directly exposed to interest-rate policy, credit regulations, and fiscal measures that affect asset quality. Real-estate markets respond strongly to changes in interest rates, stamp duties, and housing policy. Metals producers are sensitive to infrastructure spending, import duties, and industrial policy. Media firms face regulatory uncertainty and advertising-cycle volatility linked to broader economic confidence. The significant nonlinear effect on USD/INR is consistent with the role of policy uncertainty in shaping foreign-investor sentiment and capital-flow dynamics.

Third, the lack of significant causality for FMCG, automobiles, and IT suggests that these sectors may be driven more by firm-specific fundamentals, global technology cycles, or domestic consumption trends that are less immediately sensitive to the particular form of policy uncertainty captured by

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Google search intensity. The absence of a nonlinear link with the broad MCX index may reflect the heterogeneous composition of the commodity basket, in which safe-haven precious metals and cyclical energy or agricultural commodities can respond in offsetting directions.

Overall, the results support the view that Google Trends-based measures of economic policy uncertainty contain incremental information about future movements in selected Indian financial markets, but that this information is transmitted primarily through nonlinear channels.

Conclusion

This study has examined the relationship between Google-based Economic Policy Uncertainty (GEPU) and key segments of the Indian financial system NSE sectoral equity indices, the USD/INR exchange rate, and the MCX commodity index over the period 2007–2024. By combining high-frequency search data with both linear and nonlinear Granger causality techniques, the analysis provides new evidence on how digital measures of policy-related anxiety are transmitted into asset prices in an emerging-market setting.

Three principal conclusions emerge. First, all return series and the GEPU change series are stationary at levels according to ADF, Phillips-Perron, and KPSS tests, establishing a sound statistical foundation for subsequent causality analysis. Second, linear Granger causality tests detect virtually no significant predictive relationships running from GEPU to market variables (or vice versa), with only marginal evidence for the metals sector. Third, and most importantly, nonlinear Granger causality tests reveal robust unidirectional effects from GEPU to the media, metals, private-sector banking, and realty sectors, as well as to the USD/INR exchange rate. These findings indicate that the impact of Google-based policy uncertainty is both sector-specific and inherently nonlinear.

The results carry practical implications for multiple stakeholders. Portfolio managers and risk officers should monitor GEPU as a real-time indicator of latent stress in policy-sensitive sectors and in the currency market; linear risk models that ignore nonlinear dependence may understate exposure during periods of elevated search intensity. Policymakers can use the sectoral pattern of responses to refine the communication of major policy initiatives, thereby reducing unnecessary volatility in banking, real-estate, and industrial-metal markets. Financial analysts and researchers gain confirmation that alternative data sources such as Google Trends contain economically meaningful information that is not fully captured by traditional newspaper-based uncertainty indices.

Several limitations should be acknowledged. The analysis focuses on Granger causality and does not formally model volatility spillovers or time-varying connectedness; future work could usefully employ GARCH-type models, Diebold-Yilmaz spillover indices, or wavelet-based coherence measures to characterize the dynamic intensity of transmission. The study also treats GEPU as a single aggregate index; disaggregating search terms by policy domain (monetary, fiscal, trade, regulatory) may reveal more granular channels of influence. Finally, the sample ends in 2024; continuous updating of the GEPU series would allow real-time monitoring of evolving relationships.

In sum, the evidence presented here demonstrates that Google-based Economic Policy Uncertainty exerts statistically and economically significant nonlinear effects on selected Indian equity sectors and on the exchange rate. By integrating alternative data with rigorous econometric testing, the study contributes to a growing literature that seeks to understand how digital traces of collective attention shape financial market outcomes in emerging economies. Continued research along these lines promises both deeper theoretical insight and more effective practical tools for investors and policymakers navigating an increasingly uncertain economic environment.

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