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ORIGINAL RESEARCH

The Impact of Directional Global Economic Policy Uncertainty on Indian Stock Market Volatility: New Evidence

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Abstract

This paper examines the effect of economic policy uncertainty (EPU) on the Indian capital market using the generalized autoregressive conditional heteroscedastic mixed data sampling (GARCH-MIDAS) approach. This study also disintegrates the Global EPU (GEPU) on its components using identity functions such as up, down, and composite parts dependent on the adjustment in the heading of the EPU and GEPU and tests the linkages among these parameters and the Indian securities exchange instability. Our empirical study shows that GEPU positively and significantly impacts the Indian capital market's volatility. That indicates that the Indian capital exchange volatility will also be unstable when the global economic policy uncertainty is higher. Further, based on the dynamic directions of EPU and GEPU, our results show that, in diverse situations, directional GEPU may present differently in predicting the uncertainty in the Indian capital market. This is primarily so when EPU and GEPU climb in the same period when our approach can obtain more powerful prediction precision.

Keywords Economic policy uncertainty (EPU) · Global economic policy uncertainty (GEPU) · GARCH-MIDAS model

JEL Classification E60 · F40 · G30

1 Introduction

Risk management is one of the most important criteria for financial institutions, economic policymakers, and individual investors. Volatility can influence portfolio allocation, hedging strategies, instrument pricing, and risk administration decisions. Consequently, correct volatility forecasting becomes crucial for financial and economic practitioners.

Extended author information available on the last page of the article

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Economic policy uncertainty is regarded as a risk in which government guidelines and regulatory frameworks are unclear for the near future. This phenomenon may guide corporations and individuals to defer spending and investments because of uncertainty in the market. The Global Economic Policy Uncertainty Index is a GDP-weighted average of national EPU indices for 20 countries: Australia, Brazil, Canada, Chile, China, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States.

Many pieces of literature analyze the impact of policy uncertainty on the economy over 30 years (Aizenman & Marion, 1999; Bernanke, 1983; Mishra et al., 2022; Rodrik, 1991). Academicians principally concentrate on assessing the impacts of strategy vulnerability on macroeconomic factors, for example, development, growth, and speculation (Baum et al., 2010; Jones & Olson, 2013). It has been found in many studies that economic policy uncertainty (EPU) exerts essential effects on asset prices in different markets, including stock, future, commodities, and insurance; therefore, EPU can act as an essential economic tool. Economic policy uncertainty alludes to the non-zero likelihood of fluctuations in the current financial arrangements that decide monetary specialists (Baker et al., 2016). The impact of EPU on resource costs can operate along various channels. Firstly, strategy contingency could alter or postpone firms' and other monetary policy makers' meaningful choices like work, speculation, utilization, and sparing options (Gulen & Ion, 2016). Secondly, arrangement vulnerability may build financing and creation costs by influencing flexibility and request channels, increasing disinvestment, and monetary compression. Thirdly, EPU may expand chances in economic sectors by decreasing the estimation of securities given by the administration to business sectors (Pastor & Veronesi, 2012). At last, financial uncertainty may likewise influence growth and interest rates.

The rise in economic stability since the financial crisis in 2009 attracted the interest of many economists and policymakers towards the impact of economic policy uncertainty on the monetary markets, including various global macroeconomic indicators. It may cause uncertainty in business output and might also slump financial markets. However, the extent of the influence of uncertainty on these variables varies from region to region depending upon the political structure and ideology towards business, geography, and capital markets. The impact of uncertainty on growth is less obvious as it relies upon worldwide stuns, the oil crisis, oil value stuns, as indicated by Jones and Olson (2013).

Numerous studies measure spillover outcomes of economic policy uncertainty in other markets. Some studies have shown a negative long-term dependence of the economic policy certainty with the stock market returns in the framework of the GARCH-MIDAS (Asgharian et al., 2013; Conrad & Loch, 2015; Engle et al., 2013; Girardin & Joyeux, 2013). EPU can be sent to different nations at an unforeseen speed and inevitably formed into a worldwide emergency. As a source of such significant market data, any financial vulnerability in the United States will be instantly worried by unfamiliar speculators and could bring about reforms and vacillations in resource costs. Afterwards, it turns into a channel of the market virus.

Economic policy uncertainty can impact stock market volatility in several ways. EPU can create uncertainty about future economic conditions, which can lead to increased volatility in the stock market as investors may become more cautious and uncertain about the economy's future direction. It can also lead to reduced investor confidence, as investors may be uncertain about future investment returns. This can lead to increased volatility in the stock market as investors may become more cautious and uncertain about the economy's future direction. It can also increase the risk associated with investments, making it more difficult for investors to manage and mitigate risk. This can lead to increased volatility in the stock market. EPU can also lead to reduced capital flows. EPU creates an environment of uncertainty that can lead to increased volatility in the stock market as investors may become more cautious and uncertain about the future direction of the economy. This can affect the firm's overall performance and make it difficult for managers to make strategic decisions.

Economic policy uncertainty can significantly impact the volatility of the Indian stock market. Some managerial impacts include investment decisions regarding uncertainty about future investment returns, difficulty in risk mitigation, difficulties in accessing financial decisions, a decline in production and employment, and increased overheads on business operations and international trade. Economic policy uncertainty can lead to increased volatility in the stock market, as investors may become more cautious and uncertain about the economy's future direction (Mishra et al., 2022, 2023). All these impacts can affect the firm's overall performance and make it difficult for managers to make strategic decisions.

Existing papers have studied the relationship between global EPU and domestic EPU on many macroeconomic variables and the volatility of stock market returns. Chiang's (2019a, b) paper discusses the effects of international, U.S., U.K., and Japan EPU on five Asian stock market returns. However, research involving a directional index depending on the changes of GEPU and EPU on domestic stock prices has not been found. Li et al. (2020a, 2020b) discuss this index and its higher forecast accuracy regarding domestic Chinese stock returns volatility compared to the usage of GEPU. Research in the Indian stock market on the expected impacts of GEPU and EPU, especially considering their direction, is missing.

Against this backdrop, our paper examines the effect of financial strategy vulnerability (EPU) on the Indian capital market. This paper aims to study the relationship between the global and the domestic GPU in the Indian capital market and consider the direction of the movements. This study also disintegrated the Global EPU on its components using identity functions such as up, down, and composite parts dependent on the adjustment in the heading of the EPU and GEPU and tested the linkages among these parameters and Indian securities exchange instability. Our empirical study shows that GEPU positively and significantly impacts the Indian capital market's volatility. Further, based on the dynamic directions of EPU and GEPU, our results show that, in diverse situations, directional GEPU may present differently in predicting the uncertainty in the Indian capital market. This is primarily so when EPU and GEPU climb in the same period when our approach can obtain more powerful prediction precision.

The remainder of this article is organized as follows. The next section presents the relevant literature. The third section discusses the application of the GARCH-MIDAS model and other extended models, including the EPU and GEPU indices and describes the data used. The fourth section presents the empirical findings and purports to explore their implications. The concluding section summarizes the main results and concludes the study.

2 Literature Review

In their research, Li et al. (2019a, b) examined the effect of global economic policy uncertainty (GEPU) on the unpredictability of the Chinese securities exchange. They investigate the impacts of directional components of GEPU on the dynamic behaviour of GEPU and the monetary strategy vulnerability of China. The in-example assessed results show that GEPU can prompt high financial exchange instability in the Chinese mainland. The out-of-test assessed outcomes uphold the dispute that GEPU helps anticipate unpredictability. They also conclude that directional GEPU can give more valuable data to expand the conjecture exactness and locate that directional GEPU is more potent in forecasting Chinese EPU when GEPU and EPU ascend in the same month. In their paper, Liu and Zhang (2015) research the consistency of financial arrangement unsureness to securities exchange volatility. The in-sample proof supports that higher EPU prompts massive expansions in market volatility. Out-of-test results show that consolidating EPU as an extra prescient variable into the current unpredictability expectation models improves these models' determining capacity. The improvement is substantial in the model details.

Asgharian et al. (2018) in their paper, underscore the importance of U.S. economic uncertainty and other stock market types. The long-run stock market volatility of the UK, Germany, China, and Canada is significantly dependent on the U.S. economic policy uncertainty (EPU) shocks. They found regulation, taxes, and fiscal policy to be important EPU indices, while they did not find monetary policy shocks to be that important. Kearney and Lombra (2004) use the Black–Scholes options prices model and find a positive relationship between volatility and risk-free interest rates. On an unexpected announcement regarding employment changes, federal funds rate and three months Treasury bill rates were positively related.

Li et al. (2019a, b), in their paper, find significant hostile relations between Chinese stock market volatility and the EPU of China, the U.S., the U.K., and Germany, indicating the considerable effect of foreign countries' policies. Chaudhuri and Koo (2001) contradict other papers' findings of the relation between U.S. stock prices and volatility in developing countries' equity prices (India, Malaysia, South Korea, Thailand), finding it insignificant. However, Japan's stock exchange prices were found to be significantly affecting other neighbouring countries' stock prices. Strong geographical dependence and contagion effects are noticed in developing Asian countries resulting in the integration of capital markets. Government roles involving fiscal and monetary changes are correlated with stock market volatility, indicating the crucial role of government in developing countries.

Hoque et al. (2020), in their study, find that global and country-specific geopolitical risk on stock returns of developing countries like India, Indonesia, Brazil, South Africa, and Turkey is nonlinear and asymmetric, thus requiring a nonlinear model for estimation. The effects of country-specific risk are heterogeneous in different countries due to each developing country's unique characteristics. Also, political unrest negatively affects the stock market returns in developing countries. Baker et al. (2016) built up another index file of EPU because of newspaper coverage frequency. They find that policy uncertainty is related to more prominent stock value instability, decreased speculation, and work in delicate arrangement areas like safeguarding, medical care, and infrastructure. At the full-scale level, developments in policy vulnerability hint at declines in the venture, yield, and employment in the United States and, in a board vector autoregressive setting, for 12 significant economies. A related literature examines the effect of EPU on the U.S. Economy by employing a VAR with time-fluctuating coefficients (Purser & Schlosser, 2020). They discover three distinct systems which coordinate the U.S. economy's three significant times, particularly the Great Inflation, the Great Moderation, and the Great Recession. The unfavourable impacts of EPU are more dynamic during the Great Recession clarifying the moderate recovery.

The structural VAR can quantify the macroeconomic effects of policy uncertainty. The study by Colombo (2013) investigates the influence of uncertainty policy shock on macroeconomic variables in some Euro areas. The study's findings indicate one standard deviation shock in policy uncertainty in the U.S. points to a statistically significant decline in European industrial products. Stronger and developed economies usually have a contagion effect on the financial markets of the developing world. Another study by uses a wavelet approach to establish the economic policy uncertainty in Indian and Chinese markets. The results indicated a weak short-term effect of the U.S. economic policy uncertainty on both markets in the short run.

However, the effect is significant, mainly when a substantial financial occurrence occurs. Measuring the causal relationship between economic policy uncertainty and stock returns can sometimes result in inaccurate results, especially if the time series is exceedingly long due to structural changes in the entire sample. Liu and Zhang (2015) use a bootstrap rolling window approach to identify time-varying casualties. The study finds bi-causal relationships between EPU and stock returns in sub-periods rather than the entire series. A non-parametric causality in Quantiles test by Li et al. (2016) allows not only to test for causality in the mean but also in the tails of the joint distribution of variables. The study uses relative uncertainty, the differential between domestic and U.S. uncertainties. Hence, the study contributes to the existing literature by detecting a nonlinear relationship and the existence of structural breaks in exchange rate returns.

Moreover, if capital speculations are irreversible and recruiting and terminating representatives is exorbitant, organizations will concede making capital speculations or employing representatives when confronted with expanded vulnerability (Pindyck, 1990). As organizations disclose contributing and engaging, the economy eases back down. An expansion in business vulnerability will likewise build the expense of capital and administrative hazard avoidance prompting a negative effect on business ventures and recruiting (Panousi & Papanikolaou, 2012; Pastor

& Veronesi, 2012). Finally, Freidman (1968) contended that a vulnerability in financial strategy negatively affects economic development. The pessimism in markets can be sensed by an economic policy uncertainty index (EPU). However, this is not always true, as EPU might sometimes skew returns to the positive when an increase in uncertainty induces an increase in stock rose bonus and hence higher prices in the market (Brogaard & Detzel, 2015).

Paule-Vianez et al. (2020a, b) have studied the effect of Economic Policy Uncertainty (EPU) and Monetary Policy Uncertainty (MPU) on the return, volatility, and liquidity of the stock markets. They found that EPU has a more significant effect on return and volatility during periods of recession, having only an impact on liquidity during expansion periods. In contrast, MPU influences return and volatility more during periods of expansion and liquidity only during periods of recession. These findings demonstrate the existence of behavioural biases consistent with Behavioural Finance and the importance of controlling uncertainty on the part of economic policymakers to avoid the damages that EPU and MPU can generate in the stock markets. Bhagat and Bolton (2014), in their work, have studied the effects of uncertainty in the economic policy of India on the economic growth and flow of investments in the country. Their findings show that economic policy uncertainty can have a substantial economic impact and negatively affect economic growth and investment inflow. The BSE index returns are also negatively correlated with EPU as an increase in EPU increases investors' risk, leading to a decrease in investments.

Arouri et al. (2016) add to the literature by considering the effect of EPU on securities exchanges in the United States from 1900 to 2014. They show that an expansion in policy vulnerability fundamentally diminishes stock returns and that this impact is more grounded and determined during outrageous unpredictability periods. Caggiano et al. (2020) gauge a nonlinear VAR to evaluate US EPU shocks' effect on the Canadian unemployment rate during booms and recessions. Canada's unemployment rate appears to respond even more firmly to vulnerability shocks in monetary busts. Counterfactual recreations highlight a novel 'monetary approach vulnerability overflows channel.' As indicated, U.S. vulnerability movements encourage economic arrangement volatility in Canada in any case and, due to the last mentioned, lead to a transitory expansion in the Canadian unemployment rate. A record of unbalanced spillover impacts has been found for the U.K. economy, whose trade intensity with the U.S. is low.

The current research on Economic Policy Uncertainty in the Indian economy is lacking in several areas. There is a need for more comprehensive studies that examine the impact of policy uncertainty on various sectors of the economy, such as agriculture, manufacturing, and services by incorporating industry specific indices such as industrial production. Additionally, there is a need for research that analyzes the effect of economic policy uncertainty on specific industries within these sectors, as well as the impact of economic policy uncertainty on the various regions of India. Furthermore, there is a need for research comparing India's economic policy uncertainty with other developing countries to understand how it affects economic growth and development. The existing literature tends to focus on the relationship between uncertainty and risk factors in developed economies, but there needs to be more analysis in major developing economies like India. Additionally, the existing literature tends to rely on a single criterion of risk or uncertainty, which does not allow for a precise understanding of the essence of uncertainty. Furthermore, the existing literature does not use control variables to identify the difference in the average results amongst the economic and control variables that are not of significant interest in the study's goal but are controlled to affect the outcomes. Finally, it would be interesting to examine whether the asymmetric uncertainty spillover patterns also present from the Indian market to other financial markets.

3 Data and Methodology

3.1 Source of Data and Description

The monthly data cover a long-chronicled period, from 2004M1 to 2020M8, including a few scenes of monetary emergencies. The Indian stock index is taken to be the NIFTY-50 index. For EPU, we utilize the index built by Baker et al. (2016). This record is a weighted normal of three vulnerability segments:

1. The quantity of government charge code arrangements set to terminate in future years
2. A proportion of contradiction among monetary forecasters as an intermediary for vulnerability

The Indian Economic Policy Uncertainty index and GEPU is retrieved from the Economic Policy Uncertainty website (http://www.policyuncertainty.com/), and next, we procure 200 cyclical data points. Risk premium (used as a proxy for default spread) data is obtained from https://countryeconomy.com/risk-premium/india. Interest Rate and Exchange rates data are retrieved from the World Bank dataset.

4 Methodology

4.1 Linear Regression

To investigate whether economic policy uncertainty influences capital markets, we explore a class of linear regressions in which we regress the capital market return R_{it} on a constant term, the lagged return, a vector of contingency variables (UNRT), and a vector of control variables (CONTROL):

$$R_{it} = \alpha + \beta R_{i,t-1} + \phi' UNCERT + \varphi' CONTROl + \varepsilon_{it} \tag{1}$$

Equation 1 models a linear specification of stock returns when the parameters are assumed to be constant.

Here, we include some economic variables that are determined to be linked with EPU and capital markets. EPU might represent other economic and financial variables that influence stock returns. Therefore, we need to regulate these economic variables, which act as uncertain variables when examining the impact of EPU on capital markets. We introduce the control variables to investigate the difference in the mean outcome amongst the economic and control variables, which are not of significant interest in the study's goal but are controlled to influence the results. The variables we look into are: changes in industrial production (RIP_t), default spread (DS_t), Inflation (INF_t), and change in unemployment (UNEMPt).

The control variables are included to account for potential confounding factors or alternative explanations that may influence the relationship between economic policy uncertainty (EPU) and capital markets. These control variables are economic variables that have been identified as being linked to both EPU and stock returns, but they are not the primary focus of the study. By including these control variables in the regression model, we can isolate the specific impact of EPU on stock returns, while controlling for the effects of these other variables. The specific control variables mentioned are: Changes in Industrial Production, Default Spread, Inflation, Change in Unemployment. By adding these, we aim to capture the impact of these economic factors and its potential influence on stock returns, independent of EPU.

The role of these control variables is to control for the effects of these economic factors that may have a simultaneous relationship with both EPU and stock returns. By including these variables in the regression models, we aim to isolate the specific impact of EPU on stock returns, taking into account the potential influence of these control variables. This helps to provide a more accurate assessment of the relationship between EPU and capital markets by accounting for alternative explanations and potential confounding factors. In other words, this set of control variables is employed to improve the internal validity of the model by limiting the influence of confounding and other extraneous variables. This assists us in establishing a correlational or causal relationship between variables of interest and aids in the avoidance of study bias.

However, a major disadvantage of the above model is that the model parameters of the above linear relationship are assumed to be time-invariant. However, structural changes due to switching regimes or other variables may cause different states of uncertainty and affect the EPU-stock market relationship. Regime-switching environments are modelled using an n-state Markov process, with EPU being one of the variables.

$$R_{it} = \alpha_{st} + \beta_{st} R_{i,t-1} + \phi_{st}\prime UNCERT + \varphi_{st}\prime CONTROl + \varepsilon_{it} \tag{2}$$

Equation 2 tries to model a linear specification of stock returns under a regime-switching environment. Here, ε_{it} ~ N (0, $\sigma^2_{S_t}$), where S_t is a dummy variable with values ranging from 1 to n, signifying different regimes in an n-state Markov process.

The need for change among states and the term in a specific state are irregular. The changes follow a Markov cycle. We can gauge state-ward and state-free boundaries. We are permitting states to switch as per a Markov cycle. Allow for brisk changes after a difference in the state.

The model can be composed as:

$$y_t = \mu_{s_i} + x_t\alpha + z_t\beta_{s_i} + \varepsilon_s \tag{3}$$

where y_t is the dependent variable, μ_s is the state-dependent intercept, x_t is a vector of exogenous variables with state-invariant coefficients α, z_t is a vector of exogenous variables with state-dependent coefficients β_s, and ε_s is an independent and identically distributed normal error with mean 0 and state-dependent variance σ_s^2. x_t and z_t may contain lags of y_t. MSDR models allow states to switch according to a Markov process.

This model fits dynamic relapse models that show various elements across surreptitious states utilizing state-subordinate boundaries to oblige auxiliary brakes or other numerous state wonders. These models are known as Markov-exchanging models because the changes between the covert state follow a Markov chain.

4.2 GARCH-MIDAS Model

Lately, the GARCH-MIDAS model has gotten significant consideration in the scholarly community; for example, Fang et al. (2018), Engle et al., (2013), Wei et al. (2017), Pan et al. (2017), Li et al. (2020a, 2020b). We initially depict the GARCH-MIDAS demonstration and expect the gains (r) on the day i in month t can be composed as:

$$r_{j,t} = \mu + \sqrt{\tau_t g_{j,t}}\varepsilon_{j,t}, \forall j = j, \dots, N_t \tag{4}$$

where, $\varepsilon_{j,t} \mid \Phi_{j-1,t} \sim N(0,1)$ with $\Phi_{j-1,t}$ is the information set up on the day(j−1) of period t. Here, the volatility component in Eq. (4) $\sqrt{\tau_t g_{j,t}}$ can be communicated in two sections as a short-term element characterized by $g_{j,t}$ and a long-term element characterized by τ_t.

Further, following Engle et al., (2013) and Asgharian et al. (2013), we assume that the conditional variance of the short-term component is a daily GARCH (1,1) process as follows:

We expect the contingent change of the transient segment is an everyday traditional GARCH (1, 1) measure as follows:

$$g_{j,t} = (1 - \alpha - \beta) + \alpha\frac{\left(r_{j-1,t} - \mu\right)^2}{\tau_t} + \beta g_{j-1,t} \tag{5}$$

here, $g_{j,t}$ are a restrictive difference (GARCH segment), α, and β are boundaries of the ARCH and GARCH parts separately, and the boundaries ought to be happy with $\alpha > 0$ and β > 0. The long-term part τ_t is commonly characterized as a levelled acknowledged fluctuation with an exogenous variable dependent on a gradually changing weighted capacity in the system of the MIDAS model:

$$\log\log\left(\tau_t\right) = m + \theta\sum_{k=1}^{K}\varphi_k\left(w_1, w_2\right)RV_{t-k} \tag{6}$$

With $RV_t = \sum_{i=1}^{N_t} r_{i,t}^2$ where RV represents monthly realized variance, N_t is the length of the monthly realized variance, and K is the optimal lag length based on information criteria (say, for example, in our case, corresponding to the minimum value based on Schwartz Information Criteria (SIC)). Adding to this, m is an intercept term, and θ is the slope of the weighted effects of lagged monthly R.V. on the long-term volatility of the Indian stock market. Adding to this, the weighting scheme used in Eq. (6) can be calculated by the unrestricted Beta function (For details, pls. refer to Li and et al., (2020a, 2020b)). The GARCH-MIDAS model mentioned above is the basis for our standard in this writing.

4.3 The GARCH-MIDAS Model Including EPU and GEPU

The consequence of the Economic Policy Uncertainty on the Indian capital market volatility can be studied using the economic policy uncertainty. Thus, to investigate the impact of economic policy uncertainty (EPU) on Indian stock market volatility, we add EPU as an additional variable to Eq. (3), and the long-term component can be modified as below:

$$\log\log\left(\tau_t\right) = m + \theta \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) RV_{t-k} + \gamma \sum_{k=1}^{K} \varphi_k\left(w_1, w_2\right) EPU_{t-k} \tag{7}$$

On the other hand, to investigate whether the global EPU (GEPU) index contains useful predictive information for the Indian stock market, we further add GEPU to Eq. (7) and construct a new long-term component, named the GARCH-MIDAS-GEPU, and the formulation of this model is expressed by:

$$\begin{aligned} loglog\left(\tau_t\right) &= m + \theta \sum\nolimits_{k=1}^{K} \varphi_k\left(w_1, w_2\right) RV_{t-k} + \gamma \sum\nolimits_{k=1}^{K} \varphi_k\left(w_1, w_2\right) EPU_{t-k} \\ &\quad + \delta \sum\nolimits_{k=1}^{K} \varphi_k\left(w_1, w_2\right) GEPU_{t-k} \end{aligned} \tag{8}$$

Thus, to get a better understanding and have robust modelling of the Indian volatility, EPU is added as an additional variable to model long-term volatility components.

Further, whether the GEPU index helps predict volatility is verified by adding a GEPU variable to the existing Equation and constructing a new model. Also, the GEPU is disintegrated into two distinct segments dependent on the EPU direction. In particular, accepting EPU and GEPU move similarly in exact period t. As far as marked shift paces of the EPU and the GEPU, we develop two new records, up GEPU (GEPUU) and down GEPU (GEPUD), which are characterized individually as:

$$GEPUU(t) = GEPU(t).I(((GEPU(t) - GEPU(t-1))/GEPU(t-1) > 0)I((\frac{GEPU(t) - GEPU(t-1)}{GEPU(t-1)} > 0 \tag{9}$$

$$GEPUD(t) = GEPU(t).I(((GEPU(t) - GEPU(t-1))/GEPU(t-1) < 0)$$
$$I((\frac{GEPU(t) - GEPU(t-1)}{GEPU(t-1)} < 0 \tag{10}$$

where I(.) is the indicator function. According to up and down GEPU, we can use them to replace GEPU alone and have three different volatility models, named GEPU-U, -GEPU-D, and GEPU-UD.

4.4 Model Forecasting Performance Measures

In contrast to within-sample performance, the test unit fitness of a model is likewise critical to showcase standard members since they are highly concerned regarding the model's capacity to enhance future performance than its potential to study former examples (Wang et al., 2016). We partition our entire data units into segments, train data sets, and test sets. In particular, for our in-sample, we first use the time frame from 3rd February 2003 to 30th October 2020 as a test set assessment period. The simulating cycle is directed up by the end of the data unit set's time frame.

To evaluate the forecasting performance for a particular model's volatility, we use alternative measures of forecasting accuracy with the help of the loss function. The following two widely used loss functions, the root mean square error (RMSE) and the mean absolute percentage error (MAPE) in the literature on volatility forecast accuracy, are being used in the results section:

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}\left(\sigma_{i+1}^2 - E\left(\sigma_{i+1}^2\right)\right)^2}. \tag{11}$$

$$MAPE = \frac{1}{T}\sum_{i=1}^{T}\left|\frac{\sigma_{i+1} - E\left(\sigma_{i+1}\right)}{\sigma_{i+1}}\right| \tag{12}$$

where σ_{i+1}^2 is a real daily variance here and $E_i\left(\sigma_{i+1}^2\right)$ is the forecast of daily variance, and T is the number of observations to be forecasted.

5 Empirical Results

5.1 Markov-Switching Dynamic Regression (MSDR)

From the figure below (Fig. 1), there is an inverse relationship between the EPU and the stock market returns in India. Various models have been put into work in the paper to understand the impact of the EPU on stock market returns and the behaviour of this model during different periods of volatility (Table 1).

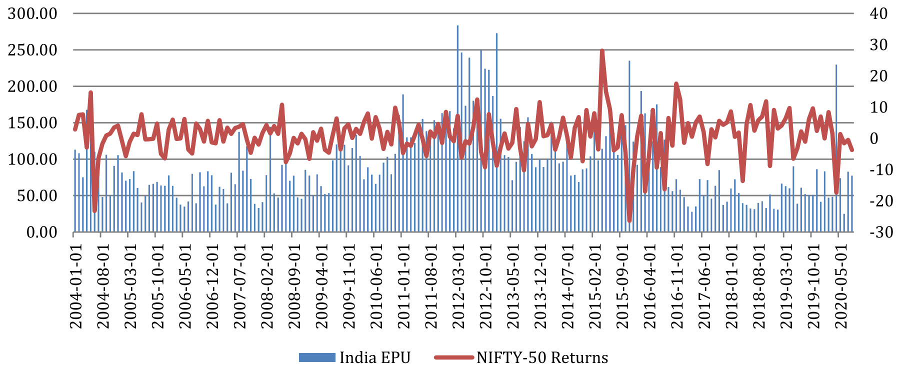

Fig. 1 The Indian EPU and Nifty-50 stock market returns(monthly data). *Source*: Generated by authors

Table 1 Indian stock market returns and changes in EPU. *Source*: Computed by authors

Variable	Obs	Mean	Std. Dev	Min	Max	Skewness	Kurtosis
Changes in EPU	200	0.5654169	40.12355	181.2115	155.6824	1.222451	4.475287
Returns	200	1.12325	6.557545	−26.41	28.07	−.4391777	6.157477

Table 2 Correlations between returns and changes in EPU. *Source***:** Computed by authors

	Rt	R_{t-1}	EPU	EPU_{t-1}	DS	IR	EXINRUS
R_t	1						
R_{t-1}	0.013	1					
EPU	−0.2052	−0.2165	1				
EPU_{t-1}	0.022	−0.2041	0.7011	1			
DS	−0.0089	0.0828	−0.0176	−0.052	1		
IR	−0.0136	0.0099	0.2396	0.2577	−0.0241	1	
EXINRUS	−0.0679	−0.0684	−0.0606	−0.0506	−0.1143	0.2434	1

(1) r_t—Returns at time t; r_{t-1}—Returns with a lag of 1 unit, epu—Economic Policy Uncertainty, epu_{t-1}—Economic Policy Uncertainty with a lag of 1 unit, ds—Default Spread; ir—Interest Rate; exinrus—Exchange Rate (INR US)

Based on the correlation matrix (Table 2), we can see from the table, and we see that the impact of EPU on the capital market returns is negative (−0.2052). Therefore, the increase in the EPU causes the stock market's returns to decrease by 0.2 units. Other factors such as Default spread, Interest rate, and exchange rate negatively affect the stock market's returns, but their values are negligible and almost independent of the market's returns.

Rather than just looking at the correlation between these variables and stock market returns, a more robust approach to looking at these variables' outcomes on the stock market returns is using a linear regression model. To begin with, we gauge the assortment of direct regression in which the securities exchange return (Rit) is regressed on a constant term, the lagged value of return, a vector of contingency factors (UNCERT), and a vector of control factors (CONTROL):

We incorporate some financial factors that have been demonstrated to be related to EPU and securities exchanges. A connection between EPU and capital market returns can mirror a fundamental "intermediary impact": EPU may speak to an intermediary for other financial factors that influence stock returns. Accordingly, we must control these financial factors when researching the impact of EPU on securities exchanges.

Our outcomes recommend that an ascent in interest rates expands financial exchanges, but it is insignificant at a 95% confidence interval. Even more, our discoveries on the impact of EPU on financial exchanges stay unaltered: the effect of economic policy vulnerability is negative and feebly determined (Table 3). Though many of the economic indicators that have been added to the model seem insignificant, the EPU is a proxy that mirrors other economic indicators that have not been considered.

5.2 Markov Switching Model and Granger Causality

Nonetheless, a significant shortcoming of the discoveries examined above is that they depend on direct determinations where the model boundaries are considered time-invariant. Hence, they do not consider conceivable essential breaks and system changes that may make fluctuating conditions of uncertainty in a regime-switching environment and influence the EPU-securities exchange relationship. In this way, it is fascinating to examine the impacts of EPU on securities exchanges under system exchanging as in Eq. (2) (Table 4).

In the above table, the mean of each state is given by _cons, and sigma indicates the single standard deviation of the entire process and p_{11}, and p_{21} shows the transition probabilities for states 1 to 1 and state 2 to 1. State two is a comparatively high rate state compared to state one based on the mean values. Both states are incredibly persistent (1- > 1 and 2- > 2 probabilities of 0.9894 and 0.9895).

Table 3 Regression analysis results. *Source***:** Computed by authors

Rt−1	EPU	EPUt−1	DS	IR	EXINRUS	_Cons
−0.0247	−0.0567***	0.0401***	−0.0121	0.1737	−0.0537	4.564
(0.0708)	(0.0123)	(0.0123)	(0.1090)	(0.3816)	(0.0430)	(3.048)

(1) r_t—Returns at time t; r_{t-1}—Returns with a lag of 1 unit, epu—Economic Policy Uncertainty, epu_{t-1}—Economic Policy Uncertainty with a lag of 1 unit, ds—Default Spread; ir—Interest Rate; exinrus—Exchange Rate (INR US)

(2) *** and ** indicate significance at the 1% and 2.5% levels, respectively

(3) The values in row 2 in () denote the standard error of the regression analysis

Table 4 Markov's switching model. *Source*: Computed by authors

EPU		Rt−1		EPUt−1		DS	IR	EXR
−0.0599***		−0.0653		0.0368***		−0.0114	0.4045	−0.046
0.0117		0.073		0.0115		0.1051	0.3744	0.0429
State1	_cons		State2		_cons	sigma	p11	p21
	2.955				20.47	5.731	0.9894	0.5455
	2.964				5.114	0.3303	0.0105	0.3090

(1) r_t—Returns at time t; r_{t-1}—Returns with a lag of 1 unit, epu—Economic Policy Uncertainty, epu_{t-1}—Economic Policy Uncertainty with a lag of 1 unit, ds—Default Spread; ir—Interest Rate; exinrus—Exchange Rate (INR US)

(2) *** indicates significance at the 1% level

(3) _cons—mean value of each state. Sigma—standard deviation. p11, p21—transition probability

(4) These results are based on Eq. (3)

We have just two states, so the likelihood of being in (state) state 2 discloses the likelihood for the two states. We can get the anticipated likelihood and chart it alongside the first information.

A two-stage model is sensible. States ∈ (State1, State 2); μ_1 is the mean in the intermediate rate state, and μ_2 is the mean in the high-rate state. We can utilize the switch with subordinate variable re-visitations to gauge the boundaries of the model. In the leading express, the state's mean estimation is 2.955%, and in the subsequent express, the meriting ends up being around 20%. What is being achieved here is the distinction between the more vulnerable and the more grounded times of the returns (maybe because of downturns or monetary ailment of the nation).

p_{11} is the assessed likelihood of remaining in state 1 in the following period, given that the cycle is in state 1 in the current period. The gauge of 0.9894 infers that state 1 is profoundly tenacious. Additionally, p_{21} is the likelihood of progressing to state 1 from state 2. The likelihood of remaining in state 2 is $1-0.5455=0.4545$, suggesting that state 2 is likewise not exceptionally relentless.

From the above graphs (Figs. 2 and 3), the returns move significantly over some periods and remain close to zero for the rest. This explains the classification by Markov's switching model with the non-switching parameters to change the state during different volatility periods. From the above table (Table 5), the expected duration of the states we get using Markov's process is approximately 7.8 years in the low volatility period and around 2 months in the high volatility period. From the graphs, we can see that the probability value of the state graph is one the entire duration where the volatility is low to moderate, i.e., the normal circumstances. Thus, the period to remain in state 1 is 78 units out of the 80 units considered. In the next set of graphs, we can see that the value of the State 2 goes to 1 only during high volatility regimes. We can see that the extreme volatility regime corresponds to these economic turmoil periods. More importantly, economic policy uncertainty influences capital market returns differently according to market states. More importantly, it

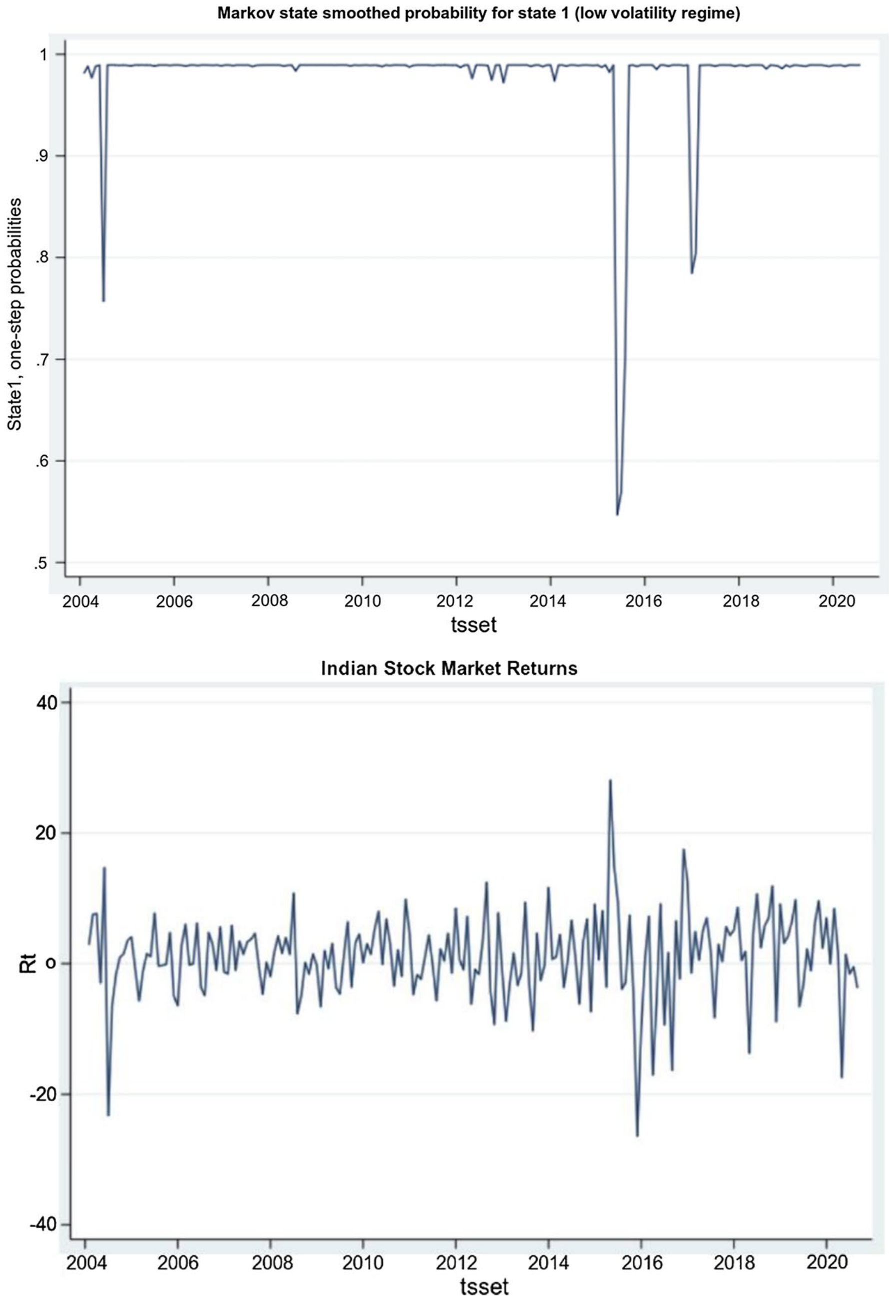

Fig. 2 Markov state smoothed probability for state 1 (low volatility regime) and Indian stock market returns. *Source*: Generated by authors

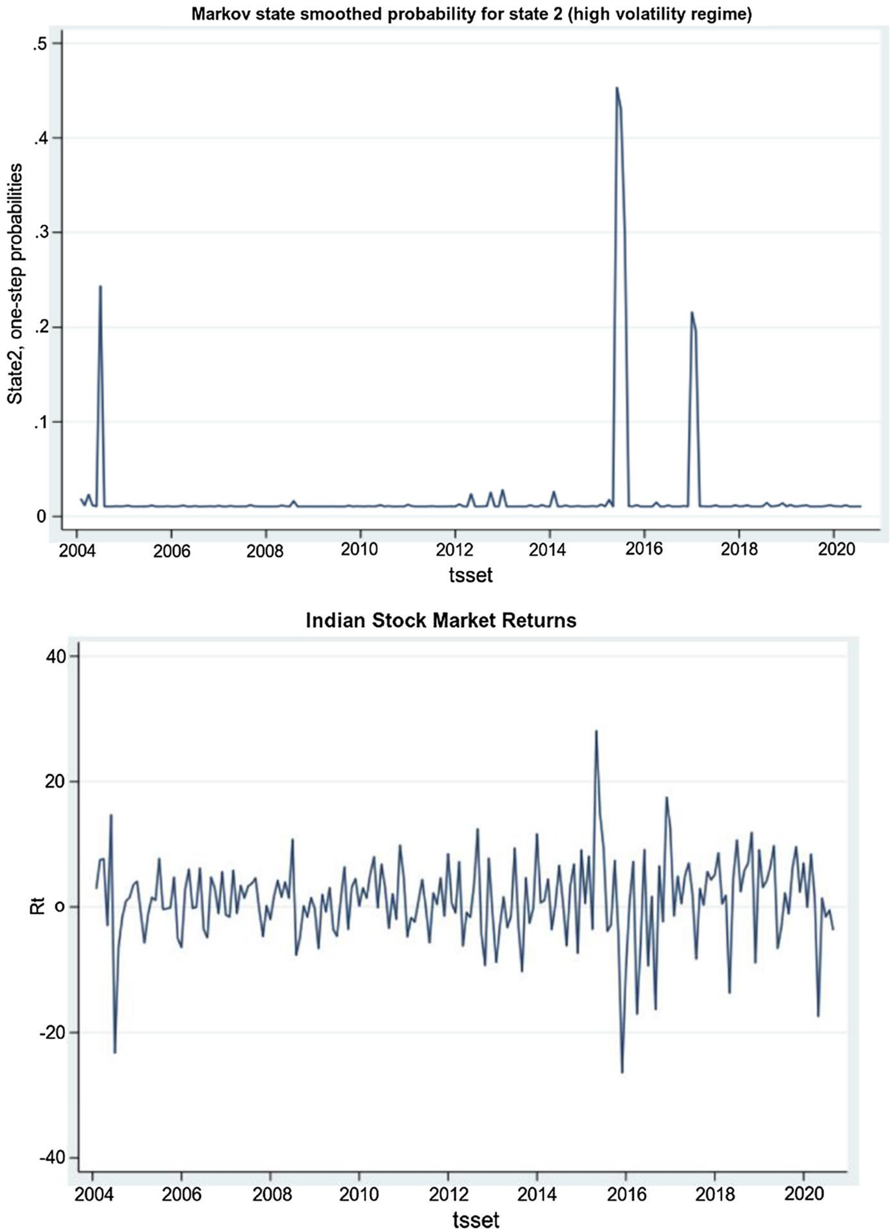

Fig. 3 Markov state smoothed probability for state 2 (high volatility regime) and Indian stock market returns. Source: Generated by authors

is negative and it is highly significant. The most ineffective effect is observed during low volatility periods, while the most robust impact is identified during extreme volatility sessions.

Table 5 Duration of the model to remain in a particular state

	Estimate	Std. Err
State1	94.45763	94.5634
State2	1.832942	1.038348

Time period of Analysis: January 2003–October 2020. Estimate is in the order of months

We also investigate whether the EPU of some of the countries that India has strong relationships with affects the EPU of the country. This can be understood as whether there is a cause-effect relationship between the countries' EPUs. This can be done with the help of the granger causality test. Based on the selection table, the AIC is minimum for a lag period of 4.

Accordingly, the following two hypotheses have been tested:

H_0: Lagged USA EPU does not cause India EPU.

H_1: Lagged USA EPU granger causes India EPU.

We use the F-statistic to check if the null hypothesis is accepted or rejected. We can see that at a 95% confidence level, the null hypothesis is not rejected, but at around 85%. Thus, we conclude that USA EPU granger causes India EPU (Table 6).

Table 6 Results of granger causality test of Indian EPU and USA EPU. *Source*: Computed by authors

Equation	Excluded	F Score
India EPU	USA EPU	1.6597
India EPU	ALL	1.6597
USA EPU	India EPU	0.64246
USA EPU	ALL	0.64246

Table 7 Results of GARCH-MIDAS Model with India EPU (Model 1). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0326	0.0000***	0.0071
alpha	0.1102	0.0000***	0.0009
beta	0.8790	0.0000***	0.0004
m	– 0.5857	0.0116**	0.2322
theta	– 0.0028	0.2329	0.0023
w2	34.5926	0.0955*	20.7480

(1) Mu—Daily Expected returns; Alpha—parameters of ARCH; Beta—parameters of the GARCH component; Gamma—Measures information of asymmetry; m—Long-term volatility; theta—measures the impact of the variable on the stock market volatility; w2—parameter that influences the decaying rate; theta.two—Measures the impact of the variable on the stock market volatility for the second covariate; and w2.two—parameter that influences the decaying rate for the second covariate

(2) ***, **, and * indicates significance at the 1% level, .5% level and 10% level, respectively

5.3 Results Based on GARCH-MIDAS Model

The tables below are the results generated by running the GARCH-MIDAS models during the in-sample period (Table 7). In model 1, we estimated the stock market volatility (realized volatility) based on only the India EPU. We can also see that the stock market volatility is positively correlated to the Indian EPU. We can also see that the estimated parameters for the Indian EPU are statistically significant and explains that Economic Policy Uncertainty has an exceptionally positive influence on the capital market's expected volatility.

Model 3 includes a supplementary variable, GEPU, instead of the first one. Moreover, we can infer that the GEPU can consist of valuable forecasting data to gauge the Indian capital market. Then, viewing the semi-quadratic alternative statistic method, we discover that Model 3 can garner better estimates than the first one, showing us that the GEPU can improve the Indian stock market's prediction correctness. From these experimental outcomes, we discover that the GEPU index is helpful in predicting the Indian capital market's performance, and the global economic policy conditions can undoubtedly affect the Indian stock market.

The first three models do not examine the co-movement of uncertainty index parameters. The most significant result is that, under the scope and semi-quadratic statistics, Model 5 displays statistically more significant predictive efficiency than Model 2, Model 3, and Model 4. From these experimental outcomes, an important primary conclusion is that working with up and down components of the GEPU collectively is more effective for forecasting volatility than GEPU alone or up GEPU, suggesting that the aggregate of up and down GEPU comprises more useful information to foretell capital market volatility.

The models differ as we have considered the co-movement of Indian economic policy uncertainty. The co-movement, the policy uncertainty, can be in the same direction (Models 4 & 5) or in the opposite direction (Model 6 & Model 7). Models 5 and 7 perform better because directional GEPU may include more valuable predictive information than GEPU alone, according to Li et al. (2020a, 2020b), but is not evidenced by our results. In all the cases, mu is positive, indicating a positive net return on the Indian stock market. Alpha and beta values are less than 1 showing the conditional volatility is a GARCH (1,1) process. One of the most interesting facts about the Global EPU is that its contribution to the Indian volatility has not been significant. But when the directional EPU is considered, the MIDAS model suggests that Indian market volatilities are influenced by an increase or decrease in Global market uncertainties. One plausible explanation could be integrating Indian markets with global ones. The markets in India are now also open to many foreign investors into Indian markets. An increase or decrease in uncertainty on the global stage influences the inflow and outflow of foreign capital.

In this part, the boundary assessment of the GARCH–MIDAS unpredictability models are first covered for the whole sample period; at that point, we consider the consistency of predictability between the GARCH–MIDAS models (Table 8).

Table 8 Results of GARCH-MIDAS Model with GEPU (Model 2). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0322	0.0000***	0.0073
alpha	0.1114	0.0000***	0.0009
beta	0.8716	0.0000***	0.0014
m	0.0697	0.9110	0.6241
theta	− 0.0085	0.0952	0.0051
w2	1.2751	0.3811	1.4558

(1) Same as above

(2) Same as above

Table 9 Results of the GARCH-MIDAS Model with India EPU and GEPU (Model 3). *Source*: Computed by authors

Parameters	Coefficients	*p* value	Robust standard error
mu	0.0205	0.0182**	0.0087
alpha	0.0327	0.0381**	0.0158
beta	0.8762	0.0000***	0.0109
gamma	0.1339	0.0000***	0.0255
m	− 0.0458	0.9314	0.5323
theta	0.0010	0.6346	0.0021
w2	6.4308	0.0426**	3.1722
theta. two	− 0.0104	0.0235**	0.0046
w2.two	1.0000	0.1438	0.6841

(1) Same as above

(2) Same as above

5.3.1 In-Sample Assessments

To examine the impact of EPU and GEPU on the Indian financial exchange's instability, they are obligated to the GARCH–MIDAS model. Furthermore, as various conventional GARCH–MIDAS models acknowledge R.V. when evaluating the long-run uncertainty and R.V. is resolute, the model also incorporated the lags of securities exchange volatility. In this segment, the GARCH–MIDAS model's evaluation consequence with India EPU is first shown (Table 9). Then, following Engle et al., (2013), the GARCH–MIDAS model's evaluation outcome with GEPU is exhibited (Table 10). Following Li et al. (2020a, b), the GARCH–MIDAS model's estimation aftereffects with GEPU directional, i.e., GEPU Up (Table 11), GEPU Down (Table 12), GEPU Up Down (Table 13), GEPU Down Up (Table 14) is displayed.

We require half-year lags, and the example covers from 3rd February 2003 to 30th October 2020. Robust standard errors and gauges are utilized. We can see that estimates μ, α, and β are significant for all the table models. The measures of α and β take traditional values. We can recognize an exciting feature of the GARCH–MIDAS

Table 10 Results of GARCH-MIDAS model with India EPU and GEPU_Up (Model 4). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0212	0.0069***	0.0079
alpha	0.0319	0.0150**	0.0131
beta	0.8831	0.0000***	0.0044
gamma	0.1273	0.0000***	0.0229
m	– 0.2213	0.8328	1.0479
theta	0.0035	0.1999	0.0028
w2	5.0045	0.2425	4.2822
theta.two	– 0.0332	0.2315	0.0277
w2.two	1.0000	0.3686	1.1123

(1) Same as above

(2) Same as above

Table 11 Results of GARCH-MIDAS model with India EPU and GEPU_Down (model 5). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0198	0.0168**	0.0083
alpha	0.0366	0.0296*	0.0168
beta	0.8726	0.0000***	0.0099
gamma	0.1332	0.0000***	0.0274
m	– 0.4414	0.4279	0.5569
theta	0.0021	0.5025	0.0031
w2	7.5422	0.4353	9.6669
theta.two	– 0.0282	0.1255	0.0184
w2.two	1.0000	0.0000***	0.2054

(1) Same as above

(2) Same as above

Table 12 Results of GARCH-MIDAS Model with India EPU and GEPU_Up_Down (Model 6). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0212	0.0024***	0.0070
alpha	0.0307	0.0623	0.0165
beta	0.8650	0.0000***	0.0079
gamma	0.1444	0.0000***	0.0209
m	0.1369	0.8043	0.5525
theta	– 0.0060	0.1378	0.0040
w2	1.0000	0.5958	1.8854
theta.two	– 0.0343	0.0001***	0.0088
w2.two	2.1026	0.0016***	0.6658

(1) Same as above

(2) Same as above

Table 13 Results of GARCH-MIDAS Model with India EPU and GEPU_Down_Up (Model 7). *Source*: Computed by authors

Parameters	Coefficients	*p* value	rob.std.err
mu	0.0203	0.0312*	0.0094
alpha	0.0365	0.1075*	0.0227
beta	0.8709	0.0000***	0.0217
gamma	0.1327	0.0000***	0.0247
m	– 0.2056	0.7586	0.6692
theta	– 0.0044	0.2894	0.0041
w2	1.0000	0.6897	2.5042
theta.two	– 0.0245	0.0008***	0.0073
w2.two	2.1476	0.0000***	0.4159

(1) Same as above

(2) Same as above

Table 14 Rolling window out-of-sample prediction errors of GARCH–MIDAS models. *Source*: Computed by authors

Model no	Name	RMSE	MAPE
Model 1	GARCH-MIDAS with India EPU	0.483144	20.1133
Model 2	GARCH-MIDAS with GEPU	2.183115	62.79098
Model 3	GARCH MIDAS with India EPU + GEPU	0.8524219	36.75442
Model 4	GARCH MIDAS with India EPU + GEPU Up	1.33805	50.00396
Model 5	GARCH MIDAS with India EPU + GEPU Down	0.7869786	30.75843
Model 6	GARCH MIDAS with India EPU + GEPU Up Down	1.533484	61.74932
Model 7	GARCH MIDAS with India EPU + GEPU Down Up	1.464999	48.61323

model that the sums of α and β are 0.988, 0.983, 0.908, 0.915, and 0.909 for the India EPU, GEPU, EPU + GEPU, EPU + GEPU_UP, EPU + GEPU_DOWN case, respectively. These qualities are discernibly under 1, while the sum in a standard GARCH model is ordinarily 1. This conclusion is like those of Engle and Rangel (2008).

Second, the estimates of the long-run part are analyzed. The θ parameter addresses the effect of long-run unpredictability on the model. We can locate that the indication of θ parameter is negative and near zero for models 1 and 2, demonstrating that highly acknowledged unpredictability will cause low instability. The sign is positive for the GEPU_Up and GEPU_Down models, which shows that highly recognized instability will cause increased volatility. Then we examine the parameter estimates of GEPU. The significantly positive signs for the estimates imply that large GEPU leads to high volatility. Overall, when the global economic policy uncertainty is higher, the Indian securities exchange unpredictability will be more unstable, which mirrors that the Indian securities exchange has been slowly coordinated into the worldwide economy.

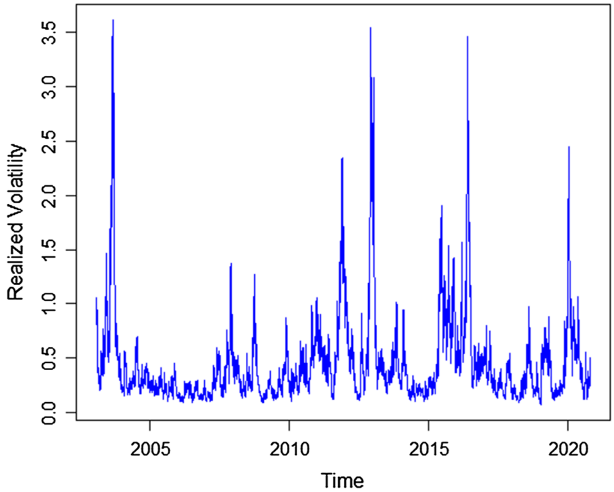

Fig. 4 GARCH-MIDAS with India EPU

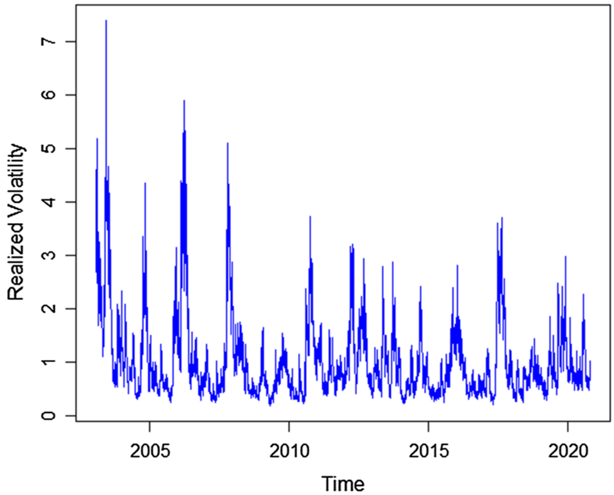

Fig. 5 GARCH-MIDAS with GEPU

The R.V.s of the Indian securities exchange are plotted (Pls. refer to Figs. 4, 5, 6, 7, 8, 9, and 10). They show the long-run uncertainty for GARCH–MIDAS models. The train and test data set term is from 3rd February 2003 and concludes on 30th October 2020. The long-run volatility is at everyday regularity. As we expect, R.V.s relate to worldwide monetary conditions.

Furthermore, the models' short-run and long-run parts follow a comparative pattern, albeit the long-run relationship is more regular. The graph additionally suggests an intriguing recurrent example regarding the evolution of

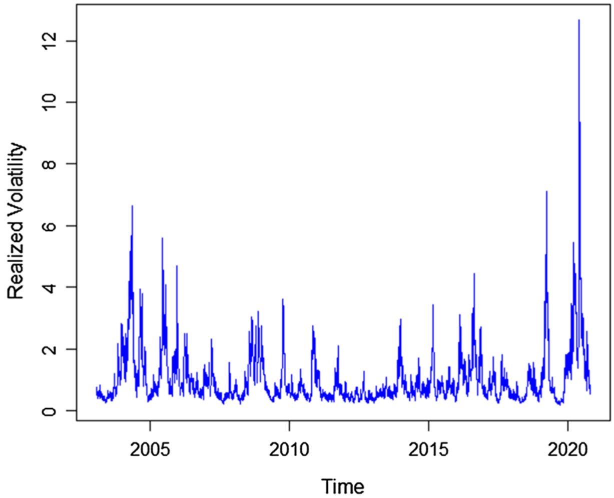

Fig. 6 GARCH-MIDAS with India EPU + GEPU

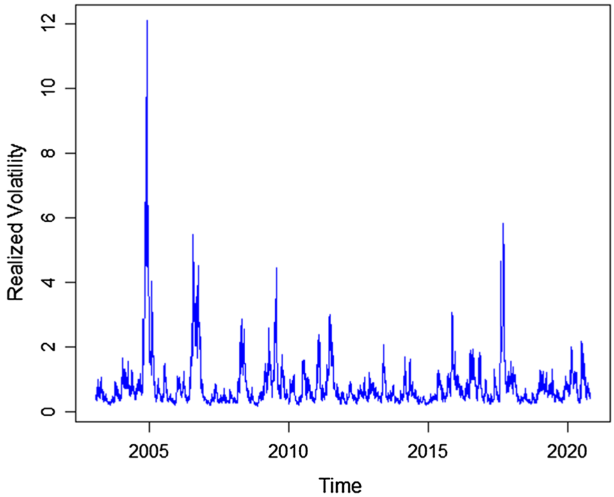

Fig. 7 GARCH-MIDAS with India EPU + GEPU up

long-run instability. The statistics encompass the recession time of 2007–2009, the long-run unpredictability expanded vigorously, whereas, through the recuperation periods of the monetary crisis, the instability diminished. The worldwide economic crisis in 2007–2009 raised the GEPU (Pls. refer to Figs. 5 and 6), which may cause the capital stream's precariousness and investor opinion in the Indian securities exchange and increment the long-run instability. Since India is one of the world's most significant economies, that reality builds the GEPU. The expanded GEPU, at that point, has positive criticism of the instability of the

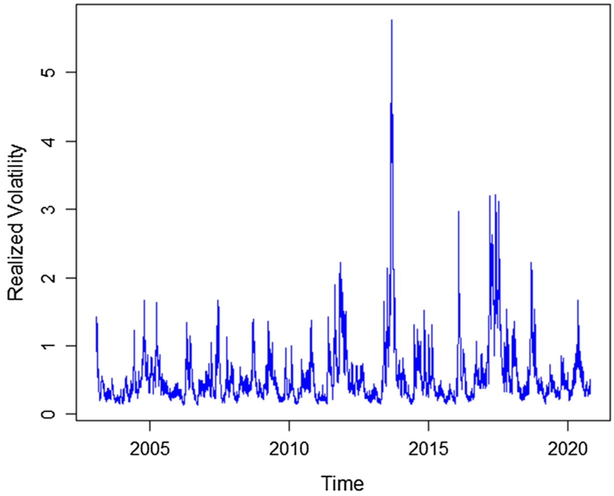

Fig. 8 GARCH-MIDAS with India EPU + GEPU down

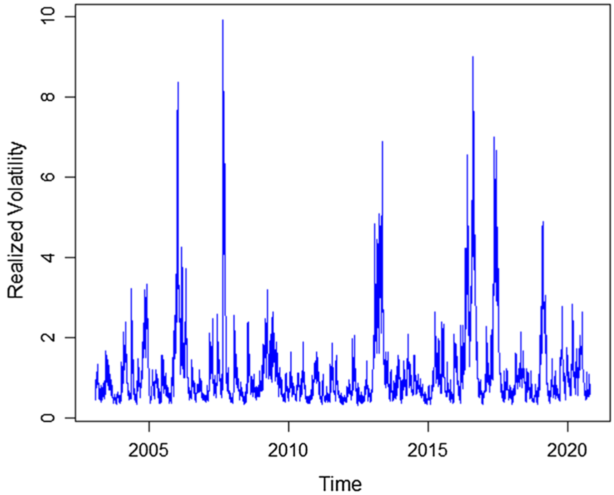

Fig. 9 GARCH-MIDAS with India EPU + GEPU up_down

Indian financial exchange. We also record that the GARCH MIDAS model with R.V. + EPU (Fig. 4) encourages a nearer coordinate long-run instability and fluctuation, proposing that the R.V. + EPU + GEPU (Pls. refer Fig. 6) model suits in a way that is better than the RV + GPU (Pls. refer Fig. 5) or RV + EPU models. We assess R.V. + EPU model's gauge performance in the following part.

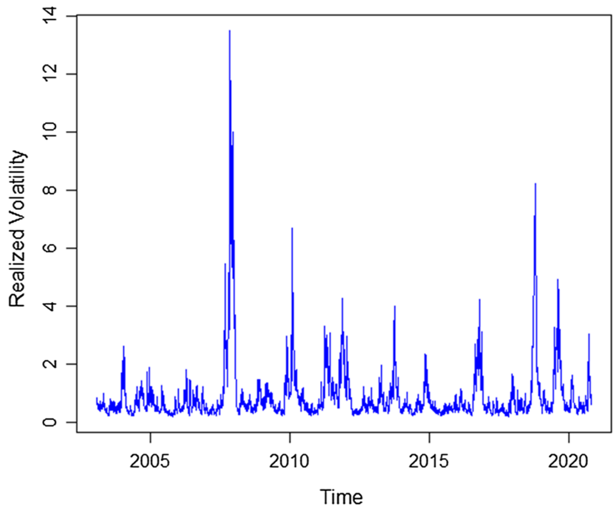

Fig. 10 GARCH-MIDAS with India EPU + GEPU down_up

5.3.2 Out-of-Sample Prediction

In this section, we investigate the predictive abilities of the GARCH–MIDAS models for Indian stock market volatilities. The assessment window begins on 3rd February 2003 and closes on 30th October 2020. Here it can be seen that the India EPU model has a lower cost value than the GEPU model indicating the superior prediction power of India EPU compared to GEPU when predicting Indian stock market volatility.

Because the GARCH model is employed in the literature for volatility prediction, we first distinguish the forecasting performance of GARCH–MIDAS with R.V. + EPU and the RV + EPU + GEPU and RV + GEPU models. The Indian stock market volatility estimate based on the GARCH–MIDAS model with RV + EPU + GEPU_DOWN_UP (Table 14) exhibits smaller loss function values than the other models' predictions.

Although the prediction power of GARCH–MIDAS with RV + EPU + GEPU_DOWN_UP is significantly better than the GARCH RV + EPU or RV + GEPU models, someone will argue that this impressive performance may be owing to the dominance of the GARCH–MIDAS model itself but not the effect of GEPU. However, since all the models consider GARCH MIDAS, there is no other model ambiguity, causing the predictive power to increase. The models with GEPU down (Models 5 and 7) have a lower cost function value than the GEPU UP model (Models 4 and 6), proposing that the market is sensitive to downward movements rather than upward movements.

Nonetheless, we can argue that the model with EPU + GEPU has the lowest cost function. It includes the single directional movement and the sensitivity to both directions, with the downward trend dominating more than the upward movement. The following conclusion follows the findings of Conrad and Loch (2015). Though this paper finds that in the Indian market, the model with EPU and GEPU works best, which is only a bit better than the directional GEPU, it agrees with the findings of Li et al. (2020a, b), which says that the directional state movement of GEPU with the direction of EPU does give a better model than the traditional EPU models and also Yu et al. (2018) who had performed a similar study on the Indian market and found that the use of GEPU with EPU makes the model better than the EPU and also the classical GARCH(1, 1) model.

Comparing with the results from the existing literature, Zhang et al. (2019) examined the impact of economic policy uncertainty on stock market volatility in emerging markets, including India. The study found that economic policy uncertainty had a negative impact on stock market volatility in these countries. Chen et al. (2020) analyzed the impact of economic policy uncertainty on stock market volatility in the BRICS countries, including India. The study found that economic policy uncertainty had a negative and significant impact on stock market volatility in these countries. These studies provide evidence that economic policy uncertainty can negatively impact stock market volatility in India and other emerging markets, supporting our analysis but failing to incorporate the directional impacts of EPU and GEPU on the stock market volatility; furthermore, understanding the impact of components of directional GEPU with the Indian securities exchange instability as every component of directional GEPU impacts the stock market volatility differently.

6 Conclusion and Policy Implications

In this paper, we investigated the significance of EPU on India's stock markets from 2003 to 2020, working with both linear and market switching models. Our outcomes indicate that an advance in policy uncertainty significantly decreases stock returns. Nevertheless, the EPU-stock return relationship is not linear, and the impact of EPU on stock market earnings is more substantial and tenacious throughout the extreme volatility terms. We utilize the GARCH–MIDAS model to assess the impact of GEPU on the volatility of the Indian capital exchange and study the forecasting capability of GEPU for Indian capital exchange volatility. Our empirical study shows that GEPU positively and significantly impacts the Indian capital market's volatility. That indicates when the global economic policy uncertainty is higher, the Indian capital exchange volatility will also be unstable.

We have also studied the impacts of GEPU on Indian securities exchange volatility using GARCH-MIDAS. This model is beneficial where the independent and dependent variables have different time frequencies. We furthermore understand GEPU depends on altering the course of EPU and GEPU into its directional components. The above results show that GEPU alone does not affect the Indian securities exchange. In any case, all over GEPU have positive impressions on securities exchange volatility, and they are statistically significant. Volatility is a measure of risk, and financial economics always revolves around maximizing Reuters per unit of risk. Hence, a robust forecasting model would have immense use in all financial institutions.

A reasonable continuation of our analysis would be to practice alternative substitutes for EPU. The best example would be the elections. This variable permits us to investigate if stock market gains in months commencing up to Presidential and midterm polls are lower because of higher uncertainty. Furthermore, in this paper, it has been seen that the GARCH-MIDAS model is a good predictor of Indian market volatility. However, the model's performance under different circumstances and market conditions concerning the Indian stock market still needs to be tested. In this regard, out-of-sample testing becomes a reasonable estimate of the model's efficacy under real-life situations. MCS test can be performed to test the model under out-of-sample data. Heteroskedasticity-adjusted MSE (Mean Square Error) and MAE (Mean Absolute Error) can measure the model's predictive ability. Further work would help understand the strengths and usability of the GARCH-MIDAS model under different specifications.

Private and institutional investors can use the models incorporating GEPU in its components and Indian EPU to forecast volatility and future stock market stability. This can lead to better risk management. Economic policymakers can also predict future instability and use tools (monetary and fiscal) to address the same. Also, the estimates produced by the GARCH–MIDAS models with EPU and GEPU have smaller errors than the GARCH Models with EPU or GEPU alone, which validates the significant purpose of GEPU in foretelling the volatility of the Indian capital market. Estimating and projecting volatility is necessary for identifying assets' valuation, modelling derivative instruments, risk administration, and policymaking. Stock market analytics could incorporate the GEPU variable within their volatility model to improve forecasting precision. If the anticipated uncertainty is deemed high, they should be further careful about managing arbitrage risk using secondary instruments during intense volatility periods. The government could employ fiscal and monetary systems to overcome the undiversifiable risk during forecasting. This will improve the predictions on the expected volatility based on the GEPU.

Data Availability The data supporting this study's findings are available on request from the corresponding author.

Declarations

Conflict of interest There is no conflict of interest among the authors for this piece of research work.

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