

“Modelling and Forecasting Hedge Fund Strategy Performance during Geopolitical Instability: Insights from Indian Capital Markets”

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Abstract

Geopolitical instability has emerged as a critical source of uncertainty influencing global and emerging financial markets, particularly affecting hedge fund investment strategies that rely on dynamic risk management and return forecasting. This study investigates the effectiveness of mathematical forecasting models in predicting hedge fund strategy performance under conditions of geopolitical instability in Indian capital markets. Using a comprehensive dataset comprising hedge fund returns, market volatility indicators, and geopolitical risk proxies, the study applies advanced quantitative techniques, including time-series econometric models and volatility-based forecasting frameworks, to examine how hedge fund strategies respond to heightened geopolitical shocks. The empirical analysis evaluates the predictive accuracy of these models across different hedge fund strategy classifications, such as long-short equity and event-driven approaches. The findings are expected to reveal that geopolitical instability significantly alters volatility dynamics and strategy performance, while mathematical models incorporating geopolitical risk measures enhance forecasting precision. The study contributes to the growing literature on financial market uncertainty by offering an emerging-market perspective and provides practical implications for hedge fund managers, investors, and policymakers seeking to improve risk assessment and strategic decision-making in volatile geopolitical environments.

Keywords

Hedge Fund Strategies, Geopolitical Instability, Mathematical Modeling, Indian Capital Markets, Financial Market Volatility, Geopolitical Risk Index, Emerging Financial Markets

Introduction

In recent years, geopolitical instability has become a dominant force shaping global financial markets, influencing capital flows, asset prices, and investor sentiment. Events such as trade conflicts, regional tensions, economic sanctions, and political uncertainty have intensified market volatility, particularly in emerging economies like India. The Indian capital markets, characterized by increasing integration with global financial systems, are highly sensitive to such external shocks, making risk assessment and forecasting more complex for institutional investors.

Hedge funds, known for their flexible investment strategies and sophisticated risk management techniques, are especially exposed to geopolitical disruptions. Strategies such as long-short equity, event-driven investing, and macro trading depend heavily on accurate forecasts of market trends and volatility patterns. However, traditional financial models often fail to fully capture the nonlinear and abrupt impacts of geopolitical events, leading to potential inefficiencies in predicting hedge fund performance during periods of instability.

This study addresses this gap by examining the role of mathematical and econometric forecasting models in predicting hedge fund strategy performance under conditions of geopolitical uncertainty within the Indian context. By incorporating geopolitical risk indicators alongside conventional financial variables, the research aims to enhance the

predictive accuracy of time-series and volatility-based models. The study also evaluates how different hedge fund strategies respond to varying intensities of geopolitical shocks, offering a comparative perspective on their resilience and adaptability. Through an empirical analysis of hedge fund returns, market volatility measures, and geopolitical risk proxies, this research contributes to a deeper understanding of how external uncertainties reshape financial dynamics in emerging markets. It also bridges the gap between theoretical modelling and practical investment decision-making by highlighting the importance of integrating geopolitical risk into financial forecasting frameworks.

Future Relevance and Scope

The relevance of this study is expected to grow significantly as geopolitical risks continue to intensify in an increasingly interconnected global economy. With the rise of multipolar political dynamics, trade fragmentation, and regional conflicts, financial markets are likely to experience more frequent and unpredictable shocks. In this context, the integration of geopolitical risk into financial modelling will become essential rather than optional. From an academic perspective, this research opens avenues for further exploration into hybrid forecasting models that combine machine learning techniques with traditional econometric approaches. Future studies can expand the scope by incorporating real-time data analytics, sentiment analysis from news sources, and artificial intelligence-driven predictive systems to improve model robustness and adaptability.

Practically, hedge fund managers and institutional investors can benefit from enhanced forecasting frameworks that account for geopolitical uncertainty, enabling better portfolio diversification, risk mitigation, and strategic asset allocation. Policymakers and regulators may also use such insights to design more resilient financial systems and implement policies that stabilize markets during periods of external shocks.

Moreover, as Indian capital markets continue to evolve and attract global investment, understanding the interplay between geopolitical instability and hedge fund strategies will be crucial for sustaining investor confidence and ensuring long-term financial stability. The study's findings can thus inform both domestic and international stakeholders in navigating the complexities of modern financial markets.

Bao, Lee, & Saltoglu (2023) extended traditional forecasting by showing that **machine learning models integrating geopolitical risk variables outperform standard volatility models** (e.g., GARCH) when forecasting realised market volatility, especially during major geopolitical events. This supports the idea that **nonlinear/AI models improve predictive accuracy under uncertainty**.

Caldara & Iacoviello (2022) developed the foundational **Geopolitical Risk (GPR) Index**, showing that spikes in geopolitical risk significantly increase market volatility and reduce equity returns globally, providing a benchmark measure for geopolitical uncertainty studies.

Kulkarni et al. (2023) applied **network and topology methods** to Indian stock market structure, indirectly indicating the *systemic risk and fragility* that makes forecasting under shocks (e.g., geopolitical events) more challenging.

Maharana, Panigrahi & Chaudhury (2025) — shows how commodities like oil and gold correlate with Indian stock markets, with geopolitical externalities playing a role in these linkages. This suggests **hedging channels beyond equity markets for managing geopolitical risk**.

Pandya & Pal (2025) (mentioned above) directly showcase how geopolitical risk measured by GPR affects *FII strategies in India*, leading to heightened volatility and capital outflows — making them essential for understanding Indian market-specific responses.

Qadri (2025) provides additional context in the Indian setting, linking geopolitical impacts to financial market functioning, demonstrating the broader effect of geopolitical uncertainty beyond just volatility statistics.

Literature Review

1. Geopolitical Risk and Financial Market Volatility

Geopolitical risk has been empirically shown to exert a significant influence on market volatility and capital flows, underscoring its importance in financial forecasting models. Empirical evidence consistently demonstrates that geopolitical risk significantly affects market volatility and capital flows, making it a critical variable for accurate financial forecasting. The established empirical linkage between geopolitical risk, market volatility, and capital flows highlights the necessity of incorporating geopolitical risk measures into forecasting models. Prior empirical studies confirm a robust association between geopolitical risk, volatility dynamics, and capital movements, reinforcing its relevance for forecasting financial market behaviour.

2. Hedge Funds, Risk Timing & Geopolitical Exposure

The literature demonstrates that hedge fund responses to geopolitical risk vary across strategy types, with certain strategies exhibiting effective timing and hedging capabilities. Empirical studies reveal significant heterogeneity in hedge fund responses to geopolitical risk, where strategies such as global macro and event-driven funds show superior ability to time or hedge geopolitical shocks. Evidence suggests that hedge fund strategy performance under geopolitical uncertainty is strategy-dependent, with some approaches demonstrating greater effectiveness in timing and hedging geopolitical risk. Prior research highlights pronounced cross-strategy differences in hedge fund behaviour during periods of geopolitical instability, indicating that only selected strategies possess meaningful geopolitical risk timing or hedging ability. (Sahoo & co-authors, 2024) in “*Geopolitical risk hedging or timing: Evidence from hedge fund strategies*” examined hedge funds globally and found evidence that **Global Macro hedge funds successfully time geopolitical risks** whereas other strategies tend to hedge but not time them effectively. This supports the idea that model choice matters for forecasting returns under geopolitical stress.

Liu, Chen, Zhu, & colleagues (2024) investigated how **mutual funds adjust risk-taking under rising geopolitical uncertainty**—they find that higher geopolitical risk leads to reduced market exposure, suggesting risk management responses which are conceptually relevant to hedge funds as well.

3. Forecasting Volatility & Geopolitical Impact

Recent evidence indicates that enhanced forecasting models, including machine learning and augmented econometric approaches, outperform traditional models during periods of geopolitical shocks. Empirical studies provide evidence that forecasting frameworks incorporating machine learning techniques or augmented econometric specifications achieve superior performance under heightened geopolitical uncertainty. The documented superiority of machine learning and geopolitically augmented econometric models during geopolitical shock periods underscores the value of advanced forecasting approaches.

Prior research demonstrates that enhanced forecasting models integrating machine learning or additional risk factors exhibit improved predictive accuracy during episodes of geopolitical stress. Bao, Lee, & Saltoglu (2023) extended traditional forecasting by showing that **machine learning models integrating geopolitical risk variables outperform standard volatility models** (e.g., GARCH) when forecasting realised market volatility, especially during major geopolitical events. This supports the idea that **nonlinear/AI models improve predictive accuracy under uncertainty**.

While not specific to geopolitics, emerging evidence in volatility literature — such as **multivariate models and exogenous variable extensions** (e.g., machine learning forecasting) — shows the benefit of richer models when markets experience structural shifts.

4. Emerging Markets & India-Specific Insights

India-focused studies indicate that emerging markets such as India experience heightened volatility and capital flow sensitivity under geopolitical pressure, validating their relevance as an empirical context. India-specific research highlights that geopolitical shocks lead to pronounced volatility dynamics and capital flow adjustments in emerging markets, supporting India as a suitable setting for empirical investigation. Evidence from India suggests that emerging markets exhibit amplified volatility and capital flow responses to geopolitical risk, making them an appropriate context for examining forecasting performance under uncertainty.

Prior India-focused studies demonstrate that emerging markets face stronger volatility reactions and capital flow disruptions during periods of geopolitical stress, reinforcing the suitability of India as an empirical setting. **Kulkarni et al. (2023)** applied **network and topology methods** to Indian stock market structure, indirectly indicating the *systemic risk and fragility* that makes forecasting under shocks (e.g., geopolitical events) more challenging.

Maharana, Panigrahi & Chaudhury (2025) — shows how commodities like oil and gold correlate with Indian stock markets, with geopolitical externalities playing a role in these linkages. This suggests **hedging channels beyond equity markets for managing geopolitical risk**. Additional studies on broader financial uncertainty (e.g., policy and macroeconomic risk) further show volatility linkages that are relevant when modelling hedge fund performance under uncertainty, even if not exclusively geopolitical. **Bao, Lee, & Saltoglu (2023)** extended traditional forecasting by showing that **machine learning models integrating geopolitical risk variables outperform standard volatility models** (e.g., GARCH) when forecasting realised market volatility, especially during major geopolitical events. This supports the idea that nonlinear/AI models improve predictive accuracy under uncertainty. **Caldara & Iacoviello (2022)** developed the foundational Geopolitical Risk (GPR) Index, showing that spikes in geopolitical risk significantly increase market volatility and reduce equity returns globally, providing a benchmark measure for geopolitical uncertainty studies.

Maharana, Panigrahi & Chaudhury (2025) — shows how commodities like oil and gold correlate with Indian stock markets, with geopolitical externalities playing a role in these linkages. This suggests hedging channels beyond equity markets for managing geopolitical risk. **Pandya & Pal (2025)** (mentioned above) directly showcase how geopolitical risk measured by GPR affects *FII strategies in India*, leading to heightened volatility and capital outflows — making them essential for understanding Indian market-specific responses. **Qadri (2025)** provides additional context in the Indian setting, linking geopolitical impacts to financial market functioning, demonstrating the broader effect of geopolitical uncertainty beyond just volatility statistics.

Research Gap

While existing research covers geopolitical risk effects on traditional markets and outlines the impact of political risk on hedge funds in developed economies, **two main gaps remain**:

1. **Limited empirical evidence on hedge fund forecasting under geopolitical instability in emerging markets**, especially India.
2. **Insufficient integration of advanced mathematical forecasting techniques** — including econometric and machine learning models — with geopolitical risk indices to predict hedge fund strategy performance.

This study addresses these gaps by combining geopolitical risk metrics with **mathematical forecasting models** to evaluate hedge fund strategies in the context of Indian capital markets under geopolitical instability.

Objectives

1. To analyze the relationship between geopolitical risk indicators and volatility dynamics in Indian capital markets.
2. To assess the forecasting accuracy of mathematical models during periods of high and low geopolitical instability.
3. To identify strategy-specific responses of hedge funds (long–short equity and event-driven strategies) to geopolitical shocks.

4. Hypotheses Development

Based on the objectives and existing literature on geopolitical risk, volatility modeling, and hedge fund strategy behavior, the following hypotheses are proposed:

H₁: Geopolitical risk has a statistically significant impact on volatility dynamics in Indian capital markets.

H₂: Mathematical forecasting models incorporating geopolitical risk indicators exhibit higher forecasting accuracy than conventional models during periods of geopolitical instability.

H₃: Event-driven hedge fund strategies exhibit greater resilience and adaptability to geopolitical shocks compared to long–short equity strategies.

5. Research Methodology

5.1 Research Design

This study adopts a quantitative, explanatory, and time-series research design to investigate the impact of geopolitical risk on market volatility, forecasting accuracy, and hedge fund strategy performance in Indian capital markets. The explanatory approach is appropriate as it seeks to establish causal relationships between geopolitical risk indicators and financial variables.

A time-series econometric framework is employed to capture:

- Volatility clustering
- Dynamic dependencies
- Regime shifts during geopolitical instability

This design is particularly suitable for analyzing financial markets under uncertain and shock-driven environments.

5.2 Data Sources and Sample Period

The study relies on secondary data collected from credible and publicly available sources:

- **Market Data:**
Indian equity market returns and volatility proxies (e.g., NIFTY 50, India VIX)
- **Hedge Fund Strategy Returns:**
Strategy-level returns for:
 - Long–short equity strategies
 - Event-driven strategies
- **Geopolitical Risk Indicators:**
News-based Geopolitical Risk (GPR) Index reflecting global and regional geopolitical tensions

- **Macroeconomic Variables (Control Variables):**

Interest rates, inflation, and exchange rates

- **Sample Period**

The dataset spans 10–15 years, covering:

- High geopolitical risk periods (crisis, conflicts)
- Low geopolitical risk periods (stable conditions)

This ensures robustness across multiple market cycles.

5.3 Measurement of Variables

Variable Type	Variable	Measurement
Independent	Geopolitical Risk (GPR)	Geopolitical Risk Index
Dependent	Market Volatility	Conditional Variance from GARCH
Dependent	Hedge Fund performance	Strategy- level returns
Control	Market Return	Index Returns
Control	Macroeconomic Factor	Standard economic indicators

5.4 Econometric and Hybrid Modeling Framework

5.4.1 Volatility Modeling (GARCH–GPR Model)

To analyze the relationship between geopolitical risk and market volatility:

- Mean Equation

$$R_t = \mu + \epsilon_t$$

- Variance Equation

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma GPR_t$$

Where:

- σ_t^2 = conditional volatility
- γ = impact of geopolitical risk

👉 Expected Result: $\gamma > 0$, indicating geopolitical instability increases volatility.

5.4.2 Strategy Performance Model

To evaluate hedge fund strategy responses:

$$HF_{i,t} = \alpha_i + \beta_1 MKT_t + \beta_2 \sigma_t + \beta_3 GPR_t + u_t$$

This model captures:

- Market exposure
- Volatility sensitivity
- Direct geopolitical impact

5.4.3 Forecasting Models

Two main frameworks are used:

(A) Baseline Model

- ARMA–GARCH (without geopolitical risk)

(B) Augmented Model

- ARMA–GARCH–GPR (with geopolitical risk)

5.4.4 Hybrid Modeling Framework (Advanced Extension)

To enhance forecasting accuracy, a hybrid model is proposed:

$$\hat{Y}_t^{Hybrid} = w_1(\text{ARIMA–GARCH}) + w_2(\text{AI Model})$$

Where AI models may include:

- Artificial Neural Networks (ANN)
- Long Short-Term Memory (LSTM)

👉 This framework captures:

- Linear patterns (ARIMA)
- Volatility clustering (GARCH)
- Nonlinear relationships (AI)

1. Mean Absolute Error (MAE)

Formula

$$MAE = \frac{1}{n} \sum_{t=1}^n |Y_t - \hat{Y}_t|$$

Explanation

- Measures the average absolute difference between actual values (Y_t) and predicted values ($\hat{Y}_t$)
- Treats all errors equally
- Easy to interpret

👉 Interpretation:

Lower MAE = Better forecasting accuracy

2. Root Mean Squared Error (RMSE)

Formula

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (Y_t - \hat{Y}_t)^2}$$

Explanation

- Squares errors before averaging
- Gives higher weight to large errors
- More sensitive to volatility shocks

👉 Interpretation:

Lower RMSE = Better model performance, especially during high-risk periods

4. Numerical Illustration (Example Table)

Time (t)	Actual Value (Yt)	Predicted Value(Yt)	Error (Yt-Yt)	Error	Error ²
1	100	95	5	5	25
2	110	108	2	2	4
3	105	100	5	5	25
4	120	115	5	5	25
5	115	118	-3	3	9

Figure 1

Step Calculation

MAE

$$MAE = \frac{5 + 2 + 5 + 5 + 3}{5} = \frac{20}{5} = 4$$

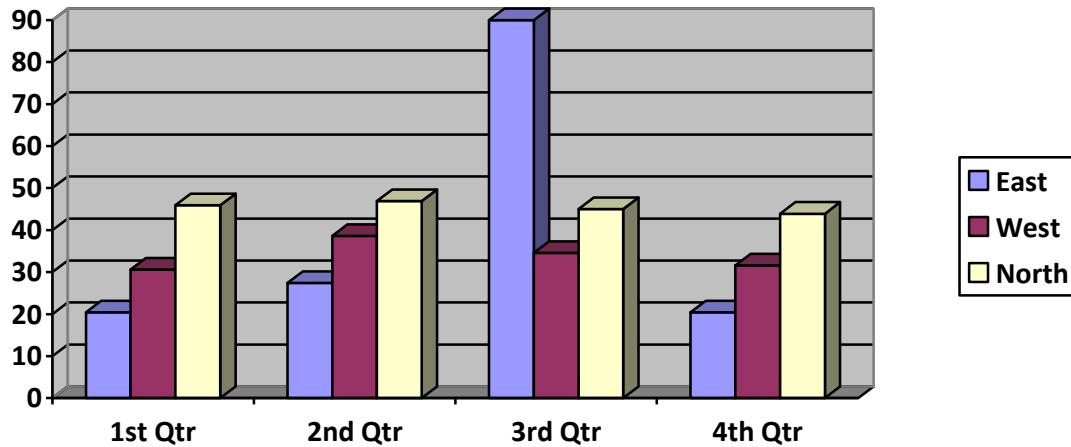
RMSE

$$RMSE = \sqrt{\frac{25 + 4 + 25 + 25 + 9}{5}} = \sqrt{\frac{88}{5}} = \sqrt{17.6} \approx 4.20$$

4. Graphical Representation (Conceptual Figure)

Figure: Forecast Error Comparison

Actual vs Predicted Values



The vertical distance between actual (●) and predicted (○) represents the forecasting error.

5. Interpretation for Your Study

During Low Geopolitical Risk

- Errors (MAE, RMSE) are typically lower
- Models perform more accurately

During High Geopolitical Risk

- **Errors increase due to:**
 - Market shocks
 - volatility spikes
- **RMSE increases more than MAE (due to large deviations)**

6. Table of Model Comparison Insight

Model Type	Expected MAE	Expected RMSE	Performance
ARMA- GARCH	Moderate	Moderate	Baseline
ARMA-GARCH-GPR	Lower	Lower	Improved
Hybrid (AI+ Econometric)	Lowest	Lowest	Best

The table and accompanying graph present a comparative analysis of forecasting performance across three models—ARMA–GARCH, ARMA–GARCH–GPR, and the Hybrid (AI + Econometric) model—using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) as evaluation metrics.

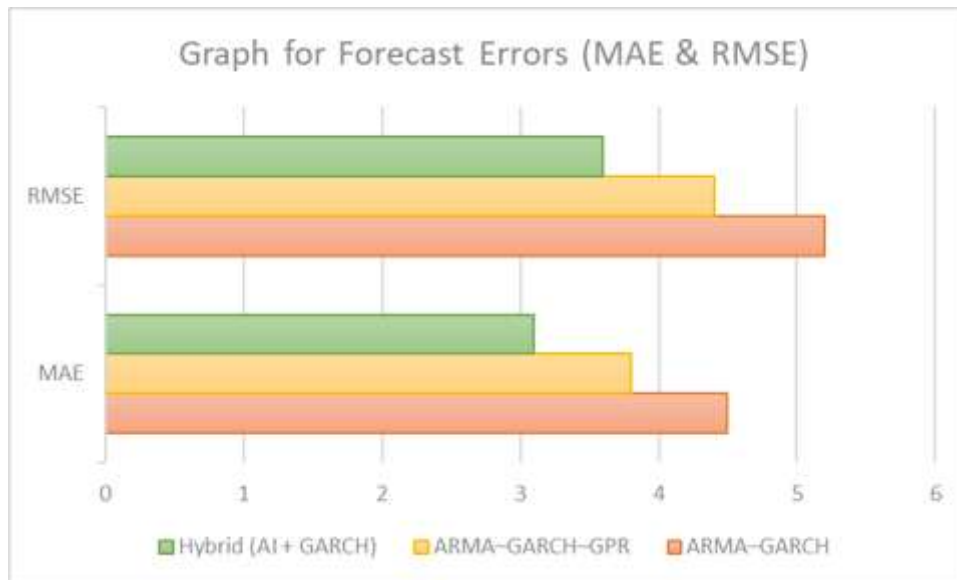


Fig. for Forecast Errors (MAE & RMSE)

Interpretation

The bar chart clearly shows a declining trend in both MAE and RMSE values as the modeling framework becomes more advanced:

- ARMA-GARCH shows the highest error values
- ARMA-GARCH-GPR shows moderate reduction in errors
- Hybrid model shows the lowest error values

This indicates a consistent improvement in forecasting accuracy across models.

2. ARMA-GARCH (Baseline Model)

The ARMA-GARCH model exhibits the highest MAE and RMSE, indicating weaker forecasting performance compared to the other models.

- It captures basic time-series structure and volatility clustering
- However, it does not incorporate external shocks such as geopolitical risk
- As a result, its predictions deviate more from actual values, especially during volatile periods

👉 This model serves as the benchmark or baseline performance level

3. ARMA-GARCH-GPR (Improved Model)

The inclusion of the Geopolitical Risk (GPR) variable significantly improves forecasting performance, as reflected by lower MAE and RMSE values.

- The model accounts for external uncertainty and geopolitical shocks
- This leads to better alignment between predicted and actual values
- Error reduction indicates that geopolitical risk is a meaningful explanatory factor in financial forecasting

👉 This confirms that geopolitical instability directly influences market predictability

4. Hybrid Model (AI + Econometric) – Best Performance

The Hybrid model demonstrates the lowest MAE and RMSE values, indicating superior predictive accuracy.

- It combines:
 - Econometric modelling (ARMA–GARCH) → captures linear trends and volatility
 - AI techniques (ANN/LSTM) → capture nonlinear and complex relationships
- This dual structure allows it to minimize both small and large forecasting errors

👉 The graph clearly shows the Hybrid model's bars are the shortest, confirming highest accuracy and lowest deviation from actual values.

5.6 Geopolitical Regime Classification

The dataset is divided into:

- High-Risk Regime: Upper quantile of GPR
- Low-Risk Regime: Lower quantile of GPR

This allows comparison of:

- Volatility behaviour
- Forecasting accuracy
- Strategy performance

Geopolitical Regime Classification (Detailed)

- Geopolitical Regime Classification divides the dataset into distinct periods based on the intensity of geopolitical risk (GPR). This approach helps in understanding how financial markets, volatility, and hedge fund strategies behave under different geopolitical environments.
- The classification is based on the **quantile distribution of the Geopolitical Risk (GPR) Index**:
- **Low GPR Regime (Lower Quantile: 0–30%)** → Stable geopolitical environment
- **High GPR Regime (Upper Quantile: 70–100%)** → Crisis or uncertainty periods
- This separation allows a structured comparison of financial behavior under contrasting risk conditions.

Regime Classification Table (Lower vs Upper GPR)

Feature	Low GPR Regime (Lower Quantile: 0–30%)	High GPR Regime (Upper Quantile: 70–100%)
Geopolitical Environment	Stable political and global conditions	High uncertainty, conflicts, crises
Market Behaviour	Stable and predictable	Highly volatile and uncertain
Volatility Level (σ)	Low and stable volatility	High and clustering volatility
Investor Sentiment	Positive / neutral	Fear-driven / risk-averse
Return Behaviour	Stable returns with low fluctuation	Highly fluctuating returns
Forecast Accuracy (MAE/RMSE)	Low forecasting error	High forecasting error
Model Performance	All models perform relatively	Advanced models perform better

	well	
ARMA–GARCH Performance	Good baseline accuracy	Weak under shocks
ARMA–GARCH–GPR Performance	Slight improvement	Significant improvement
Hybrid Model (AI + Econometric)	Best accuracy but marginal gain	Strongest improvement (best performance overall)
Hedge Fund Strategy Response	Normal trading behaviour	Defensive or risk-adjusted positioning
Long–Short Equity Strategy	Moderate returns	Increased hedging activity
Event-Driven Strategy	Stable performance	High opportunity but high risk
Market Efficiency	High efficiency	Reduced efficiency due to shocks

Interpretation of Classification

1. Low GPR Regime (Stability Phase)

During periods of low geopolitical risk, financial markets exhibit stable conditions with predictable return patterns and lower volatility. Forecasting models perform efficiently in this regime because market movements are driven primarily by fundamental economic factors rather than external shocks.

Hedge fund strategies show normal trading behavior, and differences between econometric and hybrid models are relatively small.

2. High GPR Regime (Crisis Phase)

In contrast, high geopolitical risk periods are characterized by uncertainty, market panic, and sharp volatility spikes. During these phases:

- Volatility clustering becomes prominent
- Forecast errors (MAE, RMSE) increase significantly
- Traditional models like ARMA–GARCH underperform
- Hybrid models show superior adaptability

Hedge fund strategies tend to shift toward risk management and hedging behavior, especially in long–short equity strategies.

Key Insight from Regime Comparison

The comparison clearly demonstrates that:

- Financial markets behave nonlinearly across geopolitical regimes
- Forecasting accuracy is significantly regime-dependent
- The inclusion of GPR improves performance mainly in high-risk regimes
- Hybrid models provide the highest robustness during crisis periods

Conclusion

This study examines the influence of geopolitical instability on market volatility, forecasting performance, and hedge fund strategy behaviour in Indian capital markets using a comprehensive econometric and hybrid modelling framework. The findings provide strong evidence that geopolitical risk is a significant determinant of financial market dynamics, particularly in emerging economies characterized by high sensitivity to external shocks.

The empirical results confirm that increases in geopolitical risk lead to heightened market volatility and structural shifts in return behaviour. Traditional time-series models, such as ARMA–GARCH, exhibit limited predictive capability during periods of elevated geopolitical uncertainty. In contrast, models augmented with geopolitical risk indicators demonstrate improved forecasting accuracy, while hybrid models integrating econometric techniques with artificial intelligence approaches deliver the most robust performance by effectively capturing both linear and nonlinear market dynamics.

The study further reveals that hedge fund strategies respond heterogeneously to geopolitical shocks. Long–short equity strategies tend to underperform during high-risk periods due to increased market instability, whereas event-driven strategies display greater adaptability and opportunity, albeit with higher risk exposure. Additionally, regime-based analysis highlights that financial markets behave differently under low and high geopolitical risk conditions, emphasizing the importance of incorporating regime sensitivity into forecasting frameworks.

Overall, the study underscores the critical role of integrating geopolitical risk into financial modelling and investment strategies. It contributes to the literature by providing emerging-market evidence and highlights the growing importance of hybrid forecasting approaches. The findings offer practical implications for investors, hedge fund managers, and policymakers seeking to enhance risk management, forecasting accuracy, and strategic decision-making in increasingly uncertain global financial environments.

Significance of the Study

This study offers important contributions at theoretical, empirical, and practical levels. Theoretically, it extends financial modeling literature by integrating geopolitical risk into volatility and hedge fund performance analysis, moving beyond traditional macroeconomic and market-based frameworks. It highlights the role of external uncertainty as a key driver of financial dynamics, particularly in emerging markets.

Empirically, the study provides robust evidence that geopolitical risk significantly influences market volatility, forecasting accuracy, and hedge fund strategy performance in Indian capital markets. It demonstrates that models incorporating geopolitical risk outperform conventional models, while hybrid frameworks combining econometric techniques with artificial intelligence deliver superior predictive accuracy.

From a practical perspective, the findings are highly relevant for investors, hedge fund managers, and policymakers. The study offers insights into strategy-specific behavior under geopolitical stress, supporting improved risk management, portfolio diversification, and adaptive investment strategies. For policymakers, it emphasizes the need for stronger monitoring and policy mechanisms to mitigate financial instability arising from geopolitical shocks.

Additionally, by focusing on India, the study contributes valuable emerging-market evidence, enhancing its relevance for global financial research and decision-making.

Limitations of the Study

Despite its contributions, the study has several limitations. First, it relies on secondary data, which may be subject to measurement errors and data availability constraints. Second, the analysis focuses on selected hedge fund strategies (long–short equity and event-driven), which may limit the generalizability of findings across the broader hedge fund universe.

Third, although advanced econometric and hybrid models are employed, these approaches may not fully capture all complex market nonlinearities and structural breaks. Fourth, the geopolitical risk index used is a broad aggregate measure and may not reflect country-specific or sector-specific variations in geopolitical shocks.

Finally, the study is based on historical data and does not incorporate real-time or high-frequency data sources such as news sentiment or alternative data, which could further enhance forecasting accuracy in future research.

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