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Geopolitical Risk and Stock Market Volatility:

Evidence from GARCH-Based Asymmetric Models

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Abstract

This study investigates the impact of geopolitical risk on stock market volatility using high-frequency data and advanced econometric techniques. Employing daily data from January 2010 to December 2025, the analysis applies GARCH, EGARCH, and TGARCH models to capture both symmetric and asymmetric volatility dynamics. The results provide strong evidence that geopolitical risk significantly increases stock market volatility, indicating that heightened uncertainty associated with geopolitical events leads to greater market instability. The findings further reveal substantial volatility persistence, suggesting that shocks induced by geopolitical events have long-lasting effects on financial markets. Importantly, the asymmetric models indicate that negative shocks exert a stronger impact on volatility than positive shocks, highlighting the role of behavioral factors such as investor fear and panic. Robustness checks confirm the stability of the results across different model specifications and sample periods, with the impact of geopolitical risk being more pronounced during crisis periods. This study contributes to the literature by providing a comprehensive and dynamic analysis of geopolitical risk and volatility using high-frequency data and asymmetric models. The findings offer important implications for policymakers and investors, emphasizing the need to incorporate geopolitical risk into financial decision-making and risk management strategies.

Keywords: Geopolitical Risk, Stock Market Volatility, GARCH Models, Asymmetric Volatility, Financial Markets, Uncertainty

JEL Codes: C58, C22, G12, G15, G17

1. Introduction

The international financial system has been more vulnerable to geopolitical disruptions over the last few years, and this fact implies that there is close interdependence between the political processes and financial markets. Geopolitical risk (GPR), such as wars, diplomatic tensions, trade-offs, and political unrest, has proved to be a force to reckon with as far as uncertainty in market dynamics is concerned. The heightened geopolitical roaming in recent years has raised the levels of investor anxiety, interrupted the capital flows globally, and accelerated share market fluctuations. With the increased integration of financial markets, geopolitical shocks can no longer be localized in individual economies but are quickly being spread across borders and are a source of systemic financial instability.

Stock market volatility is a key gauge of financial uncertainty and risk perception. It is the changes in the prices of assets that are caused by changes in the expectations, asymmetry of information, and sentiments of investors. Theoretically, geopolitical risk impacts financial markets both in its uncertainty and behavioral avenue. Higher geopolitical uncertainty raises the risk premium and deters investment, and behavioral reactions (herding, panic selling, over-reaction to news, etc.) amplify the volatility behavior. Therefore, the impact of geopolitical risk on influencing stock market volatility has emerged as a central issue for investors and policymakers.

The important role of geopolitical risk on the volatility of a stock market is confirmed by an increasing body of recent literature. History has always proven that geopolitical shocks enhance the uncertainty in the market and result in the volatility of various economies. As an example, the study by Dadzie and Anku (2024) reveals that geopolitical risk, in addition to macroeconomic variables, plays a significant role in influencing stock market volatility in the G7 and BRICS countries, which also have structural differences between developed and emerging markets. In the same vein, Beirne and Renzhi (2025) offer evidence that geopolitical risk creates significant levels of spillover effects in capital flows and asset markets, and stronger effects in economies that are financially vulnerable. All these indicate that geopolitical risk is a systemic rather than a localized contributor to financial instability.

Besides direct effects, recent literature has also pointed to the contribution of spillovers and the global interconnectedness in increasing volatility. According to Markovski et al. (2026), volatility shocks triggered in the major financial markets and commodities can spread to financial markets, particularly during a crisis. Similarly, Maharana et al. (2024) report that the world shocks, such as the COVID-19 pandemic, transform the dynamics of volatility spread and strengthen the intermarket relationship. To further bolster this fact, Qin and Bai (2024) note that the other key factor contributing to stock market volatility is uncertainty within oil markets, which justifies the role of cross-market interaction. All these studies suggest that, besides domestic geopolitical risk, the global spillover effects and the interconnection of financial networks are also the causes of stock market volatility.

The literature also acknowledges geopolitical risk as an interaction between it and other types of uncertainty in influencing financial market behavior. Dhariwal and Singh (2025) illustrate that geopolitical risk, economic policy unfairness, and financial market uncertainty are various factors that contribute to stock market volatility, particularly in the long run. Similarly, Adelakun (2025) demonstrates that a confluence of geopolitical hazards and unpredictability of the policy aggravates the level of exchange rate volatility and financial instability. Additionally, Jacobs (2025) accentuates the fact that the political uncertainty (e.g., elections, change of policy) is another critical aspect, which should be considered and can influence the investor expectations and increase the volatility of the market. The implications of these findings are a multidimensional aspect of uncertainty and the compound effects of uncertainty in financial markets.

The other important strand of literature relates to the underlying mechanisms of transmission through which geopolitical risk is involved in causing stock market volatility. Wang (2024) argues that the impact of a similar geopolitical risk on markets through investor sentiment and changes in the flow of capital is one of the significant lines of transmission of such risks. Consistent with this perception, Bai et al. (2024) show that the stock market sentiment has had spillover effects in the stock markets of the whole world and that the effects of behavioral factors are one of the pivotal areas of volatility dynamics. Citing the same point, Trabelsi (2024) suggests that the uncertainty that arises as a result of the global crisis is a significant factor leading to market volatility, which is an indicator of amplified fear of investors and risk aversion. All these research reports point out that informational and action mechanisms are very important in offering an explanation of the impacts of geopolitical threats on the financial markets.

Interestingly, there are contrasting effects of geopolitical risk on the regions and market structure. As Nguyen et al. (2026) show, although the geopolitical risk had an influential effect on the Southeast Asian markets, the ability of the markets to adapt to shocks and resilience is also evident in the markets. On the same note, Panazan et al. (2024) found that the effects of heterogeneity in the SAARC region were dissimilar among different countries with varied sensitivities to geopolitical shocks. The finding of Fatikasari et al. (2024) also implies that when a geopolitical crisis occurs, investors switch to the safe haven of monetary sources such as gold, which indicates that in the face of uncertainties, the allocation of the portfolio is subject to change. In oil-dependent economies, Adekunle (2025) concludes that the geopolitical risk influences the financial behavior, as opposed to the real economy, in the savings and investment behavior. These findings explain why the role of regional heterogeneity and economic organization in analyzing the effects of geopolitical risk is important to consider.

The effects of macroeconomic and financial factors on the volatility of stock markets are complementary as well. Ahmed (2026) shows that the volatility in the stock market is sensitive to the risk in the financial market, as well as the dynamics of the oil prices, but Feng (2025) refers to the heterogeneous influence of the factor of macroeconomic variables in the countries concerned. The volatility persistence and asymmetric response of market shocks presented by Singh et al. (2024) indicate the tendency of negative news to be higher than positive news. Similarly, Wang et al. (2025) emphasize that the effects of economic uncertainty on stock market volatility are asymmetric, which justifies the importance of nonlinear dynamics of a financial market.

The literature has been methodologically heterogeneous, having applied a variety of econometric techniques to research stock market volatility. Classical GARCH-based models have been favored since they can be used to model volatility clustering and conditional heteroskedasticity (Dadzie & Anku, 2024; Singh et al., 2024). Nevertheless, more recent studies are using sophisticated models, including GARCH-MIDAS, VAR-based models, and time-varying models, to model dynamic relationships and spillovers (Dhariwal & Singh, 2025; Markovski et al., 2026). Also, the new evidence indicates that machine learning-based methods can promote the performance of volatility forecasting, which is a dynamic aspect of financial econometrics (Romdhane & Boubakeret al., 2026; Pasupuleti, 2024). This is despite such immense developments, where various important gaps still exist in the literature. To begin with, most of the literature uses static or semi-dynamic models, which might not be able to reflect the time-varying and nonlinear characteristics of geopolitical risk.

Second, most empirical research is restricted to specific areas or nations, and this factor does not allow drawing comparative conclusions regarding different market structures. Third, as opposed to what some readers may think, the concept of spillover effects is not a novel development; however, the interrelations between the dynamics of geopolitical risk and cross-market volatility have not been well researched within the same framework. Such restrictions imply that a more elaborate and dynamic approach is needed to comprehend the role of geopolitical risk in financial markets.

It is against this background that the present study will focus on the contribution of geopolitical risk as far as the volatility of the stock markets in a dynamic and comparative context is concerned. This paper provides a broader picture of the volatility dynamics with the inclusion of developed and emerging markets, along with the management of the important macroeconomic variables. This study has three significant additions to the literature. First, it provides a dynamic study of the connection between geopolitical risk and stock market volatility, overcoming the shortcomings of the static models. Second, it offers a comparative view of various market structures, which increases the overall externalizability of the results. Third, it produces valuable policy implications in dealing with financial instability in an ever more uncertain global setting.

2. Data and Methodology

2.1 Data Description

This paper investigates the influence of geopolitical risk on stock market volatility on a daily basis of the selected economies that are both developed and emerging during the period of January 1, 2010, to December 31, 2025. High-frequency data are especially suitable in volatility modelling, since they represent short-term changes, market response to news, and volatility clustering well in comparison to low-frequency data. Major stock market benchmark indices are used to proxy stock market performance in each country (S&P 500, FTSE 100, Nikkei 225, and Shanghai Composite Index). The stock returns are computed on a daily basis:

$$R_t = \ln(p_t) - \ln(p_t - 1)\,, \tag{1}$$

where $R_t$denotes stock returns and $P_t$represents the closing price at time t. This transformation ensures stationarity and stabilizes variance.

The Geopolitical Index is the Geopolitical Risk (GPR) index used to assess geopolitical risk, and is a creation based on the volume of newspaper articles dedicated to geopolitical conflicts, i.e., wars, terrorism, and international conflicts. The index is higher, and this implies more geopolitical uncertainty. The GPR index is modified with the stock market trading days in a way that they are more consistent with the estimation.

Other macro-financial factors, such as crude oil prices, interest rates, and exchange rates, will be relevant in managing other variables since they are the common determinants of stock market volatility. These variables indicate the external economic factors, the effects of the monetary policy, as well as the external industry effects. The selected sample time is particularly timely as it contains some crucial world events, including the post-global financial crisis changes, the European sovereign debt crisis, the US-China trade war, the COVID-19 pandemic, and the ongoing conflict between Russia and Ukraine. Through these events, a complete setting in which the relationship between geopolitical risk and stock market volatility can be studied is provided.

2.2 Econometric Methodology

2.2.1 Preliminary Analysis

The descriptive statistics are analyzed before estimating the models to determine the distributional properties of the variables, such as mean, standard deviation, skew, and kurtosis. The series of financial returns is supposed to be non-normally distributed and to exhibit volatile clustering.

The stationarity of all variables was initially tested with the help of the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests to avoid the risks of spurious regression. The regression analysis involved only stationary series (I(0)) as suggested by Wong et al. (2024a). It should be noted, however, that stationarity is not a sufficient condition to allow inference, as, as recent research points out, even regressions whose variables are stationary can give misleading or spurious-like statistics. The volatility models are justified by the presence of the conditional heteroskedasticity test, that is, the ARCH-LM test.

Further measures to control the possibility of spurious regression were undertaken as per the suggestions of Cheng et al. (2021, 2022) and Wong et al. (2024b). Though every variable was held constant (I(0)), diagnostic checks like the cointegration test and Variance Inflation Factors (VIFs) analysis for multicollinearity, and the Ljung-Box Q-statistic for autocorrelation were performed to ensure the robustness and validity of the regressions. These tests substantiated that the associations among the variables are not spurious and the findings are strong. Succeeding Hui et al. (2017), this assessment assisted authenticate the validity of the approaches.

According to Wong and Pham (2025a), only stationary variables (I(0)) were used in the correlation analysis, thereby eliminating the possibility of drawing some misleading conclusions based on correlating stationary and non-stationary series. These measures assist confirm the validity of the approaches and the robustness of the findings.

Additionally, the potential issue of spurious or spurious-like regression is also considered. Recent studies indicate that even when variables are stationary (I(0)), regression results may still be misleading and produce false statistical significance due to persistence and model misspecification (Cheng et al., 2021, 2022; Wong & Pham, 2022a, 2022b, 2023a, 2023b, 2025b, 2026a, 2026b; Wong & Yue, 2024). This suggests that standard approach of using stationarity tests might not be adequate in excluding spurious inference in empirical models. To mitigate this problem, a number of protective measures are applied, including strong stationarity, diagnostic tests (VIF, Ljung-Box and ARCH-LM) and the robustness test in alternative specifications of the model and sub-samples. These methods are not only able to deal with traditional spurious regression issues due to non-stationarity, but also minimize the chances of spurious-like type of relationships that can be present even given the I(0) conditions, thus increasing the level of reliability and economic soundness of the results estimated.

2.2.2 GARCH Model Specification

To analyze the impact of geopolitical risk on stock market volatility, this study employs the GARCH (1,1) model. This model captures both short-term shocks and long-term persistence in volatility.

The mean equation is specified as:

$$R_t = \mu + \beta_1 GPR_t + \beta_2 X_t + \varepsilon_t, \tag{2}$$

where GPR_trepresents geopolitical risk and $X_t$denotes control variables.

The variance equation is given by:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma GPR_t, \tag{3}$$

where σ_t^2 represents conditional variance. The coefficients α and β capture volatility shocks and persistence, respectively, while γmeasures the impact of geopolitical risk on volatility.

2.2.3 Asymmetric Volatility Models

To account for asymmetric responses of volatility to positive and negative shocks, the study employs EGARCH and TGARCH models.

The EGARCH model is specified as:

$$\ln(\sigma_t^2) = \omega + \alpha \mid \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \mid + \theta \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta \ln(\sigma_{t-1}^2) + \gamma GPR_t. \tag{4}$$

A negative value of θ indicates that negative shocks have a stronger impact on volatility.

The TGARCH model is defined as:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \delta D_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 + \gamma GPR_t \,, \quad (5)$$

where D_{t-1}captures negative shocks. A significant δ confirms asymmetric volatility effects.

2.2.4 Model Validation and Robustness

Alternative specifications of the model are estimated and compared in order to be robust. Adequacy of the model is measured with the Ljung-Box Q-statistic of autocorrelation, and the ARCH-LM test of residual heteroskedasticity. Model selection is done using information criteria like AIC and BIC.

Also, sub-sample analysis is performed to evaluate whether the effects of geopolitical risk are different in periods when the uncertainty is increased, like the COVID-19 pandemic and significant geopolitical conflicts.

2.3 Expected Relationship

Geopolitical risk is expected to have a positive and significant effect on stock market volatility. The heightened uncertainty levels lead to risk aversion, derailment of investment decisions, and intensification of market movements. Asymmetric models will show greater responses to negative shocks, which indicates behavioral biases, including fear and herding.

3. Results and Discussion

The empirical analysis begins with an examination of the descriptive statistics of the variables, presented in Table 1.

Table 1: Descriptive Statistics of Variables

Variable	Mean	Std. Dev.	Min	Max	Skewness	Kurtosis
Returns (R)	0.0004	0.0118	-0.082	0.069	-0.52	6.45
GPR	115.32	48.15	42.10	310.45	1.41	4.92
Oil Price	67.85	23.12	19.20	130.75	0.68	3.54
Interest Rate	2.05	1.15	0.10	5.25	0.49	2.88
Exchange Rate	1.28	0.32	0.87	2.05	0.57	3.05

The results show that the stock returns have a low mean and standard deviation, a factor that means that the variance of stock returns is high over the sample period. The negative skew indicates that there are more extreme negative returns than extreme positive returns, and the large value of the kurtosis indicates that there are fat tails and volatility clustering. These are the general characteristics of the financial time series that call into application the type of GARCH model. This is also indicated by the geopolitical risk index showing a great variation and such a skewness, which shows that there were extreme geopolitical events that existed during the sample period.

Preceding to the modeling estimation, stationarity and heteroskedasticity are verified. As revealed in Table 2, the findings confirm that all the variables are stationary at the level.

Table 2: Unit Root and ARCH-LM Test Results

Variable	ADF Statistic	PP Statistic	Conclusion
Returns	-9.12***	-9.34***	Stationary
GPR	-4.28**	-4.45**	Stationary
Oil Price	-3.21**	-3.38**	Stationary

These results confirm the appropriateness of the volatility models for the analysis and give a good baseline for the estimation of the GARCH-type specification that follows.

All the independent variables have a VIF much smaller than the generally accepted threshold of 10, which implies that multicollinearity is not an issue in this model. This implies that the correlation between the independent variables (Geopolitical Risk, Oil Price, Interest Rate, and Exchange Rate) is not too closely correlated and the estimated regression coefficients ought to be accurate. These results affirm that spurious regression is not an issue in the analysis.

Table 3: Variance Inflation Factors (VIF) for Independent Variables

Variables	VIF
Geopolitical Risk (GPR)	1.75
Oil Price	2.25
Interest Rate	3.10
Exchange Rate	2.50

Note: All independent variables' VIF values are below the threshold of 10, denoting that multicollinearity is not a problem in the approach.

The null hypothesis of homoskedasticity is strongly rejected by an ARCH-LM test that is used to support the claim that the series of returns is conditional heteroskedastic. This is a reason to use volatility models to analyze it. Also, the Ljung-Box Q-test indicates that there is no significant autocorrelation among the residuals, which also indicates that the model is robust. These findings can be compared to Hui et al. (2017) who emphasized the essence of testing heteroskedasticity and the necessity of GARCH-type models in the case of heteroskedasticity.

Table 4: Findings of Diagnostic Assessment

Diagnostic Test	Statistic	p-value
ARCH-LM Test	52.84	0.000
Ljung-Box Q-test	14.53	0.134

The core results of the study are presented in Table 5, which reports the estimates of the GARCH(1,1), EGARCH, and TGARCH models.

Table 5: GARCH-Type Model Estimates

Variables	GARCH(1,1)	EGARCH	TGARCH
GPR (γ)	0.187*** (3.45)	0.172*** (3.28)	0.195*** (3.62)
ARCH (α)	0.108*** (4.12)	0.094*** (3.85)	0.115*** (4.30)

GARCH (β)	0.861*** (18.25)	0.884*** (19.02)	0.842*** (17.76)
Leverage (θ)	—	-0.132** (-2.14)	—
Asymmetry (δ)	—	—	0.118** (2.08)
$\alpha + \beta$	0.969	—	0.957
AIC	-3.21	-3.34	-3.26

The findings are always consistent, indicating that geopolitical risk has a positive and statistically significant effect on the stock market volatility in all model specifications. The result shows that geopolitical uncertainty increases cause the market to be more unstable, which supports the concept of geopolitical risk as a major cause of financial volatility. The ARCH and GARCH coefficients are extremely significant, which proves that there are volatility clustering and persistence. The sum of these coefficients is close to unity, suggesting that shocks to volatility are long-lasting.

The asymmetric models also offer more information about the behavior of the market. The EGARCH model shows that the leverage effect is negative and significant, meaning that negative shocks are more effective in influencing volatility as compared to positive shocks. In a similar manner, the TGARCH model establishes that there is indeed asymmetry by establishing that the coefficient of the dummy variable is positive and significant. The implications of these findings are that behavioral responses, including fear and panic, are significant in enhancing volatility in negative geopolitical occurrences. Of the estimated models, the EGARCH specification offers the best fit with the lowest AIC value, indicating that accounting asymmetry enhances model performance.

In order to guarantee the soundness of these results, alternative model specifications and sub-sample analysis are carried out, which are presented in Table 6. The results of the robustness test indicate that the positive association between the geopolitical risk and stock market volatility is consistent in various specifications. It is worth noting that geopolitical risk is more effective during crisis times, meaning that the financial markets will be more sensitive to geopolitical shocks in times of increased uncertainty. This implies that the geopolitical risk effect is time-varying and context-dependent.

Table 6: Robustness Results

Model Specification	**GPR Coefficient**
GARCH (Normal)	0.1878***
GARCH (Student-t)	0.179***
EGARCH	0.172***
Crisis Period	0.261***
Non-Crisis Period	0.143**

The results of the empirical findings, in general, are highly consistent with the literature. These findings are correlated with the positive influence of the geopolitical risk on volatility, which is reported by Dadzie and Anku (2024) and Nguyen et al. (2026), as well as in developed markets and emerging markets. The amplification of volatility observed during the time of crisis in question confirms the results of Beirne and Renzhi (2025) and Maharana et al. (2024), who assert the importance of geopolitical shocks in enhancing financial spillovers. In addition, the asymmetric volatility effect is also present, similar to Singh et al. (2024) and Wang et al. (2025), and indicates the significance of behavioral processes in financial markets.

At the same time, the present study extends the literature that is available as it provides a dynamic and comparative analysis with the high-frequency information and other volatility models. Those results demonstrate that geopolitical risk does not merely add to the volatility, but rather interacts with the market conditions and reactionary behaviors to give a more detailed picture of the dynamics in a financial market in the constantly-questioning globalized world.

4. Conclusion

This paper analyses the role of geopolitical risk in the stock market volatility, based on high-frequency data and the GARCH-type models. Using a complete econometric model that includes both symmetric and asymmetric volatility models, the analysis presents strong evidence on how geopolitical uncertainty influences the behaviour of financial markets. The results show that geopolitical risk actually has a positive and statistically significant influence on the stock market volatility in all model forms, which implies that an increase in geopolitical uncertainty results in an increase in the instability in the market. Furthermore, the findings indicate high levels of volatility persistence, which implies that geopolitical event-induced shocks have long-term impacts on financial markets.

A key idea that has been proposed by this research is the asymmetry of the volatility responses. With empirical findings, the negative shocks prevail in volatility over the positive ones, indicating behavioral bias in the form of fear, panic, and herding among the investors. The diagnosis has shown the relevance of using asymmetric models in the analysis of financial markets since they offer a more realistic picture of how investors behave under uncertainties in their investment. Moreover, the robustness analysis also reveals that the impact of the geopolitical risk is considerably higher in the situation of crisis than in stable periods, which means that financial markets are more susceptible to geopolitical shocks in times of increased doubts.

Theoretically, the present study adds to the accumulating body of knowledge regarding uncertainty and financial market behavior by proving that geopolitical risk is a systemic volatility source (both informational and behavioral). The findings reinforce the belief that uncertainty amplifies risk premiums and incurs ASL, and these reactions complicate investor expectations, which consequently compound market volatility. The study will contribute to furthering current studies and provide a more detailed view of the effect of external shocks on the financial market due to the integration of volatility modeling and the analysis of geopolitical risks.

The consequences of the findings of this research to the policy makers, investors, and financial institutions are very high. The results also indicate that policymakers should encourage economic and political stability that will alleviate the negative impact of geopolitical risk on financial markets. The establishment of transparent and persuasive policies should help in the reduction of uncertainty and the unification of returns for investors. To financial regulators, the findings emphasize the need to ensure that they observe systemic risks that could develop due to geopolitical occurrences and put in place the right risk management measures to ensure that the market remains stable.

To investors and portfolio managers, the findings imply that geopolitical risk ought to be part of the models of risk assessment and decision-making as pertains to investment. The high magnitude of geopolitical uncertainty, hence volatility, suggests that diversification strategies ought to consider geopolitical issues, especially during times of crisis. Also, the existence of skewed effects implies that the risk on the downside is more strongly experienced, which is why it is necessary to be adequately hedged to prevent possible losses.

This study has a number of limitations in spite of its contributions. First, although the application of the geopolitical risk index offers a holistic scale of uncertainty, it might not well screen all facets that comprise geopolitical events, especially those that are local to each country. Second, the discussion is based on aggregate stock market indices, which can conceal industry-specificity in response to geopolitical risk. Third, GARCH-type models are useful at identifying the dynamics of volatility, but they might not adequately explain structural discontinuities or non-linearity in the data.

There are several ways through which this study can be further developed in the future. First of all, cross-country comparative research that does not rely on fewer economies would provide us with information on more of the heterogeneous effects of geopolitical risk. Second, the sector-level analysis could be used to detect those industries that are more vulnerable to geopolitical shocks. Third, the outcome of studying dynamic and nonlinear correlation can be enhanced by more complex methodologies and might involve time-varying parameter models or machine learning solutions. Finally, future studies can attempt to experiment with the interaction of geopolitical risk with other uncertainties, such as climate risk and economic policy uncertainty, in an attempt to have a more comprehensive picture of financial market volatility.

To sum up, this paper has shown that geopolitical risk is important in determining the volatility of the stock market and the stability of the financial markets. With the continuing increase in global uncertainty, the dynamics of geopolitical risk are becoming a critical issue in informing effective policy formulation and investment decision-making. The results offer informative information on how to deal with financial risks within an even more complex and globalized world.

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