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Article

Russo-British Geopolitical Conflict and Pound Sterling Volatility: Estimation Using an EGARCH-X Model

Feriel Dermechi [1,*] and Amine Tammar [2]

[1] Department of Economics, National Higher School of Statistics and Applied Economy (E.N.S.S.E.A), Kolea (42003), Tipaza, Algeria
[2] Department of Economics, Lounici Ali University of Blida 2, El-Affroun (09011), Blida, Algeria
* Correspondence: dermechi.feriel@enssea.edu.dz

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Abstract: This article examines the influence of the recent Russo-British geopolitical conflict on the volatility of sterling returns, utilizing an Exponential Generalised Autoregressive Conditional Heteroskedasticity model with exogenous variables (EGARCH-X) under a generalised error distribution (GED), which incorporates both geopolitical and macroeconomic-financial exogenous factors. The findings reveal a pronounced negative asymmetry, indicating that adverse shocks substantially heighten sterling volatility. Although the variable representing the geopolitical event of May 3, 2025, between Russia and the United Kingdom is statistically insignificant under the GED specification, global geopolitical risk exerts a moderately significant effect. This divergence suggests that markets respond more sharply to systemic tensions than isolated bilateral disputes. From an economic perspective, Sterling's heightened sensitivity to oil prices and Gilt yields reflects the United Kingdom's structural vulnerabilities regarding energy dependence and fiscal sustainability. Overall, the observed volatility appears to be primarily driven by global exogenous shocks rather than discrete events, underscoring the growing importance of risk perceptions in an increasingly interconnected international environment.

Keywords: Russo-British Geopolitical Conflict; Sterling Returns; EGARCH-X; Generalised Error Distribution; Negative Asymmetry; Global Geopolitical Risk

1. Introduction

Exchange rate volatility constitutes a central focus in international finance, as it reflects market expectations, risk aversion, and investors' immediate reactions to economic and geopolitical shocks. Among the determinants of currency volatility, international geopolitical tensions play a central role, particularly when they involve major powers with significant economic, military, and diplomatic influence. The pound sterling, as the currency of a nation deeply embedded in global geopolitical dynamics, provides a particularly salient example of sensitivity to external shocks.

Since early 2025, relations between the United Kingdom and Russia have deteriorated against the backdrop of the ongoing Russia–Ukraine war. The UK, having intensified its military support to Ukraine, including the provision of long-range weaponry and the deepening of strategic cooperation, has been directly targeted by a series of threats from Russia. In May 2025, Russia announced military exercises involving nuclear manoeuvres near Ukraine and threatened British military targets,

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according to the UK Foreign Secretary. These statements coincided with hostile diplomatic actions. This escalation was followed by a modest depreciation in the pound sterling's return, falling from 1.00 on May 1, 2025, to 0.96 on May 6, 2025, according to Trading Economics data.

In this context, the present study examines the impact of the bilateral geopolitical conflict between Russia and the United Kingdom on the volatility dynamics of the pound sterling. Geopolitical tensions may disrupt trade by increasing transaction costs, thereby reducing imports, foreign investment, and consumption of external goods, all of which ultimately influence exchange rate volatility [1, 2, 3]. They may also trigger capital flight towards perceived safer economies, as rising uncertainty prompts investors to reallocate assets, exerting additional pressure on exchange rates [4, 5, 6]. Furthermore, market participants may revise their expectations regarding future economic developments, which in turn influences investment decisions [5]. Overall, the extent to which geopolitical tensions affect exchange rate returns depends on a country's exposure and the global prominence of its currency [7, 8].

Previous studies provide insight into these dynamics. Within the context of the Russia–Ukraine conflict, [9] investigated its ramifications on financial markets across Russia and Europe, highlighting European equities and Russian sovereign bonds as key channels of financial shock transmission. [10] examined the conflict's short-term impact on European exchange rates, identifying a pronounced negative market response. [11] reported downward pressure on currencies in countries geographically and economically proximate to the conflict. [12] analysed the Russian trouble, revealing rapid and substantial depreciation relative to counterfactual forecasts. Finally, [13] studied five EU currencies: the Polish zloty, Hungarian forint, Czech koruna, Swedish krona, and Romanian leu, finding heterogeneous responses, with some currencies highly sensitive while others remained relatively stable.

The present study is guided by two hypotheses:H1 – Russo-British geopolitical tensions increase pound sterling volatility; H2 – Intensification of these tensions produces an asymmetric volatility response, with greater sensitivity to negative shocks. To test these hypotheses, an EGARCH-X model (Exponential Generalised Autoregressive Conditional Heteroskedasticity with exogenous variables) is estimated. This framework models conditional volatility while explicitly incorporating exogenous variables capturing the intensity of geopolitical tensions, including a binary dummy representing the UK–Russia conflict. Unlike standard GARCH models, EGARCH-X allows direct integration of geopolitical events into the volatility equation, enhancing understanding of how political shocks propagate in financial markets. Moreover, the logarithmic specification of conditional variance ensures positivity and accommodates stronger reactions to negative shocks without imposing parameter restrictions.

No prior study has specifically examined the effect of a bilateral Russo-British conflict on pound sterling volatility using an EGARCH-X framework incorporating both event-specific geopolitical variables and global indices. This research, therefore, fills an empirical and methodological gap in the literature on the transmission of geopolitical shocks to foreign exchange markets. Its primary objectives are twofold: (1 to empirically assess the effect of Russo-British tensions on sterling volatility and, (2 to demonstrate the methodological relevance of EGARCH-X in modelling recurrent exogenous shocks of geopolitical origin. The study's originality lies in its focus on a recent geopolitical event and its use of an econometric approach that allows clear identification of the impact of these tensions on volatility dynamics.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature on geopolitical shocks, exchange rate volatility, and the application of GARCH-family models. Section 3 sets out the materials and methods, including the data and model specification. Section 4 reports the estimation results, while Section 5 discusses their economic and policy implications. Finally, Section 6 concludes and suggests directions for future research.

2. Literature Review

2.1. GARCH and EGARCH Models

Since their introduction by [14], GARCH-type models have become central tools for analysing conditional volatility in financial time series. They capture the time-varying variance commonly observed in exchange rate returns as a consequence of conditional heteroscedasticity. To address volatility asymmetries, the EGARCH model proposed by [15] employs a logarithmic specification of the conditional variance. This ensures non-negativity without the need for parameter restrictions and accommodates asymmetric shock effects; whereby negative shocks exert a stronger influence on volatility than positive shocks of equal magnitude. Empirical studies provide strong support for this framework. [16] showed in the Indian market that negative returns cause disproportionately higher volatility increases, consistent with the leverage effect. Similarly, [17] identified pronounced asymmetry and leptokurtosis in Indian asset returns using EGARCH and asymmetric PARCH models, underscoring the value of such approaches for accurate volatility modelling.

2.2. Incorporating Exogenous Variables

Subsequent evidence has demonstrated that the incorporation of exogenous factors, such as oil prices, geopolitical risk indices, and structural break indicators, into GARCH-type models improves our understanding of market responses to external shocks. For instance, [18] employed a Copula-GARCH-X model and found that rising oil prices are generally associated with currency depreciation in BRICS economies. In a related study, [19] employed univariate and bivariate GARCH models with structural break dummies to examine volatility spillovers between oil prices and the US dollar. Conversely, [20] reported no significant effect of a geopolitical risk index on financial asset volatility, highlighting the importance of careful model specification and variable selection. These studies illustrate the increasing use of enriched volatility models that integrate macroeconomic and geopolitical variables.

2.3. Geopolitical Risk and Exchange Rate Volatility

Advanced GARCH frameworks, particularly GARCH-X and GARCH-MIDAS, have proven effective in capturing exchange rate dynamics when extended to incorporate geopolitical risk measures, especially during periods of heightened political tension. For instance, [21] employed a GARCH-MIDAS-X model and showed that recent geopolitical shocks exert stronger effects on BRICS exchange rates than historical trends, with global risks outweighing country-specific ones. Similarly, [22] applied a GARCH-X model to the IDR/USD exchange rate, revealing amplified and asymmetric responses to both global and domestic geopolitical tensions. More sophisticated variants, such as the regime-switching GARCH-MIDAS-X used by [23], further demonstrate that incorporating geopolitical factors enhances volatility forecasting.

While these studies establish the effectiveness of GARCH-X-based approaches, growing attention has been devoted to EGARCH-X models, which are particularly well suited to capturing asymmetries in volatility responses. [24], for example, examined Nigerian exchange rate volatility using an EGARCH-X model under three alternative distributional assumptions, confirming that the results remained consistently significant across specifications.

Collectively, this evidence underscores the value of EGARCH-X frameworks in modelling exchange rate volatility in the presence of geopolitical shocks. Consistent with this literature, the present study applies an EGARCH-X model to British pound fluctuations during the UK–Russia conflict, offering fresh insights into how geopolitical risk shapes currency dynamics.

3. Materials and Methods

3.1. GARCH Model

The GARCH (1, 1) model, originally introduced by [14] and subsequently extended by [15] and [7], is defined as follows:

$$h_t = \omega + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-1}^2 + \sum_{i=1}^{q} \beta_i \, h_{t-i}, \tag{1}$$

where the parameters $\alpha_1, \ldots, \alpha_p, \beta_1, \ldots, \beta_q$ are constants; ε_{t-1}^2 denotes past shocks, while h_{t-i} refers to the lagged values of the conditional variance.

The GARCH model, as an extension of the ARCH framework, assumes that the impact of a shock on conditional volatility decays geometrically over time [7]. Although widely applied in empirical research, this model exhibits a key limitation: it fails to account for the asymmetry of shocks. Specifically, volatility is modelled solely as a function of the magnitude of past shocks (ε_{t-1}^2), without regard to their sign, even though negative shocks, often associated with adverse events, tend to have a more pronounced effect [15].

3.2. EGARCH Model

Asymmetry occurs when an unexpected shock increases conditional volatility more than its size would suggest. This contradicts the usual assumption that past shocks affect variance symmetrically. To address this, [15] introduced the Exponential GARCH (EGARCH) model, which explicitly captures such asymmetric effects. Its formulation is as follows:

$$\log(h_t) = \omega + \beta . \log(h_{t-1}) + \gamma . \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi} \right], \tag{2}$$

where ω denotes the constant term; β captures the persistence of volatility (the GARCH effect); γ represents the asymmetry coefficient; the expression $\gamma . \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ is the asymmetry term, also referred to as the leverage effect; and α measures the sensitivity to the magnitude of past shocks (the ARCH effect).

The inclusion of the term $\gamma . \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}$ introduces asymmetry into the model, as it depends on the sign of the standardised residuals (ε_{t-1}). Thus, when the shock is positive $(\varepsilon_{t-1} > 0)$, the asymmetry term is positive; when the shock is negative $(\varepsilon_{t-1} < 0)$, the term becomes negative. This implies that negative shocks impact volatility more strongly than positive shocks of the same magnitude.

Volatility evolves exponentially in both directions, but with different parameters depending on the sign of the innovation. The lagged conditional variance reverts to its unconditional level, σ^2, which is defined by:

$$h_t = A.\exp\left[\frac{(\gamma+\alpha)}{\sigma}.\varepsilon_{t-1}\right] \text{ when } \quad (\varepsilon_{t-1} > 0), \tag{3}$$

$$h_t = A.\exp\left[\frac{(\gamma-\alpha)}{\sigma}.\varepsilon_{t-1}\right] \text{ when } \quad (\varepsilon_{t-1} < 0), \tag{4}$$

where

$$\mathrm{A} = \sigma^{2\beta}.\exp\left[\omega - \alpha\sqrt{2/\pi}\right], \tag{5}$$

3.3. EGARCH-X Model

Although the EGARCH model is effective in capturing asymmetry and volatility persistence, it suffers from a significant limitation: it does not explicitly account for the influence of exogenous variables that may directly affect the dynamics of conditional volatility. This shortcoming has been noted by several authors, most notably [25], who emphasized that omitting relevant macroeconomic or financial variables can lead to an incomplete specification of the variance process, thereby reducing both the explanatory power and forecasting accuracy of the model. It is in this context that the EGARCH-X model was introduced to enhance the conditional variance equation by incorporating external explanatory variables (represented by the "X" in the model), defined as follows:

$$\log(h_t) = \omega + \beta.\log(h_{t-1}) + \gamma.\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{2/\pi}\right] + \sum_{i=1}^{k}\delta_i X_{t-1}, \tag{6}$$

where δ_i denotes a (k×1) vector of coefficients measuring the impact of the exogenous variable on volatility, while X_{t-1} represents a vector of k observable exogenous variables at time *t–1*. The product $\delta_i X_{t-1}$ is a scalar, and the summation $\sum_{i=1}^{k}\delta_i X_{t-1}$ captures the cumulative effect of the lagged exogenous variables.

The central behaviour of the dependent variable is modelled through the mean equation, which is defined as:

$$y_t = \mu + \phi y_{t-1} + \theta' Z_t + \varepsilon_t, \tag{7}$$

where y_t denotes the dependent variable; μ is a constant term; ϕ is an autoregressive coefficient capturing the persistence effect of y_{t-1} on Z_t is a vector of explanatory variables included in the mean equation (which may differ from or coincide with X_t); θ is a vector of coefficients measuring the marginal impact of each explanatory variable in Z_t on y_t; and $\varepsilon_t \sim \mathrm{N}(0, h_t)$ is a zero-mean white noise process with conditional variance h_t.

The choice of the error distribution ε_t in EGARCH and EGARCH-X models plays a crucial role in the accuracy of volatility estimation and forecasting [26]. While the assumption of normality may be acceptable in the absence of leptokurtosis or asymmetry, it is often unsuitable for financial data, which are typically characterised by extreme events. [27] highlighted that relying on the normal distribution can lead to inefficient estimation.

To better capture the fat tails observed in financial returns, the Student's t-distribution, introduced by [28], is commonly employed. It offers a more accurate representation of extreme shocks. Furthermore, [26], using a Bayesian framework, demonstrated that asymmetric distributions, such as the standardised asymmetric Student-t, significantly enhance the prediction of tail risk, including

Value-at-Risk.

An additional flexible alternative is the Generalised Error Distribution (GED), proposed by [15]. With its shape parameter k, the GED allows for tail thickness adjustment and includes the normal distribution as a special case, making it particularly suitable for modelling series with excess kurtosis, as follows:

$$f(z_t) \propto \exp\left(-\frac{1}{2}|z_t|^k\right), \tag{8}$$

The selection of an appropriate error distribution in GARCH models is guided by the statistical residuals' dynamics. In practice, this decision hinges on whether the residuals exhibit asymmetry and heavy-tailedness [18, 26]. Preliminary assessments, using normality tests such as the Jarque–Bera test alongside evaluations of skewness and kurtosis, provide essential guidance in this respect. In situations where significant asymmetry is combined with leptokurtosis, it is advisable to adopt error distributions that can accommodate both features [7, 18, 26].

Examples include the asymmetric Student's t and the Generalised Error Distribution (GED). In this context, [29], using a Monte Carlo simulation, demonstrated that the GED outperforms conventional distributions in terms of both goodness-of-fit and forecast accuracy.

3.4. Overview of Data and Sources

The data employed in this study are of daily frequency and span the period from 2 January 2022 to 7 May 2025, a timeframe marked by escalating geopolitical tensions between Russia and European countries, particularly the onset of the Russia-Ukraine conflict, which triggered the recent diplomatic dispute between Russia and the United Kingdom.

The dependent variable is constructed using the daily GBP/USD exchange rate, obtained from reuters.com, and calculated as the logarithmic return according to the following expression:

$$GBP_t = ln\left(\frac{EXR_t}{EXR_{t-1}}\right), \tag{9}$$

where let GBP_t denote the logarithmic return of the British pound; EXR_t and EXR_{t-1} represent the GB/USD exchange rate at time *t* and *t*−*1*, respectively.

The inclusion of exogenous variables in the EGARCH-X model is based on sound economic and geopolitical considerations:

Global Geopolitical Risk (*GPR*): This index measures global geopolitical uncertainty through semantic analysis of international press reports, as developed by [8]. It captures exogenous geopolitical shocks likely to influence perceptions of macroeconomic risk. Monthly frequency data are sourced from the publicly available *GPR* database (matteoiacoviello.com) and interpolated to a daily frequency for trading days.

UK Gilt Yield (*GBY*): Representing the 10-year yield on UK government bonds (Gilts), expressed as a percentage, this indicator, sourced from (Investing.com), reflects market expectations regarding monetary policy and sovereign risk, both of which are critical determinants of exchange rate movements.

Brent Crude Oil Price (*P*): Quoted in US dollars per barrel, the Brent price serves as a key indicator of global energy market conditions. Its daily fluctuations affect energy-sensitive currencies and constitute an external macro-financial transmission channel [19]. Data are obtained from Trading Economics (tradingeconomics.com).

RU-UK: denotes a manually coded binary dummy variable. It equals 1, from 3 May 2025, reflecting the renewed phase of diplomatic tensions between Russia and the United Kingdom, marked by sanctions and trade disruptions. Otherwise, it equals 0.

Despite its low frequency, this variable is intended to capture the structural effects of targeted geopolitical shocks on volatility.

Except for the dummy variable (*RU-UK*), all other variables are introduced in logarithmic form to ensure stationarity.

4. Results

4.1. Descriptive Statistics

The analysis of the descriptive statistics of the variables presented in Table 1 highlights several key characteristics relevant to understanding the volatility dynamics of the British pound's returns.

Table 1. Descriptive Statistics.

-	*GBP*	*GPR*	*GBY*	*P*	*RU-UK*
Mean	0.999958	1.555636	3.657196	86.47792	0.004095
Median	1.000000	1.387184	4.033000	83.40000	0.000000
Maximum	1.024658	5.980000	4.954800	133.1800	1.000000
Minimum	0.969119	0.908126	1.205100	59.20000	0.000000
Std. Dev.	0.004935	0.650780	0.969271	13.17818	0.063887
Skewness	-0.013748	2.261258	-1.224744	1.198703	15.53075
Kurtosis	8.056970	9.513378	3.240403	4.118001	242.2041
Jarque-Bera	1301.062 (0.000000)	3198.880 (0.000000)	308.1898 (0.000000)	355.9968 (0.000000)	2960082. (0.000000)
Sum	1220.949	1899.432	4465.436	105589.5	5.000000
Sum Sq. Dev.	0.029716	516.6886	1146.174	211870.7	4.979525

Source: authors' own calculation. Note: () P-value.

The *GBP* variable exhibits a mean close to unity (0.999958), suggesting relative stability over the observed period. However, its low standard deviation (0.0049) masks a highly leptokurtic distribution (K = 8.05) with slight negative skewness (S = –0.013), indicating the presence of fat tails. These features justify the use of conditional heteroskedastic models, particularly EGARCH, which are better suited to non-normal distributions.

The daily Geopolitical Risk Index (*GPR*) has a mean of 1.55, pronounced positive skewness (2.26), and high kurtosis (9.51), reflecting the sporadic yet intense nature of global geopolitical tensions. This non-normal distribution suggests that major geopolitical shocks occur episodically and can amplify market volatility.

The yield on long-term UK government bonds (*GBY*) averages 3.65%, indicating a moderately restrictive monetary environment. Its negatively skewed distribution (S = –1.22) may signal frequent shifts towards accommodative monetary policies. Although its kurtosis is moderate (3.24), normality is statistically rejected.

The price of Brent crude oil (*P*), averaging USD 86.47 per barrel, reflects a constrained energy market. Its positive skewness and kurtosis exceeding 4 indicate susceptibility to sharp upward movements driven by geopolitical shocks, reinforcing its potential role as an external pressure factor on the pound's exchange rate.

Finally, the *RU–UK* dummy variable, coded as "1" from May 3, 2025, onwards to identify days of heightened UK–Russia tensions, exhibits a very low mean (0.004) and an extremely skewed distribution (S = 15.53; K = 242.20), reflecting the rarity and temporal concentration of such events. Although its immediate statistical impact is limited, its estimated coefficient may reveal a structural vulnerability of the pound to diplomatic tensions.

Overall, several variables display fat-tailed distributions with elevated kurtosis, justifying the use of the EGARCH model to capture volatility dynamics in a geopolitically uncertain environment.

4.2. Empirical Analysis

4.2.1. Stationarity of Variables

All variables, except for the dummy, were tested for unit roots (Table 2).

Table 2. Unit root tests.

-	(ADF)		(PP)	
	I(0)	I(1)	I(0)	I(1)
l(GBP)	[-35.8738]*** (0.0000)	-	[-35.8742]*** (0.0000)	-
l(GPR)	[-0.8646] (0.9580)	[-30.9976]*** (0.0000)	[-1.4400] (0.8489)	[-31.7457]*** (0.0000)
l(GBY)	[-2.6842] (0.2433)	[-35.0979]*** (0.0000)	[-2.6794] (0.2454)	[-35.1022]*** (0.0000)
l(P)	[-1.8039] (0.3789)	[-33.2908]*** (0.0000)	[-1.8762] (0.3438)	[-33.2651]*** (0.0000)

Source: authors' own calculation. Notes: () p-value; [] t-stat; *** significant at the 1% level.

Table 2 shows that only the exchange rate return (GBP) is stationary in levels (I(0)), as confirmed by strongly negative ADF and PP statistics (–35.87). In contrast, GPR, GBY, and P are non-stationary in levels, with p-values above 0.05 in both tests. After the first differencing, the three series become stationary (I(1)), with test statistics below critical values and p-values close to 0.

The estimation results of the EGARCH(1,1)-X model under three different distributional assumptions are reported in Table 3.

The findings indicate that the specification based on the Generalised Error Distribution (GED) provides the best fit, yielding the highest log-likelihood value (23,536.87) and the lowest values for the Akaike and Schwarz information criteria (AIC = –38,571; BIC = –38,538). This demonstrates a formal superiority over the two alternative specifications. These findings reflect the GED's ability to model leptokurtosis and asymmetric shocks, both of which are recurrent in GBP exchange rate returns [31, 17, 30, 24].

Table 3. Estimation Results of the EGARCH(1,1)-X Model.

-	Gaussian distribution	t−Student distribution	GED distribution
ω	-15.507	0.0000	0.0006
	[-12.639]***	[2.9258]***	[3.432]***
	(0.0000)	(0.0034)	(0.0028)
β	0.289	0.5142	0.822
	[6.843]***	[3.9126]***	[2.3360]**
	(0.0000)	(0.0001)	(0.0195)
γ	0.967	0.9744	-0.380
	[176.16]***	[175.86]***	[2.3470]**
	(0.0000)	(0.0000)	(0.0189)
α	-0.214	-0.172	0.733
	[-2.188]**	[-2.021]**	[4.156]***
	(0.0286)	(0.0433)	(0.0000)
GPR	-0.937	-1.341	0.241
	[-0.9976]	[-1.337]	[1.950]*
	(0.3185)	(0.1809)	(0.0512)
GBY	3.389	3.483	2.041
	[1.6675]*	[1.538]	[5.969]***
	(0.0954)	(0.1239)	(0.0000)
P	-2.467	-3.758	1.426
	[-1.6438]*	[-3.203]***	[3.719]***
	(0.0923)	(0.0014)	(0.0002)
RU-UK	2.323	2.165	0.396
	[1.7957]*	[1.572]	[0.701]
	(0.0725)	(0.1158)	(0.4831)
Akaike info criterion	-9.615876	-9.719816	-38.57191
Schwarz criterion	-9.586576	-9.690516	-38.53842
Log likelihood	5872.685	5936.088	23536.87
ARCH-LM	0.0847	0.0976	0.0507
	(0.7710)	(0.7547)	(0.8218)
Q-stat	44.408	45.900	43.094

Source: authors' own calculation. Notes: [] t-stat; () p-value; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level.

The coefficients of the conditional variance intercept term (ω) are statistically significant under all three distributions: Gaussian (-15.507; $p=0.000$), Student-t (0.0000; $p=0.003$), and GED (0.0006; $p=0.000$). However, the negative sign of the constant under the normal distribution may indicate potential misspecification [32].

The persistence parameter (β), capturing the memory of past volatility shocks, is statistically significant ($p < 0.05$) across all specifications, reflecting a long memory in volatility dynamics.

The asymmetry parameter (γ) is positive and significant at the 1% level under both the Gaussian and Student-t distributions, as indicated by highly significant t-statistics ($p < 0.01$). On the other hand, under the GED specification, γ is negative (-0.380) and statistically significant at the 5% level (p = 0.0189), reflecting a strong negative asymmetry: a 1% negative shock increases conditional volatility by approximately 0.38%, whereas a positive shock of the same magnitude reduces volatility by an equivalent amount.

The shock parameter (α), which measures the immediate response to past innovations, is negative and significant at the 5% level under the Gaussian (-0.214) and Student-t (-0.172) distributions, implying that a 1% rise in past squared returns reduces volatility by about 0.21% and 0.17%, respectively. Under the GED specification, however, α is positive (0.689; $p < 0.01$), suggesting that a 1% increase in past shocks amplifies volatility by nearly 0.69%. This divergence highlights how volatility sensitivity depends on the tail behaviour assumed, in line with evidence that shock structure shifts under heavy-tailed distributions [33, 10, 29].

The Global Geopolitical Risk Index (GPR) is positively significant at the 10% level (0.241; p = 0.0512), meaning that a 1% rise in global geopolitical risk raises GBP volatility by about 0.24%. While modest in magnitude, this effect is economically meaningful given the systemic transmission of geopolitical tensions. Gilt yields (GBY) also display a positive and significant effect at the 10% level under the Gaussian distribution (p = 0.0954) and the 1% level under GED (p = 0.0000). This suggests that a 1% increase in gilt yields leads to an increase in volatility of roughly 0.10% to 0.35%, reflecting markets' anticipation of tighter monetary policy conditions [34].

Brent crude oil prices (P) exert a significant negative effect at the 10% and 1% levels under the Gaussian and Student-t distributions (-2.460 and -3.758, respectively), indicating that a 1% rise in oil prices reduces sterling volatility by between 2.5% and 3.8%. By contrast, under GED, the coefficient turns positive and highly significant (p = 0.0002), implying that a 1% increase in oil prices raises volatility by nearly 3.8%. This pattern reflects that, under heavy-tailed distributions, higher energy costs amplify exchange rate uncertainty by heightening macro-financial instability, consistent with [35] and [19].

The *RU–UK* dummy variable is marginally significant at the 10% level only under the Gaussian distribution (coefficient = 2.323; p = 0.0725). This suggests that the onset of geopolitical tensions increased sterling volatility by approximately 2.3%. However, its significance fades under heavy-tailed distributions, implying that the direct market impact of the conflict is less robust than the broader persistence of global shocks.

The ARCH-LM test, yielding p-values above the 5% threshold across all three distributions, indicates the absence of residual heteroscedasticity, thereby validating the EGARCH-X specification. The Ljung-Box Q statistics, ranging from 43.094 to 45.9, similarly point to no autocorrelation in the standardised residuals. Overall, these findings confirm the superiority of the GED-based EGARCH-X model, both in terms of fit and in its ability to capture the effects of geopolitical and macro-financial variables on GBP volatility.

The asymmetry test proposed by **[7]** is applied to verify that the model adequately captures the leverage effect and that no residual bias linked to the sign or magnitude of shocks remains. The test involves three separate regressions of the squared standardised residuals: (i) a sign-bias test, examining the differential impact of negative shocks; (ii) a negative size-bias test, measuring the combined effect of a negative sign and shock magnitude; and (iii) a positive size-bias test, evaluating the corresponding effect for positive shocks. A joint F-test is then conducted to detect any remaining asymmetries [7, 16].

The EGARCH-X estimates ($\gamma = –0.380$, $p < 0.05$) indicate a stronger volatility response to negative shocks. These results are supported by the Engle–Ng asymmetry test, which confirms that the model captures this effect (Table 4).

Table 4. Engle–Ng Asymmetry Test Results.

Sign-Bias	[0.8423]
	(-0.4735)
Negative-Bias	[-0.9211]
	(-0.3317)
Positive-Bias	[0.6132]
	(-0.4647)
Joint-Bias (F-test)	1.0456
	(-0.3535)

Source: authors' own calculation. Notes: [] t-stat; () p-value.

Statistically, the sign-bias coefficient (0.8421; p= 0.4735) is not significant, indicating that negative shocks do not exert an additional impact on volatility once the EGARCH-X structure is taken into account. Although the positive sign would imply a stronger volatility response to negative shocks, the lack of significance rules out such an effect. The negative size-bias coefficient (–0.9211; p = 0.3317) is likewise insignificant. While the coefficient's size hints that large negative shocks may dampen volatility compared with smaller ones, the absence of statistical significance shows that the model effectively accounts for the leverage effect. The positive size-bias coefficient (0.6132; p = 0.4647) is insignificant, indicating no systematic impact of shock size on volatility.

The joint F-test (F = 1.0456; p = 0.3535) confirms that the EGARCH-X model effectively captures asymmetric dynamics and accounts for leverage effects throughout the sample period.

To assess the stability of the estimated parameters of the EGARCH(1, 1)-X model, the Nyblom test was applied, with the results presented in Table 5.

Table 5. Stability Analysis of the EGARCH(1,1)-X Model under (GED) specification.

Parameters	t-stat
ω	0.142
β	0.149
γ	0.239
α	0.145
GPR	0.269
GBY	0.14
P	0.358
RU-UK	0.000
Joint statistic	1.872
α=5% Crit.	0.47

Source: authors' own calculation.

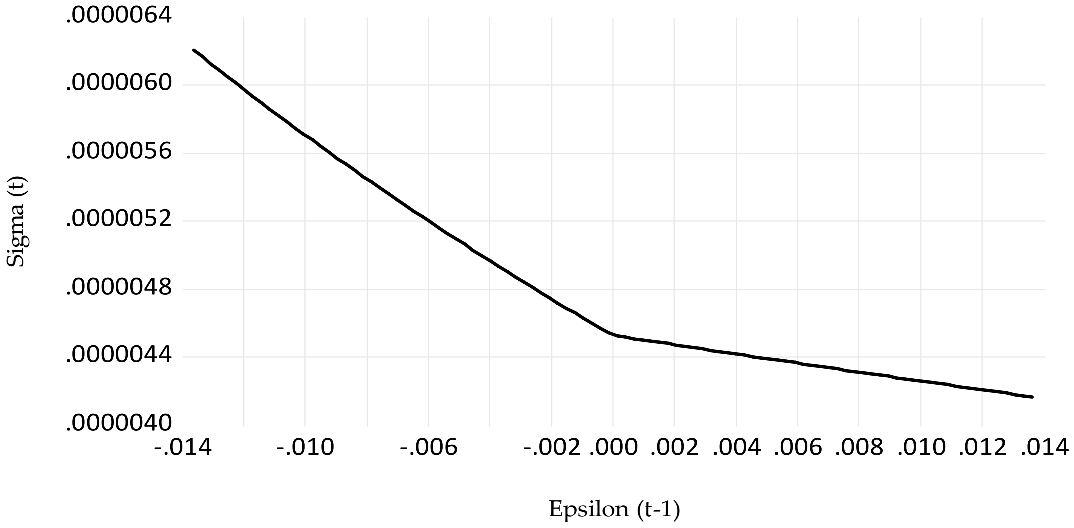
All individual statistics are below the 5% empirical critical value of 0.47 (the highest being 0.358 for *P*), indicating no parameter instability. The joint statistic (1.872) also falls below the theoretical 5% critical value of 2.10, so the null of parameter stability cannot be rejected.

Figure 1 illustrates the News Impact Curve. The figure highlights the influence of past shocks on conditional volatility, considering the exogenous variables in the variance equation. The resulting curve reveals a pronounced asymmetry, indicative of a disproportionate sensitivity of volatility to negative shocks.

Under the assumption of a Generalised Error Distribution (GED), conditional volatility $\sigma(t)$ exhibits a strictly decreasing structure concerning the innovation axis:

- For $\varepsilon_{t-1}< 0$, there is a rapid increase in volatility, peaking locally around ε_{t-1} = –0.014, where $\sigma(t)$≈0.000064. This behaviour reflects heightened risk anticipation in the presence of adverse news.
- As ε_{t-1} approaches zero, the curve flattens sharply, indicating a steep decline in $\sigma(t)$, which reaches a local minimum ($\sigma(t)$≈ 0.000044) when the shock is null or negligible.
- For $\varepsilon_{t-1}> 0$, the slope becomes almost flat, suggesting a muted volatility response to positive shocks.

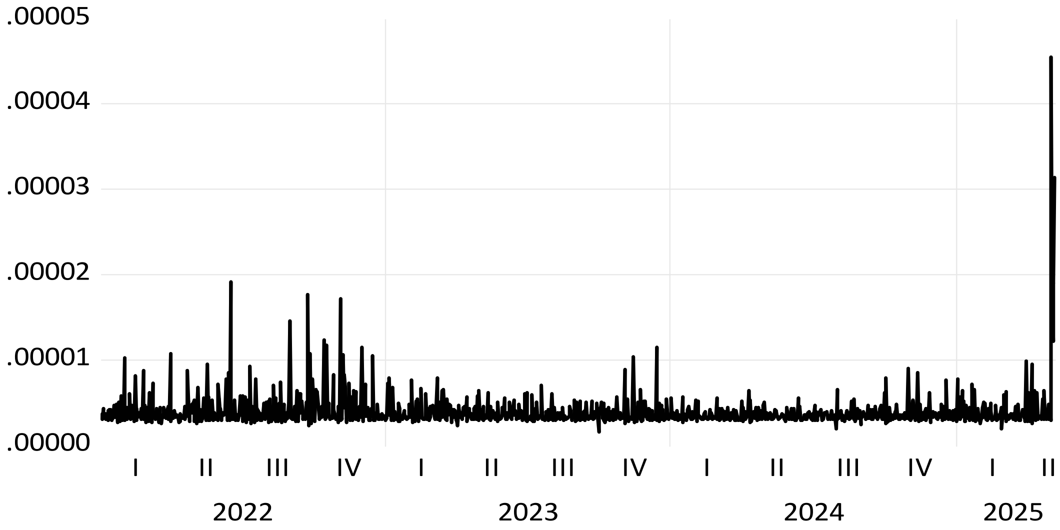
The asymmetric shape statistically reflects a pronounced negative leverage effect, as shown by a significantly negative coefficient in the EGARCH-X model. This indicates that negative shocks induce a much stronger increase in volatility than positive shocks of the same magnitude, consistent with the theoretical findings of [7]. The observation questions the notion that volatility reacts symmetrically to shocks. Instead, it points to a skewed risk profile, in which economic agents respond more strongly to deteriorating conditions (i.e., adverse shocks), thereby mechanically amplifying expected volatility.



Note: authors' own calculation.

Figure 1. New impact Curve.

The temporal trajectory of the conditional variance (Figure 2) remains strictly positive, as expected under an exponential specification. It also exhibits pronounced spikes that correspond to periods of economic turmoil and heightened geopolitical tensions.



Note: authors' own calculation.

Figure 2. Conditional variance Curve.

Several notable peaks are discernible: 1 June, 1 September, and 14 and 18 October 2022, with values reaching 0.000019, and a pronounced spike on 4 May 2025, which reached 0.000045. Broadly, these episodes correspond to events of significant geopolitical and economic importance. At the 10% significance level, the GPR variable suggests that global geopolitical instability has a persistent, though partial, effect on the conditional volatility of sterling returns.

The October 2022 dates correspond to a period of heightened tensions related to the war in Ukraine and its associated energy repercussions. Robust statistical significance of oil prices within the model reinforces the interpretation of October 2022 as a period of intensified geopolitical and energy-related pressures. As a major source of global macroeconomic uncertainty, oil price volatility contributes to currency market instability by influencing expectations of inflation, economic growth, and monetary policy [20, 1]. In addition, the GBY variable, also found to be significant, serves as a transmission channel for domestic market expectations [34].

In this context, upward movements in conditional variance partly reflect anticipated interest rate changes, capturing uncertainty about domestic monetary and fiscal policy.

Regarding the RU–UK dummy variable, the 3 May 2025 peak occurred amid intensifying bilateral tensions. The variable's statistical insignificance indicates that it has no distinct structural effect on conditional volatility. This implies that, despite the apparent severity of the event, markets did not perceive the shock as sufficiently unique or persistent to alter the volatility trajectory in an autonomous manner.

This pattern reflects a key characteristic of developed foreign exchange markets. In these markets, responses to broad structural risks typically outweigh reactions to specific political signals, unless a verifiable systemic shock occurs.

5. Discussion

Exogenous macroeconomic, financial, and geopolitical shocks appear to drive the volatility of pound sterling returns. Three key factors stand out in the transmission of uncertainty: UK sovereign

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bond yields, the international price of oil, and the level of global geopolitical tension. Each of these factors conveys distinct signals that shape market participants' expectations in the foreign exchange market.

The positive effect of gilt yields on the volatility of sterling returns reflects a dual interpretation. On one hand, these yields reflect expectations of monetary tightening in response to inflationary pressures, which in turn amplify exchange rate adjustments through interest rate differentials [34, 32]. On the other hand, rising yields may also signal a loss of fiscal credibility or an increased sovereign risk premium [5]. In both cases, rising yields introduce uncertainty, contributing to greater volatility in sterling. This effect is especially evident post-Brexit, as the twin deficits continue to exert sustained pressure on UK public finances [35].

The price of oil constitutes a central factor of external instability, directly affecting the British economy owing to its energy dependence. As a net importer of hydrocarbons, any fluctuation in global oil prices has repercussions for the current account, inflation, and monetary policy. Rising oil prices generate inflationary pressures, causing monetary authorities to modify interest rates to stabilise the currency [36, 33, 37, 5]. Against a backdrop of escalating geopolitical tensions, such as the war in Ukraine, oil serves as an indicator of geo-economic imbalances, thereby heightening market uncertainty [38].

Sterling volatility reacts significantly to the intensification of global geopolitical tensions, although this effect remains moderate. This response may stem from the semi-international role of the pound sterling, which is often regarded as a haven during crises [35]. In contexts marked by pronounced negative asymmetry, adverse shocks trigger a much stronger response than positive developments. This pattern reflects heightened market risk aversion in response to macroeconomic or geopolitical deterioration.

The lack of a significant effect from the recent Russo-British conflict can be understood within the broader geopolitical context of the ongoing war in Ukraine, which is already incorporated into the composite geopolitical risk index. This overlap reduces the likelihood of a distinct market response to the event. Furthermore, the conflict's recent onset, coupled with the absence of any direct threat to British territory, may account for investors' muted reaction.

The contrast highlights a pronounced negative asymmetry in the volatility response of the pound sterling, indicating that investors react more strongly to adverse news. It also demonstrates the market's sensitivity to declining fundamentals, which exacerbates volatility during periods of negative stress. Consequently, even when positive shocks, such as expectations of monetary tightening, occur, their effect remains limited relative to negative shocks. This structure reflects an asymmetric perception of risk among market participants, whereby bad news is regarded as more credible, severe, or urgent, confirming a significant leverage effect.

6. Conclusions

The EGARCH-X model applied to sterling returns reveals important structural dynamics linked to macro-financial and geopolitical risks between the UK and Russia, with conditional volatility accurately captured by the generalised error distribution. It accommodates leptokurtosis and extreme fluctuations, which are typical in foreign exchange markets during periods of systemic stress.

Results show a marked negative asymmetry in volatility. Negative shocks, particularly geopolitical or macro-financial ones, increase uncertainty more than positive shocks of similar magnitude. This confirms Hypothesis (H2) and indicates a clear negative leverage effect: markets react more strongly to adverse news, in line with [19].

The primary hypothesis (H1) receives partial support. The dummy variable representing UK–Russia tensions on 3 May 2025 is not statistically significant under the GED specification, although it reaches marginal significance under the normal distribution. This suggests that the market responded cautiously, possibly due to the already heightened global tensions stemming from the Russo-Ukrainian conflict. Despite the modest direct effect, the model indicates that volatility is structurally sensitive to negative signals even without direct domestic shocks.

A key strength of the EGARCH-X model is its ability to capture both internal volatility dynamics and reactions to external shocks depending on their direction. Accounting for asymmetry, the analysis shows that markets are particularly sensitive to negative news. This heightened sensitivity reflects increased risk aversion and contributes to the transmission of instability across economic and geopolitical channels.

From a policy and market perspective, these findings carry important implications. Sterling volatility is not only influenced by the intensity of global shocks but also by the asymmetric perception of risk among investors, which amplifies downside movements. Understanding this behaviour is crucial for central banks, policymakers, and financial institutions seeking to design effective interventions, hedging strategies, or risk management frameworks in the face of geopolitical uncertainty.

Future research could extend this analysis by applying multi-horizon stochastic volatility EGARCH-X models. These models would allow researchers to differentiate responses according to both the type of shock (economic, political, or military) and its timing. Heavy-tailed and asymmetric distributions such as Skewed-GED or Skewed-t should be used to better capture extreme events. Furthermore, disaggregated geopolitical uncertainty indices by region or theme would help identify dominant risk sources more precisely.

In conclusion, sterling volatility reflects both the magnitude of global shocks and an asymmetric focus on downside risks. Recognition of this pattern is essential not only for accurate forecasting and effective hedging strategies but also for understanding how geopolitical developments propagate through currency markets, shaping investors and financial stability.

Contributions: Conceptualization, F.D.; methodology, F.D.; software, A.T.; validation, F.D. and A.T.; formal analysis, F.D.; investigation, F.D. and A.T.; resources, F.D. and A.T.; data curation, F.D. and A.T.; writing—original draft preparation, F.D; writing—review and editing, A.T.; visualization, F.D.; supervision, F.D. and A.T.; project administration, F.D. All authors have read and agreed to the published version of the manuscript.

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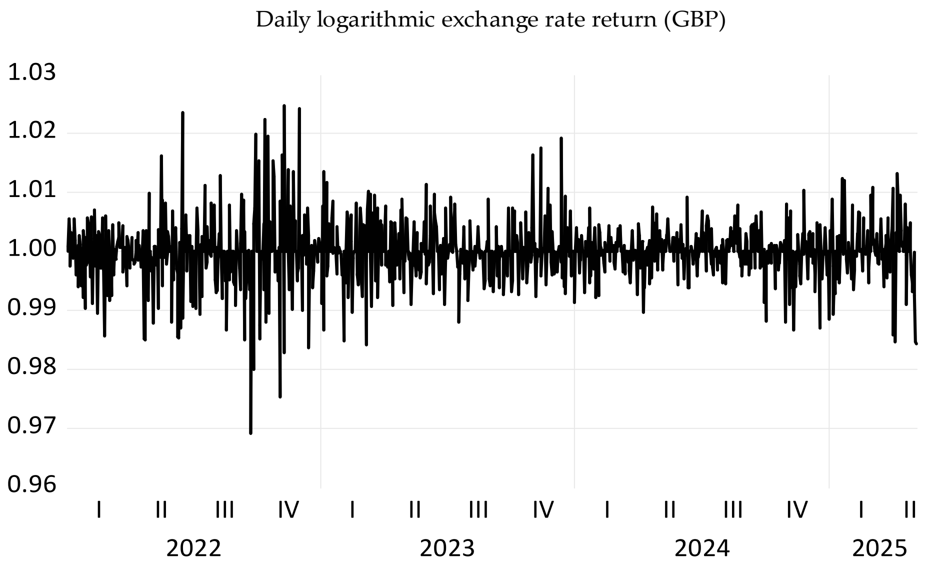
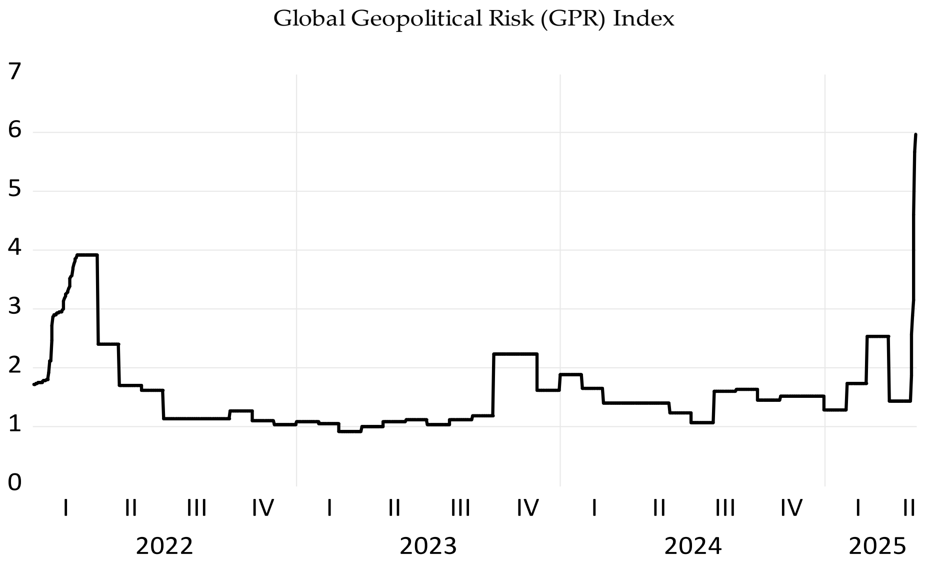
Conflicts of Interest: The authors declare no conflict of interest.

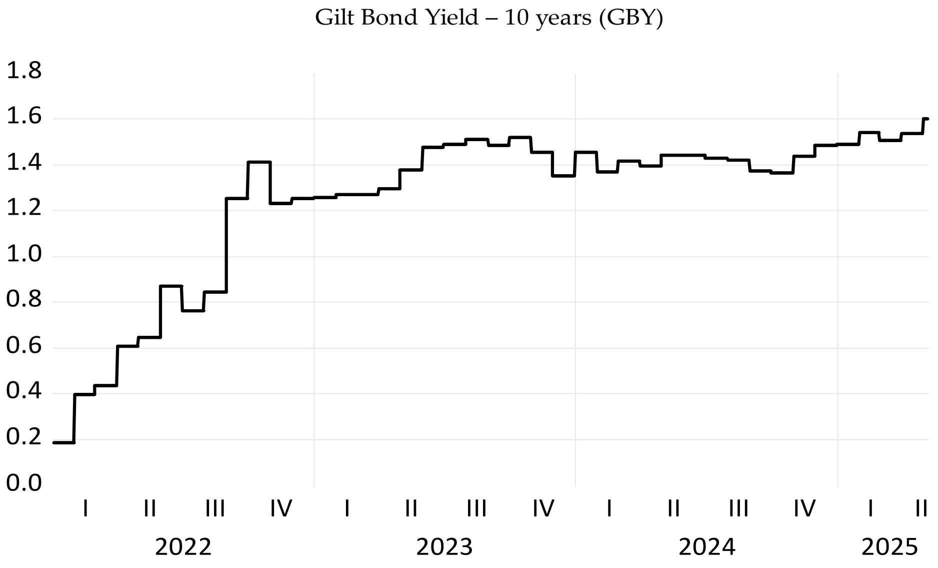
Appendix A



Daily logarithmic exchange rate return (GBP)



Global Geopolitical Risk (GPR) Index



Gilt Bond Yield – 10 years (GBY)

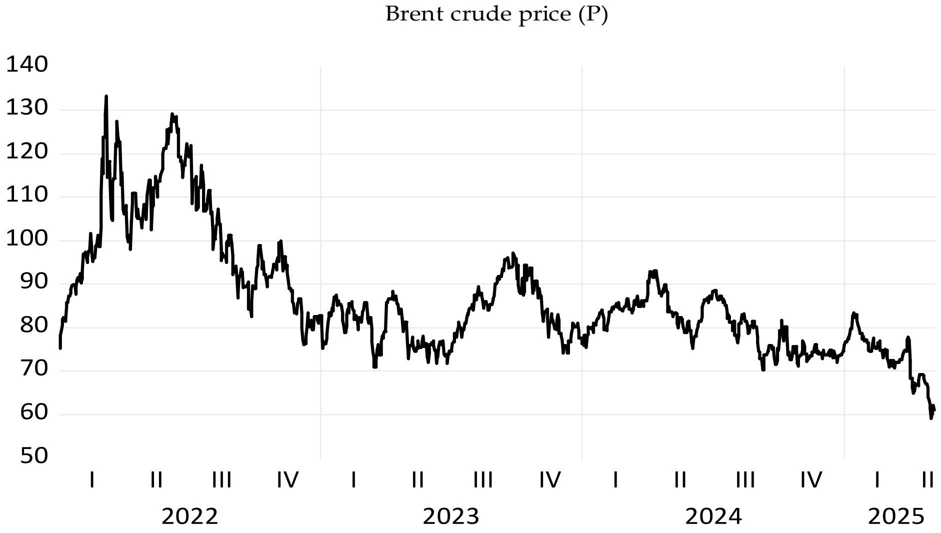


Figure A1. Descriptive Plots of the Variables.

Appendix B

Table B1. Rolling-Window EGARCH-X estimation under GE Distribution [Subsample: 2 January 2022 – 2 February 2024].

ω	β	γ	α	*GPR*	*GBY*	*P*	*RU-UK*	AIC	BIC
0.00054	0.740	-0.420	0.565	0.129	1.837	1.569	0.436	- 36.442	- 36.412
[3.21]**	[2.79]**	[2.21]**	[4.02]***	[2.68]**	[5.71]***	[3.65]***	[0.68]		
(0.001)	(0.022)	(0.027)	(0.000)	(0.032)	(0.000)	(0.000)	(0.497)		

Notes: [] t-stat; () p-value; * significant at the 10% level; ** significant at the 5% level; *** significant at the 1% level. The results of the subsample estimation confirm the persistence of volatility ($\beta = 0.740$) and the negative leverage effect ($\gamma = -0.420$). The exogenous variables *GPR, GBY* and *P* exert a significant influence on volatility at 5% level, whereas *RU-UK* has no significant impact. The difference in the significance of the *GPR* variable can be attributed to the concentration and intensity of geopolitical shocks within the subsample. During this period, geopolitical events were particularly pronounced and focused, making the GPR coefficient significant at the 5 % level. In the full sample, these effects are diluted by other macro-financial events, reducing the significance to the 10 % level.

Table B2. Variance Inflation Factors (VIF) for Exogenous Regressors.

-	VIF	Tolerance (1/VIF)
GPR	1.0002	0.9998
GBY	1.0020	0.9979
P	1.0151	0.9850

Notes: VIF values close to 1 indicate that the regressors are almost uncorrelated, and there is no evidence of multicollinearity. Common cut-off values are VIF < 5 (or tolerance > 0.2) for critical levels.

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