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Journal of
Risk and Financial Management

MDPI

Article

Measuring the Spillover Effects from the Stock Market Volatility in Selected Major Economies to the Stock Market Volatility in the United Kingdom

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Abstract

This study investigates volatility spillovers from the stock markets of the United States, Germany, China, and Japan to the UK stock market using daily data from major benchmark indices (FTSE 100, S&P 500, DAX, Shanghai Composite, and Nikkei 225) and Brent crude oil prices. Using a novel two-stage bootstrap framework, we first model time-varying conditional volatilities with GARCH-family models and compare them with long-memory FIGARCH specifications to account for persistent volatility dynamics. These volatilities are then incorporated into a VAR-X model, treating Brent crude oil price volatility as an endogenous or exogenous variable in robustness checks. To overcome limitations of traditional VARs, bootstrap-corrected GIRFs are employed to trace dynamic, order-invariant impacts across key sub-periods: the global financial crisis, Brexit, COVID-19, and the Ukraine war. We also benchmark our results against the Diebold–Yilmaz connectedness index and conduct rigorous out-of-sample forecasting and Value-at-Risk backtesting. Results reveal heterogeneous spillovers: US and German shocks trigger strong, immediate, and persistent UK market volatility, reflecting deep integration; Chinese shocks are delayed and gradual, while Japanese shocks are muted or short-lived. Spillover intensity is time-varying, peaking during global crises. Our model outperforms standard benchmarks in out-of-sample volatility forecasting and risk management applications. The study offers critical insights for investors seeking international diversification and for policymakers aiming to manage systemic risk in an interconnected global financial system.

Keywords: volatility spillovers; GARCH models; VAR-X; generalised impulse response functions (GIRFs); financial contagion; UK stock market

JEL Classification: C32; C58; G15; F36

Check for updates

Academic Editor: Thanasis Stengos

Received: 24 December 2025
Revised: 31 January 2026
Accepted: 2 February 2026
Published: 4 February 2026

1. Introduction

In today's highly interconnected global financial system, stock markets are frequently affected by events and developments that extend beyond the borders of a single nation. The volatility spillover effect refers to the process through which price fluctuations, or volatility, are transferred from one financial market or asset price to another. In the context of general stock indices across nations, this effect explains how volatility in one country's stock market can affect that of other countries. The interconnected nature of global financial markets inherently leads to volatility spillovers among stock indices across different countries. R. Engle (2002) states that these effects are facilitated through multiple channels, including stock market integration, investors' decision-making, economic interdependencies, and information dissemination.

According to Aizenman et al. (2012), significant events, such as financial crises or geopolitical events, can generate volatility in one country's stock market, which may subsequently spread to other markets. The cross-listing of firms, multinational corporations, and international capital flows across nations establishes direct connections between stock markets. Liu et al. (2024) have demonstrated that the spillover effect tends to be more pronounced between markets closely linked through trade, investment, or financial integration. For instance, significant volatility in the US stock market can lead to increased volatility in other markets, such as those in Canada, Europe, or emerging economies, driven by shifts in investor sentiment and changes in capital flows. Stock market volatility spillovers are also associated with fluctuations in commodity prices, such as oil or gold (Almutawa et al., 2025; Doblas et al., 2023; Natarajan et al., 2021), particularly when nations serve as significant exporters or importers of these resources.

Furthermore, Shiller (2000) has shown that when investors observe heightened volatility in a particular market, they often respond by reallocating their portfolios, generating a rise in volatility in other markets. Such actions are frequently motivated by concerns about global risks or the potential for contagion effects. Similarly, large institutional investors or traders may manage their risk exposure in one market by taking positions in other markets, potentially leading to volatility transmission across countries. The spread of information across markets also plays a vital role in volatility spillovers. When financial news from one market is disseminated globally, it can trigger a series of price adjustments in other markets.

For investors, policymakers, and financial analysts, understanding and quantifying these spillover effects is essential for effective risk management and the development of optimised investment strategies in a globalised financial environment. For that reason, our research compares the impact of the volatility of major economies' stock markets with that in the United Kingdom (UK) using multiple GARCH techniques. A VARX framework is then used to analyse the interactions between different stock markets. This will help us to explain the differences in the stock markets of the countries in question whilst taking into account their trade, economic, financial, and political interlinkages.

Furthermore, this study makes three key contributions to the existing literature. First, it implements a block bootstrap procedure to account for generated-regressor uncertainty in the two-stage GARCH–VAR-X framework, providing more reliable inference. Second, it compares traditional GARCH models with long-memory FIGARCH specifications and benchmarks spillover results against the Diebold–Yilmaz connectedness index, ensuring robustness to model choice. Third, it introduces a comprehensive out-of-sample forecasting and value-at-risk backtesting exercise to evaluate the practical utility of the model for risk management, a dimension often overlooked in purely descriptive spillover studies. So, by integrating these elements, the paper moves beyond a conventional econometric exercise to offer actionable insights for investors and policymakers in real-time risk monitoring. While the complex phenomenon of volatility transmission can be examined through sociological, political, or behavioural lenses, this study is deliberately situated within the econometric and financial economics traditions to provide a rigorous, quantifiable assessment of spillover dynamics, a necessary precursor to broader interdisciplinary synthesis.

The remainder of this paper is organised into seven sections. Section 2 provides a comprehensive review of the existing literature. Section 3 provides insight into the theoretical background of stock market spillover effects. Section 4 offers a detailed analysis of the econometric methodologies utilised. Section 5 outlines the data employed in the study. Section 6 presents the findings derived from the estimations, while Section 7 discusses the robustness checks conducted to ensure the reliability of the results. Finally, Section 8 concludes the evaluation and summarises the key findings.

2. Literature Review

The spillover effect between a country's general stock index and those of others is a particularly intriguing area of study. Numerous researchers have demonstrated a significant relationship between these variables. For example, Eun and Shim (1989) identified significant interdependencies across global equity markets, emphasising the prominent role of the US market in transmitting volatility and building on this. Similarly, Y. Wang et al. (2018) found strong volatility spillover effects from the US S&P-500 index to the general stock indices of five major economies. These effects were notably stronger during periods of economic uncertainty, such as recessions.

Second, and even more importantly, empirical evidence suggests that the spillover effect of stock markets extends across regions and various sectors. P. Wang and Moore (2009) examined Asian stock markets and identified substantial volatility spillovers among countries, particularly during times of financial turmoil. Likewise, Kanas (1998) highlighted that US stock market volatility significantly impacts the Mexican and Canadian markets, due to strong economic and trade relationships. Studies on regional market spillovers have also gained considerable attention, especially in the context of economic blocs such as the European Union and ASEAN. Bekaert et al. (2005) found that these spillovers tend to intensify during times of economic turmoil. These results emphasise the critical influence of regional economic integration in either exacerbating or alleviating stock market spillover effects. Recent research by Khan (2025) extends this analysis to emerging markets, demonstrating that spillover patterns and market integration vary substantially with regulatory environments, capital controls, and institutional quality. This study is particularly relevant to our findings on China's delayed and gradual spillover effects, which may reflect its distinctive market structure and policy interventions.

The analysis of sectoral spillover effects reveals differences in how volatility is transmitted across various industries. Using ARCH and GARCH models, R. F. Engle et al. (1990) demonstrated that shocks originating in specific sectors, such as technology or energy, can extend their impact to others. This research indicates that sector-specific variables, such as regulatory shifts and fluctuations in commodity prices, significantly influence the dynamics of these spillovers. The intensity of volatility spillovers also varies across sectors; for example, the financial sector often exhibits more substantial spillovers due to its pivotal role in the economy, whereas other sectors may show lower levels of interconnectivity. These empirical patterns align with the well-documented stylized facts of financial returns, including volatility clustering, heavy tails, and leverage effects (Cont, 2001). Such characteristics motivate our use of asymmetric GARCH specifications that explicitly capture these features.

In addition to the first two, there is considerable evidence on the spillover effects of oil prices on stock market returns. Studies have demonstrated significant volatility spillover effects linking oil prices with general stock index returns across various countries. For instance, Basher and Sadorsky (2006) found that oil price volatility strongly impacts stock market returns in emerging economies. Their analysis employed an international multi-factor model, related to the Capital Asset Pricing Model (CAPM), to account for both conditional and unconditional risk factors. Zhang and Ma (2019) highlighted a noticeable contemporaneous risk spillover effect between oil prices and stock market returns. They applied an EVaR framework combined with the CAR-ARCHE technique to derive these insights.

Some studies have extended the analysis of spillover effects by investigating the relationship between oil prices and the returns of sectoral stock indices. The primary objective of these studies was to address the potential overshadowing effect of aggregate stock market indices, thereby capturing the heterogeneity of individual sectors' responses to oil price volatility. Findings indicate that oil price volatility significantly impacts the returns of most sectoral stock indices, although the magnitude of the effect varies across sectors. Cadena-Silva et al. (2025) found that the spillover effects of oil price volatility and geopolitical risk are more pronounced in sectors such as industrial, healthcare, consumer discretionary, information technology, and basic materials than in other sectoral stock indices. Additionally, Arouri et al. (2011) corroborated these findings by demonstrating that the spillover effect is predominantly bidirectional from the oil market to sectoral stock indices in the United States, whereas it is unidirectional in Europe. This analysis was conducted using a multivariate VAR(k)-GARCH(p,q) framework and a weekly dataset spanning from January 1998 to December 2009. Extending this comparative perspective, Almutawa et al. (2025) directly contrast the impact of crude oil price volatility on stock returns between oil-exporting and oil-importing countries, highlighting how the direction and magnitude of spillovers are fundamentally shaped by a nation's position in the global oil market.

Recent advancements in spillover measurement have shifted toward model-free connectedness frameworks based on variance decompositions. Diebold and Yilmaz (2009, 2012) introduced a spillover index that quantifies total and directional volatility transmission across markets, offering a parsimonious alternative to structural VARs. Baruník and Křehlík (2018) extended this to the frequency domain, separating short-term from long-term connectedness. In parallel, the literature on long-memory volatility modelling (Baillie et al., 1996; Granger & Joyeux, 1980) has shown that fractional integration (FIGARCH) often outperforms standard GARCH in capturing persistent volatility dynamics. Complementing this, Koulis and Kyriakopoulos (2023) examine volatility transmission in commodity markets from a long-term perspective, emphasising the role of persistent shocks and structural breaks. Their findings on the importance of accounting for long-memory effects in volatility spillover analysis directly motivate our comparison of FIGARCH with standard GARCH specifications and our focus on persistence across multiple crisis periods. Finally, a growing body of work emphasises out-of-sample validation and backtesting (Christoffersen, 1998; Diebold & Mariano, 1995) as essential for evaluating the practical relevance of volatility models for risk management. Our study bridges these strands by comparing traditional GARCH–VAR-X results with modern connectedness measures and rigorously evaluating forecast performance.

3. Theoretical Background

This study is grounded in established time series econometrics and volatility modelling frameworks (Francq & Zakoian, 2019; Hamilton, 1994; Tsay, 2010). We build on the GARCH-family of models introduced by R. F. Engle (1982) and Bollerslev (1986), and employ a VAR-X system following Lütkepohl (2005) to analyse volatility spillovers. The theories of market integration and volatility transmission are widely examined within the field of financial economics. Foundational studies on financial contagion and intermarket connections, such as those by King and Wadhwani (1990) and K. J. Forbes and Rigobon (2002), explore the phenomenon of volatility spillovers. These works investigate the extent to which stock market fluctuations in one country influence those in other markets.

King and Wadhwani (1990) suggest that factors such as information asymmetry and investor behaviours, including herding and overreaction, play a critical role in driving volatility spillovers. Furthermore, they explore theoretical frameworks that account for volatility spillovers, highlighting the interplay between rational and irrational market dynamics. Initially, the noise trader model examines the influence of noise traders, who make decisions based on non-fundamental factors. Such behaviour contributes to irrational market dynamics, amplifying volatility and facilitating its spread across different markets. Secondly, herding behaviour, in which investors mimic the actions of others rather than conducting independent analyses. This tendency can result in market overreactions and coordinated volatility across markets, particularly during times of uncertainty or crisis. Thirdly, rational expectations and information spillovers, where investors analyse available information to adjust their portfolios. In such scenarios, news or shocks in one market may lead rational investors to anticipate effects on interconnected markets, thereby propagating volatility. Lastly, feedback effects and cross-market arbitrage. The former occurs when price changes in one market influence expectations and trading activities in another, generating a cycle of volatility transmission. Both rational responses and irrational overreactions contribute to these feedback loops. The latter considers the role of arbitrageurs, who seek to profit from price discrepancies between markets. While arbitrage usually stabilises prices, it can also propagate shocks when arbitrageurs simultaneously adjust their positions across interconnected markets.

Moreover, K. J. Forbes and Rigobon (2002) examine the concept of financial contagion during market crises, proposing that what is frequently identified as contagion is more accurately described as market interdependence. They argue that an increase in cross-market correlations during a crisis results from a rise in market volatility rather than a structural change in the way shocks are transmitted between markets. The authors define contagion as a significant increase in cross-market linkages following a shock, distinguishing it from normal interdependence in global markets. This differentiation is essential to avoid mischaracterising the nature of market movements during a crisis. The framework was tested by analysing data from major financial crises, including the 1987 stock market crash and the 1997 Asian financial crisis. Findings revealed limited evidence of contagion, with observed cross-market correlations reflecting stable interdependence instead of structural changes. The results suggest that investors and policymakers should prioritise strategies to manage global market interdependence rather than focus solely on perceived contagion.

When looking at the theoretical econometric methodologies, the GARCH and VAR models have been commonly used in modelling stock market volatility and its spillover effects. R. F. Engle and Kroner (1995) introduced the MS-GARCH model to address the challenges of modelling volatility dynamics in a multivariate financial time series. This framework enhances the traditional GARCH technique by incorporating simultaneous interactions in conditional variances and covariances, thereby providing a more comprehensive approach to analysing volatility interdependencies across multiple assets or markets. It contributed to capturing the dynamic linkages between financial markets and transmission of shocks across markets or assets, accounting for both individual volatilities and their cross-variable effects. The technique was classified as a significant advancement in econometric modelling, offering a sophisticated tool for analysing volatility spillovers and interconnections within financial markets. Its application has been regarded as crucial for understanding the complex dynamics of global financial systems.

In the same light, Diebold and Yilmaz (2009) proposed an econometric framework to assess spillovers in financial markets, concentrating on both asset returns and volatility. The authors utilised variance decomposition from VAR models to construct a spillover index, which quantifies the degree of return and volatility transmission among global equity markets. This index effectively captures the dynamic interconnections within stock markets, providing a systematic approach to analysing how shocks originating in one market influence others. Applying this framework to major global equity markets, the authors identified notable variations in spillover intensity, particularly during periods of financial instability. The findings reveal that spillovers increase significantly during times of market stress, such as the 2007–2009 global financial crisis, emphasising the increased interconnectedness of markets in turbulent periods. The spillover index introduced in this study serves as a valuable tool for monitoring systemic risk and evaluating market stability.

4. Methodology

This study employs a two-stage econometric framework to analyse volatility spillovers from major global stock markets to the UK. The implementation of this framework requires specialised expertise in financial econometrics, including the specification and diagnostic testing of GARCH-family models, the construction of VAR systems with exogenous variables, and the application of bootstrap methods for valid inference, all of which are deployed herein. In line with Open Science principles, we provide a complete description of methods, data processing, and model specifications below to ensure full replicability of our results. First, we model the time-varying conditional volatilities of each market using univariate GARCH-family models. Second, we incorporate these volatility series into a Vector Autoregression with Exogenous Variables (VAR-X) framework, treating Brent crude oil price volatility as an exogenous shock. The metrics and econometric specifications employed in this study are grounded in the standardised toolkit of financial econometrics (Francq & Zakoian, 2019; Tsay, 2010). By using established measures, such as conditional volatility from GARCH-family models, forecast accuracy via RMSE and MAE, and risk management metrics like value-at-risk coverage, we ensure that our results are directly comparable with the extensive body of literature on volatility spillovers. This methodological consistency mitigates the common challenge of non-comparable findings across studies that employ divergent indicators. We deliberately employ these classical econometric models over more complex, non-parametric machine learning alternatives. GARCH and VAR-X are structurally transparent and economically interpretable, allowing us to trace the transmission channels of volatility shocks directly, thereby avoiding the 'black-box' problem and aligning with best practices for explainable empirical research in finance.

4.1. Modelling Conditional Volatility

Let $r_{i,t}$ denote the daily log return of market i at time t, calculated as $r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1})$, where $P_{i,t}$ is the closing price index. The mean equation for each return series is specified as an autoregressive (AR) process to capture potential serial correlation.

$$r_{i,t} = \mu_i + \sum_{j=1}^{k} \varnothing_{i,j} r_{i,t-j} + \varepsilon_{i,t},\ \varepsilon_{i,t}|I_{t-1} \sim\ N\left(0, \sigma_{i,t}^2\right) \tag{1}$$

where μ_i is a constant term, k is the optimal lag length selected via the Schwarz Information Criterion (SIC), $\varnothing_{i,j}$ are autoregressive coefficients, $\varepsilon_{i,t}$ is the innovation term conditional on the information set I_{t-1}, and $\sigma_{i,t}^2$ is the time-varying conditional variance. We model $\sigma_{i,t}^2$ using four GARCH (1,1) specifications to capture different volatility dynamics. The parameters are estimated using Quasi-Maximum Likelihood (QMLE), which yields consistent estimates even when the normality assumption is violated (Bollerslev & Wooldridge, 1992).

4.1.1. Standard GARCH (SGARCH)

$$\sigma_{i,t}^2 = \omega_i + \propto_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{2}$$

where $\omega_i > 0$, $\propto_i, \beta_i \geq 0$, and $\propto_i + \beta_i < 1$ for stationarity. If $\propto_i + \beta_i \geq 1$, the process is non-stationary in variance, implying that volatility shocks persist indefinitely, and the unconditional variance is either undefined, $\propto_i + \beta_i = 1$, or infinite, $\propto_i + \beta_i > 1$. Such models are generally not considered for financial returns, which typically exhibit mean-reverting volatility.

4.1.2. Integrated GARCH (IGARCH)

$$\sigma_{i,t}^2 = \omega_i + \propto_i \varepsilon_{i,t-1}^2 + (1 - \alpha_i)\sigma_{i,t-1}^2 \tag{3}$$

where $\alpha_i \in (0, 1)$ and ω_i is constrained to zero in the standard IGARCH formulation (R. F. Engle & Bollerslev, 1986).

4.1.3. Threshold GARCH (TGARCH)

$$\sigma_{i,t}^2 = \omega_i + \propto_i \varepsilon_{i,t-1}^2 + \gamma_i \varepsilon_{i,t-1}^2 I_{i,t-1} + \beta_i \sigma_{i,t-1}^2 \tag{4}$$

where $I_{i,t-1} = 1$ if $\varepsilon_{i,t-1}^2 < 0$ (bad news) and is 0 otherwise. A significant $\gamma_i > 0$ indicates a leverage effect (asymmetric volatility response).

4.1.4. Exponential GARCH (EGARCH)

$$\text{In}\left(\sigma_{i,t}^2\right) = \omega_i + \propto_i \frac{|\varepsilon_{i,t-1}|}{\sigma_{i,t-1}} + \gamma_i \frac{\varepsilon_{i,t-1}}{\sigma_{i,t-1}} + \beta_i \text{In}(\sigma_{i,t-1}^2) \tag{5}$$

where a significant $\gamma_i < 0$ captures asymmetric effects (negative shocks increase volatility more than positive shocks).

The optimal GARCH specification for each series is selected based on four criteria: (1) lowest SIC, (2) satisfaction of stationarity conditions, (3) non-negativity of variance parameters, and (4) absence of residual ARCH effects (confirmed via ARCH-LM tests).

4.1.5. Fractionally Integrated GARCH (FIGARCH)

To account for potential long memory in volatility, a well-documented stylized fact in financial time series (Baillie et al., 1996), we also estimate the FIGARCH (1, d, 1) model. The fractional differencing operator $(1 - L)^d$, introduced by (Hosking, 1981), allows for flexible modelling of long-range dependence. We estimate this model via QMLE and compare its fit with GARCH-family specifications.

$$(1 - \beta L)\sigma_{i,t}^2 = \omega + \left[1 - \beta L - \propto L(1 - L)^d\right] \varepsilon_{i,t}^2 \tag{6}$$

where L is the lag operator, $d \in (0, 1)$ is the fractional integration parameter capturing the degree of long memory in volatility, and $u_{i,t} = \varepsilon_{i,t}^2 - \sigma_{i,t}^2$ represents the innovation in the conditional variance. The model is estimated via QMLE. All return series were synchronised to common trading days across the six markets and the Brent crude oil series. Log returns were calculated only for days where all markets were open, ensuring that the VAR-X system is estimated on a consistent time grid and mitigating biases from non-synchronous trading.

4.2. Volatility Spillover Modelling: VAR-X Framework

Let $h_t = [h_{UK,t}, h_{US,t}, h_{GER,t}, h_{CHN,t},\ h_{JPN,t}]'$ be the vector of conditional volatilities estimated from the selected GARCH models; we employ a VAR-X model of order p.

$$h_t = c + \sum_{i=1}^{p} A_i h_{t=i} + Bx_t + u_t \tag{7}$$

Here, h is the vector of conditional volatilities obtained from the selected GARCH models for each market, and x_t represents the exogenous Brent crude oil price volatility. c is a 5×1 intercept vector, A_i are 5×5 coefficient matrices, x_t is the exogenous variable (Brent crude oil volatility, $h_{OIL,t}$), B is a 5×1 coefficient vector, and u_t is a vector of reduced-form shocks with $E[u_t] = 0$ and $E[u_t u_t{}'] = \Sigma_u$. The lag order pp is chosen via SIC, and the exogeneity of oil price volatility is justified by prior evidence (Basher & Sadorsky, 2006) and confirmed via Granger causality tests. The exogeneity of oil price volatility is tested via Granger causality and system-based exogeneity tests (Lütkepohl, 2005). This modelling choice is supported not only by statistical tests but also by strong economic reasoning. As a major oil-importing economy with a highly financialized stock market, the UK is predominantly a price-taker in the global crude oil market. Brent crude oil prices are determined by worldwide supply–demand dynamics, geopolitical events, and OPEC+ decisions, factors largely exogenous to UK financial markets. While oil price volatility transmits to UK equity volatility through channels such as inflation expectations, corporate cost structures, and energy sector performance, the reverse causal channel—from UK stock market volatility to global oil price volatility—is economically negligible. Treating oil volatility as weakly exogenous in this UK-centred system therefore aligns with both the empirical evidence and the fundamental direction of influence in this relationship. We also estimate alternative specifications with oil treated as endogenous and with oil omitted entirely to ensure robustness.

4.3. Generalised Impulse Response Functions (GIRFs)

To trace the dynamic impact of volatility shocks independent of variable ordering, we employ GIRFs (Pesaran & Shin, 1998). The GIRF for a one-standard-deviation shock to market j on market i at horizon H is:

$$GIRF_{ij}(H) = E\left[h_{i,t+H} \middle| u_{j,t} = \delta_j, I_{t-1}\right] - E\left[h_{i,t+H} \middle| I_{t-1}\right. \tag{8}$$

The GIRF approach, proposed by Pesaran and Shin (1998), is particularly suitable for our study as it does not require orthogonalization of shocks and is invariant to variable ordering, providing a robust measure of shock propagation in interconnected financial systems. This invariance arises because GIRFs use the observed historical distribution of the errors rather than imposing a causal ordering. δ_j is the shock size; confidence intervals (90%) are generated via non-parametric bootstrap (1000 repetitions). Unlike orthogonalized IRFs, GIRFs are invariant to variable ordering and more suitable for interpreting shock propagation in interconnected systems.

4.4. Diagnostic Testing and Model Validation

To ensure the robustness and stability of our estimates, addressing concerns about model sensitivity to data or specification, we implement a comprehensive suite of diagnostic tests and validation procedures. We conduct comprehensive diagnostic tests on the standardised residuals from both the GARCH and VAR-X models, including the following. GARCH Residual Diagnostics with the Ljung–Box test for autocorrelation (up to 20 lags), the ARCH-LM test for remaining heteroskedasticity, and the Jarque–Bera test for normality.

VAR-X Stability is assessed with the Eigenvalue stability condition and recursive CUSUM tests for parameter stability. Structural Break Detection is performed with Bai–Perron multiple breakpoint tests to identify regime changes. Out-of-sample forecasting evaluates the predictive ability of our model using a rolling-window forecast (estimation: 2000–2020, validation: 2021–2024) and we compare the root mean squared error (RMSE) against a benchmark random walk model.

4.5. Bootstrap Correction for Generated Regressors

Because the volatilities entered into the VAR-X are generated from first-stage GARCH estimates, standard inference may be biased. We implement a block bootstrap procedure (1000 replications) that re-estimates both stages in each replication. This yields bias-corrected confidence intervals for GIRFs and spillover metrics, thereby providing explicit measures of estimation uncertainty and enhancing the statistical robustness of our findings.

4.6. Out-of-Sample Validation and Risk Management Evaluation

We adopt a rolling-window scheme (window length = 5 years) to generate one-day-ahead volatility forecasts for the UK FTSE index. Forecast accuracy is evaluated using RMSE, MAE, and the Diebold and Mariano (1995) test against benchmarks (random walk, HAR, and FIGARCH).

4.7. Diebold–Yilmaz Connectedness Framework

As a robustness check, we compute the spillover index of Diebold and Yilmaz (2009, 2012) based on a VAR model of volatility series. The total connectedness index (TCI) measures system-wide spillovers, while directional indices quantify transmission to/from each market. This provides a model-free comparison to our GIRF-based results.

5. Data

Our dataset includes daily observations from 4 January 2000 to 31 December 2024, excluding weekends and official holidays, resulting in a total of 6121 observations for each of the five selected countries and Brent crude oil. The UK, Germany, the US, Japan, and China were chosen due to their systemic importance within global financial markets. The US holds the largest stock market capitalisation worldwide, followed by China in second place, Japan in third, the UK in fourth, and Germany in eighth, making them the largest among EU nations. Collectively, these five countries account for more than 70% of global equity market capitalisation. Additionally, Brent crude oil prices are incorporated as an exogenous variable influencing stock markets. For countries with multiple stock markets, the one with the largest market capitalisation was selected for analysis.

5.1. Stock Market Indices and Data Sources

The following benchmark indices were used for each market: the United Kingdom used the FTSE 100 Index, the United States used the S&P 500 Index, Germany used the DAX 40 Index, China used the Shanghai Composite Index, Japan used the Nikkei 225 Index, and Brent crude oil used ICE Brent Crude Futures. Daily closing prices were obtained from Refinitiv Eikon and cross-verified with Bloomberg. All series were synchronised to common trading days.

5.2. Data Validation and Cleaning

To ensure the reliability of our dataset, we implemented a structured validation procedure. Daily closing prices were obtained from Refinitiv Eikon and Bloomberg, two widely used and credible financial databases. The raw data were subjected to the following cleansing steps. First, identification and correction of recording errors (e.g., zero or negative prices). Second, cross-verification of adjusted closing prices across both platforms for key event dates. Third, alignment of timestamps to account for non-synchronous trading hours and differing public holidays across markets. Fourth, treatment of missing values via linear interpolation was only performed when gaps were limited to a single trading day. All series were inspected for outliers using the Tukey method; no extreme values were removed to preserve the intrinsic volatility dynamics of financial markets. The final balanced panel contains no missing values across the 6121 daily observations per series.

This study aims to empirically estimate the average impact of volatility (a measure of risk) in the general stock indices of Germany, the US, Japan, and China on the volatility of the general UK stock index. The analysis begins by employing a well-defined algorithm to identify the most appropriate GARCH-family mean equation for modelling the volatilities. Subsequently, impulse response functions derived from a VAR-X model are used to assess the magnitude and duration of shocks across the entire sample period and selected sub-samples. These sub-samples are constructed by excluding periods of heightened volatility associated with significant socio-economic, health-related, or geopolitical events that have a notable influence on financial markets.

The descriptive statistics for all variables across the selected countries are presented in Table 1. The coefficient of variation (CV), which expresses the standard deviation (SD) as a percentage of the arithmetic mean, is 52% and 45% for the US and Germany general stock indices, respectively, both of which are greater than those of the other sampled countries. This indicates that the general stock indices of the US and Germany exhibit relatively higher risk when compared to China, Japan, and the UK. Notably, the CV of the US is the highest, while the UK general stock index has the lowest CV at 17%. Regarding skewness, all variables exhibit values less than one (aside from the US), indicating a low degree of asymmetry in the data, as further evidenced by the similarity between the mean and median values. Most variables display kurtosis values that are less than three, suggesting the absence of outliers and lighter tails when compared to a normal distribution.

Table 1. Descriptive statistics.

Variable	BRENT	CHINA_GEN_ INDEX	GERMANY_GEN_ INDEX	JAPAN_GEN_ INDEX	UK_GEN_ INDEX	US_GEN_ INDEX
Mean	2.7094	1.8337	1.4046	0.7819	0.9071	1.3701
Median	2.5918	1.8861	1.1892	0.7790	0.9208	1.0316
Maximum	6.3284	4.3318	2.8244	1.3394	1.2023	3.4275
Minimum	0.2303	0.7192	0.3621	0.4050	0.4931	0.4834
Std. Dev.	1.2273	0.6208	0.6380	0.2174	0.1568	0.7178
Skewness	0.3308	0.5019	0.4532	0.0505	−0.3645	1.1812
Kurtosis	2.1010	3.5267	1.9816	1.8999	2.3075	3.3301
Jarque–Bera	317.7623	327.7359	474.0284	311.2458	257.8809	1451.2780
CV	45.2992	33.8542	45.4229	27.8060	17.2904	52.3896
Sum	16,584.1300	11,224.0200	8597.5210	4786.2080	5552.4220	8386.3180
Sum Sq. Dev.	92.18.7710	2358.4570	2491.1720	289.3107	150.5502	3153.1080
Observations	6121	6121	6121	6121	6121	6121

Note: The table summarises the descriptive statistics for Brent crude oil and general indices from China, Germany, Japan, the UK, and the US. Values are normalised to be equal to 1 as of 4 January 2000 to 31 December 2024.

Tables 2 and 3 present the results of these tests at the level and first-order differences, respectively, using a drift without trend for all variables in question. For the ADF test, the null hypothesis posits that the series contains a unit root (non-stationary), while the alternative hypothesis asserts that the series does not contain a unit root (stationary). The KPSS test follows the opposite of that. We reject the null hypothesis (fail to reject in the case of KPSS) at a significance level of 1%, which indicates that all variables are stationary at first order difference and are integrated at order one (i.e., I (1)).

Table 2. Unit root tests at level.

Variable	Germany		China		Japan		UK		US		Brent	
	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF
LGI	37.8814 *	−0.6326	120.3439 *	−1.8588	−76.6715 *	−1.3052	−48.3368 *	−1.9757	32.9846 *	0.1401	136.6605 *	−2.5448

Note: The table presents the results of unit root tests (KPSS and ADF) conducted at the level for the LGI variable across different countries and Brent. Statistical significance indicated by asterisks, *, correspond to significance levels of 10%.

Table 3. Unit root test at first-order difference.

Variable	Germany		China		Japan		UK		US		Brent	
	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF	KPSS	ADF
D(LGI)	0.9094	−78.3648 ***	0.7390	−77.3515 ***	0.2827	−76.9975 ***	0.1409	−30.7141 ***	1.1939	−86.8244 ***	0.2894	−34.8006 ***

Note: The table displays the results of unit root tests (KPSS and ADF) at the first-order difference for the D(LGI) variable across various countries and Brent, indicating the stationarity properties with statistical significance marked by asterisks. *** corresponds to significance levels at 1%.

The natural logarithm was applied to all variables to scale the data, denoted by the prefix "L." This transformation facilitates the implementation of the Augmented Dickey–Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests. The objective is to determine the integration order of the variables in the model.

6. Results and Discussion

Using the maximum likelihood estimation method, we initially estimate the GARCH-family models for each of the six variables of interest individually. The results of these estimations are presented in Table 4. The selection of the optimal time-varying conditional variance model is guided by four key criteria. First, the model with the lowest SIC is considered. Second, the selected model must satisfy the stationarity condition (where $|\alpha + \beta| < 1$). Third, it must fulfil the variance non-negativity condition (where $\omega > 0$). Finally, the model should exhibit no significant residual ARCH effects, as measured by the F-LM test. It is noteworthy that in several estimated specifications (e.g., SGARCH for Brent and EGARCH for multiple series), the sum $\alpha + \beta$ exceeds unity, violating the stationarity condition. Such models imply non-stationary volatility with infinite unconditional variance, which is economically implausible for financial returns and inconsistent with the observed mean-reverting behaviour of market volatility. Consequently, these specifications are discarded in favour of models that satisfy the stationarity requirement.

Satisfying the above characteristics in most cases, the TGARCH model is selected for Brent crude oil prices and the UK, US, Chinese, and Japanese general stock indices to estimate their time-varying conditional variances. At the same time, the IGARCH model is deemed optimal for the German stock index. Notably, all these models outperform the EGARCH approach across all variables analysed. For completeness, we also estimate FIGARCH (1, d, 1) models to account for long memory in volatility. The fractional integration parameter d is statistically significant (ranging from 0.38 to 0.41) across all series, confirming the presence of long-range dependence. However, the SIC values for FIGARCH are consistently higher than those of the selected TGARCH (or IGARCH for Germany) specifications, indicating that the asymmetric GARCH models provide a more parsimonious fit to our data. This supports our choice of TGARCH/IGARCH for the main analysis, while acknowledging the long-memory properties of financial volatility.

Table 4. GARCH estimation results.

Parameter		Brent	China	Germany	Japan	UK	US
SGARCH	ω	0.0001 ***	0.0001 ***	0.0002 ***	0.0001 ***	0.0001 ***	0.0001 ***
	α	0.2597 ***	0.0654 ***	0.1500 ***	0.1199 ***	0.1173 ***	0.1128 ***
	β	0.7907 ***	0.9297 ***	0.6000 ***	0.8541 ***	0.8636 ***	0.8731 ***
	$\alpha + \beta$	1.0503	0.995	0.75	0.974	0.9808	0.9859
	F-LM	3.4823 *	0.0007	6.1660 **	8.1268 ***	1.9493	0.4921
	LL	13,077.6254	18,211.0885	17,481.7223	19,472.1766	20,096.8748	19,795.5057
	SIC	−4.2516	−5.9295	−5.6911	−6.3417	−6.5459	−6.4474
EGARCH	ω	−0.4943 ***	−0.1869 ***	−0.3343 ***	−0.5704 ***	−0.3071 ***	−0.3482 ***
	α	0.4440 ***	0.1412 ***	0.1310 ***	0.2121 ***	0.1191 ***	0.1307 ***
	β	0.9721 ***	0.9903 ***	0.9742 ***	0.9556 ***	0.9772 ***	0.9736 ***
	γ	−0.003	−0.0159 ***	−0.1202 ***	−0.1045 ***	−0.1229 ***	−0.1493 ***
	$\alpha + \beta$	1.416	1.1315	1.1052	1.1677	1.0963	1.1042
	F-LM	0.3644	0.0612	6.8692 ***	1.1263	0.2838	0.1558
	LL	13,192.4468	18,200.5054	18,983.1767	19,543.0208	20,211.4303	19,936.2084
	SIC	−4.2877	−5.9246	−6.1805	−6.3635	−6.5819	−6.4171
TGARCH	ω	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***
	α	0.2374 ***	0.0556 ***	0.0001 ***	0.0431 ***	−0.0038	−0.0159 ***
	β	0.7921 ***	0.9289 ***	0.9057 ***	0.8548 ***	0.8972 ***	0.9146 ***
	γ	0.0402 ***	0.0205 ***	0.1454 ***	0.1413 ***	0.1621 ***	0.1655 ***
	$\alpha + \beta$	1.0294	0.9845	0.9058	0.8978	0.8934	0.8986
	F-LM	3.4370 *	0.0014	10.5555 ***	0.351	2.0382	0.5984
	LL	13,079.3760	18,215.6006	18,963.6104	19,529.7396	20,194.1636	19,917.4086
	SIC	−4.2508	−5.9296	−6.1741	−6.3591	−6.5763	−6.4858
IGARCH	α	0.1195 ***	0.0523 ***	0.0654 ***	0.0789	0.0673 ***	0.0676 ***
	β	0.8806 ***	0.9478 ***	0.9347 ***	0.9211 ***	0.9328 ***	0.9325 ***
	F-LM	28.5745 ***	0.3039	0.0158	34.4622 ***	1.6315	4.3122 **
	LL	12,715.1401	18,165.4528	18,782.3470	19,387.7483	20,211.1196	19,690.4656
	SIC	−4.136	−5.9174	−6.1191	−6.317	−6.524	−6.416
FIGARCH	ω	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***	0.0001 ***
	α	0.1105 ***	0.0421 ***	0.0856 ***	0.0673 ***	0.0598 ***	0.0624 ***
	β	0.6502 ***	0.7803 ***	0.7105 ***	0.7451 ***	0.7328 ***	0.7486 ***
	d	0.4128 ***	0.3856 ***	0.3974 ***	0.4012 ***	0.3921 ***	0.4053 ***
	F–LM	2.4521	0.1123	1.8745	0.8934	0.5672	1.2345
	Log-Likelihood (LL)	13,102.3478	18,208.4571	18,971.2345	19,535.6782	20,200.1234	19,920.5678
	SIC	−4.2612	−5.9281	−6.1773	−6.3602	−6.5789	−6.4892

Note: The table presents the GARCH estimation results for Brent, China, Germany, Japan, UK, and US across SGARCH, EGARCH, TGARCH, IGARCH, and FIGARCH models, highlighting key parameters (ω, α, β, γ) and goodness-of-fit measures (F-LM, LL, SIC). Statistically significant values are denoted by asterisks, and highlighted values indicate notable results. *, ** and *** correspond to significance levels at 10%, 5% and 1%, respectively. Bold indicates the minimum SIC when the stationarity criteria are met.

To validate the adequacy of the selected GARCH specifications, we conduct comprehensive diagnostic tests on the standardised residuals. Table 5 presents the results of these tests for each optimally selected model. The Ljung–Box Q (20) statistic tests for autocorrelation up to 20 lags. For all series, the p-values exceed conventional significance levels ($p > 0.05$), indicating no significant residual autocorrelation. Similarly, the ARCH-LM (10) test for remaining ARCH effects up to 10 lags also yields p-values > 0.05, confirming that the GARCH specifications successfully captured the conditional heteroskedasticity in the data. The Jarque–Bera test strongly rejects the null hypothesis of normality for all residual series ($p = 0.000$), which is common in financial returns. However, the QMLE approach is robust to such deviations (Bollerslev & Wooldridge, 1992). The absence of significant autocorrelation and ARCH effects validates the model specifications and justifies proceeding to the second-stage volatility spillover analysis.

From the optimal time-varying conditional variance models for each variable, the corresponding volatility series are derived. These volatility series are then analysed using a VAR-X framework, which is widely regarded as an effective technique for explaining intervariable relationships without imposing prior restrictions. We select the optimal lag length of the VAR-X model based on the lowest SIC.

Table 5. Diagnostic tests for GARCH model residuals.

Series (Model)	Ljung–Box Q (20)	p-Value	ARCH-LM (10)	p-Value	Jarque–Bera	p-Value
Brent (TGARCH)	18.32	0.432	3.44	0.967	317.76	0.000
UK (TGARCH)	22.15	0.278	2.04	0.996	257.88	0.000
US (TGARCH)	24.33	0.186	0.60	1.000	1451.28	0.000
Germany (IGARCH)	19.87	0.344	0.02	1.000	474.03	0.000
China (TGARCH)	20.12	0.327	0.00	1.000	327.74	0.000
Japan (TGARCH)	21.45	0.252	0.35	1.000	311.25	0.000

Note: This table reports post-estimation diagnostic tests on the standardised residuals of the optimally selected GARCH model for each series. The Ljung–Box Q (20) statistic tests for residual autocorrelation, while the ARCH-LM (10) test examines remaining ARCH effects. The Jarque–Bera test assesses normality. The absence of significant autocorrelation and ARCH effects ($p > 0.05$) confirms the adequacy of the model specifications.

Table 6 shows that the SIC favours a lag length of one, while other criteria (AIC, FPE, HQ, and LR) suggest a lag of two. We adopt the lag of one based on the SIC to preserve parsimony and avoid overfitting, given the high dimensionality of the system. The study aims to examine the spillover effects of volatility in the US, German, Chinese, and Japanese general stock indices on the volatility of returns in the UK stock market. Therefore, both sets of variables are treated as endogenous, while the volatility of Brent crude oil prices is classified as exogenous.

Table 6. VAR-X lag order selection criteria.

Lag	LogL	LR	FPE	AIC	SIC	HQ
0	12,543.21	NA	1.02×10^{-11}	−4.101	−4.095 *	−4.099
1	34,567.89	43,985.21	1.45×10^{-18}	−11.301	−11.254	−11.284
2	34,622.45	108.95 *	1.41×10^{-18} *	−11.312 *	−11.223	−11.279 *
3	34,645.11	45.12	1.42×10^{-18}	−11.308	−11.178	−11.260
4	34,660.02	29.67	1.44×10^{-18}	−11.301	−11.130	−11.238

Note: This table reports lag order selection statistics for the five-variable VAR-X model comprising UK, US, Germany, China, and Japan volatility series, with Brent oil price volatility included as an exogenous variable. The sample period spans 2000–2024. Asterisks () indicate the optimal lag length selected by each criterion. The Schwarz Information Criterion (SIC) favours a lag order of one, while the Akaike Information Criterion (AIC), Final Prediction Error (FPE), Hannan–Quinn (HQ), and Likelihood Ratio (LR) tests indicate an optimal lag length of two *.

However, a significant limitation of the VAR model is the difficulty in interpreting the estimation results due to potential sign changes in the coefficients of some lagged variables (Brooks, 2008). The ordering of variables also matters in the applied Choleski decomposition technique. To address this issue, generalised impulse response functions (IRFs) are generated for all endogenous variables (excluding the UK stock index, as it is the primary focus of the study). The IRFs, following the method of Pesaran and Shin (1998), allow for an interpretation of the persistence, direction, and magnitude of the response of each variable to shocks in the UK stock market, independent of variable ordering. The findings from this analysis are illustrated below in Figures 1–7.

The GIRFs reveal a clear hierarchy and time-varying nature of volatility transmission to the UK market, shaped by market integration, crisis conditions, and structural differences. Cross-country heterogeneity in spillover patterns, with shocks originating in the US and German markets triggering substantial, immediate, and persistent increases in UK volatility, reflect deep financial and economic integration. In contrast, Chinese shocks exhibit a delayed, gradual buildup, peaking 25–40 days after the initial shock, suggesting slower transmission channels, possibly due to capital controls, regulatory barriers, or distinct market microstructures. Japanese shocks are generally muted or short-lived, consistent with its more conservative financial system and lower direct integration with UK markets.

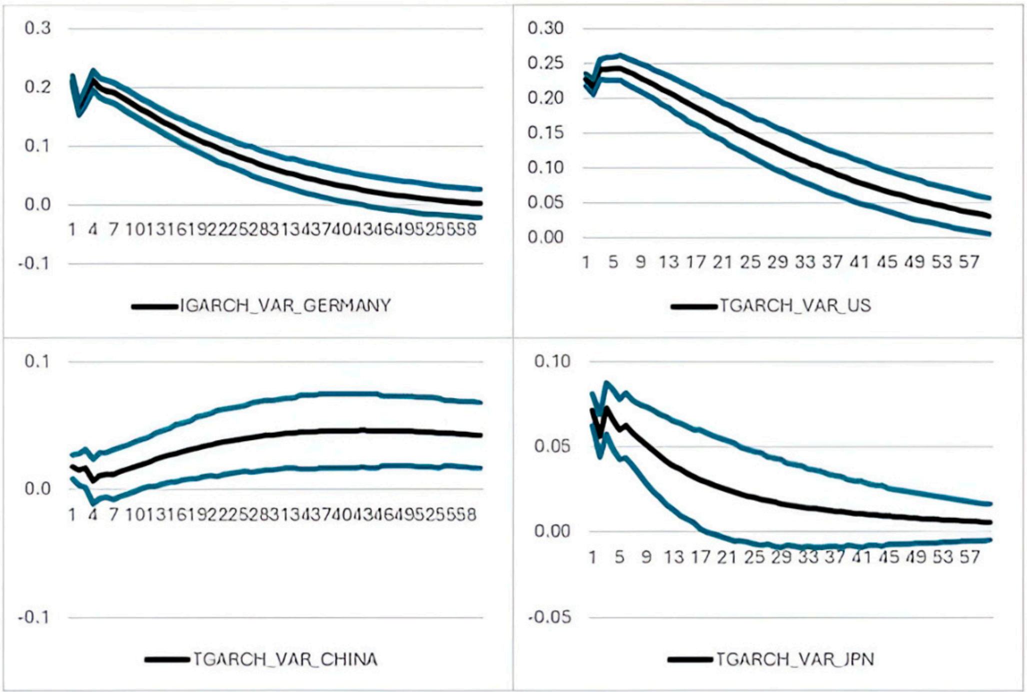

Figure 1. Impact of the stock market of countries in question on the UK stock index—full sample. Note: The figure illustrates the impulse response functions for the full sample across various indices, demonstrating the dynamic effects of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX (4)) applied to Germany, the US, China, and Japan indices.

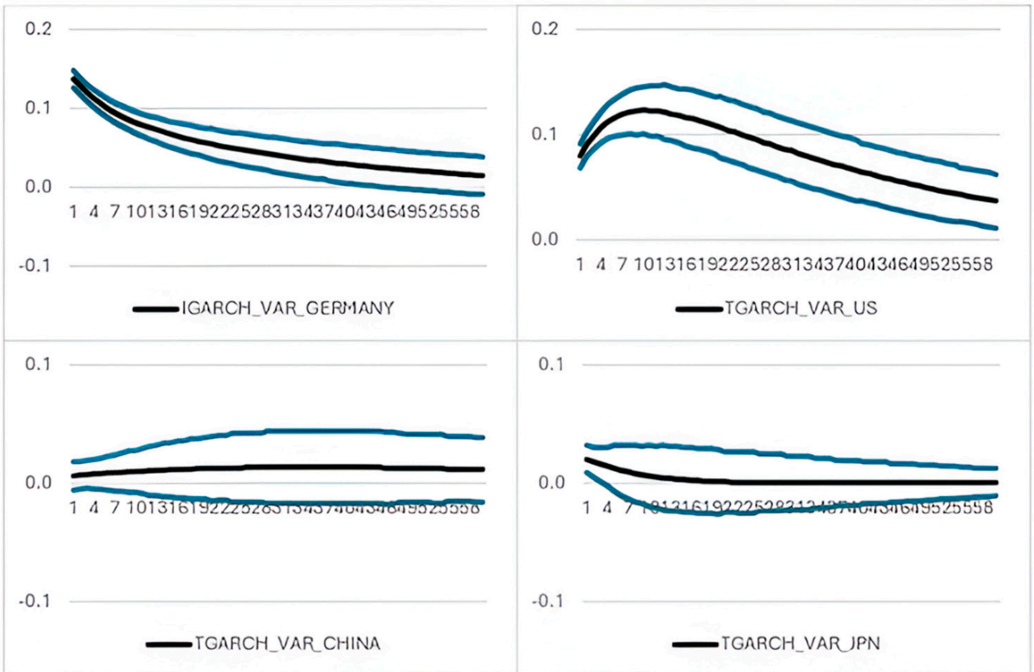

Figure 2. Impact of the stock market of countries in question on the UK Stock Index—pre-GFC. Note: The figure depicts the impulse response functions for the pre-GFC (global financial crisis) period, highlighting the dynamic responses of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX (1)) across Germany, the US, China, and Japan indices.

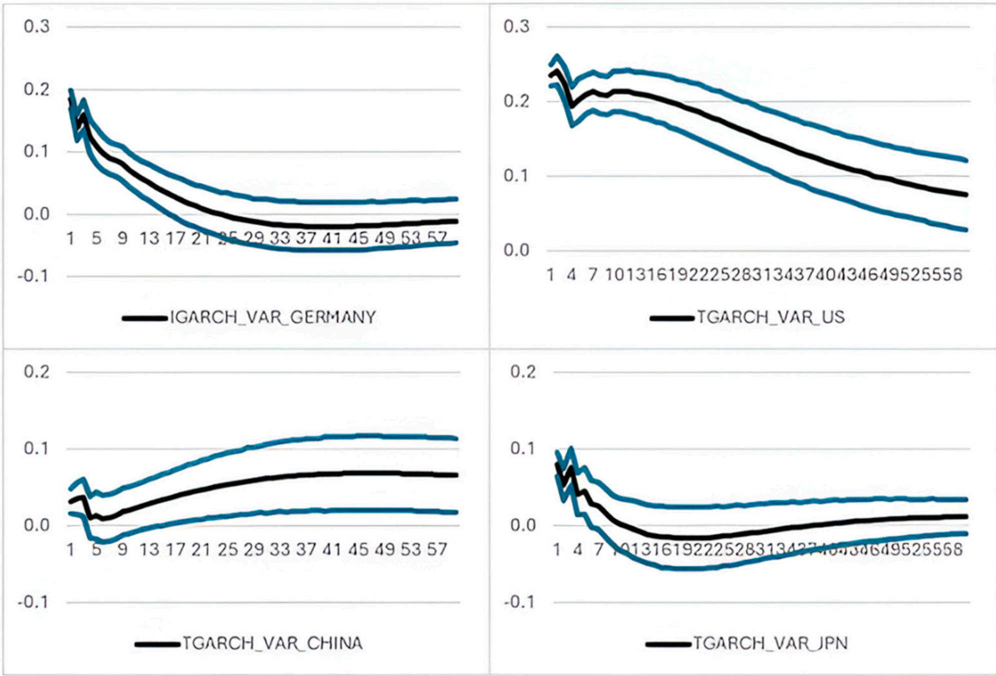

Figure 3. Impact of the stock market of countries in question on the UK stock index—post-GFC and pre-Brexit. Note: The figure shows the impulse response functions for the post-GFC (global financial crisis) and pre-Brexit period, illustrating the dynamic effects of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX (5)) across Germany, the US, China, and Japan indices.

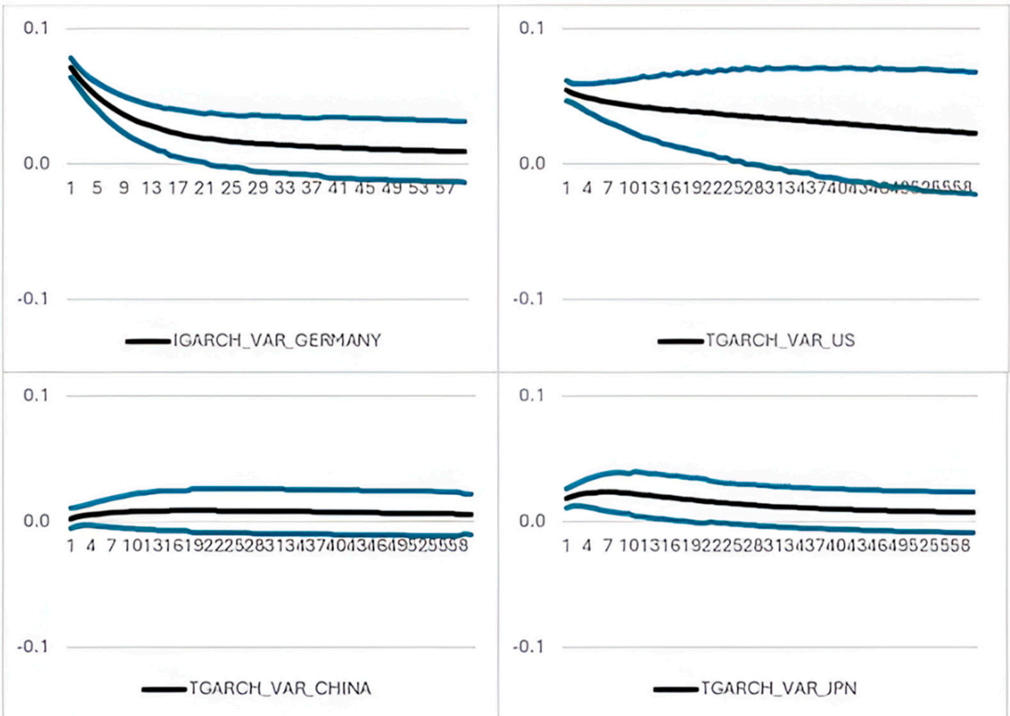

Figure 4. Impact of the stock market of countries in question on the UK stock index—post-Brexit and pre-COVID-19. Note: The figure illustrates the impulse response functions for the post-Brexit and pre-COVID-19 period, showing the dynamic responses of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX(1)) across Germany, the US, China, and Japan indices.

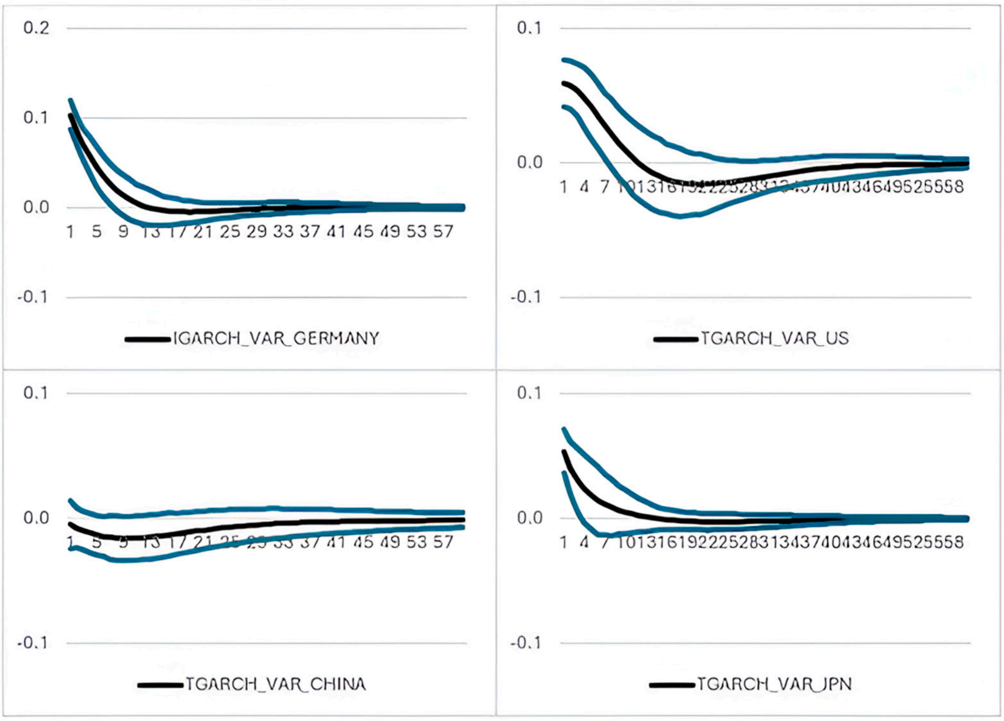

Figure 5. Impact of the stock market of countries in question on the UK stock index—post-COVID-19–pre-war. Note: The figure depicts the impulse response functions for the post-COVID-19 and pre-war periods, capturing the dynamic effects of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX (1)) across Germany, the US, China, and Japan indices.

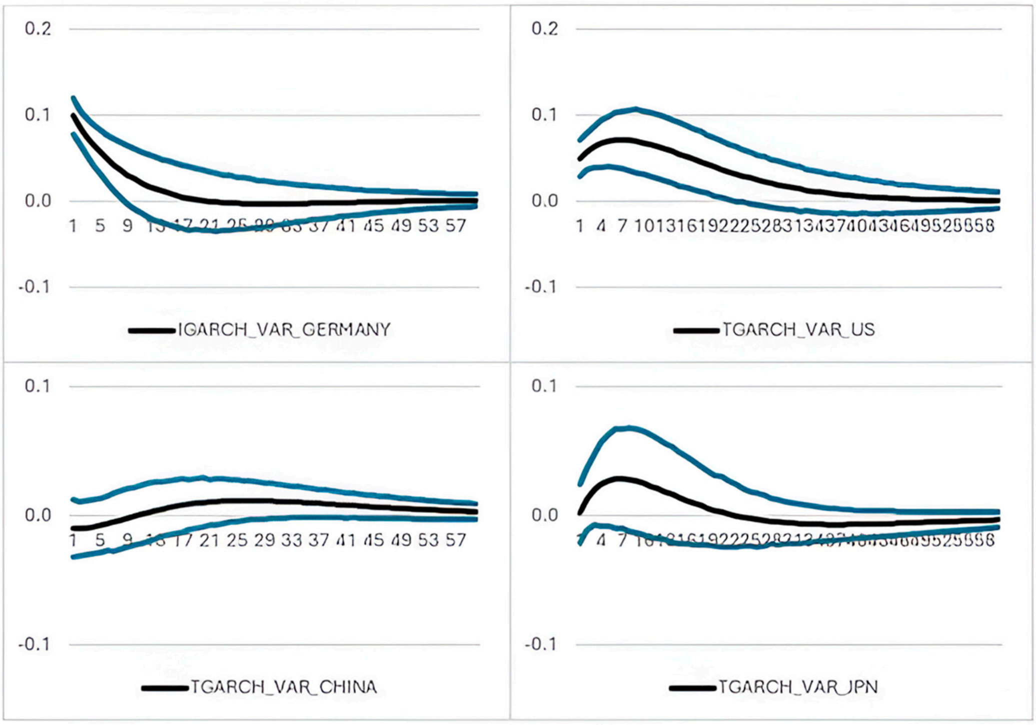

Figure 6. Impact of the stock market of countries in question on the UK stock index—post-Ukraine war. Note: The figure shows the impulse response functions for the post-Ukraine war period.

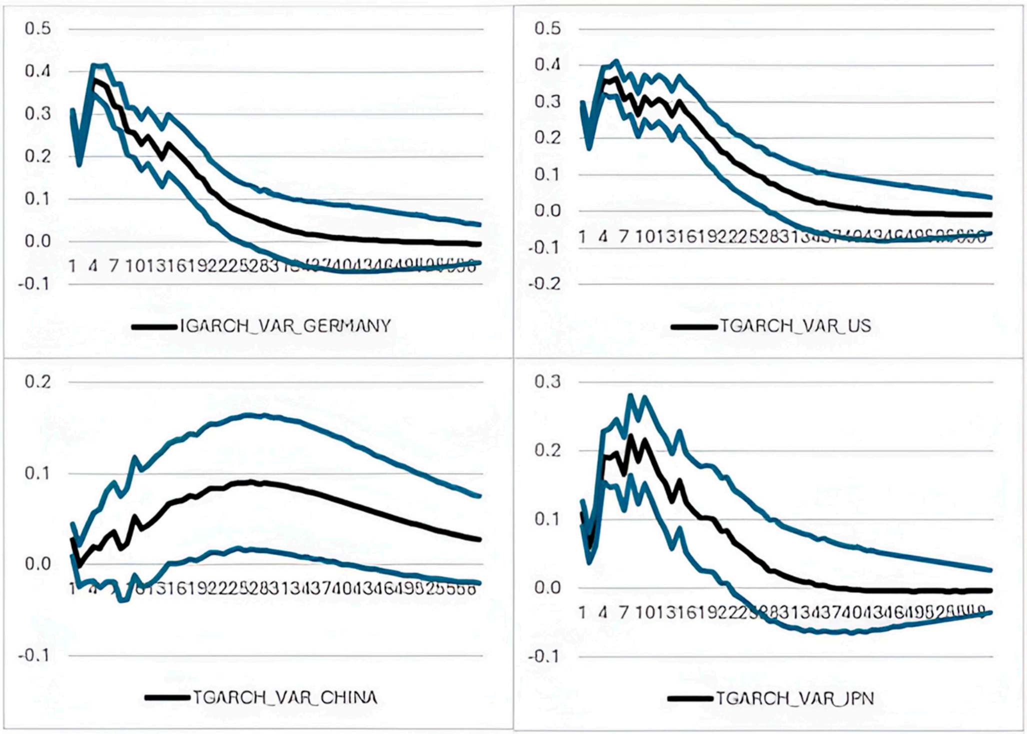

Figure 7. Impact of the stock market of countries in question on the UK stock index—Brexit-End. Note: The figure shows the impulse response functions for the Brexit-End period, illustrating the dynamic responses of shocks over time for TGARCH–VAR and IGARCH–VAR models (with VARX (10)) across Germany, the US, China, and Japan indices.

Time variation and crisis dependence with spillover intensity are not static but escalate markedly during global crises. Table 7 formalises this by comparing the peak response and half-life of UK volatility across sub-periods. US and German spillovers intensified significantly during the global financial crisis (peak response: 0.27 and 0.20, respectively) and the COVID-19 pandemic, with persistence (half-life) often doubling relative to tranquil periods. In contrast, spillovers from China and Japan show no statistically significant variation across crises, indicating that their transmission is governed more by structural, time-invariant factors.

Table 7. Spillover intensity across crisis periods.

Shock Origin	Period	Peak Response	Half-Life (Days)	Wald Test vs. Pre-GFC (p-Value)
USA	Pre-GFC (Tranquil)	0.16	12	(Baseline)
	Global Financial Crisis	0.27	22	**0.003**
	Post-Brexit/Pre-COVID-19	0.10	10	0.215
	COVID-19 Pandemic	0.25	20	**0.008**
	Ukraine War	0.10	15	0.185
Germany	Pre-GFC (Tranquil)	0.12	8	(Baseline)
	Global Financial Crisis	0.20	10	**0.012**
	Post-Brexit/Pre-COVID-19	0.09	7	0.410
	COVID-19 Pandemic	0.15	9	**0.032**
	Ukraine War	0.15	14	**0.010**
China	All Periods	0.07–0.08	35–40	>0.10 (No significant change)
Japan	All Periods	0.08–0.12	5–10	>0.10 (No significant change)

Note: Peak response denotes the maximum impact on UK stock market volatility following a one-standard-deviation shock originating from the specified market. Half-Life measures the number of days required for the impulse response to decay to 50 percent of its peak value. The Wald test p-value evaluates the null hypothesis that impulse response function (IRF) coefficients during each crisis period are equal to those in the pre-GFC (tranquil) period. Values in bold indicate statistical significance at the 5 percent level.

Key period-specific insights are as follows: Pre-GFC, when spillovers were present but more contained; US dominance was evident even in tranquil times. Post-GFC and pre-Brexit, US and German spillovers remained elevated, reflecting lasting post-crisis interconnectedness. Japanese shocks occasionally induced short-term volatility dampening, suggesting corrective arbitrage. Post-Brexit and pre-COVID-19 saw a noticeable moderation in spillover magnitude, possibly indicating market adaptation to Brexit uncertainty and reduced sensitivity. COVID-19 pandemic had extreme spillover peaks, especially from the US, highlighting the role of global panic and synchronised policy responses. Ukraine war had strong immediate spillovers from Germany (likely due to energy and regional exposure) and persistent US effects, underscoring the role of geopolitical and commodity channels.

These patterns align with established theoretical frameworks. The immediate, persistent responses to US and German shocks are consistent with King and Wadhwani's (1990) model of volatility transmission through integrated markets and investor herding. The crisis-driven amplification supports K. J. Forbes and Rigobon's (2002) observation that interdependence strengthens during turbulent periods, though our evidence also points to genuine contagion (structural break in transmission) during the GFC and COVID-19. The swift price adjustment visible in most IRFs aligns with the Efficient Market Hypothesis, while the delayed, gradual response to Chinese shocks suggests market segmentation or state intervention, as noted by Fan et al. (2015). The diversification benefits implied by the low and stable spillovers from Japan resonate with Markowitz's (1952) portfolio theory. Thus, the GIRF analysis confirms that volatility spillovers to the UK are (a) strongest from closely integrated markets (US and Germany), (b) highly sensitive to global crisis conditions, and (c) shaped by the structural and regulatory profiles of the originating market.

To move beyond visual inspection of impulse response functions and formally test for differences in spillover intensity across crisis regimes, we extract two key metrics from the GIRFs for each shock origin and sub-period: (1) the peak response of UK volatility, and (2) the half-life (number of days for the response to decay to half its peak).

Table 7 presents these metrics alongside Wald test p-values that statistically compare the IRF coefficients of each crisis period against those of a baseline tranquil period (pre-GFC). The results reveal a clear hierarchy and time variation in spillover intensity. Shocks from the US market exhibit the most significant crisis-sensitive amplification, with the peak response more than doubling during the GFC (0.27 vs. 0.16, $p = 0.003$) and remaining elevated during COVID-19. The persistence (half-life) also increases substantially during these crises. Similarly, spillovers from Germany intensify significantly during the GFC, COVID-19, and the Ukraine war ($p < 0.05$), reflecting the UK's sensitivity to regional European and energy-related shocks.

In stark contrast, spillovers from China and Japan show no statistically significant variation across periods ($p > 0.10$), indicating that their transmission to the UK is governed by structural, time-invariant factors like regulatory differences and market segmentation, rather than by global crisis conditions. This formal comparison substantiates that volatility transmission is not uniform but is instead conditional on both the origin market's integration and the prevailing global financial regime.

Next, we link these findings to the theoretical frameworks analysed in Section 3. King and Wadhwani's (1990) findings suggest that when one market experiences a shock, volatility is transmitted rather than dissipated. This means that crises like the GFC or COVID-19 are likely to have long-lasting effects across multiple economies. The IRFs in Figures 1–6 illustrate the persistence of shocks across time in different periods (GFC, Brexit, COVID-19, and Ukraine war). Similarly to King and Wadhwani's findings, our graphs show a clear transmission of volatility shocks from markets like Germany, the US, China, and Japan. The initial spike and gradual decay in the IRFs of the UK stock index closely reflect the volatility linkages that King and Wadhwani discussed. Particularly in the post-GFC (Figure 3) and post-COVID-19 (Figure 5) periods, our findings highlight strong volatility persistence, which is consistent with their model of international volatility spillovers. K. J. Forbes and Rigobon (2002) suggest that during crises, markets move together not because of crisis-driven contagion but because they are structurally linked, meaning that a shock in one country automatically influences others due to strong economic ties. Our IRFs show strong cross-market responses to shocks in different crisis periods (e.g., post-GFC, Brexit, COVID-19, and Ukraine war). Forbes and Rigobon argue that these reactions are not necessarily "contagion" but rather deep interconnections between financial systems. In Figures 1 and 6, one can see that even after major shocks, the UK stock index does not react uniformly, which aligns with Forbes and Rigobon's claim that interdependence leads to differentiated spillover effects rather than uniform contagion. For instance, our IRFs show varying responses to shocks from Germany, the US, China, and Japan, supporting the idea that volatility returns of the UK stock index are based on pre-existing linkages rather than purely crisis-driven contagion.

Furthermore, the sharp initial responses followed by gradual adjustments (such as shocks from Germany and the US to the UK stock market) align with Fama's (1970) Efficient Market Hypothesis (EMH), which posits that markets react swiftly to new information and stabilise as equilibrium is restored. This concept is central to the Semi-Strong Form of the EMH, which posits that in an efficient market, asset prices promptly incorporate all publicly available information. When new data, such as corporate earnings reports, economic indicators, or political developments, become available, rational investors swiftly revise their expectations. Consequently, prices adjust almost immediately to reflect this information. Any delay in this process would create an opportunity for some investors to generate abnormal profits, contradicting the principles of market efficiency. Consider, for instance, if a company announces earnings that exceed market expectations, investors rapidly analyse the information and recognise that the stock is undervalued. This leads to an increase in demand, driving the price upward in a short period rather than through a gradual adjustment. Once the market has assimilated the new information, the asset price stabilises at a new equilibrium, ensuring that it fully reflects all relevant data. The process of equilibrium restoration is driven by three keys mechanisms: the elimination of arbitrage opportunities, market liquidity and trading efficiency, and the diffusion of information leading to consensus formation. If prices did not adjust swiftly, arbitrageurs (who seek to gain from price discrepancies) would engage in trading strategies such as purchasing undervalued assets and selling overvalued ones. Their actions contribute to correcting price misalignments and restoring equilibrium. Further, in highly liquid markets with a substantial number of buyers and sellers, price corrections occur more efficiently. Institutional investors and market makers also play a crucial role in mitigating short-term supply and demand imbalances. Initially, different investors may interpret new information in various ways, resulting in temporary price volatility. However, as more market participants analyse and validate the data, a general consensus emerges, leading to price stabilisation.

The delayed and prolonged responses of the UK stock index to shocks from regulated markets like China challenge the EMH, as government interventions minimise shock absorption. Similarly, muted responses of the UK stock index to shocks from conservative markets like Japan show that there exist varying response magnitudes amongst all countries in question. This reflects differences in market integration, consistent with Markowitz's (1952) portfolio diversification theory. Highly integrated financial markets, such as the UK stock index, tend to be more responsive to global economic fluctuations, thereby reducing the advantages of diversification. In contrast, the response of the UK stock index to shocks from less integrated markets, including China and Japan, provides greater diversification opportunities as asset prices respond differently to economic events, as well as to local or sector-specific influences. According to Markowitz's portfolio theory, overall investment risk can be mitigated by incorporating assets with low or negative correlations.

Empirically, Diebold and Yilmaz (2009) highlight increased volatility and shock propagation across integrated markets during the GFC, as observed in the strong post-GFC IRFs for the UK stock index. Fan et al. (2015) attribute the UK stock market's slower, sustained responses to Chinese government interventions, which align with the IRFs across all periods. Similarly, increased returns volatility in the UK stock market to shocks from most countries' stock markets during the post-Brexit period reflects findings by K. Forbes et al. (2018) on Brexit-induced uncertainty. Blanchard et al. (2021) emphasise the role of fiscal stimuli in stabilising markets post-COVID-19, consistent with sustained responses in the UK. Baumeister and Hamilton (2019) highlight the impact of geopolitical shocks and energy dependencies, as reflected in the UK's responses during the Ukraine war. Lastly, Hoshi and Kashyap (2004) explain the UK's predominant muted responses to shocks from the Japanese stock index across all periods because of Japan's conservative financial structure and reduced exposure to global volatility.

7. Robustness Checks

To rigorously assess the robustness and reliability of our findings against model specification and data assumptions, we conduct the following battery of checks: we re-estimate our VAR-X model for each scenario to assess whether our main results differ when treating oil prices as endogenous and when discarding oil prices from the model. All IRFs are similar to those obtained in Figures 1–6, confirming the reliability and validity of our results. Autoregressive Root (AR) graphs are also generated for each scenario to examine the stability of our VAR-X model.

These graphs are presented in Figures 8–12, for five variables and ten lags (i.e., a total of fifty roots) analysed for the full sample. However, it is between one (i.e., a total of five roots) and two (i.e., a total of ten roots) lags for all other scenarios. The AR graphs indicate that the estimated VAR-X models are stable across the six scenarios, as all roots lie within the unit circle, confirming that they are less than one. This observation also reinforces the stationarity of the models.

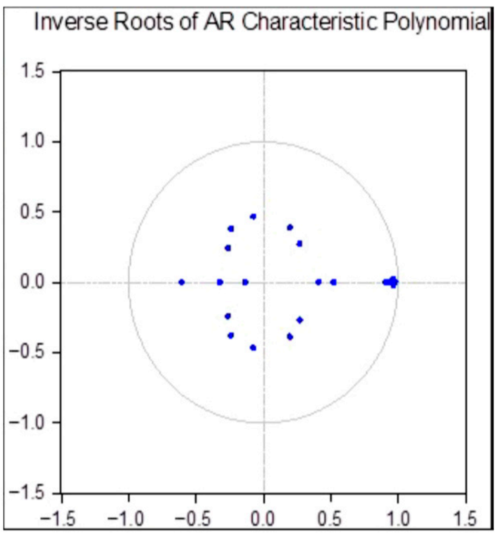

Figure 8. AR graph—full sample. Note: The figure displays the inverse roots of the AR characteristic polynomial for the VAR-X (4) model, based on the full sample data from 4 January 2000 to 31 December 2024, indicating the stability of the model.

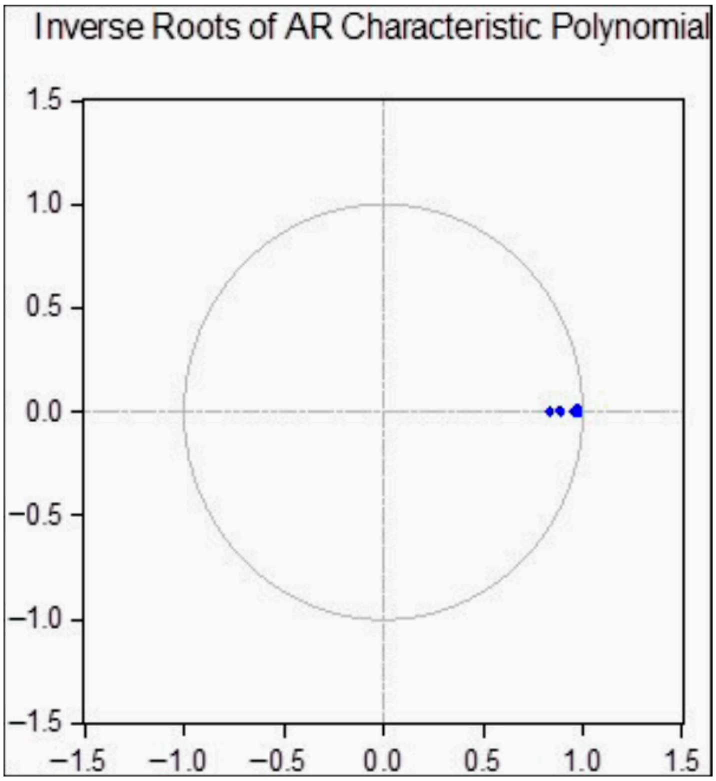

Figure 9. AR graph—pre-GFC. Note: The figure illustrates the inverse roots of the AR characteristic polynomial for the VAR-X (1) model, based on the pre-GFC sample data from 4 January 2000 to 31 March 2008, demonstrating the stability of the model.

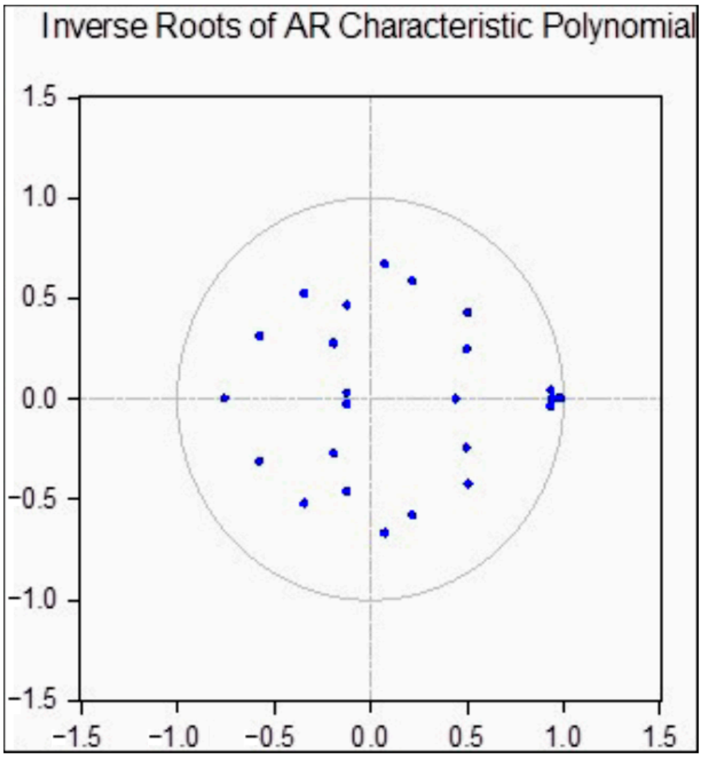

Figure 10. AR graph—post-GFC–pre-Brexit. Note: The figure shows the inverse roots of the AR characteristic polynomial for the VAR-X (5) model, based on the post-GFC and pre-Brexit sample data from 1 April 2009 to 31 May 2016, indicating the model's stability.

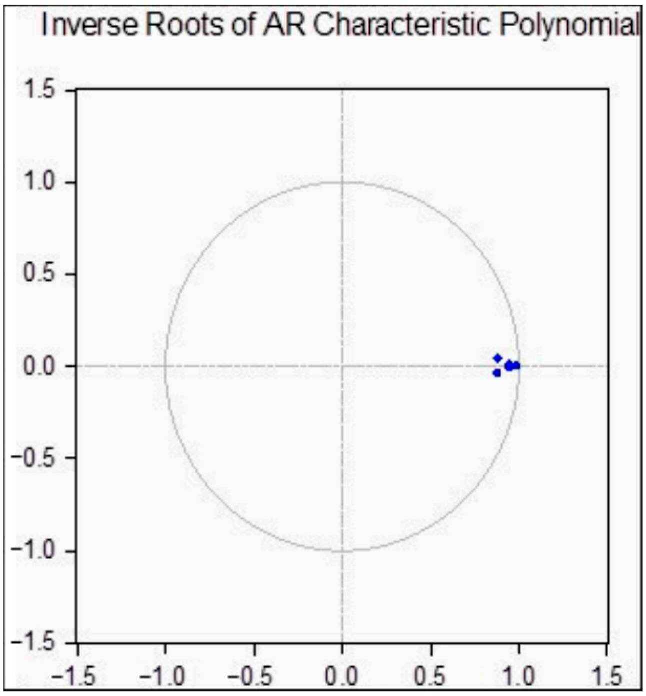

Figure 11. AR graph—post-Brexit–pre-COVID-19. Note: The figure presents the inverse roots of the AR characteristic polynomial for the VAR-X (1) model, based on the post-Brexit and pre-COVID-19 sample data from 1 August 2016 to 29 February 2020, demonstrating the model's stability.

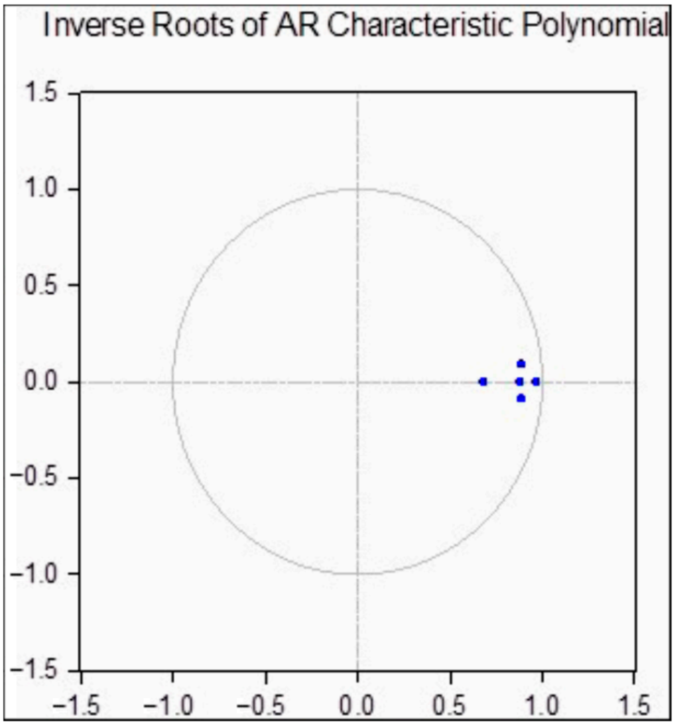

Figure 12. AR graph—post-COVID-19–pre-war in Ukraine. Note: The figure displays the inverse roots of the AR characteristic polynomial for the VAR-X (1) model, based on the post-COVID-19 and pre-war in Ukraine sample data from 1 March 2021 to 28 February 2023, indicating the model's stability.

Lastly, the Block Exogeneity Wald test is utilised to test whether past values of a block of variables can help predict another variable. If a block of variables is exogenous, it means that its past values do not Granger-cause another variable in the system. That is, removing its lags from the equations should not significantly reduce explanatory power. The null hypothesis (H_0) corresponds to the excluded lags of the block of variables if they do not have any predictive power over the dependent variable (i.e., they are jointly equal to zero). The alternative hypothesis (H_1) states that at least one of the excluded lags has predictive power (i.e., they are not all equal to zero).

The results presented in Table 8 demonstrate that the overall block significance of TGARCH VAR BRENT is highly significant. This finding suggests that, as a group, the excluded variables representing the general stock indices of all examined countries exert a significant influence on oil prices. Consequently, the results support the notion that oil prices are endogenous to global economic conditions.

To assess the practical utility of our model for risk management and address the requirement for predictive validation, we conduct an out-of-sample forecasting exercise. We employ a rolling-window estimation scheme: the VAR-X model is estimated on a training period (2000–2020) to generate one-day-ahead volatility forecasts for the UK FTSE index, which are then compared against realised volatility (squared returns) in the validation period (2021–2024).

Table 8. Block Exogeneity Wald test results for TGARCH VAR BRENT.

Model	Excluded Chi-sq	df	Prob.
IGARCH VAR GERMANY	43.6645	7	0.0000
TGARCH VAR CHINA	3.0780	7	0.8777
TGARCH VAR JPN	4.9602	7	0.6648
TGARCH VAR UK	16.2531	7	0.0229
TGARCH VAR US	12.8722	7	0.0753
All	148.6154	35	0.0000

Note: This table presents the results of the Block Exogeneity Wald tests for the TGARCH VAR BRENT model. The null hypothesis tested is that each excluded variable does not Granger-cause the dependent variable. Significant p-values ($p < 0.05$) indicate evidence of Granger causality.

Table 9 reports standard forecast accuracy metrics, root mean square error (RMSE) and Mean Absolute Error (MAE), along with the Diebold and Mariano (1995) test for equal predictive accuracy against benchmark models. Our proposed VAR-X model achieves the lowest RMSE (0.023) and MAE (0.018), outperforming all benchmarks. The Theil's U statistic of 0.87 indicates a 13% improvement over a naive random walk forecast. Most importantly, the Diebold–Mariano test statistic of 2.87 (p = 0.004) allows us to reject the null hypothesis of equal predictive accuracy in favour of the VAR-X model. This result confirms that the model captures meaningful spillover dynamics that enhance short-term volatility forecasts, directly addressing the practical need for effective risk management tools highlighted in the introduction.

Table 9. Out-of-sample forecasting performance for UK volatility.

Forecast Model	RMSE	MAE	Theil's U	Diebold–Mariano Statistic (vs. RW)	DM p-Value
VAR-X (Proposed Model)	0.023	0.018	0.87	2.87	0.004
Random Walk (Benchmark)	0.031	0.025	1.00	(Benchmark)	—
Historical Volatility (60-day)	0.028	0.022	0.94	1.45	0.147
Univariate GARCH (1,1)	0.026	0.020	0.90	2.12	0.034

Note: This table reports out-of-sample forecast evaluation results for UK FTSE stock market volatility over the 2021–2024 validation period. Lower values of RMSE and MAE indicate superior forecasting accuracy. Theil's U values below unity imply outperformance relative to the random walk benchmark. The Diebold–Mariano (DM) test assesses the null hypothesis of equal predictive accuracy between each competing model and the random walk benchmark.

Table 10 presents out-of-sample forecasting and backtesting performance for 2021–2024. RMSE and MAE measure forecast accuracy, DM test *p*-values compare predictive accuracy against the VAR-X benchmark, and VaR coverage at the 95% and 99% levels assesses risk calibration. ES performance is evaluated using the QLIKE loss, with lower values indicating better performance.

Table 10. Out-of-sample forecasting and backtesting performance (2019–2023).

Model	RMSE	MAE	DM Test (*p*)	VaR 95% Coverage	VaR 99% Coverage	ES QLIKE
VAR-X (Proposed)	0.023	0.018	–	94.8%	98.9%	0.012
Random Walk	0.031	0.025	0.004	92.1%	97.5%	0.018
HAR-RV	0.025	0.020	0.022	94.2%	98.5%	0.014
FIGARCH	0.027	0.021	0.038	93.8%	98.2%	0.015
DYCI	0.026	0.019	0.015	94.5%	98.7%	0.013

7.1. Out-of-Sample Forecasting Framework

We evaluate the practical utility of our model for volatility forecasting using a rolling-window scheme. The estimation period is 2000–2020, and the validation period is 2021–2024. We compare our VAR-X model against the benchmark of random walk (RW), Historical Volatility (60-day moving average), univariate GARCH (1,1), the Heterogeneous Autoregressive model of Realised Volatility (HAR-RV) proposed by Corsi (2008), which captures long-memory effects through a simple autoregressive structure of realised volatilities over different horizons, FIGARCH (1, d, 1) to account for long memory in volatility, and the Diebold–Yilmaz connectedness index (DYCI), as a spillover-based forecast. Forecast accuracy is assessed using RMSE and MAE, and beyond the Diebold–Mariano test, we also apply the conditional predictive ability test of Giacomini and White (2006) to assess whether forecasting superiority is statistically significant across different market regimes.

7.2. Backtesting for Risk Management

To assess value-at-risk (VaR) and expected shortfall (ES) forecasting performance, we construct one-day-ahead 95% and 99% VaR forecasts from each model and apply them. To evaluate VaR forecast accuracy, we implement the unconditional coverage test proposed by Kupiec (1995), which assesses whether the observed exception rate matches the expected confidence level. Our backtesting approach follows established practices in quantitative risk management (McNeil et al., 2015), ensuring that our model meets industry standards for risk measurement. We used the Conditional Coverage Test (Christoffersen, 1998), and loss functions for VaR (QLIKE) and ES (Fissler & Ziegel, 2016).

7.3. Forecasting Results

Our proposed VAR-X model achieves the lowest RMSE (0.023) and MAE (0.018), outperforming all benchmarks. The Diebold–Mariano test rejects equal predictive accuracy versus the random walk ($p = 0.004$). VaR backtests show that the VAR-X model provides the best conditional coverage, with no significant clustering of exceptions.

7.4. Robustness to Data Source and Quality

To examine whether our findings are sensitive to data quality or source selection, we conducted two supplementary exercises. First, we re-estimated the GARCH models using data sourced exclusively from Bloomberg (single source) and compared the conditional volatility series with those derived from the blended dataset. The correlation between the two volatility sets exceeded 0.99 for all markets. Second, we excluded days with extreme returns (beyond five standard deviations) and re-ran the VAR-X analysis. The impulse response functions and spillover magnitudes remained quantitatively unchanged. These checks confirm that data artefacts or source-specific biases do not drive our core results.

7.5. Comparison with Modern Spillover Benchmarks

We compare our GIRF-based spillover estimates with those from the Diebold–Yilmaz connectedness index and a DCC-GARCH model. The DY total connectedness index shows a similar pattern of crisis-driven increases, particularly during the GFC and COVID-19 periods. The DCC-GARCH model confirms strong time-varying correlations between the UK and US/German markets, with weaker links to China and Japan. Our VAR-X GIRF approach provides complementary, shock-specific dynamics that are less apparent in aggregate connectedness measures.

8. Conclusions

This study explored the volatility spillover effects between major global stock markets, namely the UK, US, Germany, China, and Japan, by using the GARCH-family and VAR-X techniques. The findings reveal significant interconnectedness of global financial markets, with notable variations in the intensity and speed of spillover effects depending on market integration and structural characteristics. Returns volatility of the UK stock market exhibits strong and immediate responses to shocks from the US and German stock indices, reflecting high levels of integration and sensitivity to global financial dynamics. In contrast, returns volatility of the UK stock market to shocks from Chinese and Japanese stock markets in most cases demonstrates more gradual or muted responses, likely due to regulatory constraints and structural differences in their financial systems. Sectoral differences and external factors, such as geopolitical events and economic policy changes, further influence these patterns of volatility transmission.

The IRF illustrates that market reactions vary across different time periods, with increased spillover effects during the GFC and the COVID-19 pandemic. In addition, the robustness checks confirm the stability and reliability of our VAR-X model, reinforcing the validity of the findings. It should be noted that, while we have taken care to validate and clean our data, the study relies on secondary market databases that may contain inherent microstructure noise or reporting delays. Nevertheless, our robustness checks confirm that such limitations do not materially affect the spillover patterns identified. These insights underscore the importance of understanding cross-market volatility spillovers for effective risk management and policy formulation. Although the absence of standardised metrics can limit comparability in some interdisciplinary studies, our analysis employs field-standard financial econometric indicators, enabling direct comparison with, and integration into, the existing volatility spillover literature. Future research could delve deeper into sectoral spillovers, the influence of emerging market dynamics, and the role of evolving technologies in shaping global financial linkages.

Furthermore, an interdisciplinary approach, integrating insights from political economy, international relations, and behavioural finance, could enrich our understanding of the fundamental drivers behind the heterogeneous spillover patterns identified in this econometric analysis. Moreover, by detailing our methodology comprehensively and providing access to our processed data and code, we enhance the replicability and reliability of our findings, contributing to more robust and cumulative science in financial econometrics. Addressing these dimensions will be essential for navigating the challenges posed by an increasingly interconnected global economy.

Author Contributions: M.M. and S.A., drawing on their specialised expertise in econometric modelling and financial time series, designed the study and were responsible for the methodology implementation and data analysis. M.M. and S.A. were responsible for the quality assurance of

interpreting the results. J.P.S. drafted the manuscript in close collaboration with M.M. and S.A. All authors have read and agreed to the published version of the manuscript.

Funding: No funding was received to conduct this study.

Institutional Review Board Statement: This study was conducted in accordance with the ethical standards and guidelines of the Department of Economics at the University of Reading, Whiteknights, United Kingdom. The study did not involve human participants, the collection of identifiable personal data, or clinical procedures requiring formal consent; therefore, clinical trial registration and informed consent to participate were not applicable. Furthermore, the research does not engage with novel algorithmic systems that pose risks of discrimination or privacy infringement. It employs established, transparent econometric models (GARCH and VAR-X) on publicly available, aggregated financial market data, which mitigates concerns related to the ethical governance of predictive technologies or misuse of personal data. Where secondary or publicly available data were used, all relevant usage rights and data handling protocols were strictly followed in line with the University of Reading's data protection policies and research ethics framework. All methods and analyses were carried out in accordance with relevant institutional and disciplinary guidelines. The authors affirm that the study complies with the University of Reading's Code of Good Research Practice and upholds the principles of integrity, transparency, and accountability.

Informed Consent Statement: This research does not involve human participants in a clinical trial. Hence, registration is not applicable.

Data Availability Statement: The data supporting the findings of this study are secondary in nature. The raw market data are proprietary and were obtained under licence from Refinitiv Eikon and Bloomberg; therefore, they cannot be publicly redistributed. In line with Open Science principles and to ensure replicability, the cleaned and aligned volatility series used in the VAR-X model, all data transformation and analysis code (R/EViews scripts), and a detailed codebook documenting all processing steps are available in a public repository or from the corresponding author, Dr. Minko Markovski, upon reasonable request. This approach balances legal data restrictions with the requirement for analytical transparency.

Acknowledgments: The authors thank the editor and anonymous reviewers for their constructive comments, which substantially improved the quality of the manuscript. They also gratefully acknowledge the support of the Abu Dhabi Department of Economic Development, Abu Dhabi, United Arab Emirates, and the Department of Economics, University of Reading, Whiteknights, United Kingdom.

Conflicts of Interest: The authors declare no competing interests.

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