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Macroeconomic Determinants of Stock Market Volatility: A Comparative GARCH Analysis across Financial Markets with Varying Depth and Liquidity

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ABSTRACT

This research investigates how selected macroeconomic determinants influence stock market returns and volatility across financial systems characterized by varying degrees of market depth and liquidity. The analysis focuses on four stock indices—FTSE 100, FTSE China A50, BUDAPEST SE, and SBITOP—over the period 2012–2022, which is further divided into pre-crisis and crisis/post-crisis subperiods to capture the effects of the COVID-19 shock. To account for time-varying and asymmetric volatility dynamics, the study employs customized multivariate GARCH-type models, including EGARCH, PGARCH, and TGARCH specifications, with model selection guided by information criteria. The empirical results confirm that macroeconomic factors such as inflation, interest rates, exchange rates, and commodity prices exert statistically significant effects on stock index returns and volatility, although the magnitude and direction of these effects differ across markets and across time periods. Developed and less liquid markets display distinct volatility transmission mechanisms, particularly during crisis periods. Overall, the findings highlight the relevance of flexible GARCH-based frameworks for understanding market-specific volatility dynamics and provide useful insights for investors and policymakers operating under conditions of heightened uncertainty.

1. Introduction

Recent episodes of global economic turbulence have underscored the high responsiveness of financial markets to movements in fundamental macroeconomic variables such as inflation, interest

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rates, and the prices of key commodities. However, empirical evidence suggests that neither the intensity nor the channels through which these effects are transmitted are uniform across markets. Differences in market structure, liquidity conditions, and institutional capacity lead to heterogeneous reactions, whereby less mature financial markets tend to exhibit heightened vulnerability to external shocks when compared to more developed and liquid market environments.

Against this background, the central research question addressed in this study is whether the effects of macroeconomic factors on stock index returns differ significantly between highly developed markets (the United Kingdom and China) and less developed markets (Hungary and Slovenia), particularly during periods of pronounced global economic disturbances such as the COVID-19 pandemic. The main value added of this study stems from its comparative approach, which systematically examines financial markets characterized by different levels of development across clearly defined economic regimes—namely the pre-crisis, crisis, and post-crisis phases—over the 2012–2022 period.

The selection of the analyzed markets is additionally motivated by the specific global and regional economic developments that affected these financial systems during the observed period. The United Kingdom was included due to the structural uncertainties associated with Brexit and the redefinition of its trading and regulatory relations following its withdrawal from the European Union. China represents a particularly relevant case given the effects of the trade tensions with the United States, as well as its central role in the initial phase of the COVID-19 crisis. Hungary and Slovenia were selected as geographically and economically relevant neighboring markets to Serbia, the authors' domestic economy, which have already been partially examined in previous regional studies and whose stock exchange systems are considerably more developed and liquid than the Serbian capital market. Such a comparative setting additionally makes it possible to observe the actual effects that major crisis events exerted on the analyzed financial markets, as well as the extent to which different economies and financial systems adapted to and recovered from the resulting disturbances.

This study aims to provide empirical insights into the magnitude and direction of the effects exerted by selected macroeconomic factors through the application of tailored GARCH-type models. In doing so, it advances the understanding of volatility behavior from the perspective of financial market participants and provides an analytical basis for more effective investment-related decisions. At the same time, the research extends the existing body of literature by offering a systematic comparison of financial markets characterized by different degrees of development within explicitly defined crisis and non-crisis periods.

To adequately model volatility transmission, this study relies on the Generalized Autoregressive Score (GAS-GARCH) framework, in which model parameters evolve according to the score of the conditional likelihood function, enabling rapid adaptation to new information embedded in financial returns. As an alternative mixed-frequency specification, the MIDAS-GARCH model separates volatility into short-run and long-run components, thereby allowing macroeconomic indicators observed at lower frequencies to be explicitly incorporated. Whereas the GAS-GARCH approach captures short-term volatility dynamics in high-frequency data, the MIDAS-GARCH framework links daily market movements with broader macroeconomic conditions. This conceptual distinction clarifies the rationale for the methodological choices adopted in the present analysis and highlights potential avenues for future research based on mixed-frequency or hybrid volatility models.

Main Hypothesis H0: The application of tailored multivariate GARCH-type models enables the detection of statistically meaningful effects of key macroeconomic factors on stock index daily returns in markets characterized by heterogeneous levels of financial development, providing a robust analytical basis for investment-related inference.

Derived Hypotheses:

H1: Macroeconomic influences on stock returns and conditional volatility differ significantly across markets characterized by different levels of financial development and liquidity.

H2: Within the 2020–2022 crisis interval, adverse macroeconomic influences on stock index returns are significantly more intense in financially less developed markets characterized by limited depth and liquidity than in comparatively mature and liquid financial systems.

The remainder of the paper is organized as follows. The introductory section defines the research focus, objectives, and hypotheses. This is followed by a review of the relevant academic literature. The subsequent section describes the data and methodological framework employed in the analysis. Empirical findings and their interpretation are then presented, after which the paper concludes with final remarks and a list of references.

2. Review of Relevant Empirical and Theoretical Research

The present study examines the volatility behavior of stock market index returns, with particular emphasis on the macroeconomic factors that drive and shape its underlying dynamics. As highlighted by Buczynski and Chlebus [1], a comprehensive examination of financial asset volatility requires consideration of several fundamental properties. First, volatility clustering implies that large price movements are typically followed by further substantial changes, regardless of direction. Second, volatility exhibits mean-reverting behavior, reflecting fluctuations between periods of heightened market instability and relative calm. Third, asymmetric effects arise when new information affects volatility unevenly, often as a consequence of leverage effects or variations in risk premiums. Fourth, volatility dynamics are highly responsive to exogenous shocks, as external economic and financial forces can materially affect market behavior. Fifth, the unconditional distribution of asset returns frequently displays excess kurtosis, resulting in fat tails that deviate from the normal distribution. Finally, although volatility models provide useful forecasting insights, their predictive accuracy remains limited.

A major source of global economic disruptions arises from cross-country spillover effects propagated through intensive trade connections, which can undermine financial stability across markets characterized by differing levels of development [2,3]. Such destabilization significantly affects investment activity, as investors often respond to heightened uncertainty and abrupt market movements by adopting precautionary strategies that further amplify financial risk [4,5,6]. In this context, volatility may be interpreted both as an indicator of market risk and as an analytical instrument for its assessment and management [7]. Public authorities play a central role in mitigating the depth of financial crises through the prompt and well-targeted implementation of economic policy measures [8,9,10]. The magnitude of a crisis is largely determined by the level of systemic risk, which primarily stems from uncertainty surrounding firms' operations within competitive market environments [11]. Timely economic responses typically involve the application of a range of monetary and fiscal policy instruments aimed at stabilizing financial conditions and restoring market confidence [12,13]. These findings collectively highlight the relevance of examining volatility dynamics within interconnected financial systems, particularly in the context of macroeconomic shocks and cross-market spillover effects.

The assessment of macroeconomic influences on stock index volatility has been extensively addressed through the application of GARCH-type econometric models. As emphasized by Xiang and Zhang [14], the structural characteristics of these models are intrinsically linked to the conditions ensuring stationarity in higher-order moments, which is essential for their theoretical validity and empirical reliability. Owing to their numerous extensions and distinct specifications, GARCH models have been shown to be particularly effective in modeling conditional variance dynamics. In their empirical application to the Chinese financial market over the period from January 4, 2010, to April 8, 2020, the authors further subdivided the sample into several sub-periods to enhance analytical precision. Their results demonstrate that alternative GARCH specifications provide reliable Value-at-Risk (VaR) estimates, thereby highlighting the practical importance of these models for financial risk measurement and management.

Glavaški *et al.,* [15] investigate the transmission of oil price shocks to stock market indices across a group of European economies—namely Germany, France, the Netherlands, Ireland, Bulgaria, and Croatia—within a Value-at-Risk (VaR) framework over the 2013–2023 period. Their empirical evidence points to heterogeneous transmission mechanisms: in large oil-importing economies such as Germany, France, and the Netherlands, oil price movements exert a predominantly inverse effect on stock market performance, whereas in smaller importing countries, including Ireland, Bulgaria, and Croatia, the relationship is largely positive. The study additionally highlights the sustained influence of crude oil price dynamics in recent years, attributing this persistence to the sequence of global economic and geopolitical crises. They emphasize that distinguishing between supply-side and demand-side sources of oil price shocks is essential for assessing their implications for endogenous economic growth and exogenously driven price declines. This evidence underscores the heterogeneous transmission of commodity price shocks across countries with differing levels of energy dependence and market structure.

Jiang and Liu [16] examine how fluctuations in oil prices influence stock market performance in a set of oil-importing economies over the May 2001–December 2019 period, including China, France, Germany, India, Italy, Japan, South Korea, the Netherlands, Spain, and the United States. Employing advanced time-series methodologies, with particular emphasis on GARCH-based volatility models, their analysis shows that increased oil price volatility amplifies uncertainty in financial markets, which may in turn shape investment decisions and affect macroeconomic stability across the observed countries. This evidence further supports the role of oil price volatility as a key source of risk transmission in global financial markets.

Milošević *et al.,* [17] analyze the existence of the holiday effect in stock market returns across selected emerging European markets—Slovenia, Croatia, and Hungary—over the 2003–2016 period. By applying ARCH and GARCH specifications within distinct sub-periods (pre-crisis, crisis, and post-crisis), their findings indicate that both the strength and statistical relevance of the holiday effect differ considerably across markets and over time. The findings highlight the necessity of adapting econometric specifications to specific market conditions, particularly in environments characterized by heightened volatility and market inefficiencies across different phases of the economic cycle.

Prabheesh *et al.,* [18] analyze the relationship between oil price dynamics and stock market returns during the COVID-19 crisis using a Dynamic Conditional Correlation GARCH (DCC-GARCH) model. The study focuses on major Asian economies—China, India, and Japan—over the period from January 2 to April 28, 2020. The results indicate a positive and time-varying correlation between oil prices and equity returns during the pandemic, suggesting that net oil-importing countries became particularly sensitive to oil price fluctuations under conditions of elevated global uncertainty.

Zhang *et al.,* [19] examined the effects of the COVID-19 pandemic on global financial markets, focusing on major stock indices in the United States (S&P 500), Europe (DAX and FTSE 100), and Asia (Shanghai Composite and Nikkei 225), as well as key commodity markets, including oil, gold, and silver. Through the application of multiple GARCH model specifications, the authors identify a substantial surge in market volatility alongside sharp contractions in leading stock indices during the pandemic phase. These results provide further evidence of the sensitivity of global equity and commodity markets to large-scale systemic shocks.

Topcu and Gulal [20] investigate the effects of the COVID-19 outbreak on stock market performance in a broad set of emerging economies. Their empirical evidence shows that equity markets in developing countries were initially hit by a severe negative shock, manifested through abrupt price declines during the early stage of the pandemic. Nevertheless, from mid-April 2020 onward, the magnitude of these adverse effects diminished, indicating a gradual stabilization and partial recovery of market conditions. Based on an analysis of 26 emerging markets over the March 10–April 30, 2020 period, the study incorporates dynamic time-series specifications, thereby confirming the relevance of GARCH-type models for capturing volatility dynamics across different phases of the pandemic.

Investors continuously seek to construct portfolios that best reflect their individual preferences and expectations regarding investment performance [21]. As noted by Hiller [22], an optimal portfolio is defined as one that maximizes expected returns for a given level of risk. Within this framework, investors typically choose between active investment strategies aimed at outperforming the market and passive strategies based on holding securities until favorable market conditions emerge [23]. In line with this theoretical perspective, the existing literature emphasizes the relevance of macroeconomic factors—such as inflation rates, policy interest rates, exchange rates, gold prices, and oil prices, in shaping stock market returns and guiding investment decision-making processes.

Recent contributions increasingly highlight the role of macro-financial linkages and global uncertainty as key drivers of volatility dynamics across financial markets. Empirical evidence suggests that external shocks—such as geopolitical tensions, pandemic-related disruptions, and systemic financial spillovers—are transmitted through interconnected financial systems in asymmetric and non-linear ways. For instance, Mati *et al.,* [24] investigate trade asymmetries arising from regional economic divergence, while Alsakarneh *et al.,* [25] employ hybrid modeling approaches to examine exchange rate volatility during the Russia–Ukraine conflict. In a related context, Mati *et al.,* [26] analyze how uncertainty influences inflation expectations in West African economies by incorporating pandemic- and conflict-related shocks into forecasting frameworks. Collectively, these studies emphasize the importance of simultaneously accounting for structural market characteristics and global risk factors when examining volatility transmission across heterogeneous financial environments.

Balaban *et al.,* [27] analyze the impact of the COVID-19 pandemic as an exogenous shock on the euro exchange rate, applying GARCH-based econometric techniques to capture volatility persistence and market resilience. Their findings demonstrate that crisis-driven uncertainty significantly alters the dynamics of key financial variables, highlighting the relevance of advanced volatility models for strategic decision-making in turbulent environments. This contribution underscores the value of incorporating econometric volatility frameworks when assessing financial stability and managerial investment decisions under crisis conditions, thereby providing important theoretical support for studies examining macroeconomic shocks and financial market responses.

In parallel with the heightened attention to global uncertainty and risk interdependence, methodological developments have increasingly shifted toward more advanced volatility modeling frameworks that explicitly link macroeconomic fundamentals with financial market dynamics. Recent contributions extend beyond traditional GARCH specifications by incorporating mixed-frequency data, systemic risk indicators, and evolving dependence structures. For example, Yang and Hamori [28] provide a comprehensive overview of stochastic volatility (SV) models, emphasizing their capacity to capture nonlinear behavior and latent volatility processes that evolve stochastically over time, thereby offering greater flexibility than standard GARCH approaches. Building on this line of research, Yang and Hamori [29] examine systemic risk transmission between crude oil markets and economic policy uncertainty within a MIDAS-CoVaR framework, showing that macroeconomic uncertainty amplifies downside risk and that mixed-frequency models effectively capture such dynamics. Similarly, Yang *et al.,* [30] propose a MIDAS-CoVaR-QR model to analyze risk spillovers between global financial markets and China's macroeconomic environment, demonstrating that incorporating low-frequency macroeconomic indicators enhances forecasting performance and facilitates the detection of periods of elevated systemic risk. Complementing these findings, Yuan and Yang [31] apply a GAS-DCS-copula approach to study asymmetric risk transmission between financial uncertainty and the carbon market, highlighting the ability of score-driven copula models to capture time-varying dependence and tail-risk interactions. Overall, this body of research underscores the increasing relevance of advanced volatility modeling techniques that integrate macroeconomic conditions, systemic risk, and cross-market linkages, thereby providing a strong methodological foundation for comparative analyses across heterogeneous financial markets [32,33].

Recent contributions to the financial and economic literature increasingly emphasize the application of advanced quantitative, forecasting, and decision-support methodologies in the analysis of financial markets, investment risk, and sustainable economic systems. Maity and Majumder [34] apply the Box–Jenkins methodology to forecast gold prices in the Indian market using monthly data covering the 2004–2025 period. Their empirical analysis identifies the ARIMA (1,1,1) specification as the optimal forecasting model, while the results indicate a projected increase in gold prices driven by inflationary pressures, seasonal consumer demand, currency depreciation, and heightened global uncertainty. The study additionally highlights the growing importance of gold-backed ETFs and digital gold platforms, confirming the relevance of quantitative time-series methodologies for commodity price forecasting and investment-related risk assessment.

The growing complexity of financial decision-making under uncertainty has additionally stimulated the development of advanced fuzzy and multi-criteria decision-support frameworks [35]. Sarfraz and Božanić [36] introduce new aggregation operators for interval-valued intuitionistic fuzzy sets within a multi-attribute group decision-making framework, demonstrating their applicability in market risk optimization problems. Their findings confirm that advanced fuzzy aggregation methodologies may significantly improve decision-support processes in environments characterized by uncertainty, incomplete information, and complex market interactions. Recent studies also increasingly combine data-driven methodologies with machine-learning approaches in financial forecasting. Ozcalici *et al.,* [37] investigate stock price forecasting in the large-cap segment of the U.S. financial market through the integration of multi-criteria decision-making weighting techniques and transformer neural network models. Their results indicate that the application of objective feature-weighting procedures substantially improves forecasting performance, highlighting the growing importance of hybrid machine-learning and quantitative decision-making frameworks in financial market prediction.

The growing complexity of modern economic and financial systems has additionally stimulated the application of quantitative and decision-support methodologies beyond traditional stock market analysis. In this context, Ricoy-Casas *et al.,* [38] examine sustainability-related governance and economic challenges associated with cobalt production in the Democratic Republic of Congo through an integrated SWOT–PESTLE framework. Their findings highlight the importance of institutional transparency, regulatory efficiency, and risk-management mechanisms in environments characterized by elevated uncertainty and structural instability. Similarly, Modarresi *et al.,* [39] develop an integrated framework for sustainable cryptocurrency selection by combining ARMA–GARCH models with fractional normal inverse Gaussian innovations and Data Envelopment Analysis (DEA). Their results demonstrate that incorporating stochastic volatility behavior and energy-related mining costs significantly improves cryptocurrency efficiency evaluation and risk assessment.

Although these studies differ methodologically from the GARCH-based framework adopted in the present paper, they collectively confirm the growing importance of advanced quantitative, forecasting, optimization, and decision-support methodologies in financial and economic analysis. They additionally highlight the increasing relevance of volatility modeling, risk assessment, forecasting accuracy, and investment-related decision-making under conditions of elevated uncertainty and rapidly changing global economic environments.

Despite this extensive body of research, comparative analyses that explicitly contrast financial markets at different stages of development across clearly defined crisis and non-crisis periods remain relatively limited in the existing literature. Most previous empirical studies primarily focus either on single-country analyses or on relatively homogeneous groups of financial markets, while fewer contributions simultaneously examine developed and less developed markets within a unified econometric framework capable of capturing heterogeneous volatility dynamics under changing macroeconomic conditions. In addition, the existing literature rarely combines asymmetric GARCH-type modeling and the application of different tailored GARCH specifications with a comparative perspective centered on differences in market depth, liquidity conditions, and institutional maturity.

This study addresses these research gaps by conducting a comparative assessment of identical macroeconomic determinants in highly developed and globally integrated financial markets (the United Kingdom and China) and in less developed and relatively less liquid European financial systems (Hungary and Slovenia) across distinct pre-crisis and crisis/post-crisis periods associated with the COVID-19 pandemic and related global economic disturbances. The analysis is additionally strengthened through the incorporation of an extensive dataset covering daily stock index return dynamics together with selected macroeconomic indicators over the 2012–2022 period, while different GARCH-type specifications are applied and adapted according to the specific volatility characteristics of each observed market and period. A further specific contribution of the study lies in the investment-oriented interpretation of the estimated results, as the empirical findings allow for an approximate assessment of potential gains or losses associated with stock index return movements under the observed macroeconomic conditions and across different market and crisis periods.

By doing so, the paper contributes additional empirical evidence to the literature and provides new insights into how financial markets characterized by different levels of development responded to major crisis events from the perspective of stock index return dynamics and volatility transmission.

3. Data Description and Econometric Methodology

3.1 Data Description and Variable Specification

This study examines daily stock index returns across financial markets with different levels of development, using data for the FTSE 100 (United Kingdom), FTSE China A50 (China), BUDAPEST SE (Hungary), and SBITOP (Slovenia). Daily returns are computed from closing prices over the 1 January 2012–31 December 2022 period. The sample is divided into a pre-crisis phase (2012–2019) and a crisis/post-crisis phase (2020–2022), reflecting objective structural breaks associated with the COVID-19 pandemic and subsequent geopolitical and supply-chain disruptions widely documented in the literature [18,19].

In addition to stock index returns as dependent variables, the analysis incorporates key macroeconomic determinants, including inflation, benchmark interest rates, exchange rates, and gold and oil prices. Inflation and interest rates are expressed in percentage terms, while commodity prices and exchange rates (GBP/USD, CNY/USD, USD/HUF, and USD/EUR) are reported in nominal USD values. The joint analysis of financial returns and macroeconomic indicators allows for an assessment of their interdependence.

Acknowledging differences in data frequency—daily stock returns versus monthly macroeconomic indicators—the study adopts a mixed-frequency approach commonly used in empirical finance, under the assumption that monthly indicators capture prevailing macroeconomic conditions. To address potential aggregation bias, volatility dynamics are modeled using a Generalized Autoregressive Score (GAS) framework, which enables rapid parameter updating in response to new information. In contrast, the MIDAS-GARCH specification explicitly separates short- and long-run volatility components, offering a useful benchmark and a potential extension for future research on mixed-frequency dynamics.

From a methodological standpoint, the GARCH-type models applied in this study—namely GAS-GARCH, TGARCH, EGARCH, and FIGARCH—can be positioned within a broader class of volatility modeling frameworks extensively discussed in the recent literature. Among alternative approaches, stochastic volatility (SV) models treat variance as a latent, unobservable process that follows its own stochastic evolution within a state-space representation and is typically estimated through simulation-based or filtering methods. Although SV models provide substantial flexibility in modeling nonlinear dynamics and time-varying volatility persistence, they are associated with considerably higher computational complexity and require stronger distributional assumptions or prior specifications than standard GARCH-type estimators [28].

Recent literature increasingly emphasizes the application of advanced econometric and quantitative methodologies for modeling financial volatility, systemic risk, and macro-financial interdependence. MIDAS-based frameworks integrate macroeconomic variables observed at lower frequencies with high-frequency financial data, enabling the analysis of mixed-frequency volatility dynamics and systemic-risk transmission, particularly through measures such as CoVaR [29,30]. In parallel, GAS–DCS–copula approaches rely on score-driven parameter updating and time-varying dependence structures, making them particularly suitable for capturing asymmetric co-movements and volatility spillovers across financial markets [40].

At the same time, broader econometric frameworks such as Vector Autoregression (VAR) models are frequently employed to examine the dynamic transmission of macroeconomic shocks and impulse-response relationships among financial variables [41], while cointegration techniques are commonly used to investigate long-run equilibrium relationships between integrated series [41]. Market risk assessment is additionally supported through widely applied measures such as Value-at-Risk (VaR), which provides a standardized framework for evaluating potential investment losses. Although these methodologies provide important analytical insights into volatility dynamics, systemic-risk transmission, and financial interdependence, they are often characterized by substantial computational complexity and elevated data requirements. By comparison, GARCH-type models offer a relatively parsimonious and economically interpretable framework that remains highly effective in examining the effects of macroeconomic variables on stock market volatility, which directly corresponds to the primary objectives of the present study.

To more accurately capture the time-varying nature of volatility observed in financial series, econometric modeling has increasingly relied on the GARCH family of models, which offer substantial improvements in conditional variance estimation [42]. It is important to note that volatility dynamics are shaped not only by macroeconomic fundamentals but also by behavioral factors and the transmission of information across complex networks. In this regard, insights from social network–based decision-making models [43] can complement traditional econometric frameworks by offering a broader perspective on market interactions. The integration of econometric models significantly improved the accuracy of forecasts of movements in the values of analyzed macroeconomic variables [44]. Guided by these considerations, the present study employs econometric methods tailored to its specific research objectives. Customized GARCH-type specifications are employed to evaluate both the main and auxiliary hypotheses, with optimal models selected for each market and observation period using the Akaike (AIC) and Schwarz (SIC) Information Criterion. The empirical results confirm the persistence of interdependencies among the analyzed variables.

3.2 Specification of the Econometric Modeling Approach

Brooks [45] provides a formal representation of the basic GARCH specification that is widely employed in empirical financial analysis:

$$Y_t = c + X'_t\theta + \varepsilon_t \tag{1}$$

$$\varepsilon_t = \sqrt{h_t\eta_t},\ \eta_t \xrightarrow{IID} N(0,1) \tag{2}$$

$$h_t = a_0 + \sum_{i=1}^{q} a_i\varepsilon^2{}_{t-i} + \sum_{j=1}^{p} b_j h_{t-j} \tag{3}$$

$$h^2{}_t = c + \alpha\varepsilon^2{}_{t-1} + \beta h^2{}_{t-1} \tag{4}$$

within this specification, Y_t denotes the dependent variable representing stock index returns, while h_t denotes the conditional variance, while ε_t given the information set available at time t. The parameter c represents the model constant, whereas $X'_t\theta$ summarizes the contribution of exogenous information, typically proxied by lagged squared residuals derived from the mean equation. The term $h^2{}_{t-1}$ reflects the most recent forecast of conditional variance. Coefficient α corresponds to the ARCH component measuring the immediate impact of past shocks on current volatility, while β quantifies the degree of volatility persistence over time, abstracting from other contemporaneous market influences.

Starting from the mean equation $Y_t = c + X'_t\theta + \varepsilon_t$, the parameter c denotes the intercept of the specified GARCH framework, while Y_t corresponds to the dependent variable, interpreted here as the daily return of the analyzed stock index The vector ($X'_t\theta$): incorporates the selected explanatory macroeconomic variables—namely the inflation rate, exchange rate, benchmark interest rate, gold price, and oil price—thereby extending the basic specification to a multivariate setting. The disturbance term ε_t captures unexplained variations in returns that are subsequently modeled through the conditional variance process.

The subsequent stage in deriving the conditional variance of the adjusted baseline GARCH specification is defined as follows:

$$h^2{}_t = c + \sum_{i=1}^{p} \alpha_i\varepsilon^2{}_{t-i} + \sum_{j=1}^{q} \beta_j h^2{}_{t-j} + Z'_t\pi \tag{5}$$

Within this modified specification, h_t denotes the conditional variance of the residuals derived from the estimated return equation of the analyzed stock index. The parameter c continues to represent the model constant, whereas h_{t-1} reflects the persistence of volatility captured through the GARCH component. The term $\varepsilon^2{}_{t-1}$ corresponds to the squared residual from the preceding period, measuring the immediate impact of past shocks on current volatility. The framework is further extended by introducing a vector of exogenous variables ($Z'_t\pi$), allowing macroeconomic influences to be incorporated directly into the variance dynamics. Finally, the coefficients α and β retain their functional interpretation consistent with the initial stage of the model specification, governing the sensitivity of volatility to past disturbances and its temporal persistence.

An essential characteristic of GARCH-type processes is the requirement that the conditional variance remains strictly positive at all points in time. This non-negativity condition ensures the statistical validity and stability of the variance dynamics.

In the case of a conventional GARCH(1,1) specification, the evolution of conditional variance is defined by the following variance equation:

$$h_t=\omega + \alpha\, \varepsilon^2_{t-1}+\beta\, h_{t-1} \tag{6}$$

For the conditional variance h_t to remain strictly positive at each point in time, several parameter and structural requirements must be fulfilled.

1. Parameter restrictions.
   - The standard GARCH specification imposes positivity constraints on the model coefficients, such that $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$. Given that the squared residual term ε^2_{t-1} is inherently non-negative, these restrictions ensure that the resulting conditional variance cannot take negative values.
2. Recursive dynamics and stationarity.
   - Provided that the initial variance h_{t-1} is positive, the recursive formulation of the GARCH process preserves positivity for all subsequent periods. In addition, the covariance-stationarity condition $\alpha + \beta < 1$ prevents explosive variance behavior and ensures mean-reverting volatility dynamics.
3. Positivity in logarithmic variance specifications.
   - Alternative formulations, such as the EGARCH model, guarantee positivity through a logarithmic representation of conditional variance, expressed as:

$$\ln h_t =\omega + \beta \ln h_{t-1} + \alpha\, (h_{t-1}/|\varepsilon_{t-1}|) + \gamma\, (h_{t-1}/\varepsilon_{t-1}) \tag{7}$$

   - This specification inherently preserves the positivity of h_t, since the exponential transformation applied to the logarithmic variance formulation ensures that the conditional variance remains strictly greater than zero for all time periods.

Imposing suitable parameter constraints within GARCH-class formulations guarantees, in both theoretical and empirical terms, the non-negativity of the conditional variance throughout the observed time horizon. In its conventional univariate form, the standard GARCH specification assumes volatility symmetry, meaning that shocks of identical magnitude produce equivalent forward-looking volatility responses regardless of their sign. Such symmetry constitutes an important limitation of the basic framework, as empirical financial data frequently reveal asymmetric volatility adjustments that the standard specification cannot adequately capture. This limitation is addressed by the EGARCH representation, which directly embeds information on both the size and direction of past innovations within the variance equation. In contrast to traditional GARCH structures that depend exclusively on squared residuals, the EGARCH approach permits differentiated volatility reactions to positive and negative disturbances. This structure enables formal detection of the leverage effect, whereby unfavorable shocks—commonly linked to negative information or declining market conditions—induce a stronger volatility expansion than equally sized favorable shocks. The relevance of this asymmetric mechanism becomes particularly evident during episodes of intensified financial stress, including systemic disruptions such as the COVID-19 crisis, when volatility behavior tends to deviate markedly from symmetric patterns. The adoption of GARCH-type specifications in the present analysis is grounded in the well-established literature on volatility propagation and macro-financial linkages. Prior empirical studies consistently document that disturbances in central macroeconomic and financial indicators, including interest rates, inflation, and exchange rate movements, generate persistent and frequently asymmetric effects on return volatility, especially under conditions of elevated global uncertainty. These dynamics are often amplified in markets characterized by weaker liquidity and structural fragility. By applying asymmetric volatility models—most notably EGARCH and TGARCH—the empirical framework explicitly accommodates heterogeneous volatility responses to shocks of differing signs, thereby offering a more faithful representation of real-world market behavior.

This constraint originates from the specification of the conditional variance in standard GARCH models, where volatility depends solely on squared residual components and therefore does not retain information about shock direction. As a result, the model is unable to distinguish between positive and negative innovations—a short-coming commonly associated with the leverage effect [46,47]. In empirical financial markets, adverse shocks are frequently observed to exert a disproportionately stronger influence on volatility than favorable shocks of equal magnitude. Motivated by this asymmetry in market behavior, alternative GARCH-type specifications were developed to explicitly account for the leverage effect and to better capture the differential impact of shocks on volatility dynamics.

In the process of identifying the most appropriate GARCH specification, the analysis further considers several model extensions, including the EGARCH framework, which can be expressed in the following functional form:

$$\log(h_t) = a_0 + \sum_{i=1}^{q} a_i g(\eta_{t-1}) + \sum_{i=1}^{p} b_i \log(h_{t-i}) \tag{8}$$

Within the specification$\boldsymbol{\varepsilon_t} = \sqrt{h_t \eta_t}$ the function $g(\eta_t) = \theta\eta_t + \gamma[|\eta_t| - \mathrm{E}|\eta_t|]$ captures the weighted impact of innovations, allowing for asymmetric responses to positive and negative shocks in financial returns, where θ and γ denote model parameters. Building on this framework, the analysis also employs a tailored TGARCH specification implemented in the EViews software environment, defined as follows:

$$h^2{}_t = c + \sum_{i=1}^{p} \alpha_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{q} \beta_j h^2{}_{t-j} + \sum_{k=1}^{r} \varepsilon^2{}_{t-k} I_{t-k} + Z'{}_t \pi \tag{9}$$

The parameters α and β are restricted to non-negative values and are subject to the standard stability condition $\alpha + \beta < 1$. Within the customized TGARCH specification, the conditional variance $\mathrm{h_t}^2$ remains strictly positive, with asymmetry captured through an additional indicator component. Covariance stationarity is ensured under the condition $\alpha + \left(\frac{1}{2}\right) + \beta < 1$, which prevents explosive volatility dynamics. The model is further extended by incorporating macroeconomic determinants $(\mathrm{Z'}_t\pi)$, treated as exogenous explanatory variables influencing the volatility process.

Ding and Granger [48] define the PGARCH model as follows:

$$\sigma_t^{\delta} = \omega + \sum_{i=1}^{q} \omega > 0\,;\ \alpha_i|\varepsilon_{t-1}|\delta\ 1\varepsilon_{t-1} \geq 0 + \ \alpha_i|\varepsilon_{t-1}|\delta\ 1\ \varepsilon_{t-1} < 0 + \sum_{j=1}^{p} \beta_j {\sigma_{t-j}}^{\delta} \tag{10}$$

$$\varepsilon_t = \ \sigma\eta_t \tag{11}$$

The coefficients α_i and β_j are defined as non-negative parameters, while ω denotes a strictly positive constant. The parameter space is constrained such that αi> 0, βj> 0, 1 > δ> -1, and σ> 0. The asymmetry parameter δ captures the differential impact of shocks on conditional variance. Specifically, positive values of δ imply that negative shocks exert a stronger influence on volatility, whereas negative values indicate a relatively greater effect of positive shocks.

Recognizing the limitations inherent in the baseline FIGARCH framework, Ruiz and Perez [49] developed a refined specification designed to address these shortcomings, expressed as follows:

$$(1-\phi 1L)(1-L)^d h_t^{\lambda/2}-1/\lambda=\alpha_0*+\alpha(1+L)h_{t-1}^{\lambda/2}[f_v(zt-1)-1] \tag{12}$$

$$\varepsilon_t=h^{1/2}z_t \tag{13}$$

Where $zt_{(iid)}\sim$ D(0, 1) with D (0,1) denoting a standardized distribution characterized by zero mean and unit variance. In the case where $\lambda = 0$, the model becomes insufficiently specified, as it fails to adequately capture the persistence of conditional volatility. Conversely, when $v = \lambda = 2$, the parameter constraints ensure non-negativity and lead to more reliable estimation results. A key property of the FIGARCH framework is its ability to model long-memory behavior, allowing for the examination of volatility dynamics and persistence over extended time horizons [50].

3.3 Procedure for Econometric Model Selection

All empirical estimations are conducted using the EViews software environment. Model parameters are estimated via maximum likelihood methods, implemented with the Marquardt optimization algorithm and complemented by Bollerslev–Wooldridge robust standard errors to ensure reliable inference. Model selection is guided by the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), which jointly balance goodness of fit and model complexity.

While both criteria penalize overparameterization, the SIC imposes a stricter penalty and therefore serves as the primary benchmark for selecting optimal specifications in this study, with lower values indicating superior model adequacy. Consequently, the choice among alternative GARCH-type formulations—including EGARCH, TGARCH (GJR-GARCH), PGARCH, and FIGARCH—is based on systematic performance evaluation rather than arbitrary selection.

In addition to information criteria, theoretical model properties are assessed in relation to the empirical characteristics of the data across different observation periods. EGARCH models are employed in settings marked by volatility asymmetry and leverage effects, particularly during crisis and post-crisis phases. PGARCH and FIGARCH specifications are favored when volatility persistence and long-memory dynamics dominate, typically under more stable market conditions. TGARCH (GJR-GARCH) models are applied in the presence of threshold effects, allowing negative shocks to exert a stronger impact on volatility than positive shocks of comparable magnitude.

Model identification is performed separately for each observation window (pre-crisis, crisis/post-crisis, and the full sample) using AIC and SIC values recognized as objective selection tools [44]. Following selection, all GARCH-type models are estimated using maximum likelihood techniques. When residuals deviate from normality, quasi-maximum likelihood (QML) estimation is employed. To capture stylized features of financial returns, including asymmetry and excess kurtosis, both symmetric and asymmetric Student's t-distributions are specified. Model adequacy is finally verified through residual diagnostics, focusing on the absence of serial correlation and remaining conditional heteroskedasticity. The use of alternative GARCH-type specifications across different observation periods, together with residual diagnostics and information-criterion-based model selection, additionally contributes to the robustness and stability assessment of the obtained empirical results.

Gujarati and Porter [51] calculate AIC and SIC as follows:

$$\mathrm{AIC} = \varepsilon^{2k/n}\frac{\mathrm{RSS}}{n},\ \ln\mathrm{AIC} = \frac{2k}{n} + \ln\frac{\mathrm{RSS}}{n} \tag{14}$$

$$\mathrm{SIC} = n^{k/n}\frac{\mathrm{RSS}}{n},\ \ln\mathrm{SIC} = \frac{k}{n}\ln_n + \ln\frac{\mathrm{RSS}}{n} \tag{15}$$

Where n denotes the sample size, k is the number of estimated parameters, and RSS refers to the residual sum of squares. The term $\frac{2k}{n}$ represents the penalty component associated with the AIC criterion, while $\frac{k}{n}\ln_n$ corresponds to the penalty imposed by the SIC criterion.

4. Empirical Results and Interpretation

4.1 The United Kingdom – FTSE 100

This section presents the empirical findings derived from the estimation of GARCH-type models, with the objective of evaluating the influence of selected macroeconomic variables on stock index return dynamics in the United Kingdom, China, Slovenia, and Hungary. The selection of optimal model specifications is based on the AIC and SIC criterion, where lower values indicate superior model performance over the sample period.

The analysis further includes an examination of model residuals through autocorrelation and partial autocorrelation diagnostics applied to daily return series. Estimated coefficients from the selected GARCH models are reported to illustrate both the direction and strength of the relationships between returns and their macroeconomic determinants. Covering the 2012–2022 period, the empirical results are supplemented with diagnostic tests assessing the distributional properties of the return series. The subsequent subsection focuses on the case study of the United Kingdom.

The comparative information-criterion results for selecting the preferred econometric specification of the FTSE 100 index are presented in Table 1.

Table 1
Information-criterion evidence for identifying the preferred econometric specification – FTSE 100

Observation period	Information criterion	TGARCH/GJR-GARCH	EGARCH	PGARCH	FIGARCH
Pre-crisis period	SIC	2.376713	2.332713	2.332226	2.380662
	AIC	2.350794	2.303915	2.300548	2.351863
Crisis/post-crisis period	SIC	3.020868	2.958922	2.972931	3.043247
	AIC	2.972197	2.904167	2.912092	2.988492
Entire period	SIC	2.549539	2.506880	2.503103	2.546366
	AIC	2.530306	2.485510	2.479596	2.524996

The temporal evolution of standardized return residuals for the FTSE 100 index over the 2012–2022 observation period is illustrated in Figure 1.

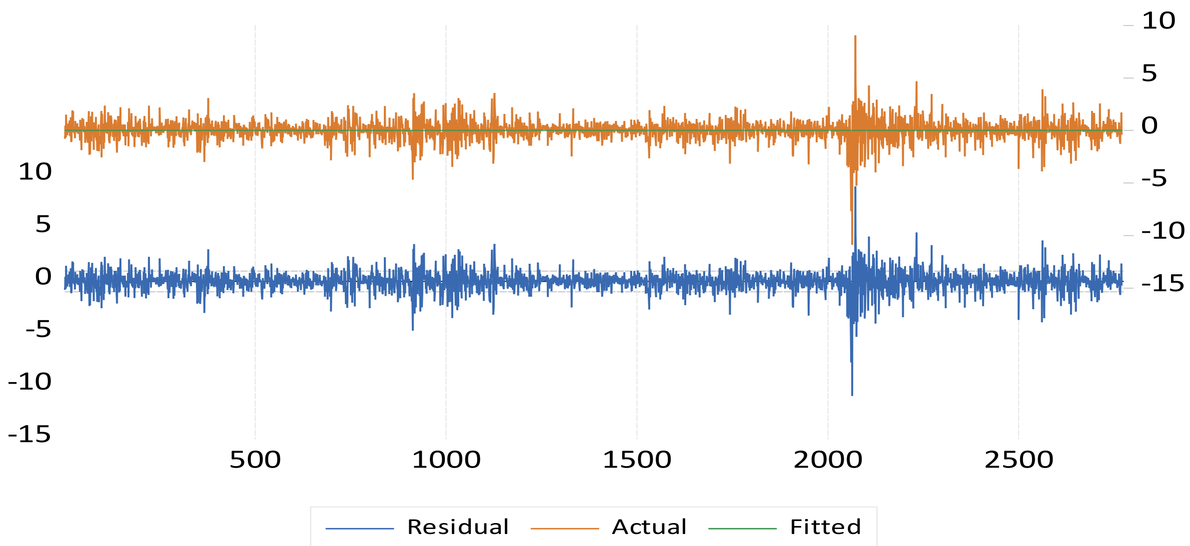

Fig. 1. Temporal dynamics of FTSE 100 return residuals over the 2012–2022 observation horizon

The estimated coefficients of the selected GARCH specifications for the FTSE 100 index across different observation periods are reported in Table 2.

Table 2
Estimated coefficient of selected GARCH specifications for the FTSE 100 index in different observation periods

FTSE 100 – entire period		FTSE 100 - pre-crisis period		FTSE 100 - crisis/post-crisis period	
Optimal model PGARCH		Optimal model PGARCH		Optimal model EGARCH	
K(1)	-0.007024	K(1)	-0.001425	K	-0.004489
K(2)	0.081586	K(2)	0.031046	K(1)	0.582991
K(3)	0.092225	K(3)	0.094363	K(2)	0.075355
K(4)	0.990689	K(4)	0.999995	K(3)	-0.206601
K(5)	0.879971	K(5)	0.840168	K(4)	0.934660
ref_int_rate_UK	-0.001040	ref_int_rate_UK	0.049104	ref_int_rate_UK	-0.019287
inf_rate _UK	-0.001713	inf_rate _UK	-0.000690	inf_rate _UK	-0.009012
price_of_oil_usd	7.96E-05	price_of_oil_usd	-0.000193	price_of_oil_usd	7.96E-05
price_of_gold_usd	-0.016738	price_of_gold_usd	0.001271	price_of_gold_usd	0.328013
gbp_usd	-0.028694	gbp_usd	0.016256	gbp_usd	-0.455744

The coefficients reported in the tables include model constants, lagged squared standardized residuals capturing ARCH effects, GARCH terms reflecting volatility persistence, and asymmetric components accounting for leverage effects. Macroeconomic variables represent changes in the reference interest rate, inflation rate, oil prices, gold prices, and relevant exchange rates. Unless stated otherwise, this interpretation applies to all subsequent tables presenting estimated parameters for the analyzed stock market indices across different observation periods.

Table 1 reports the results of the AIC and SIC information criteria applied to the selection of the most appropriate econometric models for the FTSE 100 index across three observation horizons: the full sample, the pre-crisis period, and the crisis/post-crisis period. In line with established model selection rules, smaller values of these criteria indicate a better balance between goodness of fit and model parsimony. The results indicate that the adjusted PGARCH specification provides the best overall fit for both the full observation period and the pre-crisis sub-period, while the crisis/post-crisis phase is more adequately captured by the adjusted EGARCH model, reflecting changes in volatility dynamics under heightened uncertainty.

Figure 1 depicts the evolution of standardized return residuals for the FTSE 100 index over the same observation segments. When considering the full sample, episodes of pronounced residual volatility coincide with major systemic shocks, including the COVID-19 outbreak and subsequent geopolitical disturbances. The lower panel of the figure illustrates the mean residual trajectory, highlighting the overall dispersion pattern. During the pre-crisis phase, sharp and frequent residual oscillations are evident, corresponding to the period of elevated uncertainty surrounding the United Kingdom's withdrawal from the European Union, which adversely affected market stability and trading activity. In the crisis period, the earliest phase is characterized by exceptionally large residual deviations, signaling intense market reactions following the pandemic announcement. Although volatility remains elevated thereafter, the magnitude of residual fluctuations gradually moderates, suggesting a partial stabilization following the initial shock.

Table 2 reports the optimal GARCH specifications for the FTSE 100 stock market index, together with the direction and magnitude of the effects exerted by selected macroeconomic variables on its daily return rates. The estimated results are presented for three distinct observation periods. For the full sample, the adjusted optimal PGARCH model indicates that daily returns of the FTSE 100 index are negatively influenced by several macroeconomic factors, including the inflation rate, the policy interest rate, gold prices, and the exchange rate, whereas oil prices exhibit a positive, albeit relatively modest effect.

The negative effects of inflation, policy interest rates, and exchange rate movements on FTSE 100 returns may reflect the sensitivity of the British financial market to tightening monetary conditions, rising production and financing costs, and increased uncertainty regarding future economic growth. Higher inflationary pressures and interest rate adjustments are often associated with weaker investor sentiment and reduced corporate profitability expectations, particularly in periods characterized by elevated macroeconomic instability. The negative impact of exchange rate fluctuations may additionally indicate the exposure of the United Kingdom's internationally integrated financial system to external trade and currency-related uncertainties, especially during periods associated with Brexit-related adjustments and broader global market disturbances. By contrast, the positive effect of oil prices, although relatively moderate, may be linked to the structure of the FTSE 100 index itself, which includes a significant share of multinational energy and commodity-related corporations that tend to benefit from rising global energy prices.

Based on the results obtained from the adjusted PGARCH model, the estimated coefficients suggest that changes in the analyzed macroeconomic variables are associated with variations in the daily returns of the FTSE 100 stock market index over the full observation period. The reported aggregate value of 1.989341 represents an illustrative combined coefficient effect derived from the estimated parameters presented in Table 2 and should therefore be interpreted with caution from an econometric perspective. In illustrative investment terms, such an estimated effect could be associated with an approximate positive daily portfolio movement equivalent to around 19,893.41 monetary units for a hypothetical portfolio allocation of 1,000,000 monetary units under the observed market conditions. However, this interpretation should be viewed only as an indicative representation of the relative magnitude and direction of the estimated macroeconomic influences rather than as a precise forecast of realized investment gains.

Table 3 summarizes the key descriptive statistics of daily returns for the FTSE 100 stock market index across the three analyzed sub-periods, as follows: Mean (M), Median (Med), Maximum (Max), Minimum (Min), Standard deviation (SD), Skewness (Skew), Kurtosis (Kurt), Jarque-Bera (JB) and Probability (Prob.).

Table 3
Distributional characteristics of the sample across distinct observation periods

FTSE 100 - entire period		FTSE 100 - pre-crisis period		FTSE 100 - crisis/ post-crisis period	
M	-0.037547	M	-0.038374	M	-0.001965
Med	0.024313	Med	0.019960	Med	0.070712
Max	3.675296	Max	3.511284	Max	4.613765
Min	-5.546960	Min	-4.739005	Min	-5.309086
SD	0.991551	SD	0.995392	SD	0.999370
Skew	-0.443237	Skew	-0.275500	Skew	-0.503125
Kurt	4.725815	Kurt	4.050029	Kurt	5.518453
JB	410.4624	JB	117.8832	JB	233.5258
Prob.	0.000000	Prob.	0.000000	Prob.	0.000000

*The sample taken into consideration when observing the entire period is 2774, for the pre-crisis period of 2012, while for the crisis and post-crisis periods there are 762 observations.

The results indicate that the mean daily return is negative throughout the sample, reaching −0.03 for both the full and pre-crisis periods, and −0.002 during the crisis period. In addition to average returns, the table reports the range of observed values as well as the dispersion of returns. Volatility, measured by the standard deviation, amounts to 0.99 for the full observation period, while the highest level of variability is recorded during the crisis period (1.00), coinciding with heightened uncertainty linked to the COVID-19 pandemic and subsequent geopolitical shocks. The return distributions exhibit negative skewness in all periods (−0.44, −0.28, and −0.50), indicating a dominance of downside movements. Moreover, kurtosis values exceed the benchmark value of three across all sub-periods (4.73, 4.05, and 5.52), pointing to leptokurtic distributions and an increased likelihood of extreme return realizations, which reflects elevated investment risk.

4.2 China – FTSE CHINA A50

The subsequent section presents the empirical findings for the case study focusing on China. The information-criterion results used for identifying the preferred econometric specification of the FTSE CHINA A50 index are presented in Table 4.

Table 4
Information-criterion evidence for identifying the preferred econometric specification – FTSE CHINA A50

Observation period	Information criterion	TGARCH/GJR-GARCH	EGARCH	PGARCH	FIGARCH
Pre-crisis period	SIC	2.259810	2.199185	2.200569	n/a
	AIC	3.744173	3.691808	3.695651	n/a
Crisis/post-crisis period	SIC	2.259810	2.199185	2.200569	n/a
	AIC	3.290333	3.291081	3.293167	n/a
Entire period	SIC	2.446548	2.399187	2.399302	n/a
	AIC	3.641128	3.610874	3.618023	n/a

n/a - denotes that the EViews software did not identify a statistically adequate model for the specified observation period, which may reflect the influence of policy interventions and regulatory measures affecting financial market behavior.

The temporal dynamics of standardized return residuals for the FTSE CHINA A50 index over the 2012–2022 observation horizon are illustrated in Figure 2.

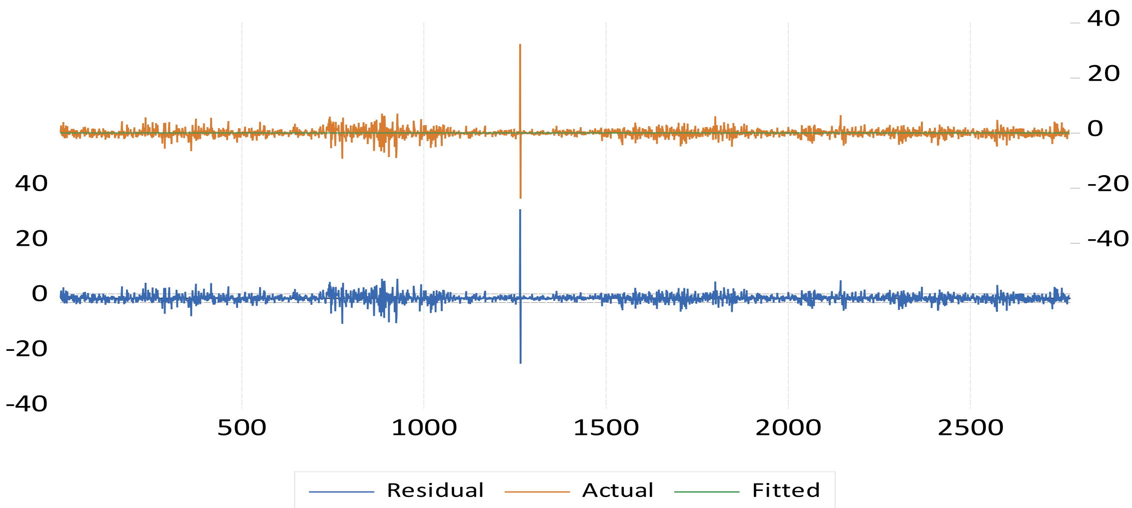

Fig. 2. Temporal dynamics of FTSE CHINA A50 return residuals over the 2012–2022 observation horizon

The estimated coefficients of the selected GARCH specifications for the FTSE CHINA A50 index across different observation periods are reported in Table 5.

Table 5
Estimated coefficient of selected GARCH specifications for the FTSE CHINA A50 index in different observation periods

FTSE CHINA A50 - entire period		FTSE CHINA A50 - pre-crisis period		FTSE CHINA A50 - crisis/post-crisis period	
Optimal model		Optimal model		Optimal model	
EGARCH		EGARCH		EGARCH	
K	0.067425	K	0.071734	K	-0.020912
K(1)	0.701990	K(1)	1.002120	K(1)	-0.350148
K(2)	0.191622	K(2)	0.182292	K(2)	0.204072
K(3)	-0.054717	K(3)	-0.457491	K(3)	-0.039306
K(4)	0.942042	K(4)	0.957727	K(4)	0.919895
ref_int_rate_CHN	0.041804	ref_int_rate_CHN	0.037900	ref_int_rate _CHN	0.147715
inf_rate _CHN	-0.019066	inf_rate _CHN	-0.055518	inf_rate _CHN	-0.013410
price_of_oil_usd	-0.000435	price_of_oil_usd	0.000613	price_of_oil_usd	0.000525
price_of_gold_usd	0.328938	price_of_gold_usd	0.289261	price_of_gold_usd	0.132403
cny_usd	-5.940847	cny_usd	-7.765166	cny_usd	-2.322831

Table 4 reports the selection of the most suitable adjusted econometric specifications for the FTSE China A50 stock market index across the three analyzed sub-periods. The results indicate that the EGARCH model consistently provides the best fit for both the full observation period and the pre-crisis period. In the crisis period, the information criteria yield different recommendations: while the AIC favors the TGARCH (GJR-GARCH) specification, the SIC points to the EGARCH model as the preferred alternative. Given the stricter penalization of model complexity inherent in the SIC criterion, the EGARCH model is ultimately retained as the optimal specification for the crisis phase.

Figure 2 depicts the dynamics of return residuals for the FTSE China A50 index across the defined observation periods. In the pre-crisis phase, extreme residual movements appear only sporadically and are confined to a single episode, followed by a prolonged period of relative stabilization with no pronounced volatility spikes. During the crisis period, residual fluctuations persist but remain moderate in magnitude and occur less frequently compared to other markets. When assessed over the entire sample, the residual behavior suggests the absence of substantial disruptions in trading activity, indicating a relatively high degree of resilience of the Chinese stock market to macroeconomic and microeconomic shocks, as well as a stable overall market environment.

Table 5 presents the optimal GARCH specifications for the FTSE CHINA A50 stock market index, along with the direction and magnitude of the effects exerted by relevant macroeconomic variables on the daily returns of the analyzed index. For the full observation period, the adjusted optimal EGARCH model indicates that the daily returns of the FTSE CHINA A50 index are negatively affected by several macroeconomic factors, including the inflation rate, oil prices, and the exchange rate, whereas positive effects are observed for the policy interest rate and gold prices.

The negative influence of inflation, oil prices, and exchange rate movements on the FTSE CHINA A50 index may reflect the vulnerability of the Chinese financial market to rising production costs, external trade pressures, and currency-related uncertainties during the observed period. Given the strong export orientation of the Chinese economy, exchange rate fluctuations and increases in global commodity prices may adversely affect industrial profitability and investor expectations, particularly during periods marked by trade tensions with the United States and disruptions associated with the COVID-19 pandemic. The negative effect of oil prices may additionally indicate the sensitivity of manufacturing-intensive sectors to higher energy and transportation costs. In contrast, the positive influence of policy interest rates may reflect the role of monetary policy measures and state-supported financial interventions in stabilizing market expectations and supporting investor confidence during periods of heightened uncertainty. Similarly, the positive effect of gold prices may suggest the presence of broader investment inflows and increased financial market activity during periods characterized by rising global demand for safe-haven assets.

Based on the results obtained from the adjusted EGARCH model, the estimated coefficients indicate that changes in the analyzed macroeconomic variables are associated with negative movements in the daily returns of the FTSE CHINA A50 stock market index over the full observation period. The reported aggregate value of -3.7414244 represents an illustrative combined coefficient effect derived from the estimated parameters presented in Table 5 for the entire sample. From an indicative investment perspective, such an estimated relationship could correspond to an approximate negative daily portfolio movement of around -37,412.44 monetary units for a hypothetical investment allocation of 1,000,000 monetary units under the observed market conditions, interpreted in the same manner as previously discussed for the FTSE 100 index.

The main distributional characteristics of the FTSE CHINA A50 return series across the analyzed observation periods are summarized in Table 6.

Table 6
Distributional characteristics of the sample across distinct observation periods

FTSE CHINA A50 - entire period		FTSE CHINA A50 - pre-crisis period		FTSE CHINA A50 - crisis/post-crisis period	
M	-0.032581	M	-0.035414	M	0.003387
Med	-0.063952	Med	-0.076053	Med	0.002252
Max	25.62203	Max	24.28020	Max	5.006871
Min	-5.474540	Min	-5.202025	Min	-3.843955
SD	1.000093	SD	1.000152	SD	1.000119
Skew	6.075521	Skew	7.130898	Skew	-0.008652
Kurt	15.96085	Kurt	17.69077	Kurt	4.370951
JB	285.1888	JB	255.2497	JB	59.68383
Prob.	0.000000	Prob.	0.000000	Prob.	0.000000

*The sample taken into consideration when observing the entire period is 2774, for the pre-crisis period of 2012, while for the crisis and post-crisis periods there are 762 observations.

The results indicate that the mean daily return of the analyzed stock market index is negative over both the full observation period and the pre-crisis period, while a positive average return is recorded during the crisis phase. Return variability, measured by the standard deviation, remains constant at 1.00 across all three sub-periods, pointing to a broadly similar degree of volatility over time. For the FTSE China A50 index, the distribution of returns exhibits positive skewness in the full and pre-crisis samples, suggesting a heavier right tail and a relatively higher incidence of positive return outcomes in these periods. By contrast, the crisis period is characterized by negative skewness, indicating a shift toward a longer left tail and a greater prevalence of negative return realizations. Furthermore, kurtosis values substantially exceed the reference threshold of three in all sub-periods (15.96, 17.69, and 4.37), reflecting pronounced leptokurtosis and a heightened probability of extreme return observations, which implies elevated investment risk.

4.3 Hungary – BUDAPEST SE

The subsequent section presents the empirical findings for the case study focusing on Hungary. The information-criterion results for selecting the preferred econometric specification of the BUDAPEST SE index are presented in Table 7.

Table 7
Information-criterion evidence for identifying the preferred econometric specification – BUDAPEST SE

Observation period	Information criterion	TGARCH/GJR-GARCH	EGARCH	PGARCH	FIGARCH
Pre-crisis period	SIC	2.889807	2.876993	2.880663	n/a
	AIC	2.863888	2.848194	2.848984	n/a
Crisis/post-crisis period	SIC	3.521127	3.527438	3.519045	3.537433
	AIC	3.466371	3.466598	3.452122	3.476594
Entire period	SIC	2.949864	2.938475	2.935631	n/a
	AIC	2.925764	2.9116976	2.906176	n/a

n/a - denotes that the EViews software did not identify a statistically adequate model for the specified observation period, which may reflect the influence of policy interventions and regulatory measures affecting financial market behavior.

The temporal evolution of standardized return residuals for the BUDAPEST SE index over the 2012-2022 observation period is illustrated in Figure 3.

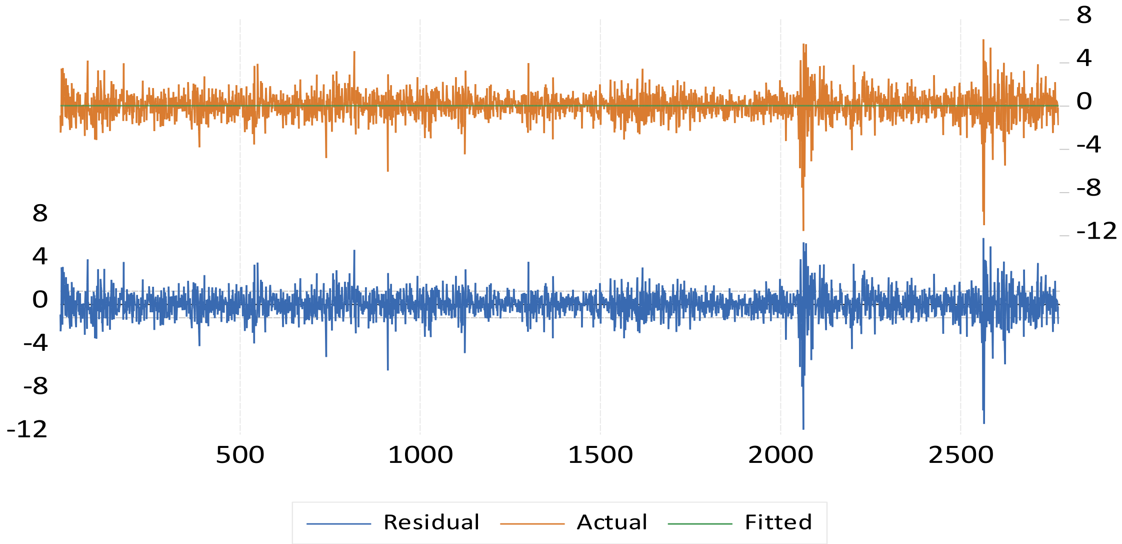

Fig. 3. Temporal dynamics of BUDAPEST SE return residuals over the 2012–2022 observation horizon

The estimated coefficients of the selected GARCH specifications for the BUDAPEST SE index across different observation periods are reported in Table 8.

Table 7 reports the results of the model selection procedure for the BUDAPEST SE stock market index based on the information criterion across the three defined observation periods. The selection outcomes indicate that the EGARCH specification offers the best empirical fit in the pre-crisis phase, while the PGARCH model is identified as the most appropriate framework for both the crisis/post-crisis period and the full observation period. This pattern suggests a shift in volatility dynamics toward more persistent behavior during periods of heightened uncertainty.

Figure 3 depicts the evolution of return residuals for the BUDAPEST SE index over the analyzed sub-periods. When the entire observation horizon is considered, sharp residual movements and pronounced volatility spikes are closely associated with major crisis events, including the outbreak of the COVID-19 pandemic and subsequent geopolitical tensions. In the pre-crisis period, residuals display relatively moderate but more frequent fluctuations, reflecting varying trading conditions in the Hungarian financial market prior to the global shock. By contrast, the crisis/post-crisis phase is marked by two distinct episodes of extreme residual oscillations—corresponding to the initial pandemic shock and the later phase of geopolitical instability—both accompanied by reduced market activity. This contrast highlights a transition from regular volatility adjustments in normal conditions to abrupt and irregular shocks during crisis episodes.

Table 8
Estimated coefficient of selected GARCH specifications for the BUDAPEST SE index in different observation periods

BUDAPEST SE - entire period		BUDAPEST SE - pre-crisis period		BUDAPEST SE - crisis/ post-crisis period	
Optimal model PGARCH		Optimal model EGARCH		Optimal model PGARCH	
K(1)	0.029559	K	0.029951	K(1)	0.017544
K(2)	-0.047216	K(1)	-0.089013	K(2)	-0.430439
K(3)	0.066404	K(2)	0.124710	K(3)	0.064218
K(4)	0.663120	K(3)	-0.080543	K(4)	0.266513
K(5)	0.864168	K(4)	0.935261	K(5)	0.715141
ref_int_rate_HUN	0.011230	ref_int_rate_HUN	0.009314	ref_int_rate_HUN	0.140473
inf_rate HUN	-0.005698	inf_rate _HUN	-0.014293	inf_rate _HUN	-0.116307
price_of_oil_usd	-7.95E-05	price_of_oil_usd	-0.000145	price_of_oil_usd	0.005388
price_of_gold_usd	0.276436	price_of_gold_usd	0.216121	price_of_gold_usd	-1.131737
usd_huf	0.000420	usd_huf	-1.95E-05	usd_huf	0.002314

Table 8 summarizes the estimated coefficients of the optimal GARCH specifications for the BUDAPEST SE index, illustrating the direction and intensity of macroeconomic influences on daily returns. Over the full observation period, the preferred PGARCH model indicates that inflation and oil price movements exert a negative effect on index returns, whereas changes in the policy interest rate, gold prices, and the exchange rate are associated with positive return responses. These findings underline the heterogeneous transmission of macroeconomic shocks to the Hungarian stock market and the relevance of volatility persistence during periods of increased uncertainty.

The negative effects of inflation and oil price movements on the BUDAPEST SE index may reflect the sensitivity of the Hungarian financial market to rising input costs, inflationary pressures, and external energy-related shocks, particularly given the relatively higher exposure of smaller and less liquid markets to changes in global economic conditions. Higher inflation rates may reduce investor confidence and weaken expectations regarding future corporate profitability, while increases in oil prices can additionally intensify production and transportation costs across key sectors of the economy. By contrast, the positive influence of policy interest rates, gold prices, and exchange rate movements may indicate the role of monetary stabilization measures and defensive investment behavior during periods of heightened uncertainty. The positive response to exchange rate fluctuations may also reflect the export-oriented structure of certain segments of the Hungarian economy, where currency depreciation can temporarily improve external competitiveness and positively affect investor expectations. Overall, these findings further emphasize the heterogeneous transmission of macroeconomic shocks and the pronounced importance of volatility persistence within smaller and relatively less liquid financial markets during crisis conditions.

The estimated coefficients from the selected PGARCH specification suggest that changes in the analyzed macroeconomic variables are associated with positive movements in the daily returns of the BUDAPEST SE index over the full sample period. The reported aggregate value of 1.835884 represents an illustrative combined coefficient effect derived from the estimated parameters presented in Table 8. From an indicative investment perspective, such an estimated relationship could correspond to an approximate positive daily portfolio movement of around 18,358.84

monetary units for a hypothetical investment allocation of 1,000,000 monetary units under the observed market conditions, interpreted consistently with the previously presented indices.

The distributional characteristics of the BUDAPEST SE return series across the analyzed observation periods are summarized in Table 9.

Table 9
Distributional characteristics of the sample across distinct observation periods

BUDAPEST SE- entire period		BUDAPEST SE - pre-crisis period		BUDAPEST SE - crisis/post-crisis period	
M	0.009892	M	-0.013449	M	0.016363
Med	0.027554	Med	-0.005776	Med	0.058364
Max	4.671866	Max	4.290419	Max	3.490657
Min	-4.757298	Min	-6.175643	Min	-5.009290
SD	0.882479	SD	0.997415	SD	1.001502
Skew	-0.219250	Skew	-0.171091	Skew	-0.300544
Kurt	4.792964	Kurt	4.334371	Kurt	4.421852
JB	299.8161	JB	159.0849	JB	75.65935
Prob.	0.000000	Prob.	0.000000	Prob.	0.000000

*The sample taken into consideration when observing the entire period is 2589, for the pre-crisis period of 2012, while for the crisis and post-crisis periods there are 762 observations.

Table 9 reports the descriptive statistics of investment returns for the BUDAPEST SE stock market index. The average daily return is negative during the pre-crisis period, while it becomes positive in the crisis period, with a positive average return recorded over the full observation period. For the full sample, the standard deviation amounts to 0.88, whereas the highest return volatility is observed during the crisis period 1.00, coinciding with the onset and intensification of crises associated with the COVID-19 pandemic and geopolitical conflicts. Skewness values are negative across all observation periods, indicating a longer left tail of the return distribution and a predominance of negative return movements. In addition, kurtosis exceeds the benchmark value of 3 in all periods (4.79, 4.33, and 4.42), suggesting a high likelihood of extreme return realizations and, consequently, an elevated level of investment risk.

4.4 Slovenia - SBITOP

The subsequent section presents the empirical findings for the case study focusing on Slovenia. The information-criterion results for identifying the preferred econometric specification of the SBITOP index are presented in Table 10.

Table 10
Information-criterion evidence for identifying the preferred econometric specification – SBITOP

Observation period	Information criterion	TGARCH/GJR-GARCH	EGARCH	PGARCH	FIGARCH
Pre-crisis period	SIC	2.292105	2.301732	2.298200	2.294551
	AIC	2.266186	2.272934	2.266521	2.265752
Crisis/post-crisis period	SIC	2.566149	2.585480	2.562138	2.566142
	AIC	2.511394	2.524641	2.495215	2.505303
Entire period	SIC	2.242902	2.254966	2.249122	2.244747
	AIC	2.218165	2.227480	2.218887	2.217261

The temporal dynamics of standardized return residuals for the SBITOP index over the 2012–2022 observation horizon are illustrated in Figure 4.

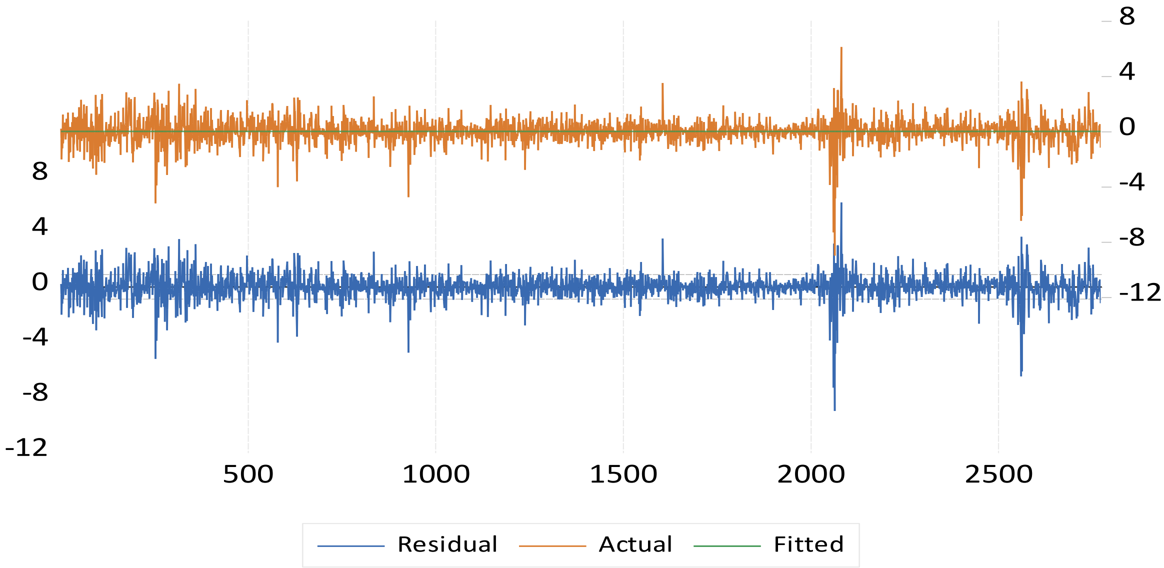

Fig. 4. Temporal dynamics of SBITOP return residuals over the 2012–2022 observation horizon

The estimated coefficients of the selected GARCH specifications for the SBITOP index across different observation periods are presented in Table 11.

Table 11

Estimated coefficient of selected GARCH specifications for the SBITOP index in different observation periods

SBITOP - entire period		SBITOP - pre-crisis period		SBITOP - crisis/post crisis period	
Optimal model TGARCH/GJR-GARCH		Optimal model TGARCH/GJR-GARCH		Optimal model PGARCH	
K	0.041917	K	0.031440	K(1)	0.059779
K(2)	0.517369	K(2)	0.434653	K(2)	-0.860863
RESID(-1)^2	0.146064	RESID(-1)^2	0.139812	K(3)	0.089319
GARCH(-1)	0.551219	GARCH(-1)	0.563019	K(4)	0.116066
ref_int_rate_SLO	0.211143	ref_int_rate _SLO	0.199245	K(5)	0.331170
inf_rate_SLO	-0.011429	inf_rate _SLO	-0.009409	ref_int_rate_SLO	-0.036810
price_of_oil_usd	0.000181	price_of_oil_usd	-0.622753	inf_rate_SLO	0.010189
price_of_ gold_usd	-0.611780	price_of_gold_usd	0.000327	price_of_oil_usd	-0.002767
usd_eur	-0.448931	usd_eur	-0.365386	price_of_gold_usd	0.013977
-	-	-	-	usd_eur	1.254392

Table 10 reports the results of the model selection procedure for the SBITOP stock market index based on the AIC and SIC information criterion . The findings indicate that the TGARCH (GJR-GARCH) specification provides the best empirical fit in the pre-crisis period, whereas the PGARCH model is identified as the most appropriate framework during the crisis/post-crisis phase. For the full observation period, the two information criteria yield different preferences: the SIC criterion selects the TGARCH (GJR-GARCH) model, while the AIC criterion favors the FIGARCH specification. Given the stricter penalization of model complexity imposed by the SIC criterion, the TGARCH-based specification is adopted as the optimal model for the full observation period.

Figure 4 illustrates the evolution of return residuals for the SBITOP index across the defined sub-periods. When the full sample is considered, substantial residual fluctuations and extreme volatility episodes are closely aligned with major crisis events, including the outbreak of the COVID-19 pandemic and subsequent geopolitical disturbances. In the pre-crisis phase, residual dynamics exhibit noticeable variability, particularly in the earlier segment of the period, followed by a phase of relative stabilization that persists until the onset of the pandemic. With the emergence of the crisis, a decline in trading activity is observed in the initial stage, which coincides with pronounced residual oscillations. In the later phase of the crisis period, the magnitude of these fluctuations decreases markedly, indicating a gradual stabilization of the Slovenian stock market following the initial shock. The presence of residual volatility prior to the pandemic further suggests that market activity in Slovenia was already sensitive to macroeconomic and microeconomic risks in the post - 2008 global financial environment.

Table 11 presents the estimated coefficients of the optimal GARCH specifications for the SBITOP index, highlighting the direction and strength of macroeconomic influences on daily returns. For the full observation period, the preferred TGARCH (GJR-GARCH) model indicates that inflation, gold prices, and exchange rate movements exert a negative effect on index returns, while policy interest rates and oil prices are associated with positive return responses. These results emphasize the importance of asymmetric volatility effects and macroeconomic transmission channels in shaping return dynamics on the Slovenian stock market.

The negative influence of inflation, gold prices, and exchange rate movements on the SBITOP index may reflect the sensitivity of the Slovenian financial market to inflationary pressures, currency-related uncertainties, and shifts in investor behavior toward safer assets during periods of heightened economic instability. As a relatively smaller and less liquid financial market, the Slovenian stock exchange may be more vulnerable to external macroeconomic disturbances and changes in regional financial conditions. The negative relationship between gold prices and stock returns may additionally indicate that investors increasingly redirect capital toward safe-haven assets during periods of elevated uncertainty, thereby reducing investment activity within the domestic equity market. Conversely, the positive effects of policy interest rates and oil prices may reflect the influence of stabilization measures and the partial recovery of economic activity during certain sub-periods characterized by stronger industrial and trade performance. Overall, these findings further support the importance of asymmetric volatility behavior and market-specific macroeconomic transmission mechanisms in explaining stock return dynamics within smaller European financial systems.

The estimates derived from the optimal TGARCH (GJR-GARCH) specification indicate that changes in the selected macroeconomic variables are associated with positive movements in the daily returns of the SBITOP stock market index over the full observation horizon. The reported aggregate value of 0.395753 represents an illustrative combined coefficient effect derived from the estimated parameter values presented in Table 11 for the entire sample. From an indicative investment perspective, such an estimated relationship could correspond to an approximate positive daily portfolio movement of around 3,957.53 monetary units for a hypothetical investment allocation of 1,000,000 monetary units under the observed market conditions, interpreted consistently with the previously analyzed stock market indices.

The distributional characteristics of the SBITOP return series across the analyzed observation periods are summarized in Table 12**.**

Table 12 summarizes the key descriptive statistics of daily investment returns for the SBITOP stock market index across the analyzed sub-periods. The mean return remains negative throughout the entire sample, including the pre-crisis and crisis/post-crisis phases. Over the full observation period, the standard deviation equals 1.00, while return dispersion is marginally higher in the pre-crisis phase compared to the crisis/post-crisis period. The return distribution of the SBITOP index exhibits consistently negative skewness in all three periods, indicating a more pronounced left tail and a higher frequency of negative return outcomes relative to positive ones. In addition, kurtosis values exceed the conventional threshold of three in each sub-period (5.38, 5.41, and 5.83), pointing to leptokurtic behavior and an increased probability of extreme return realizations, which signals elevated investment risk.

Table 12
Distributional characteristics of the sample across distinct observation periods

SBITOP - entire period		SBITOP - pre-crisis period		SBITOP - crisis/post-crisis period	
M	-0.013941	M	-0.010704	M	-0.059747
Med	-0.037256	Med	-0.034170	Med	-0.036921
Max	6.007377	Max	5.913983	Max	2.985953
Min	-6.771968	Min	-6.732794	Min	-5.011920
SD	1.000070	SD	1.000069	SD	0.954415
Skew	-0.078113	Skew	-0.074187	Skew	-0.492606
Kurt	5.375631	Kurt	5.410682	Kurt	5.832515
JB	483.1995	JB	469.8320	JB	285.5526
Prob.	0.000000	Prob.	0.000000	Prob.	0.000000

*The sample taken into consideration when observing the entire period is 2546, for the pre-crisis period of 1933, while for the crisis and post-crisis periods there are 762 observations.

5. Comparative Review of the Results Obtained and Discussion

The following section summarizes the principal empirical findings obtained from the comparative GARCH-based analysis and discusses their broader economic implications across the analyzed financial markets and observation periods. Particular attention is devoted to differences in volatility behavior, macroeconomic transmission mechanisms, and market-specific responses under varying crisis conditions.

A comparative overview of the principal empirical findings across the analyzed financial markets is presented in Table 13.

Table 13
Comparative synthesis of empirical findings across analyzed markets

BUDAPEST SE						
Model	Period	ref.int_ rate_HUN	inf_rate_ HUN	price_of_ oil_usd	price_of_ gold_usd	usd_huf
PGARCH	Entire	0.011230	-0.005698	-7.95E-05	0.276436	0.000420
EGARCH	Pre-Crisis	0.009314	-0.014293	-0.000145	0.216121	-1.95E-05
PGARCH	Crisis/post-crisis	0.140473	-0.116307	0.005388	-1.131737	0.002314
FTSE 100						
Model	Period	ref.int_ rate_UK	inf_rate_ UK	price_of_ oil_usd	price_of_ gold_usd	gbp_usd
PGARCH	Entire	-0.001040	-0.001713	7.96E-05	-0.016738	-0.028694
PGARCH	Pre-Crisis	0.049104	-0.000690	-0.000193	0.001271	0.016256
EGARCH	Crisis/Post-crisis	-0.019287	-0.009012	7.96E-05	0.328013	-0.455744
FTSE CHINA A50						
Model	Period	ref. int._ rate_CHN	inf_rate_ CHN	price_of_ oil_usd	price_of_ gold_usd	cny_usd
EGARCH	Entire	0.041804	-0.019066	-0.000435	0.328938	-5.940847
EGARCH	Pre-Crisis	0.037900	-0.055518	0.000613	0.289261	-7.765166
EGARCH	Crisis/Post-crisis	0.147715	-0.013410	0.000525	0.132403	-2.322831

Table 13
Continued

SBITOP						
Model	Period	ref_int_ rate_CRO	Inf_rate_ CRO	price_of_ oil_usd	price_of_ gold_usd	usd_eur
TGARCH/GJR-GARCH	Entire	0.211143	-0.011429	0.000181	-0.611780	-0.448931
TGARCH/GJR-GARCH	Pre-Crisis	0.199245	-0.009409	-0.622753	-0.000327	-0.365386
EGARCH	Crisis/post-crisis	-0.036810	0.010189	-0.002767	0.013977	1.254392

Based on the results reported in the table above, model selection according to the applied criteria indicates that the analyzed macroeconomic variables exert a statistically significant influence on the daily returns of stock market indices in the observed countries—namely, the United Kingdom, China, Hungary, and Slovenia. A comparative overview of the results shows that, for the full observation period, the optimal specifications are PGARCH for the FTSE 100, EGARCH for the FTSE CHINA A50, PGARCH for the BUDAPEST SE, and TGARCH (GJR-GARCH) for the SBITOP index. During the pre-crisis period, the selected models are PGARCH for the FTSE 100, EGARCH for the FTSE CHINA A50, EGARCH for the BUDAPEST SE, and TGARCH (GJR-GARCH) for the SBITOP, while in the crisis and post-crisis period the optimal specifications are EGARCH for the FTSE 100, EGARCH for the FTSE CHINA A50, PGARCH for the BUDAPEST SE, and EGARCH for the SBITOP index. A cross-market comparison of the estimated relationships indicates that negative linkages between macroeconomic variables and stock index returns are observed with the same frequency in both more developed and less developed financial markets, occurring sixteen times in each group when all periods and explanatory factors are jointly considered. However, despite this numerical symmetry, the magnitude and economic relevance of these effects vary markedly across markets and sub-periods. A shared empirical characteristic across all analyzed samples is the deviation from normality in return distributions, manifested through persistent asymmetry and distributional distortions over time. Differences in the selected GARCH specifications across markets and observation windows further signal heterogeneity in underlying market dynamics. In particular, EGARCH models are predominantly selected during crisis and post-crisis phases, reflecting their ability to capture asymmetric volatility responses, especially the disproportionate impact of adverse shocks. This feature proved especially relevant during the COVID-19 period, which was marked by heightened uncertainty and increased sensitivity of investors to negative information. By contrast, PGARCH models are more frequently favored in environments characterized by sustained volatility persistence and gradual adjustment processes, suggesting comparatively more stable structural conditions. The alignment between the theoretical properties of these models and observed market behavior strengthens the empirical credibility and conceptual coherence of the adopted modeling framework. TGARCH (GJR-GARCH) specifications are applied in cases where threshold effects are evident, allowing negative innovations to exert a stronger influence on conditional volatility than positive shocks of equal magnitude. Such asymmetries are particularly pronounced during periods of financial stress, making the TGARCH framework suitable for capturing volatility dynamics under adverse market conditions.

From the viewpoint of investors and other market participants, the empirical findings emphasize the necessity of adapting investment and risk-management strategies to the specific structural characteristics of individual financial markets. The results suggest that the transmission of macroeconomic shocks is not uniform and depends critically on the degree of market depth, liquidity, and institutional development. More mature financial markets generally benefit from deeper capital bases, higher liquidity, more robust regulatory environments, and greater predictability in monetary policy, which together contribute to more efficient price adjustment and less abrupt investor reactions to macroeconomic news. In contrast, markets with lower levels of financial maturity are often marked by limited liquidity, stronger dependence on external capital flows, weaker institutional frameworks, and heightened exchange rate volatility. As a result, such markets tend to exhibit stronger and more immediate responses to movements in commodity prices and exchange rates, particularly during periods of global economic stress. Moreover, the relatively larger presence of retail investors in less liquid markets may intensify sentiment-driven volatility, whereas developed markets are more strongly shaped by institutional investment behavior. These structural asymmetries provide a coherent explanation for the heterogeneous market responses observed in the presence of similar macroeconomic disturbances. From a practical perspective, the results imply that investors operating in less liquid markets should exercise increased caution during episodes of global commodity and currency instability, while participants in more developed markets may benefit from closer monitoring of monetary policy signals and inflation dynamics. Accordingly, the economic interpretation of the estimated effects—beyond their statistical significance—plays a central role in supporting sound and informed investment decisions. Overall, the findings underscore the broader economic significance and practical relevance of the study, offering meaningful insights for both policymakers and financial market participants.

6. Conclusion

The empirical framework of this research is based on tailored multivariate GARCH-type econometric specifications designed to evaluate how core macroeconomic indicators—specifically inflation, policy interest rates, exchange rates, and the prices of oil and gold—shape stock market volatility in financial systems with differing structural characteristics. The investigation spans the 2012–2022 period and encompasses both relatively advanced markets (China and the United Kingdom) and markets with comparatively lower depth and liquidity (Hungary and Slovenia). The estimation results reveal statistically meaningful linkages between macroeconomic conditions and volatility dynamics across all observed economies, while also indicating substantial cross-market variation in both the strength and direction of these effects, depending on institutional features and the particular time segment considered.

The empirical evidence derived from the implementation of tailored GARCH-type specifications indicates that the selected macroeconomic indicators generate statistically and economically meaningful effects on both stock return behavior and volatility dynamics across the analyzed financial markets. Consistent relationships are observed between stock index performance and key macroeconomic determinants, including interest rates, inflation, gold prices, and exchange rates, although the magnitude and direction of these effects differ across markets and observation periods. These findings confirm that tailored GARCH-based modeling approaches provide an appropriate analytical framework for interpreting financial market behavior and supporting investment-related analysis, thereby supporting the acceptance of Hypothesis H0.

A comparative analysis of the estimated coefficients indicates that the effects of macroeconomic factors differ both statistically and economically between more developed and liquid financial markets (FTSE 100 and FTSE CHINA A50) and less developed markets characterized by lower liquidity levels (BUDAPEST SE and SBITOP), particularly during the 2020–2022 crisis and post-crisis period. The empirical findings suggest that more developed markets exhibit stronger sensitivity to monetary variables such as interest rates and inflation, whereas smaller and less liquid markets are more exposed to fluctuations in commodity prices and exchange rates. These differences are additionally confirmed through the observed residual dynamics and through variations in the magnitude, direction, and intensity of the estimated macroeconomic coefficients affecting stock return movements across the analyzed markets. Collectively, these findings point to structurally distinct macroeconomic transmission mechanisms and further confirm the importance of market depth and liquidity in shaping volatility dynamics under crisis conditions, thereby supporting the acceptance of Hypothesis H1.

The analysis of the crisis and post-crisis period (2020–2022) indicates that the intensity of negative macroeconomic effects on stock index returns was not uniformly greater in financial markets characterized by lower levels of market depth and liquidity. On the contrary, the empirical findings reveal that more pronounced negative effects, particularly those associated with exchange rate movements and gold prices, were observed in the highly developed financial markets. These relationships are additionally confirmed through the estimated coefficient values obtained from the optimal GARCH-type specifications, as well as through the observed residual dynamics across the analyzed observation periods. However, despite the stronger negative coefficients identified in developed markets, investment-related outcomes remained comparatively more favorable, whereas investments in less developed markets generated negative returns during the same period. Such findings suggest that greater market depth and liquidity may partially mitigate the adverse investment consequences of macroeconomic shocks, even when short-term negative effects appear more pronounced. Nevertheless, from the perspective of the intensity and frequency of negative macroeconomic influences, Hypothesis H2 may be considered rejected.

The empirical evidence generated in this study carries relevant practical implications for investors seeking to construct efficient portfolio strategies across financial markets that differ in depth, liquidity, and institutional maturity. The statistically validated effects of inflation and policy interest rates on stock index performance indicate that market participants in more developed and liquid environments—such as the United Kingdom and China—should pay particular attention to expected adjustments in monetary policy, especially during periods of elevated macroeconomic uncertainty. The crisis episode of 2020–2022 further demonstrates heightened market responsiveness to exchange rate fluctuations and gold price movements in these economies, implying a potential need for dynamic portfolio rebalancing or diversification toward alternative asset classes. By contrast, the outcomes observed for Hungary and Slovenia underscore the role of limited market depth and liquidity in intensifying the transmission of commodity price and currency shocks to investment returns. Under such structural conditions, investors may face slower adjustment dynamics and more persistent volatility, necessitating a more cautious approach during episodes of global disturbance.

The findings of this study contribute to the growing literature on stock market volatility and macro-financial transmission mechanisms by providing a comparative analysis of developed and less developed financial markets under different crisis conditions. By applying tailored GARCH-type specifications across the United Kingdom, China, Hungary, and Slovenia over the 2012–2022 period, the research demonstrates that macroeconomic determinants such as inflation, interest rates, exchange rates, and commodity prices exert heterogeneous effects on stock market returns and volatility depending on market structure, liquidity conditions, and the degree of financial development. The results further indicate that periods of heightened global uncertainty, particularly those associated with the COVID-19 pandemic and related geopolitical disturbances, intensified volatility persistence and asymmetric market reactions, especially within smaller and less liquid financial systems. In methodological terms, the study confirms the usefulness of alternative asymmetric GARCH-type models in capturing market-specific volatility dynamics across different observation periods. From a practical perspective, the obtained findings may provide useful implications for investors, financial analysts, and policymakers in evaluating investment-related risk and understanding the transmission of macroeconomic shocks under changing global market conditions. The study additionally creates a basis for future research focused on more advanced hybrid volatility frameworks, machine-learning approaches, and mixed-frequency financial modeling techniques.

At the same time, the interpretation of the obtained findings should acknowledge several important limitations. First, although the empirical analysis incorporates multiple GARCH-type specifications, residual diagnostics, and information-criterion-based model selection procedures, the robustness of the results may still be influenced by the specific econometric assumptions underlying the selected volatility models. In this context, the application of alternative methodological frameworks, such as stochastic volatility (SV) models, MIDAS-GARCH specifications, VAR-based approaches, copula-GARCH models, or hybrid machine-learning techniques, could provide additional insights into volatility transmission mechanisms and potentially improve the robustness of the obtained estimates. Second, certain limitations arise from the structure and frequency of the employed datasets. More specifically, stock index return rates were analyzed using daily observations, whereas selected macroeconomic variables, particularly inflation rates and benchmark interest rates, were available primarily at monthly frequencies. Although such mixed-frequency structures are relatively common in empirical financial research, differences in data frequency may partially affect the precision and consistency of the estimated relationships between macroeconomic determinants and stock market volatility dynamics. Finally, the analysis is limited to a selected set of macroeconomic variables and does not explicitly incorporate several potentially relevant market-specific determinants, including liquidity indicators, trading volume, investor sentiment, fiscal policy measures, political uncertainty, or broader geopolitical risk factors. The inclusion of such variables in future research, together with the use of higher-frequency datasets and more advanced econometric approaches, could further improve explanatory power, robustness, and the overall understanding of macroeconomic shock transmission across financial markets characterized by different levels of development and liquidity.

From a methodological standpoint, subsequent studies may benefit from extending the analytical framework toward volatility models that incorporate regime-switching behavior or mixed-frequency structures, such as MIDAS-GARCH or Markov-switching GARCH specifications, which are capable of capturing heterogeneous volatility regimes across varying market environments. Broadening the empirical coverage to include additional economies, longer observation horizons, and earlier crisis periods would further strengthen cross-market comparability and deepen the understanding of volatility transmission within the global financial system.

Author Contributions

Conceptualization, P.J. and M.M.; methodology, P.J.; software, M.P. and P.J.; formal analysis, D.M. and P.J.; writing—original draft preparation, P.J., D.M. and B.D.; writing—review and editing, P.V. and B.D.; visualization, M.P., D.M., P.V. and B.D.; supervision, M.M., D.M. and B.D. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding authors.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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