DOI: 10.28934/ea.2127 First Online: March 18, 2026

ORIGINAL SCIENTIFIC PAPER

Factors Affecting Investment Funds Investing in Different Asset Classes

Mirjana Veselinović[1] | **Dejan Živkov**[1] | **Suzana Balaban**[1*]

[1] BK University - Faculty of Finance, Banking and Auditing, Belgrade, Serbia
[2] Institute of Agricultural Economics, Belgrade, Serbia

ABSTRACT
This paper examines how global financial and macroeconomic factors transmit shock and volatility spillovers to investment funds investing in different asset classes. Using daily data from January 2015 to December 2025, the authors analyse three U.S. funds representing bond, commodity, and equity exposures (PIMCO, USCI, and XLK) and five global factors: 1-month and 10-year U.S. interest rates, the S&P 500, Brent crude oil, and gold. The asymmetric TGARCH models are first estimated to obtain standardized residuals and conditional variances, after which a two-regime Markov switching framework is applied to capture the differences between high- and low-volatility periods. The results show strong regime- and fund-specific spillovers. S&P 500 shocks strongly affect XLK in both regimes, while oil and gold shocks dominate USCI during turbulent periods. Volatility spillovers are most pronounced for USCI and XLK, whereas PIMCO remains relatively insulated. These findings provide regime-aware implications for investors and fund managers.

Keywords: Investment funds, spillover effects, macro factors, regime dependence

JEL Classification: C24, D53, E44

INTRODUCTION

Global financial and macroeconomic factors significantly influence the investment decisions and performance of investment funds. Macroeconomic conditions such as global economic growth, inflation trends, and business cycle dynamics shape expectations about future returns and risks across asset classes (Bali et al., 2014; Leite, 2024). Financial factors, including global interest rates, equity market performance, and commodity prices, directly affect asset valuations and portfolio rebalancing decisions (Assefa et al., 2017). Monetary policy actions by major central banks influence global liquidity and risk-taking behaviour, while exchange rate movements and capital flow dynamics affect international investment exposure. Moreover, heightened financial integration and interconnected markets amplify the transmission of global shocks, increasing the sensitivity of investment funds to changes in global economic and financial conditions.

More specifically, interest rates, commodity prices, and equity market performance are key global factors influencing the behaviour of investment funds (Lee et al., 2015; Babalos and Balcilar, 2017; Pinto-Ávalos et al., 2024). Changes in global interest rates affect discount rates, borrowing costs, and portfolio reallocation between fixed-income and riskier assets. Gold prices are often viewed as a hedge against inflation and financial uncertainty, leading investment funds to increase

* Corresponding author, e-mail: suzana.balaban@alfa.edu.rs

exposure during periods of heightened market stress or declining real interest rates. Oil prices play a dual role, reflecting both global economic activity and supply-side shocks, thereby influencing inflation expectations and sectoral equity returns (Alsubaiei et al., 2023). Meanwhile, the S&P 500 serves as a benchmark for global equity market conditions and investor sentiment, with its movements shaping risk appetite and capital flows across international investment funds (Alexakis et al., 2005). Together, these factors interact to determine asset allocation, risk management, and return dynamics in global investment portfolios (Musawa and Mwaanga, 2017).

Understanding the role of global financial and macroeconomic factors in shaping investment fund behaviour is important for several key stakeholders. For investors, it helps improve portfolio allocation decisions, risk assessment, and diversification strategies (Đekić et al., 2017; Korenak and Stakić, 2021), especially in periods of heightened global uncertainty. For fund managers, insights into how interest rates, equity markets, and macroeconomic conditions interact enable more effective risk management, timing, and asset rebalancing. For policymakers and regulators, recognizing the sensitivity of investment funds to global shocks is essential for monitoring systemic risk and financial stability. Finally, for academics and researchers, analysing these global drivers contributes to a deeper understanding of market integration and the transmission of macro-financial shocks across asset classes and regions.

The goal of the paper is to investigate the shock and volatility effects of five global financial and macroeconomic factors, 1m interest rate, 10Y interest rate, Brent oil, gold and the S&P 500 index, on three American investment funds that invest in different asset classes – PINCO, USCI and XLK. PIMCO funds primarily focus on fixed-income markets, investing in government and corporate bonds, mortgage-backed securities, and other interest-rate–sensitive instruments, making them closely linked to global monetary policy and interest rate dynamics (Koo and Muslu, 2023). In contrast, USCI provides exposure to commodity markets through futures contracts on energy, metals, and agricultural commodities, and is commonly used for diversification and inflation hedging. XLK, on the other hand, is an equity-based ETF concentrated on the U.S. technology sector (Krause and Tse, 2013), investing in large-cap technology firms and closely tracking developments in the S&P 500 and global equity market sentiment. Together, these funds capture bond, commodity, and equity market exposures, making them useful proxies for analysing how global financial and macroeconomic factors affect investment funds across different asset classes.

According to the authors' knowledge, the existing literature has not jointly analyzed the influence of these five determinants on investment funds. Prior studies have typically focused on narrower or more specific dimensions of fund behavior. For example, Ciarlone and Miceli (2016) explore the macroeconomic drivers of Sovereign Wealth Funds' (SWFs) investment decisions, paying particular attention to how these funds adjust their activity in response to financial crises in host economies. In a different context, Jiang et al. (2026) analyze the transmission of financial uncertainty shocks to global bond funds, emphasizing four major sources of uncertainty: equity market volatility (VIX), bond market volatility (MOVE), central bank digital currency uncertainty (CBDCU), and geopolitical risk (GPR). Meanwhile, Wu (2025) investigates the role of cultural heterogeneity in shaping the investment choices of institutional investors.

This paper analyses a relatively long time period, from January 2015 to December 2025, that is permeated with numerous global turbulences, such as the COVID-19 pandemic (2020–2022), the global inflation surge (2021–2023), the global energy crisis (2021–2023) and the Russia–Ukraine War (2022 onward). From this aspect, the authors use the Markov switching (MS) model as a working horse to examine the effect on the factors on the investment funds. Using the MS model is appropriate in this context because the period 2015–2025 is characterized by repeated global turbulences that caused abrupt changes in financial market behaviour and investment fund dynamics. In other words, global financial and macroeconomic shocks – such as the COVID-19 pandemic, the inflation surge, geopolitical conflicts, and rapid interest-rate tightening – tend to generate regime changes rather than smooth, linear adjustments. Investment fund returns, volatilities, and correlations often behave very differently during normal (low-volatility) periods compared to crisis or stress (high-volatility) periods. The Markov switching model explicitly captures these unobserved regimes and allows key parameters to vary across them (Valadkhani and Marashdeh, 2026). In addition, the model does not require ex-ante identification of crisis dates. Instead, it endogenously detects regime shifts based on the data (Wu et al., 2024), which is crucial in a sample containing overlapping and evolving global shocks. This makes it well-suited for analysing how investment funds react to changing global conditions without imposing arbitrary breakpoints. Finally, the Markov switching models provide estimates of regime probabilities and transition dynamics (Çepni et al., 2023), offering insights into the persistence of turbulent periods and the likelihood of moving between regimes. This is valuable for investors, fund managers, and policymakers, as it enhances understanding of risk dynamics, improves portfolio and hedging strategies, and supports more effective monitoring of systemic risk under different global financial and macroeconomic environments.

This paper provides a comprehensive analysis of how key global financial and macroeconomic factors, such as interest rates, commodity prices, and equity market indices, transmit shock and volatility spillovers to investment funds across different asset classes. By combining asymmetric TGARCH and Markov switching models over a turbulent 2015–2025 period, it identifies regime-dependent and fund-specific spillover dynamics, highlighting the heterogeneous responses of bond, commodity, and equity funds. This approach advances the literature by linking theoretical modeling with practical implications for portfolio management and risk assessment under varying market conditions. As far as the authors are aware, this is among the first papers to attempt this type of research, and this is where the authors find the motivation for the research.

LITERATURE REVIEW

This section concisely presents papers that researched factors affecting investment funds. For instance, Shah et al. (2025) investigate how the S&P 500 index funds interact with key real-time markets, namely gold and WTI, amid periods of crisis such as the COVID-19 pandemic and the Russia-Ukraine conflict. By applying a time-varying parameter vector autoregression (TVP-VAR) framework, they identify notable interdependencies and heightened connectedness among these markets during both events. Liu and Hu (2025) examine how the COVID-19 pandemic influenced the investment outcomes of sovereign wealth funds (SWFs) across different regions and fund types. Employing empirical techniques, they assess the overall effects of pandemic-induced shocks on SWF returns and explore how variations in investment strategies and geographic allocations shaped performance. Their results show that the pandemic had a generally negative impact on returns, but funds with a greater focus on cross-border investments tended to fare better, highlighting the role of diversification and international exposure in weathering systemic shocks. Jiang et al. (2026) examine how various forms of financial uncertainty influence returns and volatility in global bond funds. Using advanced models such as TVP-SV VAR, MGARCH, and wavelet quantile regressions on weekly data from 2015-2024, they show that funds respond differently to equity, bond, geopolitical, and digital currency uncertainties. Some funds act as temporary safe havens, while others are more sensitive to specific risks, highlighting the need for tailored risk management strategies.

Dekker et al. (2024) investigate the role of liquidity buffers in open-end corporate bond funds during the COVID-19 market turmoil, focusing on how these buffers influence fund behaviour and market procyclicality. They find that higher liquidity buffers did not reduce investor outflows at the peak of the crisis but did help fund managers meet redemption requests with cash instead of selling less liquid assets, thereby mitigating procyclical fire-sale pressures. Their results suggest that liquidity buffers can support more resilient liquidity management strategies in stressed conditions. Fiszeder et al. (2023) investigate how investor attention to oil prices, measured using Google search data, affects returns, volatility, and covariances among exchange-traded funds representing oil, gold, and the stock market. They develop a new multivariate volatility model that incorporates investor attention and find that search activity can help explain and forecast the covariance dynamics between these asset markets. The results suggest that online investor interest plays a meaningful role in the co-movement of major financial and commodity markets. Amar et al. (2019) analyse how national-level factors shape the investment decisions of sovereign wealth funds, focusing on both the choice to invest and the size of those investments. Using a two-tiered dynamic Tobit panel model, they find that political stability encourages entry into a country, while less democratic but more financially open economies attract larger investment amounts, and that funds are more likely to invest repeatedly in countries where they have previously invested. Their results highlight that sovereign wealth funds' location decisions are influenced differently by country characteristics depending on whether the concern is initial entry or investment scale.

RESEARCH METHODOLOGIES

TGARCH Model

The paper uses the asymmetric threshold GARCH (TGARCH) model to create the time series of standardized residuals and conditional volatilities. Each TGARCH model consists of two equations, a mean equation and a conditional variance equation (Ausloos et al., 2020). The mean equation, given in (1), has a first-order autoregressive AR(1) form, where r_t denotes the time series of logarithmic returns. On the other hand, conditional variance, shown in equation (2), is a variance that depends on past information and changes over time. Past information is captured by the first lags of variance h_{t-1} and residuals ε_{t-1}^2. Therefore, the variance in the GARCH framework is referred to as "conditional".

$$r_t = C + r_{t-1} + \varepsilon_t, \qquad \varepsilon_t = z_t\sqrt{h_t}, \tag{1}$$

where C is a constant term in the mean equation and r_{t-1} is the autoregressive component. $z_t \sim i.i.d.(0,1)$ denotes normally distributed residuals.

The conditional variance h_t in the TGARCH(1,1) model is given by:

$$h_t = c + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{\varepsilon_{t-1}<0} + \beta h_{t-1}, \tag{2}$$

where $c > 0$ is the constant term, $\alpha \geq 0$ measures the impact of past shocks (ARCH effect), while $\beta \geq 0$ measures volatility persistence (GARCH effect). γ captures the asymmetric effect, i.e., the additional impact of shocks on conditional variance. If $\gamma > 0$, negative shocks have a larger impact on conditional variance than positive shocks; if $\gamma < 0$, positive shocks have a larger impact on conditional variance than negative shocks. $I_{\varepsilon_{t-1}<0}$is an indicator function that equals 1 if $\varepsilon_{t-1} < 0$, and 0 otherwise. To ensure that the variance is positive and the model is covariance-stationary, it is commonly required that $\alpha \geq 0$and $\beta \geq 0$.

GARCH models are useful for modelling empirical time series because they address the problems of autocorrelation and heteroskedasticity that commonly arise in most daily financial time series (Sabiruzzaman et al., 2010). In other words, including the lagged dependent variable, AR(1), in the mean equation mitigates autocorrelation, while the lagged variance term h_{t-1} addresses heteroskedasticity.

Markov Switching Model

After constructing the time series of standardized residuals and conditional variances for all variables, these variables are incorporated into the Markov switching model, where the effects of shocks and volatility of five factors are estimated on each investment fund. In other words, the six Markov switching models are estimated.

The Markov switching models are based on the assumption that the behaviour of an economic or financial time series changes over time depending on different regimes, such as periods of low and high volatility, expansions and recessions, or tranquil and crisis periods. These regimes are not directly observed. Instead, they are latent and change stochastically over time (Zhang and Zhang, 2022), i.e., regime changes occur randomly with certain probabilities, rather than deterministically or according to a known rule. The key idea of MS models is that model parameters depend on the current regime, which allows for discrete shifts in the dynamics of the series.

Regime switching in MS models is described by a Markov chain (Qian et al., 2022), where the probability of transitioning to a given regime at time (t) depends solely on the regime in the previous period. These transition probabilities are organized in a transition matrix, whose diagonal elements measure the persistence of each regime. High diagonal values indicate long-lasting regimes, whereas low values imply frequent regime changes.

Due to the latent nature of regimes, their identification relies on estimating the probability of being in a particular regime at each point in time. These probabilities are obtained using filtering and smoothing algorithms (Shi, 2022) and are often used for graphical interpretation of stable and unstable periods. This feature makes MS models particularly useful for analysing structural changes and nonlinear dynamics in macroeconomic and financial time series.

The specifications of the six MS models are given by the following equations:

$$PIMCO_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{3}$$

$$USCI_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{4}$$

$$XLK_t^{log} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,log}), \tag{5}$$

$$PIMCO_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{6}$$

$$USCI_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{7}$$

$$XLK_t^{var} = \omega_{0,st} + \omega_{n,st}\mathbb{Z}'_{n,t} + \varepsilon_t; \qquad \varepsilon_t \sim N(0, \sigma^2_{st,var}), \tag{8}$$

where notations "log" and "var" indicate that the model estimates standardized residuals or conditional variances, respectively. $\omega_{0,st}$ is the regime changing intercept in all models, while $\omega_{n,st}$ parameters capture the effects of the explanatory factors on the dependent variables, i.e., the investment funds. The vector $\mathbb{Z}'_n$ contains the five explanatory variables, where $n = 1 \dots 5$. The subscript st indicates that the parameters vary depending on the regime. All MS models are specified with two regimes or states (st): crisis and tranquil states. Specifically, regime $st(1)$ denotes the crisis period, while regime $st(2)$ denotes the tranquil period.

The transition probability matrix between regimes is presented in expression (9). The transition matrix provides the probabilities of moving between different regimes from one period to the next (Stützle, 2020). It describes how stable regimes are and how frequently they change. The matrix is interpreted such that diagonal elements (p_{11} and p_{22}) represent the probability that the system remains in the same regime. High values indicate that the regime is persistent (long-lasting). On the other hand, off-diagonal elements (p_{12} and p_{21}) represent the probability of switching to the other regime. Higher values imply more frequent regime changes.

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{pmatrix}, \quad \sum_j p_{ij} = 1 \tag{9}$$

DATASET AND DESCRIPTIVE STATISTICS

The data used in this study consist of the daily prices of three U.S. investment funds (PIMCO, USCI, and XLK), as well as five macroeconomic and financial factors (1-month U.S. bonds, 10-year U.S. bonds, the S&P 500 index, Brent crude oil, and gold). The sample period spans from January 2015 to December 2025. In other words, it covers both a turbulent period, including the COVID-19 pandemic and the war in Ukraine, as well as a relatively tranquil period prior to these crises. All time series were obtained from the website "Investing.com", and all factor series were synchronized with the available observations of the investment funds. This results in a total of 2,396 observations. Table 1 reports the descriptive statistics for all time series. Before estimating the TGARCH models, the authors transform all empirical price series into logarithmic returns according to the following equation: $r_{i,t} = 100 \times log(P_{i,t}/P_{i,t-1})$, where P denotes the daily price of a given asset. Figure 1 shows the empirical dynamics of the three funds. It is obvious that they experience different patterns, and the objective of this paper is to identify which factors had the greatest impact on the three investment funds.

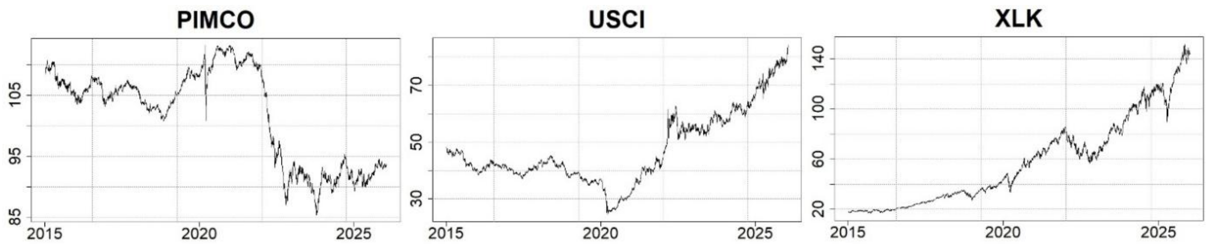

Figure 1. Empirical dynamics of three investment funds

Source: Author's own work.

Table 1. Descriptive statistics of the selected variables

	Mean	St. dev.	Skew.	Kurt.	JB	LB(Q)	LB(Q²)	ADF
PIMCO	-0.002	0.140	-1.333	20.784	37256.5	0.000	0.000	-50.929
USCI	0.008	0.413	-1.222	17.875	26179.6	0.000	0.000	-49.372
XLK	0.033	0.650	-0.304	12.819	11149.9	0.000	0.000	-17.243
1m bonds	-0.122	9.176	-0.594	26.469	55126.6	0.000	0.000	-24.851
10Y bonds	0.010	1.331	0.238	32.368	86126.0	0.000	0.000	-20.779
S&P 500	0.017	0.495	-0.615	20.293	30006.4	0.000	0.000	-17.641
Brent	-0.004	1.118	-0.932	18.258	23589.4	0.061	0.000	-47.516
Gold	0.027	0.444	-0.133	6.477	1213.9	0.384	0.000	-49.180

Note: JB denotes the Jarque–Bera statistic for normality, while LB(Q) and LB(Q^2) refer to the p-values of the Ljung–Box Q-statistic for the levels and squared log-returns, respectively, using 10 lags. The 1% and 5% critical values for the ADF unit root test with 10 lags, assuming only a constant term, are −3.433 and −2.863, respectively.

Source: Author's calculation.

Table 1 presents the descriptive statistics of the log-returns of the analysed financial instruments for the entire sample period. The average returns are generally small, which is consistent with expectations for daily (or high-frequency) data. The highest mean return is recorded for the XLK fund, while negative mean values are observed for the PIMCO fund, Brent crude oil, and 1-month bonds. These results indicate that, in the long run, returns do not deviate substantially from zero, which is typical for financial time series.

The standard deviation reveals considerable differences in volatility across the examined series. The lowest volatility is observed for the PIMCO fund and gold, whereas the XLK fund, the

USCI index, and particularly 1-month bonds exhibit substantially higher volatility. The high standard deviation of short-term bonds may be related to their sensitivity to monetary policy and changes in interest rates, while the increased volatility of equity and commodity instruments reflects market shocks and cyclical movements.

All analysed log-returns exhibit pronounced asymmetry, with most series showing negative skewness, indicating a greater intensity of negative extreme events compared to positive ones. This result is particularly strong for the PIMCO and USCI funds. In addition, kurtosis values are significantly higher than those characteristic of a normal distribution, indicating the presence of fat tails and extreme return realizations. This leptokurtosis is especially pronounced for bond instruments and equity indices.

The Jarque–Bera test results strongly reject the null hypothesis of normality for almost all series, confirming that return distributions deviate substantially from the normal distribution. This finding is consistent with previous empirical research on financial markets and further justifies the use of models that allow for nonlinearities and time-varying volatility, such as GARCH and Markov switching models.

Ljung–Box tests on the levels of log-returns indicate significant autocorrelation in the mean equation in most cases, with the exception of gold. On the other hand, Ljung–Box tests on squared returns strongly indicate the presence of autocorrelation in the variance for all series, providing clear evidence of conditional heteroskedasticity. This implies that the use of an asymmetric AR(1)–TGARCH model is justified, as it should adequately capture the stylized facts observed in financial time series.

Finally, the Augmented Dickey–Fuller (ADF) unit root test results clearly show that all analysed series are stationary, as the test statistics are substantially lower than the critical values at the 1% significance level. This confirms that log-returns are suitable for further econometric analysis within the TGARCH framework.

RESEARCH RESULTS

TGARCH Findings

This subsection presents the results of the estimated TGARCH models. The TGARCH model is used to generate standardized residuals and conditional volatility time series, which are then used to examine shock and volatility spillover effects. Shock spillovers refer to the transmission of unexpected changes in returns from one market or financial asset to another, with effects manifested through movements in the mean and typically being short-term in nature (Xu et al., 2024). In contrast, volatility spillovers represent the transmission of uncertainty and risk across markets (Boubaker et al., 2023), which does not necessarily affect the direction of returns but rather their variability, and is most often more persistent. While shock spillovers indicate a direct market reaction to new information, volatility spillovers reflect the spread of instability and heightened risk, even in the absence of significant price changes.

Shock spillover effects are assessed using the standardized residuals ($z_t = \varepsilon_t/\sqrt{h_t}$) from the asymmetric TGARCH model, while volatility spillovers are evaluated using the conditional variances from the same model. Standardized residuals are preferred to raw log-returns because they isolate the unexpected innovation from time-varying volatility. In financial time series, returns are usually heteroskedastic and volatility clusters over time, meaning that large returns may reflect high-volatility regimes rather than genuinely large shocks. By scaling the residuals by the conditional standard deviation from the TGARCH model, standardized residuals are approximately homoskedastic and more comparable across time, capturing the relative magnitude of shocks in a consistent way. This makes them particularly suitable for shock spillover analysis, while volatility spillovers can be examined separately using the conditional variance series.

Table 2 contains the findings of the estimated TGARCH models. Panel A reports the estimated TGARCH parameters. The parameter α is positive and statistically significant for all instruments, indicating that past shocks affect current volatility. The largest α values are observed for 1-month bonds and the USCI fund, implying that short-run shocks are particularly influential for these instruments. The parameter β is also positive and high across all series (0.806–0.933), which suggests strong volatility persistence, i.e., periods of high or low volatility tend to persist over time. The highest β is recorded for 10-year bonds, indicating especially long-lasting volatility in this market segment. The parameter γ (the so-called leverage effect) reveals interesting differences: a positive and statistically significant γ is found for XLK, 1-month bonds, 10-year bonds, the S&P 500, and Brent oil, suggesting that negative shocks increase volatility more than positive shocks of the same magnitude. For USCI and gold, γ is negative and statistically insignificant, indicating that asymmetry is either absent or weak for these instruments.

Table 2. Results of the estimated TGARCH models

	PIMCO	USCI	XLK	1m bonds	10Y bonds	S&P 500	Brent	Gold
Panel A: T-GARCH parameters								
α	0.071***	0.118***	0.041***	0.142***	0.045***	0.052***	0.072***	0.081***
β	0.911***	0.862***	0.861***	0.810***	0.933***	0.806***	0.852***	0.904***
γ	0.023**	-0.017	0.137***	0.250***	0.044***	0.211***	0.086***	-0.063***
Panel B: Diagnostic tests								
LB(Q)	0.266	0.920	0.266	0.064	0.389	0.390	0.367	0.758
LB(Q^2)	0.835	0.848	0.835	0.601	0.106	0.686	0.784	0.717

Note: The values of LB(Q) and LB(Q^2) represent p-values. The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Author's calculation.

Panel B presents the Ljung–Box (LB) diagnostic tests for the residuals and squared residuals. All p-values are relatively high (>0.05), implying that there is no significant serial dependence in either the residuals or the squared residuals after applying the TGARCH model. This result confirms that the model successfully captures autocorrelation and conditional heteroskedasticity, effectively removing them from the residuals.

The high β parameters, combined with positive α and γ for most instruments, confirm the typical stylized facts of financial time series: strong volatility persistence and asymmetric shock effects. The estimated TGARCH models are used for generating both standardized residuals and conditional volatilities.

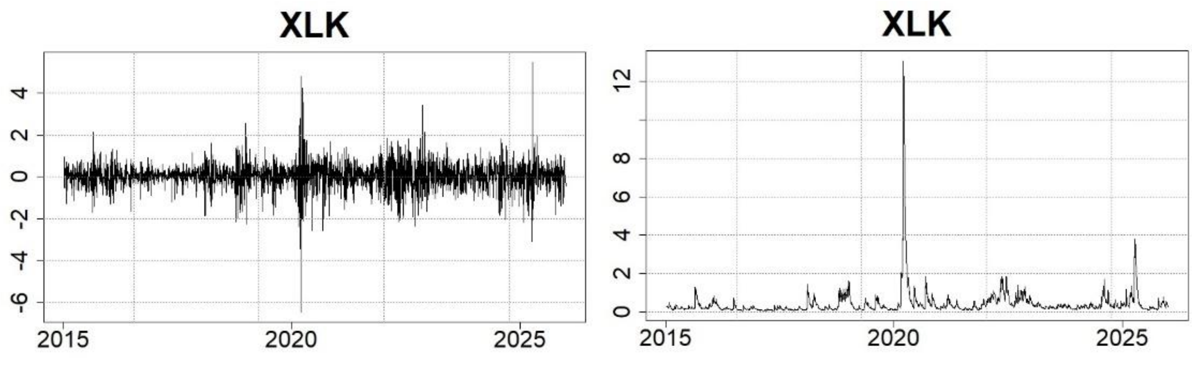

Figure 2. Estimated standardized residuals and conditional volatility of the XLK fund

Source: Author's own work.

For the sake of parsimony, Figure 2 presents only the estimated standardized residuals and conditional volatility of the XLK fund. The plots for all other instruments are available upon request.

Markow Switching Findings – Shock Spillover Effect

This subsection presents the findings of the shock spillover effect, and Table 3 presents the results. In the case of the PIMCO fund, it can be seen that only the S&P 500 has a relatively high shock spillover effect (0.344) in the low volatility regime, while all other factors have a negligible effect. This finding is in line with Jiang et al. (2026), who claimed that bond funds display heterogeneous responses to equity-market, bond-market, geopolitical, and cryptocurrency uncertainty. This might be because PIMCO funds are not purely fixed-income, i.e., they often hold credit-sensitive bonds (corporate, high-yield, emerging market debt). These bonds react to equity market sentiment because equities and corporate bonds share economic and credit risk factors. Therefore, a shock in the S&P 500 can spill over to PIMCO through these credit-sensitive components. In addition, spillovers are higher in the low-volatility regime, probably because market conditions are stable during calm periods, and correlations are relatively predictable. In that sense, a positive or negative shock in equities (S&P 500) can propagate clearly to bond prices and the fund's returns because other risk factors (credit, liquidity, volatility spikes) are small. Therefore, the relative influence of the S&P 500 shock is magnified. On the other hand, in high-volatility (crisis) periods, many shocks occur simultaneously (credit spreads widen, liquidity dries up, yields spike). These dominate fund returns, so the marginal effect of S&P 500 shocks is diluted, reducing spillover.

In the case of the USCI fund, Brent oil (0.361) and gold (0.251) have a relatively high shock spillover effect on the USCI fund in the high-volatility regime. This concurs with Shah et al. (2025), who reported strong cross-market linkages and increased connectedness between investment funds and oil and gold. On the other hand, the S&P 500 has a relatively high effect (0.147) in the low-volatility regime. High-volatility periods are often triggered by commodity shocks, geopolitical crises, or inflation spikes, so in these periods, Brent oil and gold exhibit large price swings. Since USCI is commodity-linked, these shocks directly impact its returns, producing relatively high shock spillover. On the other hand, equity shocks (S&P 500) are less influential because the main holdings of USCI are not equities. In calm periods, S&P 500 returns are a bigger driver of USCI returns than commodities because commodities are relatively stable in low-volatility periods. This means that shocks in oil and gold are small, which leads to a lower shock spillover effect.

Table 3 indicates that only the S&P 500 has a strong shock spillover effect on the XLK fund in both regimes, while all other factors have no effect. This is because XLK is basically a concentrated slice of the S&P 500, and the shock channel mainly captures new information hitting prices immediately. The shock spillover is higher in the low-volatility regime, which may look counterintuitive, but it actually makes sense econometrically and financially. In low volatility periods, XLK movements are usually cleaner and more systematic. Therefore, when the S&P 500 has a shock, it becomes a dominant driver of XLK standardized residuals. On the other hand, in high-volatility regimes, XLK is affected by many additional shocks (earnings surprises, rate shocks, sector rotations, liquidity events). That means the S&P 500 shock still remains, but it becomes less dominant relative to everything else happening.

Panel B of Table 3, as well as Figure 3, describe the regime-switching properties. In other words, Panel B presents the estimated regime transition probabilities (P_{ij}) and the expected duration of each regime for the selected instruments.

Table 3. Markov switching results of the shock spillover effect

			PIMCO	USCI	XLK
	Regimes	**Parameters**	**Panel A: Estimated MS parameters**		
1m U.S. bonds	**1**	$\boldsymbol{\omega 1_1^{log}}$	**0.000**	**0.000**	**-0.001***
	2	$\omega 1_2^{log}$	-0.001	-0.001*	0.003**
10Y U.S. bonds	1	$\omega 2_1^{log}$	-0.069***	0.002	-0.016***
	2	$\omega 2_2^{log}$	-0.097***	0.014**	-0.009
S&P 500	1	$\omega 3_1^{log}$	0.031***	0.116***	1.146***
	2	$\omega 3_2^{log}$	0.344***	0.147***	1.462***
Brent	1	$\omega 4_1^{log}$	0.003	0.361***	-0.033***
	2	$\omega 4_2^{log}$	0.010	0.098***	-0.015
Gold	1	$\omega 5_1^{log}$	0.016***	0.251***	-0.004
	2	$\omega 5_2^{log}$	0.043**	0.174***	0.019
			Panel B: Regime properties		
P11	—	—	0.667	0.996	0.989
P12	—	—	0.333	0.003	0.010
P21	—	—	0.046	0.004	0.013
P22	—	—	0.954	0.996	0.987
Expected duration – 1	—	—	3.0	269.1	95.7
Expected duration – 2	—	—	21.8	228.7	79.4

Note: The symbols ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Regime 1 corresponds to the high-volatility (crisis) period, while Regime 2 corresponds to the low-volatility (tranquil) period.

Source: Author's calculation.

For the PIMCO fund, the diagonal elements of the transition matrix are relatively high ($P_{11} = 0.667$, $P_{22} = 0.954$), suggesting that both regimes tend to persist for several periods. Regime 1 has an expected duration of 3 days, while Regime 2 is considerably longer-lasting (21.8 days), implying that short-term shocks are quickly replaced by a more stable state.

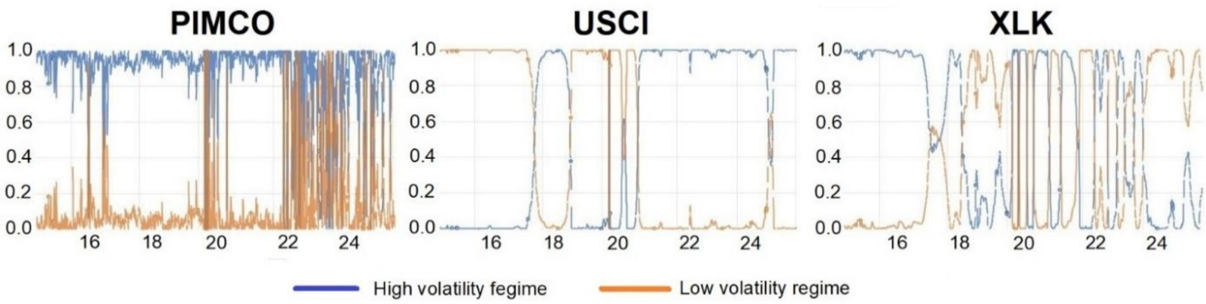

Figure 3. Dynamic regime probabilities of shock spillover effect

Source: Author's own work

For the USCI fund, the diagonal elements are extremely high ($P_{11} = 0.996$, $P_{22} = 0.996$), while the off-diagonal elements are very small, implying that the regimes are highly stable and that transitions are almost nonexistent. The expected durations are in the hundreds of days (269.1 and 228.7), meaning that the series effectively remains in the same regime for large portions of the sample. Such dynamics indicate that USCI fund volatility is not prone to abrupt regime shifts, and that the market tends to remain in the same state (calm or turbulent) for extended periods.

For the XLK fund, a similar pattern emerges: the diagonal elements are high ($P_{11} = 0.989$, $P_{22} = 0.987$)and the off-diagonal elements are low, showing that the regimes are also highly persistent. The expected duration of Regime 1 is 95.7 days, while Regime 2 lasts 79.4 days on average. This suggests that XLK fund volatility also remains within the same regime over longer time horizons, and that abrupt changes are relatively rare.

Markow Switching Findings – Volatility Spillover Effect

This subsection presents the results of the volatility spillover effects between the factors and the three funds. Table 4 contains these results. It can be seen that neither factor has an economically significant volatility spillover effect on the PIMCO fund in either regime. This may be because the PIMCO returns are largely determined by its diversified fixed-income portfolio and active duration and risk management. Consequently, even when external factors experience large volatility shocks, PIMCO's own volatility remains relatively stable, rendering spillovers from these factors negligible across both regimes.

In the case of the USCI fund, the 10-year bonds, the S&P 500 and Brent have a relatively high volatility spillover effect on the USCI fund in the low-volatility regime. In calm periods, commodity markets tend to be driven mainly by macro-financial conditions and growth expectations: The S&P 500 volatility reflects changes in global risk appetite. Even in calm regimes, shifts in equity sentiment often spill over to broad commodity exposure through portfolio rebalancing and "risk-on/risk-off" positioning. The 10-year bond volatility captures changes in interest-rate expectations and discount rates. In stable regimes, rates move mostly due to macro news (inflation/growth), which also affects commodity demand expectations and futures pricing. Finally, the Brent volatility matters strongly because energy is usually a large weight in broad commodity indices. Oil is also highly sensitive to global demand and geopolitical news, so it transmits volatility easily into USCI.

Table 4. Markov switching results of the volatility spillover effect

			PIMCO	USCI	XLK
	Regimes	**Parameters**	**Panel A: Estimated MS parameters**		
1m U.S. bonds	1	$\omega 1_1^{vol}$	0.000***	0.000	-0.000*
	2	$\omega 1_2^{vol}$	0.000***	-0.001***	-0.000***
10Y U.S. bonds	1	$\omega 2_1^{vol}$	0.002***	-0.001	-0.002
	2	$\omega 2_2^{vol}$	0.000***	0.407***	-0.034***
S&P 500	1	$\omega 3_1^{vol}$	0.042***	0.173***	0.975***
	2	$\omega 3_2^{vol}$	0.024***	2.842***	1.245***
Brent	1	$\omega 4_1^{vol}$	-0.015***	0.006***	-0.016***
	2	$\omega 4_2^{vol}$	-0.001***	0.472***	0.008***
Gold	1	$\omega 5_1^{vol}$	0.014***	0.135***	0.491***
	2	$\omega 5_2^{vol}$	0.018***	0.597	1.525***
			Panel B: Regime properties		
P11	–	–	0.980	0.984	0.990
P12	–	–	0.020	0.016	0.009
P21	–	–	0.007	0.984	0.047
P22	–	–	0.992	0.016	0.953
Expected duration – 1	–	–	50.0	61.7	105.7
Expected duration – 2	–	–	129.3	1.0	21.3

Note: See Table 3.

Source: Author's calculation.

Only the volatilities of the S&P 500 and gold have a significant volatility spillover effect on the XLK fund in both regimes, but higher in the calm regime. XLK consists almost entirely of technology stocks. Its volatility is naturally driven by equity market risk, so the S&P 500 volatility is a direct and dominant source of uncertainty. On the other hand, XLK is not directly exposed to gold, but gold volatility is often anti-correlated with equity market stability, acting as a risk or uncertainty indicator. Even in calm periods, mild changes in gold volatility may signal shifts in safe-haven demand or macroeconomic uncertainty, which can influence investor sentiment and indirectly affect tech stocks.

Panel B in Table 4 reports regime properties, while Figure 4 shows graphical dynamics of the regimes. The diagonal probabilities of the PIMCO fund are very high ($P_{11} = 0.980$, $P_{22} = 0.992$), indicating strong regime persistence. The expected duration is 50.0 days in regime 1 and 129.3 days in regime 2, suggesting that the fund spends long periods in each state and that regime shifts are relatively rare.

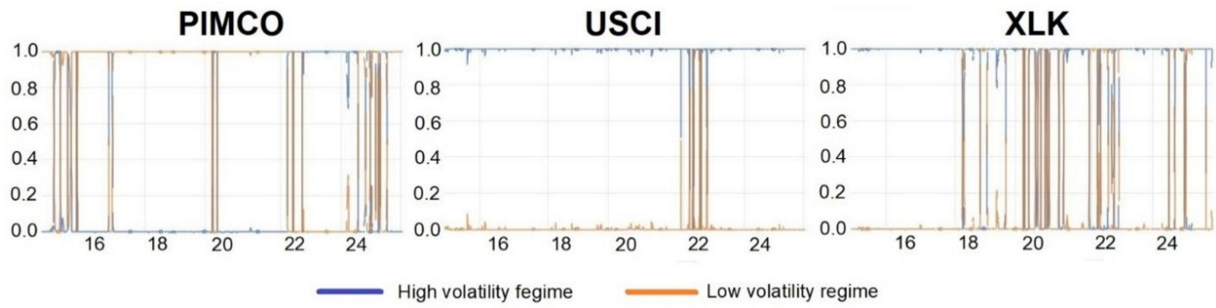

Figure 4. Dynamic regime probabilities of volatility spillover effect

Source: Author's own work

For the USCI fund, regime 1 appears highly persistent ($P_{11} = 0.984$) with an expected duration of 61.7 days, while regime 2 is extremely short-lived, with an expected duration of only 1.0 day. This pattern implies that volatility spikes are mostly transitory and that the series quickly reverts back to the dominant regime.

For the XLK fund, both regimes are also persistent ($P_{11} = 0.990$, $P_{22} = 0.953$). The expected duration is 105.7 days for regime 1 and 21.3 days for regime 2, indicating that the fund typically remains in the calm state for extended periods, while the high-volatility regime is shorter but still meaningfully persistent.

DISCUSSION

The paper reveals heterogeneous shock and volatility spillover results that may have different implications for fund managers and investors. For instance, the S&P 500 shocks transmit to PIMCO, especially in the low-volatility regime. This means that even bond-oriented funds may remain sensitive to equity-market innovations through credit-sensitive holdings and changes in risk sentiment. For fund managers, this implies that equity-market shocks should not be ignored in fixed-income strategies, especially during tranquil periods when cross-market linkages are cleaner and more visible. On the other hand,

The PIMCO fund is only weakly exposed to external volatility transmission from the selected global factors. This implies that PIMCO volatility is primarily shaped by internal portfolio structure, active duration management, credit allocation, and liquidity positioning. For investors, this suggests that PIMCO may provide a relatively stable risk profile across regimes and can serve as a defensive component in diversified portfolios.

For the USCI fund, Brent oil and gold dominate in the high-volatility regime, while the S&P 500 plays a larger role in the low-volatility regime. This implies that in crisis periods, USCI behaves as a commodity-driven instrument, where shocks in key commodity benchmarks transmit quickly into fund returns. For investors, this confirms that commodity-linked funds tend to react most strongly to commodity-specific turbulence, which typically occurs in high-volatility states.

At the same time, the volatility spillover results show that in tranquil regimes, macro-financial volatility from the S&P 500 and long-term interest rates becomes highly relevant for USCI. This indicates that even when commodity prices appear stable, the fund's risk can still be driven by changes in global risk appetite and interest-rate expectations. This means that fund managers should treat equity-market volatility and long-term bond market uncertainty as key drivers of commodity fund volatility. This is especially true during calm periods when portfolio rebalancing and global macro positioning dominate commodity pricing.

The XLK fund is strongly exposed to S&P 500 shocks in both regimes, and the magnitude is even higher in the low-volatility regime. This implies that XLK is not an independent equity segment, but rather a concentrated representation of the broader U.S. equity market. For investors, this means that holding XLK alongside broad market ETFs offers limited diversification benefits and may increase overall portfolio sensitivity to market-wide surprises.

In terms of volatility spillovers, XLK is significantly affected by S&P 500 volatility and gold volatility in both regimes, with stronger effects in the calm regime. This has two key interpretations. First, equity-market uncertainty is naturally the dominant volatility driver for technology-sector portfolios, reinforcing the importance of systematic risk management. Second, gold volatility appears to function as an uncertainty or risk-sentiment proxy, indicating that safe-haven dynamics indirectly influence technology-sector risk even without direct exposure. For fund managers, these findings imply that index-based hedging (S&P 500 futures and options) should be central to XLK risk control, especially during tranquil regimes when spillovers are strongest and hedging effectiveness is likely higher.

CONCLUSION

This paper investigated how key global financial and macroeconomic factors affect investment funds investing in different asset classes. Specifically, the authors examined the transmission of both shock and volatility spillovers from five global factors—1-month interest rates, 10-year interest rates, Brent crude oil, gold, and the S&P 500 index—into three U.S. investment funds representing bond, commodity, and equity market exposures (PIMCO, USCI, and XLK). The authors employ an asymmetric TGARCH model to construct standardized residuals and conditional variances, and subsequently estimated Markov switching models with two regimes representing high- and low-volatility market conditions.

The empirical results reveal that spillover effects are strongly fund-specific and depend on the market regime. In the shock spillover channel, the PIMCO fund is primarily influenced by shocks from the S&P 500, particularly in the low-volatility regime. For the USCI fund, the shock spillovers are regime-dependent: Brent crude oil and gold exert strong effects during high-volatility periods, while the S&P 500 becomes more influential during tranquil periods. In the case of XLK, the results show that only the S&P 500 has a strong and statistically significant shock spillover effect in both regimes, with the effect being even stronger in the low-volatility regime.

The volatility spillover findings provide additional insights. For the PIMCO fund, none of the factors generate economically meaningful volatility spillovers across regimes, indicating that the fund's volatility is largely determined by its internal portfolio structure and active risk management. For USCI, volatility spillovers from the S&P 500, 10-year interest rates, and Brent oil are particularly strong in the low-volatility regime. This suggests that macro-financial uncertainty and risk appetite are important drivers of commodity fund volatility in tranquil periods. For XLK, volatility spillovers from the S&P 500 and gold are significant in both regimes, with stronger effects in calm periods. This indicates that equity-market uncertainty is the dominant volatility driver while gold volatility acts as an indirect proxy for shifts in risk sentiment and safe-haven demand.

The results of this paper could be interesting for investors in funds and fund managers. In other words, investors should recognize that XLK offers limited diversification against U.S. equity shocks, USCI provides commodity-driven exposure that becomes highly sensitive to oil and gold shocks in crises, and PIMCO remains relatively stable in terms of volatility spillovers but is still affected by equity-market shocks through credit and sentiment channels. For fund managers, the results highlight the importance of regime-aware risk management and the need to monitor systematic equity risk, commodity-specific shocks, and interest-rate uncertainty depending on the fund asset-class exposure and the prevailing volatility state.

The analysis is restricted to PIMCO, USCI, and XLK and only five global factors, limiting generalizability and omitting other relevant variables. The TGARCH and Markov switching models rely on historical data, which may not fully capture structural breaks or unprecedented shocks, and the findings from 2015–2025 may not extend to other markets or periods. Future research could expand the fund sample, incorporate additional macro-financial variables, explore alternative econometric approaches, and compare different regions and crisis periods to improve robustness and insight.

REFERENCES

Alexakis, C., Niarchos, N., Patra, T., & Poshakwale, S. (2005). The dynamics between stock returns and mutual fund flows: Empirical evidence from the Greek market. *International Review of Financial Analysis*, 14(5), 559–569.

Alsubaiei, B.J., Calice, G., & Vivian, A. (2023). How does oil market volatility impact mutual fund performance? *International Review of Economics and Finance*, 89(PA), 1601–1621.

Amar, R., Candelon, B., Lecourt, C., & Xun, W. (2019). Country factors and the investment decision-making process of sovereign wealth funds. *Economic Modelling, 81*, 72–85.

Assefa, T. A., Esqueda, O. A., & Mollick, A. V. (2017). Stock returns and interest rates around the world: A panel data approach. *Journal of Economics and Business, 89*, 20–35.

Ausloos, M., Zhang, Y., & Dhesi, G. (2020). Stock index futures trading impact on spot price volatility: The CSI 300 studied with a TGARCH model. *Expert Systems with Applications,* 160, 113688.

Babalos, V., & Balcilar, M. (2017). Does institutional trading drive commodities prices away from their fundamentals? Evidence from a nonparametric causality-in-quantiles test. *Finance Research Letters*, 21, 126–131.

Bali, T. G., Brown, S. J., & Caglayan, M. O. (2014). Macroeconomic risk and hedge fund returns. *Journal of Financial Economics,* 114(1), 1–19.

Boubaker, S., Karim, S., Naeem, M. A., & Sharma, G. D. (2023). Financial markets, energy shocks, and extreme volatility spillovers. *Energy Economics*, 126, Article 107031.

Çepni, O., Christou, C., & Gupta, R. (2023). Forecasting national recessions of the United States with state-level climate risks: Evidence from model averaging in Markov-switching models. *Economics Letters,* 227, 111121.

Ciarlone, A., & Miceli, V. (2016). Escaping financial crises? Macro evidence from sovereign wealth funds' investment behaviour. *Emerging Markets Review, 27*, 169–196.

Dekker, P., Vivar, L.M., Wedow, M., & Weistroffer, C. (2024). Liquidity buffers in open-end corporate bond funds during the COVID-19 market turmoil. *International Review of Financial Analysis, 87*, 101909.

Đekić, M., Gavrilović, M., Roganović, M., & Gojković, R. (2017). The role of investment funds in countries with transition economies. *Economic Analysis*, 50(1–2), 1–12.

Fiszeder, P., Fałdziński, M., & Molnár, P. (2023). Investor attention to oil prices and the comovement of ETFs: A multivariate volatility approach. *Energy Economics, 118*, 106643.

Jiang, Z., Ozcelebi, O., Lü, Z., El Khoury, R., & Yoon, S.-M. (2026). Global bond fund responses to financial uncertainty: Evidence from volatility, geopolitical risk, and digital currency shocks. *Global Finance Journal, 53*, 101227.

Koo, M., & Muslu, V. (2023). Fund flows and asset valuations of bond mutual funds: Effect of side-by-side management. *Journal of Banking and Finance*, 154, 106961.
Korenak, B., & Stakić, N. (2021). Beyond the returns - the U.S. mutual funds value and growth style weighted sector portfolios investment performance attribution. *Economic Analysis*, 54(2), 1–19.
Krause, T., & Tse, Y. (2013). Volatility and return spillovers in Canadian and U.S. industry ETFs. *International Review of Economics and Finance*, 25, 244–259.
Lee, B.-S., Paek, M., Ha, Y., & Ko, K. (2015). The dynamics of market volatility, market return, and equity fund flow: International evidence. *International Review of Economics and Finance*, 35, 214–227.
Leite, P. (2024). Performance and investment styles of international multi-asset funds during market crises. *Empirica*, 51, 783–805.
Liu, Y., & Hu, J. (2025). Sovereign wealth fund performance during the COVID-19 pandemic: Regional and strategic perspectives. *Digital Finance, 3*(1), 100047.
Musawa, N., & Mwaanga, C. (2017). The impact of commodity prices, interest rate and exchange rate on stock market performance: Evidence from Zambia. *Journal of Financial Risk Management,* 6(3), 300–313.
Pinto-Ávalos, F., Bowe, M., & Hyde, S. (2024). Revisiting the pricing impact of commodity market spillovers on equity markets. *Journal of Commodity Markets,* 33, 100369.
Qian, L., Zeng, Q., & Li, T. (2022). Geopolitical risk and oil price volatility: Evidence from Markov-switching model. *International Review of Economics and Finance,* 81(C), 29–38.
Sabiruzzaman, M., Huq, M. M., Beg, R. A., & Anwar, S. (2010). Modeling and forecasting trading volume index: GARCH versus TGARCH approach. *The Quarterly Review of Economics and Finance,* 50(2), 141–145.
Shah, W. U., Missaoui, I., Younis, I., & Liu, X. (2025). Evaluating market downturn connectedness between S&P 500 index funds, gold, and oil markets. *Journal of Futures Markets,* 45(9), 1278–1297.
Shi, Y. (2022). A closed-form estimator for the Markov switching in mean model. *Finance Research Letters,* 44, 102107.
Stützle, M. (2020). Persistence of averages in financial Markov switching models: A large deviations approach. *Physica A: Statistical Mechanics and Its Applications,* 553, 124237.
Valadkhani, A., & Marashdeh, H. (2026). Regime-dependent causality between Chinese and U.S. equity markets: Evidence from Markov switching models. *Research in International Business and Finance,* 83, Article 103285.
Wu, H., Li, P., Cao, J., & Xu, Z. (2024). Forecasting the Chinese crude oil futures volatility using jump intensity and Markov-regime switching model. *Energy Economics,* 134, 107588.
Wu, H. (2025). Cultural biases in the investment decision-making process of institutional investors. *International Review of Financial Analysis, 106*, 104576.
Xu, Y., Guan, B., Lu, W., & Heravi, S. (2024). Macroeconomic shocks and volatility spillovers between stock, bond, gold and crude oil markets. *Energy Economics*, 136, 107750.
Zhang, X., & Zhang, T. (2022). Barrier option pricing under a Markov regime switching diffusion model. *The Quarterly Review of Economics and Finance,* 86, 273–280.

Article history:	Received: 9.2.2026.
	Revised: 12.3.2026
	Accepted: 17.3.2026.