Scientific Annals of Economics and Business
73 (SI), 2026, 59-114
DOI: 10.47743/saeb-2026-0023

Asymmetric Shocks and Long-Memory Volatility: An Egarch Approach to Global Oil and Local Import Dynamics

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Abstract: This study investigates the volatility dynamics of commodity import prices in Republic of Moldova and global Brent crude oil prices, employing advanced econometric models to enhance understanding of risk in small open economies and energy markets. Utilizing monthly data from 1992 to 2025 for Republic of Moldova's Commodity Import Price Index and from January 1990 to May 2025 for Brent oil, the analysis confirms that both series are integrated of order one, with no significant structural breaks in the mean, supporting constant-parameter modelling. For Republic of Moldova's Commodity Import Price Index, an AR (1)-GARCH (1,1) specification effectively captures high volatility persistence and symmetric shock responses, indicating long-memory effects without asymmetry. In contrast, Brent oil exhibits leverage effects, where negative shocks amplify volatility more than positive ones, best demonstrated via AR(1)-EGARCH(1,1,1). Comprehensive diagnostics, including ADF tests, Bai-Perron structural break analysis, ARCH-LM, Ljung-Box, and Nyblom stability tests, validate model adequacy, confirming residual whiteness and structural stability. These findings underscore the need for symmetric risk management in Republic of Moldova's import sector and asymmetric hedging in oil markets, with implications for macroeconomic stability and policy formulation. Research gaps highlight opportunities for multivariate spillover analysis and regime-switching models to address cross-market dependencies.

Keywords: volatility modeling; GARCH; EGARCH; commodity import price index, structural breaks, leverage effects, small open economies.

JEL classification: C22; C58; Q02; Q41; Q43; F41.

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Article history: Received 5 November 2025 | Accepted 5 June 2026 | Published online 23 July 2026

To cite this article: Diavor, M., Pârțachi, I. (2026). Asymmetric Shocks and Long-Memory Volatility: An Egarch Approach to Global Oil and Local Import Dynamics. *Scientific Annals of Economics and Business*, 73(SI), 59-114. https://doi.org/10.47743/saeb-2026-0023.

1. INTRODUCTION

Commodity markets play a pivotal role in the global economy, influencing everything from energy prices to agricultural outputs and, by extension, the macroeconomic stability of nations. Volatility in these markets – characterized by sudden and unpredictable price fluctuations – poses significant challenges for policymakers, investors, and businesses, particularly in small open economies like Republic of Moldova that rely heavily on imports. This research delves into the intricate dynamics of commodity price volatility, with a specific focus on Republic of Moldova's *Commodity Import Price Index, Individual Commodities Weighted by Ratio of Imports to GDP with Recent Fixed Weights (CIPI)* and *global Brent crude oil prices*.

We use the full monthly histories available at the time of the study, data are from the IMF's Primary Commodity Price System (IMF, 2025), 1992–2025 for the Republic of Moldova's Commodity Import Price Index (CIPI) and January 1990 - May 2025 for Brent oil – because these spans maximize information, improve statistical power, and ensure the analysis reflects all major commodity and energy price regimes observed to date. The CIPI begins in 1992 due to data availability following Republic of Moldova's statehood; Brent is available earlier, so we retain its pre-1992 observations to better characterize its own dynamics and volatility. Employing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) techniques – standard GARCH and Exponential GARCH (EGARCH) – we uncover high persistence, symmetric shock responses for import prices, and pronounced asymmetry with leverage effects in oil markets. These insights enhance understanding of risk transmission to vulnerable economies and inform hedging, policy design, and resilience strategies.

Commodity prices exhibit clustering, long-memory effects, and differential responses to shocks – phenomena theorized by Engle's (1982) ARCH and Bollerslev's (1986) GARCH. For the Republic of Moldova, a landlocked nation dependent on imported energy and raw materials, import price volatility directly impacts inflation, trade balances, and fiscal stability. Our empirical investigation (1992–2025) reveals Moldova's CIPI series is integrated of order one (I(1)), displaying symmetric volatility with near-unit-root persistence ($\alpha + \beta \approx 0.97$), implying a volatility half-life of approximately two years. This symmetry indicates positive and negative shocks affect volatility equally, without leverage effects seen in financialized assets. Comprehensive diagnostics – Augmented Dickey-Fuller (ADF) for stationarity, Bai-Perron for structural breaks (none detected in mean), HEGY for seasonality (absent), and post-estimation ARCH-LM, Ljung-Box, and Nyblom stability tests – confirm AR(1)-GARCH(1,1) model robustness. Conversely, Brent oil exhibits asymmetric dynamics where negative shocks amplify volatility more than positive ones (leverage effect), captured by AR(1)-EGARCH(1,1) with shorter half-life (~1.6 months), highlighting faster mean reversion in highly traded commodities.

Volatility modeling has proven essential across energy, agriculture, and metals sectors. In developing economies, fluctuations exacerbate external vulnerabilities, as seen in Moldova's exposure to global supply shocks, geopolitical tensions, and currency risks. Bridging theory with evidence, the present paper is deliberately univariate in scope: it estimates and diagnoses conditional-volatility models for the two series individually – AR(1)-GARCH(1,1) for CIPI and AR(1)-EGARCH(1,1) for Brent – and compares their persistence, asymmetry and stability properties within a common methodological frame. Extensions that fall outside this scope – multivariate spillover analyses quantifying cross-market volatility transmission and regime-switching frameworks accommodating dynamic parameter shifts – are identified as directions for future research and are not claimed as contributions of the present study. Findings underscore tailored risk management –diversification for symmetric, persistent import basket volatilities and asymmetric hedging for oil-driven asymmetries – contributing to macro-stability and sustainable development in small open economies. This introduction sets the stage for detailed exploration of methodologies, results, and policy implications, building on rigorous diagnostics to provide actionable insights for stakeholders navigating an increasingly volatile global landscape.

Current state of research. The literature on commodity-price volatility has developed along four broad pillars that together define the current state of the art. The first pillar is methodological: Engle's (1982) ARCH and Bollerslev's (1986) GARCH frameworks established the baseline for modelling time-varying conditional variance, and Nelson (1991)'s EGARCH and Zakoïan's (1994) TGARCH/TARCH extensions introduced the asymmetric responses to positive and negative shocks that have since become a defining stylised fact of financial and commodity series. The second pillar consists of single-commodity empirical applications, predominantly on energy: Sadorsky (2006) and Kang *et al.* (2009) documented strong volatility clustering, persistence and leverage effects in crude oil; Wei *et al.* (2010) and Hung *et al.* (2018) showed that asymmetric specifications systematically outperform symmetric GARCH in forecasting oil volatility; and more recent work by Mușetescu *et al.* (2022) and Merabet *et al.* (2021) has applied AR–EGARCH and ARIMA–EGARCH frameworks to Brent and WTI with a forecasting focus. The third pillar broadens the empirical base to non-energy commodities and to the long-run record: Pindyck and Rotemberg (1990), Karali and Power (2013) and Jacks *et al.* (2011) established that volatility clustering, long memory and time-varying co-movement are pervasive across agricultural, metals and aggregate commodity series, while Bai and Perron (1998, 2003), Hammoudeh and Li (2008) and Aloui and Jammazi (2009) developed and applied structural-break and regime-switching tools that have become standard preliminaries to any GARCH-family estimation. The fourth pillar addresses transmission to small open and import-dependent economies, emphasising how global commodity volatility passes through to domestic inflation, trade balances and fiscal stability; this strand remains dominated by large emerging markets and resource exporters, with relatively few studies of diversified import baskets in post-transition landlocked economies. The present study sits at the intersection of the second and fourth pillars: it brings the asymmetric-GARCH toolkit developed for single-commodity oil markets and the structural-break and seasonality diagnostics developed for commodity time series to a small open economy – the Republic of Moldova – and, by estimating both an aggregated import-price index and Brent oil within the same methodological frame, delivers a direct comparison of persistence and asymmetry across levels of aggregation that the existing literature does not provide.

The remainder of this Introduction states, in order, the rationale for analysing these two indicators in parallel, the specific objectives of the study, its contributions to the literature, and its novelty relative to prior GARCH-family work on oil and commodity prices.

Rationale for the parallel analysis. The two indicators are studied side by side for four related reasons. First, they are economically linked rather than independently chosen: Brent is the dominant global price signal for the energy complex and, through direct fuel imports and indirect pass-through into the prices of transported, processed and petroleum-intensive goods, is a primary external driver of the Republic of Moldova's import bill. Any framework aimed at informing Moldovan stabilisation policy must therefore characterise both the upstream benchmark and the downstream aggregate. Second, the two series sit at deliberately different levels of aggregation – a single globally-traded commodity versus a diversified, GDP-weighted import basket – which allows us to test whether the stylised facts established for individual commodities (volatility clustering, asymmetric leverage, rapid mean reversion) survive aggregation into a national import index, or whether diversification reshapes them. Third, estimating both series with the same preliminary tests (ADF, Bai-Perron, HEGY) and the same GARCH-family toolkit, and subjecting both models to the same post-estimation diagnostics (ARCH-LM, Ljung-Box, Nyblom), yields an apples-to-apples comparison of persistence, asymmetry and stability that neither series could deliver on its own. Fourth, this comparison is directly policy-relevant for a small open economy: the horizon over which shocks dissipate, and the sign-dependence of the volatility response, differ sharply between the external benchmark and the domestic aggregate, implying that hedging strategies calibrated to oil dynamics cannot be transplanted to the management of the wider import basket. The empirical contrast that emerges – short-horizon, asymmetric volatility in Brent versus long-horizon, symmetric volatility in CIPI – is therefore not an incidental by-product of the analysis but its central finding, and it is available only because the two indicators are modelled jointly within a common methodological frame.

Objectives. Against this backdrop, the present study pursues four explicit objectives. First, it characterizes and models the conditional volatility of the Republic of Moldova's Commodity Import Price Index (CIPI) over the period 1992–2025 using an AR(1)-GARCH(1,1) specification, uncovering the degree of volatility persistence and the symmetric nature of shock responses in an aggregated import-price basket. Second, it models global Brent crude oil price volatility (January 1990–March 2025) through an AR(1)-EGARCH(1,1) framework, documenting asymmetric leverage effects and estimating the speed of mean reversion. Third, it subjects both models to a comprehensive battery of diagnostics– Augmented Dickey-Fuller unit-root tests, Bai-Perron structural-break detection, HEGY seasonality tests, post-estimation ARCH-LM and Ljung-Box residual tests, and Nyblom parameter-stability tests–to ensure statistical robustness and model adequacy. Fourth, it translates the empirical findings into actionable risk-management and policy recommendations tailored to small open economies exposed to commodity-price uncertainty.

Contributions. This paper makes several additions to a well-developed literature. It addresses a recognized gap by applying rigorous univariate volatility modeling to a diversified commodity import-price index for a post-transition, landlocked small open economy–a context largely absent from the existing GARCH literature, which has concentrated on individual energy commodities or large emerging markets. It demonstrates empirically that the symmetric GARCH specification is the appropriate model for an aggregated import-price basket, in contrast to the asymmetric EGARCH model required for a single energy commodity, thereby clarifying the modeling choice for researchers working with composite price indices. It further establishes that Moldova's import-price volatility carries a half-life of approximately two years, implying that standard short-horizon stabilization policies are insufficient to absorb persistent external price shocks, a finding with direct fiscal and monetary-policy implications. Finally, the study provides a replicable methodological template–integrating stationarity testing, structural-break detection, seasonality testing, and

GARCH-family estimation with full diagnostics–that can be applied to other small open economies seeking to quantify and manage commodity-price risk.

Novelty relative to the literature. The novelty of the present study is twofold. First, prior GARCH-family applications to oil have focused overwhelmingly on individual benchmarks and have been conducted on developed-market or large emerging-market perspectives: Sadorsky (2006) and Kang *et al.* (2009) established asymmetric leverage effects in WTI and Brent returns; Mușetescu *et al.* (2022) estimated AR–EGARCH dynamics on Brent with a forecasting focus; and Merabet *et al.* (2021) documented ARIMA–EGARCH forecast performance on daily oil data. Our Brent estimates (AR(1)-EGARCH(1,1,1), 1990m01–2025m05, leverage coefficient γ statistically significant and negative, volatility half-life ≈ 1.6 months) are directionally consistent with the asymmetry and clustering documented in these studies, while extending the sample to the full post-2020 period that incorporates the pandemic and post-pandemic regimes not available to earlier work. Second, and more substantively, we document that these oil-market stylized facts do not carry over mechanically to an aggregated import-price basket: our CIPI estimates (AR(1)-GARCH(1,1), $\alpha + \beta \approx 0.97$, no leverage effect in TARCH specification, volatility half-life ≈ 23 months) show that diversification across commodities in an import basket damps the asymmetric response observed in single-commodity oil studies while preserving–indeed amplifying–the persistence. To our knowledge, this contrast has not previously been documented for a post-transition, landlocked small open economy, and it carries direct implications for the design of stabilization policies, which we develop in §4.5.

Key Concepts and Theoretical Underpinnings

- **Volatility Clustering and Persistence**: Commodity prices often show periods of high volatility followed by calm, with effects lingering over time, as modeled by GARCH parameters where the sum of α (arch effect) and β (garch effect) approaches unity, indicating long-memory processes.
- **Asymmetry and Leverage Effects**: In assets like oil, negative news (e.g., supply disruptions) disproportionately increases uncertainty, a feature EGARCH models by incorporating the sign and magnitude of shocks.
- **Structural Stability**: The absence of significant breaks in our series supports constant-parameter modeling, validated against tests for regime changes, ensuring reliable forecasts for policy applications.

This synthesis draws from extensive empirical validation, establishing a foundation for understanding how global commodity dynamics ripple into local economies like Republic of Moldova's, with implications extending to risk assessment, portfolio optimization, and economic forecasting.

Structure of the paper. The remainder of the paper is organised as follows. Section 2 presents a comprehensive literature review of volatility modelling in commodity markets, covering the GARCH-family methodological foundations, single-commodity empirical evidence from energy and agricultural markets, stylised facts and modelling challenges specific to commodity series, and applications to small open economies and import-price dynamics. Section 3 describes the methodological framework, including the data sources (IMF (2025) Primary Commodity Price System for Brent, and the Republic of Moldova's Commodity Import Price Index), the preliminary testing strategy (Augmented Dickey-Fuller unit-root tests, Bai-Perron structural-break detection and HEGY seasonality tests), and the specification of the AR(1)-GARCH(1,1) and AR(1)-EGARCH(1,1) models. Section 4 reports the empirical results for both series, including parameter estimates, the full battery of post-estimation diagnostics (ARCH-LM, Ljung-Box and Nyblom tests), a comparative discussion of persistence, asymmetry and mean reversion across the two models, and the implications for risk management and public policy in small open economies (Section 4.5). Section 5 concludes, summarising the main findings and outlining directions for future research. Supporting tables – correlograms, full diagnostic output and auxiliary test statistics – are provided in the Annex.

2. VOLATILITY MODELING IN COMMODITY MARKETS: A COMPREHENSIVE LITERATURE REVIEW

Synthesis, Controversies and Research Gaps. The GARCH-family literature on commodity volatility has converged on a small set of stylised facts and an equally small set of persistent controversies. Four points of broad consensus can be identified.

(i) Commodity prices exhibit time-varying conditional variance with pronounced clustering and long memory, documented across energy, agricultural and metals markets Sadorsky (2006), Kang *et al.* (2009), Karali and Power (2013), Jacks *et al.* (2011).

(ii) Single-commodity series, and crude oil in particular, display statistically significant asymmetric leverage effects, with negative shocks amplifying volatility more than positive shocks of equal magnitude Nelson (1991), Wei *et al.* (2010), Hung *et al.* (2018), Olanrewaju and Oseni (2021).

(iii) Preliminary testing for unit roots, structural breaks and seasonality is a necessary precondition for GARCH estimation on commodity series Hylleberg *et al.* (1990), Bai and Perron (1998, 2003), Hammoudeh and Li (2008).

(iv) Global commodity volatility transmits to domestic economies through import costs, exchange rates and input-output linkages, with particular intensity in small, open and import-dependent economies (Cashin *et al.*, 2000; Raddatz, 2007; van der Ploeg and Poelhekke, 2009; Frankel, 2012).

Against these points of consensus three active controversies remain. First, whether parsimonious GARCH(1,1) is adequate or whether higher-order and mixed-data-sampling alternatives deliver material forecasting gains – Hansen and Lunde (2005) argue that little beats GARCH(1,1), whereas Wang *et al.* (2023) and Lin *et al.* (2020) document improvements from regime-switching and MIDAS extensions. Second, whether the appropriate framework for commodity-market shocks is a stable asymmetric GARCH specification or a regime-switching / structural-break model with time-varying parameters Aloui and Jammazi (2009), Lin *et al.* (2020) – an unresolved question directly relevant to any study that must decide whether to impose constant parameters. Third, whether asymmetric leverage effects established for individual energy commodities survive aggregation into a diversified commodity basket: Pindyck and Rotemberg (1990) and Creti *et al.* (2013) suggest that composition and diversification effects can dampen or even eliminate the asymmetry observed at the single-commodity level, but the empirical evidence on aggregate import-price indices is thin.

These controversies open three research gaps that frame the present study. First, the GARCH-family literature is dominated by applications to individual commodities – especially oil – and by large emerging markets; rigorous univariate modelling of a diversified national import-price index in a post-transition, landlocked small open economy remains largely absent. Second, there is no direct comparison, within a single methodological frame and common diagnostic battery, of the persistence and asymmetry properties of a global single-commodity benchmark against those of an aggregated import basket that includes that benchmark among its drivers. Third, the literature offers limited guidance on whether the short-horizon hedging strategies calibrated to oil-market asymmetry are appropriate for managing the risk of a diversified import basket in a small open economy with limited monetary-policy space. The present study is designed to address these three gaps directly.

The volatility of commodity prices presents a fundamental challenge for policymakers and researchers analyzing international trade and economic stability. Since Engle (1982) and Bollerslev (1986), sophisticated econometric models for time-varying volatility have revolutionized understanding of financial and commodity markets. Early applications of these frameworks to commodity markets quickly confirmed their relevance: Pindyck and Rotemberg (1990) documented pronounced time-varying co-movement and volatility in a broad cross-section of commodity prices, while Sadorsky (2006) and Kang *et al.* (2009) provided seminal GARCH- and EGARCH-based evidence of volatility clustering, persistence and asymmetric leverage effects in crude oil markets. These studies established that conditional-variance models originally devised for inflation and equity returns are equally – and in some respects more – informative for commodity prices, where supply disruptions, inventory shocks and speculative pressures generate the very volatility dynamics that standard homoskedastic models fail to capture. GARCH models and their extensions now provide powerful tools for analyzing commodity price movements.

This literature review examines volatility modeling in commodity markets, emphasizing GARCH family models' application and performance across sectors and contexts. It synthesizes theoretical developments, empirical findings, and applications spanning four decades, from foundational volatility clustering work to contemporary machine learning and regime-switching advances.

Commodity price volatility profoundly impacts economic policy, risk management, and development, particularly in small open economies dependent on commodity imports. Stylized facts – volatility clustering, asymmetric shock responses, and long memory properties – present unique modeling challenges distinct from traditional financial market research.

Beginning with theoretical foundations from Engle (1982), Bollerslev (1986), and Nelson (1991) – namely the ARCH, GARCH and EGARCH specifications, respectively – we trace symmetric and asymmetric GARCH specifications adapted to commodity markets. We examine empirical literature across energy, agricultural, and metal sectors, noting that asymmetric models consistently outperform symmetric specifications in capturing commodity price volatility.

The review emphasizes applications for small open economies, examining how global commodity price volatility transmits domestically through import prices and exchange rates. We analyze the growing multivariate GARCH and volatility spillover literature, increasingly important as markets become interconnected and financialized.

Contemporary developments – machine learning integration, structural breaks and regime change modeling, and high-frequency data incorporation – are examined for theoretical and forecasting contributions. We focus on policy implications, particularly for developing and import-dependent countries.

The synthesis reveals consistent patterns: asymmetric volatility models' superiority, heavy-tailed error distributions' importance, volatility shock persistence, and increasing global commodity market interconnectedness. Significant gaps remain in understanding diversified commodity import basket dynamics, transmission mechanisms between global commodity volatility and domestic conditions, and global supply chain structural changes' impact on volatility.

This review provides researchers, policymakers, and practitioners comprehensive understanding of current knowledge in commodity volatility modeling while identifying research directions addressing challenges in an increasingly complex global commodity market environment.

2.1. Modeling Commodity Price Volatility: Foundations, Developments, and Applications in Small Open Economies

2.1.1. Commodity Price Volatility: Theoretical Foundations and Modeling Approaches

The volatility of commodity prices represents one of the most significant sources of economic uncertainty for small open economies, particularly those heavily dependent on commodity imports. The development of sophisticated econometric models to capture, predict, and manage this volatility has become increasingly critical for policymakers and risk managers. This literature review examines the extensive body of research on volatility modeling in commodity markets, with particular emphasis on GARCH family models, their extensions, and applications to import price dynamics in emerging and small open economies.

The theoretical foundations of volatility modeling in commodity markets have evolved substantially since the pioneering work of Engle (1982) on Autoregressive Conditional Heteroskedasticity (ARCH) models and the subsequent generalization by Bollerslev (1986) into GARCH specifications. These developments emerged from the recognition that traditional econometric models, which assume constant variance, fail to capture the distinctive stylized facts observed in commodity price series: volatility clustering, leptokurtosis, and time-varying conditional variance. The adaptation of these models to commodity markets has revealed unique characteristics that distinguish commodity price volatility from traditional financial asset volatility. Empirical applications of these frameworks to commodity data quickly validated their relevance: Sadorsky (2006) documented strong volatility clustering and persistence in petroleum futures, Kang *et al.* (2009) confirmed the same stylized facts for crude oil across multiple GARCH specifications, Karali and Power (2013) demonstrated long-memory volatility in agricultural commodities, and Jacks *et al.* (2011) showed that these volatility features have characterized commodity prices over more than a century. Together, these studies provide the empirical foundation on which subsequent commodity-specific volatility modeling has been built.

2.1.2. Evolution of GARCH Models in Commodity Market Analysis

The standard GARCH(1,1) model, while foundational, has proven insufficient for capturing the full complexity of commodity price dynamics. Nelson (1991) introduced the EGARCH model to address the asymmetric response of volatility to positive and negative shocks, a phenomenon initially observed in equity markets but subsequently documented in various commodity markets. The EGARCH specification allows for leverage effects, where negative price shocks generate disproportionately larger volatility responses than positive shocks of equal magnitude. This asymmetry has particular relevance for energy commodities, where supply disruptions and geopolitical events often manifest as sharp price increases accompanied by heightened uncertainty.

Threshold GARCH (TARCH) models, developed by Zakoïan (1994) provide an alternative framework for modeling asymmetric volatility responses. These models partition the impact of innovations based on their sign, allowing for different volatility responses to positive and negative shocks while maintaining the computational simplicity of the original GARCH framework. The choice between EGARCH and TARCH specifications often depends on the specific commodity market under investigation and the nature of the asymmetric effects present in the data. Empirical applications across commodity markets have generally favoured the asymmetric specifications: Wei *et al.* (2010) find that EGARCH and TGARCH outperform symmetric GARCH in forecasting crude oil volatility, Hung *et al.* (2018) identify EGARCH(1,1) with Student-t errors as the preferred model for world oil prices, Olanrewaju and Oseni (2021) document significant leverage effects in Nigerian crude oil price volatility, and Dinku and Worku (2022) report that EGARCH and TGARCH provide the best fit across major agricultural commodities in Ethiopia. These studies establish empirically that asymmetric responses to positive and negative shocks are a pervasive feature of commodity price data rather than a purely theoretical possibility.

2.1.3. Commodity Market Stylized Facts and Modeling Challenges

Commodity markets exhibit several distinctive characteristics that differentiate them from traditional financial markets and create unique modeling challenges. First, commodity prices often display pronounced seasonality patterns, particularly for agricultural products, which necessitate careful treatment of deterministic seasonal components before applying volatility models Hylleberg *et al.* (1990), Canova and Hansen (1995). Second, commodity markets frequently experience structural breaks associated with policy changes, technological innovations, or shifts in global supply and demand patterns, as documented by Bai and Perron (1998, 2003) and Hammoudeh and Li (2008). These breaks can significantly affect volatility persistence and require sophisticated modeling approaches such as regime-switching GARCH models or models with time-varying parameters Aloui and Jammazi (2009), Lin *et al.* (2020).

The concept of convenience yield, unique to commodity markets, introduces additional complexity to volatility modeling. Unlike financial assets, commodities provide utility through their physical properties and storage characteristics, creating non-monetary benefits that affect price dynamics and volatility patterns Yang *et al.* (2001), Pindyck and Rotemberg (1990). This convenience yield can vary substantially over time, particularly during periods of supply stress, leading to complex volatility dynamics that challenge standard GARCH specifications Sadorsky (2006), Wei *et al.* (2010).

2.1.4. Applications to Small Open Economies and Import Price Dynamics

For small open economies, commodity price volatility poses distinctive challenges that have attracted increasing research attention Raddatz (2007), van der Ploeg and Poelhekke (2009). These economies typically face price-taking behavior in international commodity markets, making them vulnerable to external price shocks without the ability to influence global price formation Cashin *et al.* (2000), Frankel (2012). The transmission of international commodity price volatility to domestic economies occurs through multiple channels: direct import costs, exchange rate effects, and second-order impacts through input-output linkages across sectors Abdulkareem and Abdulkareem (2016).

Research on import price volatility in small open economies has revealed several important empirical regularities. Import price indices often exhibit higher volatility persistence than individual commodity prices due to aggregation effects across multiple commodities and the influence of domestic factors such as exchange rate fluctuations and trade policies Cashin *et al.* (2000), Jacks *et al.* (2011). The volatility of aggregate import price indices may also display different asymmetric properties compared to individual commodity prices, as the composition effects and domestic economic conditions can dampen or amplify external shocks in complex ways Pindyck and Rotemberg (1990), Creti *et al.* (2013).

2.1.5. Methodological Considerations and Model Selection

The application of GARCH models to commodity markets requires careful attention to model specification, diagnostic testing, and parameter interpretation Hansen and Lunde (2005), Patton (2011). The choice between symmetric and asymmetric GARCH models should be guided by formal testing procedures, including likelihood ratio tests and information criteria, rather than a priori assumptions about market behavior Laurent *et al.* (2012). Diagnostic tests for remaining heteroskedasticity, normality of standardized residuals, and parameter stability are essential for ensuring model adequacy Nyblom (1989), Hansen (1990).

Methodological advances have emphasized the importance of robust estimation procedures and finite-sample properties of GARCH estimators, particularly relevant for commodity price series that may contain outliers or structural breaks Brooks *et al.* (2001), Hammoudeh and Li (2008). The development of quasi-maximum likelihood estimation and robust standard errors has improved the reliability of inference in GARCH models applied to commodity data Bollerslev (1986), Hansen and Lunde (2005).

2.1.6. Contemporary Research Frontiers

Current research in commodity price volatility modeling is expanding along several dimensions, including multivariate volatility spillovers Diebold and Yilmaz (2012), high-frequency and mixed-data-sampling approaches Wang *et al.* (2023), and the integration of fundamental macroeconomic and weather variables into volatility models Karali and Power (2013). Multivariate GARCH models increasingly examine volatility spillovers between related commodity markets and transmission mechanisms across the global commodity complex Diebold and Yilmaz (2012), Silvennoinen and Thorp (2013), Chevallier and Ielpo (2013). These models are particularly valuable for analyzing interconnections between energy and agricultural markets, where biofuel policies and climate considerations create complex linkages Serra (2011), Nomikos and Pouliasis (2011).

High-frequency volatility modeling, utilizing intraday price data, represents another active research area Liu and Wan (2012). Availability of real-time commodity price data has enabled application of realized volatility measures and mixed-data sampling (MIDAS) approaches, providing more accurate volatility forecasts and better understanding of intraday volatility patterns in commodity markets Wang *et al.* (2023).

Integration of fundamental variables into volatility models constitutes a third frontier, where researchers link commodity price volatility to underlying supply and demand factors, weather conditions, inventory levels, and macroeconomic variables Karali and Power (2013), Wang *et al.* (2023). These structural approaches promise to improve both explanatory power and forecasting performance of volatility models while providing deeper insights into economic drivers of commodity price uncertainty Kristjanpoller and Minutolo (2015), Ramos-Pérez *et al.* (2019).

2.2. Theoretical Foundations of Volatility Modeling

The canonical references for the methods operationalised in this study are already standard in the specialised literature and are therefore summarised here only to the extent needed to signpost the research approach; for a fuller treatment the reader is referred to Section 2.1 above and to the original sources. The GARCH-family apparatus adopted below rests on three foundational contributions: Engle (1982), who introduced ARCH and established that conditional variance is time-varying and predictable; Bollerslev (1986), who generalised ARCH to the parsimonious GARCH(p,q) specification that has since become the workhorse for volatility analysis; and the asymmetric extensions of Nelson (1991) and Zakoïan (1994), which admit leverage effects and thereby accommodate the differential impact of positive and negative innovations documented in the empirical commodity-market literature reviewed in Section 2.1.2.

2.3. GARCH Applications in Commodity Markets

2.3.1. Energy Markets and Oil Price Volatility

The application of GARCH models to commodity markets has been extensive, with energy markets receiving particular attention due to their economic importance and volatility characteristics. Kang *et al.* (2009) conducted a comprehensive study of oil price volatility using various GARCH specifications, finding that the EGARCH model outperformed standard GARCH models in capturing asymmetric volatility patterns in crude oil markets. Their research demonstrated that negative oil price shocks generate higher volatility than positive shocks, confirming leverage effects in energy markets. This has important implications for risk management, suggesting that downside risk measures should receive greater attention in portfolio optimization and hedging strategies.

Recent empirical evidence has further strengthened the case for asymmetric volatility models in oil markets. Al-Sharoot and Al-Rashide (2024) compared GARCH, EGARCH, and ARMA-GARCH models for OPEC oil prices, finding that EGARCH(1,1) with Student's t-distributed errors best predicts oil price fluctuations as indicated by information criteria (AIC, SIC, H-QIC). This supports using EGARCH for capturing asymmetric and leptokurtic nature of oil price volatility.

Hung *et al.* (2018) provided additional confirmation by forecasting world oil price volatility using GARCH(1,1), EGARCH(1,1), and GJR-GARCH(1,1) models under various error distributions. Their findings demonstrated that EGARCH(1,1) with Student's t-distribution provides the most accurate forecasts, emphasizing the importance of modeling asymmetry and heavy tails in oil price returns. Importantly, their study noted that past volatility is a strong predictor of future volatility, while price shocks have relatively minor direct impact.

The COVID-19 pandemic provided a unique natural experiment for testing volatility models under extreme market conditions. Amiri and Remita (2022) investigated crude oil price volatility during this period using the GARCH(1,2) model for WTI oil prices. Interestingly, while EGARCH and TGARCH models are theoretically superior at capturing volatility asymmetry, their analysis demonstrated that GARCH(1,2) outperformed them in forecasting accuracy for the pandemic period, with predicted and actual values closely aligning. This highlights the importance of model validation under different market conditions and suggests that forecasting performance may vary significantly during crisis periods.

Sadorsky (2006) examined volatility dynamics of petroleum futures using various GARCH models, providing evidence that energy futures volatility exhibits both clustering and asymmetric responses to market shocks, highlighting the importance of accurately modeling and forecasting volatility in these key markets for developing investment and hedging strategies.

Wei *et al.* (2010) investigated crude oil price volatility using a comprehensive set of GARCH family models, including standard GARCH, EGARCH, and threshold GARCH (TGARCH) specifications. Their comparative analysis revealed that while all models successfully captured volatility clustering, the asymmetric models (EGARCH and TGARCH) provided superior forecasting performance, particularly for short-term horizons, reinforcing the importance of accounting for asymmetric volatility effects in commodity price modeling.

2.3.2. Advanced Modeling Approaches for Oil Markets

Recent research has explored more sophisticated approaches to modeling oil price volatility. Wang *et al.* (2023) proposed an augmented EGARCH-MIDAS model to incorporate the effects of extreme shocks (such as wars and financial crises) on oil price volatility. Their results demonstrated that extreme shocks significantly increase volatility, with negative shocks having a larger effect than positive ones. The EGARCH-MIDAS-ES model, which accounts for asymmetry and long-term shock effects, outperformed conventional GARCH-MIDAS models in both in-sample and out-of-sample forecasts.

Lin *et al.* (2020) compared uni-regime GARCH-type models and hidden Markov regime-switching models for WTI and Daqing crude oil markets. The HM-EGARCH model outperformed all competitors, effectively capturing different volatility states and providing superior forecasting performance in both developed and emerging markets. This research highlights the importance of considering regime changes and structural breaks in oil market volatility modeling.

Mușetescu *et al.* (2022) estimated and forecasted Brent crude oil volatility using GARCH(1,1), GARCH-M(1,1), and EGARCH(1,1) models. They found that EGARCH(1,1) is preferred for measuring conditional variance due to its ability to capture negative reactions to market shocks. However, for forecasting purposes, the symmetric GARCH-M(1,1) model proved most efficient over their analyzed period, suggesting that the choice between symmetric and asymmetric models may depend on the specific application and time period.

Merabet *et al.* (2021) applied ARIMA-GARCH and EGARCH models to daily oil price data, concluding that the ARIMA(3,1,1) + EGARCH(1,2) model provides the best forecasts, with predicted and actual values closely matching. This underscores the value of combining ARIMA for mean dynamics with EGARCH for volatility modeling.

Nomikos and Pouliasis (2011) analyzed the volatility spillover effects between crude oil and refined product markets using multivariate GARCH models. Their research documented significant volatility transmission mechanisms across the petroleum complex, with implications for integrated oil companies and refiners' risk management strategies. The study demonstrated that understanding cross-market volatility dynamics is crucial for effective hedging in interconnected commodity markets.

2.3.3. Oil Market Applications in Developing Economies

The application of GARCH models to oil markets in developing economies has revealed important insights about volatility patterns and their macroeconomic implications. Abdulkareem and Abdulkareem (2016) analyzed macroeconomic and oil price volatility in Nigeria using GARCH, GARCH-M, EGARCH, and TGARCH models. Their findings highlighted that all macroeconomic variables, including oil price, are highly volatile. Importantly, asymmetric models (EGARCH and TGARCH) outperformed symmetric GARCH models, indicating the significance of accounting for asymmetry in volatility modeling. The study concluded that oil price volatility is a major source of macroeconomic instability in Nigeria and recommended economic diversification to mitigate these effects.

Olanrewaju and Oseni (2021) examined Nigerian crude oil price volatility using GARCH and its variants, finding that GARCH(2,1) best models price volatility, while IGARCH(1,1) is optimal for production and export volatility. The study confirmed that positive and negative shocks have asymmetric effects on volatility, supporting the use of asymmetric models in oil-dependent economies.

Two findings from the non-energy commodity literature bear directly on the analysis of the Republic of Moldova's aggregate import price index, in which food and agricultural goods form a substantial share of the basket. Karali and Power (2013) provide FIGARCH evidence of long-memory volatility in agricultural commodity prices, showing that shocks to agricultural price volatility persist over extended horizons – a property directly relevant to the CIPI persistence hypothesis (H1). Serra (2011) documents significant volatility spillovers from oil to agricultural commodity markets that intensified following the 2007–2008 food crisis, reinforcing the rationale for analysing Brent and a diversified Moldovan import basket within one methodological frame.

2.3.4. Import Price Dynamics and Small Open Economies

The specific application of volatility modeling to import price dynamics in small open economies represents a crucial but relatively understudied area of research. Cashin *et al.* (2000) examined commodity price volatility and its impact on developing countries using a comprehensive dataset spanning multiple decades. Their analysis revealed that commodity price shocks tend to be highly persistent, with half-lives typically exceeding several years. This persistence has significant implications for fiscal and monetary policy in commodity-dependent economies, as it suggests that temporary shocks can have long-lasting effects on government revenues and balance of payments.

Jacks *et al.* (2011) investigated the historical evolution of commodity price volatility over more than a century, finding that while the average level of volatility has remained relatively stable, there have been significant changes in volatility persistence and cross-commodity correlations. Their research suggests that globalization and financialization have altered the nature of commodity price risks, making diversification strategies less effective and increasing the importance of sophisticated risk management techniques.

Pindyck and Rotemberg (1990) examined the co-movement of commodity prices using factor models and found evidence of "excess co-movement" that cannot be explained by common macroeconomic fundamentals alone. Their findings suggest that psychological factors and speculative behavior play important roles in commodity price dynamics, with implications for the effectiveness of traditional hedging strategies based on fundamental analysis.

2.3.5. Asymmetric Volatility Effects and Leverage

The documentation and modeling of asymmetric volatility effects in commodity markets has been a significant focus of recent research. Glosten *et al.* (1993) introduced the TGARCH model, providing an alternative framework for capturing asymmetric volatility responses. Their model allows for different volatility responses to positive and negative innovations of the same magnitude, offering greater flexibility than the standard GARCH specification while maintaining computational tractability.

The empirical evidence consistently supports the superiority of asymmetric models across various commodity markets and time periods. The studies reviewed demonstrate that EGARCH and TGARCH models, which account for asymmetry and leverage effects, generally outperform symmetric GARCH models in modeling and forecasting oil and commodity price volatility. This finding has been confirmed across different commodities, markets, and shock characteristics, making the case for asymmetry modeling particularly robust.

Awartani and Maghyereh (2013) analyzed the dynamic spillovers between oil prices and stock markets in the Gulf Cooperation Council (GCC) countries, finding that these spillovers are significant and have important implications for portfolio diversification in the region.

Chevallier and Ielpo (2013) investigated volatility spillover effects across a range of commodity markets, providing evidence of the interconnectedness of market-specific shocks and highlighting how volatility is transmitted between different assets. Their work demonstrates that volatility effects are not limited to individual markets but are part of a broader system of commodity interdependencies.

2.3.6. Risk Management and Hedging Applications

The practical application of volatility models to risk management and hedging in commodity markets represents a crucial bridge between academic research and industry practice. Ederington and Salas (2008) examined the effectiveness of various hedging strategies for commodity price risk, finding that the choice of volatility model significantly affects hedging performance. Their research highlighted the importance of accurate volatility forecasting for optimal hedge ratio determination and demonstrated that asymmetric models generally produce superior hedging outcomes.

Chang *et al.* (2013) investigated the conditional correlations and volatility spillovers between crude oil markets and stock index returns, finding that the relationship between these markets is time-varying, which has critical implications for investors hedging oil risk with equity instruments.

Brooks *et al.* (2001) examined the statistical accuracy of GARCH model parameter estimation, finding that the choice of estimation technique can significantly impact the reliability of the model's parameters, which is a foundational concern for any subsequent application like forecasting or hedging.

2.3.7. Structural Breaks and Regime Changes

The presence of structural breaks and regime changes in commodity markets has important implications for volatility modeling and forecasting. Hammoudeh and Li (2008) examined sudden structural changes in the volatility of Gulf Arab stock markets using the Bai-Perron methodology, finding multiple break points corresponding to major regional and global economic events. Their research demonstrates the importance of testing for structural stability in volatility models.

Liu and Wan (2012) examined the impact of financialization on commodity market volatility regimes, finding that increased financial market participation has led to more frequent regime switches and higher volatility persistence. Their findings suggest that traditional volatility models may need to be adapted to account for the changing nature of commodity markets in an increasingly financialized global economy.

2.4. Policy Implications and Small Open Economies

The implications of commodity price volatility for small open economies have received increasing attention in the literature, particularly following the commodity price boom and bust cycles of the 2000s and 2010s. Raddatz (2007) examined the impact of commodity price shocks on small open economies using a comprehensive cross-country dataset, finding that these economies are particularly vulnerable to external price shocks due to their limited diversification capabilities and constrained policy space.

Frankel (2012) investigated the resource curse phenomenon and its relationship to commodity price volatility, arguing that the volatility of commodity prices rather than their level may be the primary driver of the resource curse. Frankel's research suggests that volatility management through appropriate fiscal and monetary policies may be more important than traditional concerns about Dutch disease effects.

Van der Ploeg and Poelhekke (2009) examined the impact of commodity price volatility on economic growth in developing countries, finding that volatility has a significant negative effect on growth prospects. Their research highlights the importance of developing institutions and policies that can effectively manage commodity price risks, including the establishment of stabilization funds and the development of domestic financial markets that can provide hedging opportunities.

2.5. Emerging Market Considerations

Volatility modeling in emerging market commodity sectors presents unique challenges due to data limitations, structural changes, and institutional factors. Malik and Hammoudeh (2007) examined volatility spillovers between US and Gulf equity markets in the context of oil price shocks, finding that spillover effects are asymmetric and time-varying. Their research highlights the importance of considering institutional and structural differences when applying volatility models developed in advanced market contexts to emerging markets.

Aloui and Jammazi (2009) investigated crude oil and stock market interactions in emerging markets using a regime-switching approach, finding evidence of non-linear dependence structures that vary with market conditions. Their research suggests that traditional linear correlation measures may be inadequate for capturing the full range of dependencies between commodity and financial markets in emerging economies.

Creti *et al.* (2013) examined the financialization of commodity markets and its impact on emerging market economies, finding that increased financial market participation has altered the traditional relationships between commodity fundamentals and prices. Their research has important implications for emerging market policymakers, as it suggests that traditional commodity market analysis may be less reliable in an increasingly financialized environment.

2.6. From the Literature to the Present Study: Justification and Research Hypotheses

Justification

The literature reviewed above establishes that (a) the GARCH-family toolkit is the standard device for modelling commodity-price volatility, (b) asymmetric specifications are typically needed for individual energy commodities, (c) structural-break and seasonality testing are preconditions for valid inference, and (d) transmission to small open economies operates through multiple channels. Yet the existing evidence has been built almost entirely on single-commodity series and on large emerging or developed markets. The Republic of Moldova – a landlocked, post-transition small open economy whose import bill combines energy, food, metals and manufactures – provides a setting in which the diagnostic and modelling questions raised by the literature can be addressed jointly for a single global benchmark (Brent crude oil) and a diversified national aggregate (the Commodity Import Price Index, CIPI). The present study is therefore not a redundant re-estimation of known oil-market facts but a deliberate test of whether those facts carry over to the aggregate import-price series that actually drives Moldovan external vulnerability. The contrast between the two series is the analytical payoff of the exercise.

Research hypotheses.

Guided by the literature synthesised above, the study tests four hypotheses:

H1: *(persistence in the aggregate basket). The conditional volatility of the Republic of Moldova's CIPI exhibits high persistence in the sense of an AR(1)-GARCH(1,1) specification with $\alpha + \beta$ close to unity, consistent with the long-memory features documented across aggregate commodity indices by* Karali and Power (2013) *and* Jacks *et al.* (2011).

H2: *(symmetry in the aggregate basket). Because diversification across commodities and composition effects dampen individual-commodity asymmetries* (Pindyck and Rotemberg, 1990; Creti *et al.*, 2013), *the CIPI does not exhibit statistically significant leverage effects*

– formally, the asymmetry parameter of a TARCH/EGARCH specification estimated on CIPI is not significantly different from zero.

***H3**: (asymmetric leverage in Brent). Global Brent crude oil prices exhibit statistically significant negative leverage effects in an AR(1)-EGARCH(1,1,1) specification, consistent with the body of evidence from* Sadorsky (2006)*,* Kang *et al.* (2009)*,* Wei *et al.* (2010)*,* Hung *et al.* (2018) *and* Olanrewaju and Oseni (2021)*, and extending this evidence to a sample that includes the post-2020 pandemic and post-pandemic regimes.*

***H4**: (differential mean reversion). The half-life of a volatility shock is substantially shorter in Brent than in the CIPI, reflecting the difference between a financialised, continuously traded global benchmark and a monthly aggregated national import index – an implication consistent with the market-integration and financialisation evidence of* Tang and Xiong (2012) *and* Büyükşahin and Robe (2014).

These four hypotheses are taken to Sections 3 and 4, where the methodology and estimation results test each one explicitly.

3. METHODOLOGICAL REVIEW

This section presents the empirical framework used to model the conditional volatility of CIPI and Brent. The methods are standard in the specialised literature and are therefore described only to the extent needed to indicate the research approach; fuller expositions are available in the original sources cited below. The framework addresses the four stylised features documented in Section 2 – volatility clustering and long memory Sadorsky (2006), Karali and Power (2013), asymmetric responses to positive and negative innovations (Nelson, 1991; Zakoïan, 1994; Wei *et al.*, 2010), seasonality in monthly commodity series Hylleberg *et al.* (1990), Canova and Hansen (1995), and endogenous structural change Bai and Perron (1998, 2003), Hammoudeh and Li (2008) – through a sequential pipeline that runs preliminary unit-root and seasonality tests on the log-differenced series before any conditional-variance modelling is attempted.

Structural change is detected endogenously via the Bai and Perron (1998, 2003) procedure, which accommodates regime shifts without imposing prior break dates. Conditional variance is then estimated with the GARCH family – GARCH(p,q) (Bollerslev, 1986), EGARCH (Nelson, 1991) and TARCH (Zakoïan, 1994) – with model selection driven by empirical performance and diagnostic adequacy in the manner recommended by Hansen and Lunde (2005) and Laurent *et al.* (2012), rather than by prior assumptions about the sign of asymmetry.

Post-estimation diagnostics assess residual behaviour and parameter stability using the standard battery – ARCH-LM Engle (1982) for remaining conditional heteroskedasticity, Ljung–Box for serial correlation in standardised and squared standardised residuals, and the Nyblom (1989) / Hansen (1990) stability tests for time-invariance of the estimated parameters – and model selection integrates information criteria with economic and forecasting performance along the lines discussed by Patton (2011) and Brooks *et al.* (2001).

The same pipeline is applied to both series, delivering the apples-to-apples comparison of persistence, asymmetry and stability between a global single-commodity benchmark and a diversified national import basket that motivates this study (see Sections 2.6 and 4).

3.1. Analytical Framework and Research Design

This study employs a comprehensive econometric framework to analyze the volatility dynamics of two monthly price series: the Republic of Moldova's Commodity Import Price Index (CIPI, 1992m01–2025m05) and the global Brent crude oil price (1990m01–2025m05). Because both series are non-stationary in levels but stationary in first differences of their logarithms (see Section 4), the object of estimation throughout is the monthly continuously-compounded return r_t = Δlog P_t = log(P_t) − log(P_(-1)), denoted dlog(CIPI) and dlog(Oil Brent) respectively. The methodology is structured in three distinct phases: (i) preliminary data analysis including unit-root and seasonality testing on the log-differenced series, (ii) endogenous identification of structural breaks via the Bai–Perron procedure, and (iii) volatility modeling using GARCH-family specifications fitted to r_t. This sequential approach ensures that the statistical properties of r_t are fully characterized before proceeding to conditional-variance modeling, thereby enhancing the reliability and interpretability of the empirical findings.

At each stage, diagnostic test outcomes inform the next modelling choice – a sequencing consistent with best practice in the GARCH-family literature Hansen and Lunde (2005), Patton (2011) – and the monthly sample runs from 1992m01 to 2025m05 for CIPI and from 1990m01 to 2025m05 for Brent.

3.2. Preliminary Data Analysis

3.2.1. Unit Root Testing

The order of integration of each series is established via the Augmented Dickey–Fuller test applied first to the price level log(P t) and then to the log-differenced return r_t; the ADF regression is:

$$\Delta y_{s,t} = \alpha_{0,s} + \alpha_{1,s}\, t + \gamma_s y_{s,t-1} + \sum_{j=1}^{p_s} c_{s,j} \Delta y_{s,t-j} + \varepsilon_{s,t}, \quad s \in \{CIPI, Brent\}, \quad t = 1, \dots, T_s \tag{1}$$

where:

y_{s,t} denotes the series under test for s ∈ {CIPI, Brent} (either the log-price log P_{s,t} in levels or the log-return r_{s,t} = *Δ*log P_{s,t});

Δ is the first-difference operator; *α*_{0,s} is the series-specific intercept;

*α*_{1,s}·t the deterministic linear trend;

*γ*_{s} the unit-root coefficient on the lagged level;

{c_{s,j}}_{j=1}^{p_s} the coefficients on the augmenting lagged differences;

p_{s} the lag length selected by information criterion separately for each series;

*ε*_{s,t} a zero-mean white-noise disturbance;

T_{s} the sample size for series s.

The null hypothesis of a unit root is H_{0}: *γ*_{s} = 0 against the stationary alternative H_{1}: *γ*_{s} < 0. Tables 1–2 (CIPI) and the analogous Brent tables in Section 4 confirm that both series are I(1), so that r_{s,t} = *Δ*log P_{s,t} is the stationary variable entering the volatility models.

3.2.2. Seasonality Tests

Because monthly commodity series may display both deterministic and stochastic seasonality, the log-differenced return r_t is subjected to a standard battery of seasonality diagnostics: the Levene test for seasonal heteroskedasticity, the Kruskal–Wallis non-parametric test for seasonal location differences, the Canova and Hansen (1995) test for deterministic-seasonal stability, and the HEGY test for seasonal unit roots at the zero, Nyquist and annual frequencies Hylleberg *et al.* (1990). These tests are standard in the commodity-volatility literature – see, inter alia, Hammoudeh and Li (2008) – and full formal statements are available in the original sources; their joint purpose here is to establish whether any deterministic or stochastic seasonal component must be removed before GARCH estimation. The empirical outcomes for CIPI and Brent are reported in Tables no. 3 and no. 14 of Section 4.

3.3. Structural Break Analysis: Bai–Perron Test

Endogenous breaks in the conditional mean of r_t are identified via the Bai and Perron (1998, 2003) multiple-break procedure, which jointly estimates the break dates and the regime-specific coefficients without imposing prior break locations. The linear regression with m breaks (m+1 regimes) is:

$$y_t = x_t'\beta^{(j)} + u_t \quad \text{for } t = T_{j-1} + 1, \dots, T_j \tag{2}$$

with j = 1,…,m+1,unknown break dates (T_1,…,T_m),T_0 = 0,T_{m+1} = T.The break dates are estimated by minimising the sum of squared residuals:

$$min_{\{\beta^{(j)}\}_{j=1}^{m+1},\{T_j\}_{j=1}^{m}} \sum_{j=1}^{m+1} \sum_{t=T_{j-1}+1}^{T_j} \left(y_t - x_t'\beta^{(j)}\right)^2 \tag{3}$$

Model selection uses the SupF(l+1|l) sequential test along with the BIC and LWZ information criteria, subject to the standard minimum segment length restriction of ε = 0.15T (at least 15% of observations per regime). Full formal statements, including break date confidence intervals, are given in Bai and Perron (1998, 2003); their application in commodity volatility studies is illustrated by Hammoudeh and Li (2008).

3.4. Volatility Modeling Framework

Conditional volatility is modelled with the GARCH family (Bollerslev, 1986; Nelson, 1991; Zakoïan, 1994). In the standard GARCH(p,q) specification the variance is driven by past squared innovations (ARCH terms) and past conditional variances (GARCH terms), with covariance stationarity requiring $\alpha + \beta < 1$. We consider three specifications – AR(1)-GARCH(1,1), TARCH (Glosten *et al.*, 1993; Zakoïan, 1994) and EGARCH Nelson (1991) – and select between them on the basis of in-sample diagnostic adequacy and information criteria Hansen and Lunde (2005), Laurent *et al.* (2012). For a fuller formal exposition the reader is referred to the original sources.

3.4.1. AR(1)-GARCH(1,1)

To absorb short-run serial correlation in r_t, the mean equation is augmented with an AR(1) term:

Mean equation:

$$r_t = \mu + \phi r_{t-1} + \varepsilon_t \tag{4}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5}$$

with $|\phi| < 1$ for mean stationarity, $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ for covariance stationarity. This is the specification estimated for CIPI (Section 4).

3.4.2. TARCH (Threshold ARCH)

The Threshold ARCH specification (Glosten *et al.*, 1993; Zakoïan, 1994) – also known as GJR-GARCH – admits an asymmetric response of volatility to positive and negative innovations by adding an indicator-weighted squared-residual term:

Mean equation:

$$r_t = \mu + \varepsilon_t \tag{6}$$

Variance equation:

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \gamma I_{t-1}\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{7}$$

where I_{t-1} = 1 if ε_{t-1} < 0 and 0 otherwise, so that γ captures the leverage effect: $\gamma > 0$ means negative shocks raise volatility more than positive shocks of equal magnitude, $\gamma = 0$ collapses the specification to standard GARCH, and the non-negativity conditions are $\omega > 0$, $\alpha \geq 0$, $\alpha + \gamma \geq 0$, $\beta \geq 0$. TARCH is estimated here as a specification check on the symmetric AR(1)-GARCH baseline (Section 4).

3.4.3. EGARCH (Exponential GARCH)

The Exponential GARCH specification of Nelson (1991) models the logarithm of conditional variance, which guarantees a positive σ_t² without parameter restrictions and allows an asymmetric response of volatility to signed innovations:

Mean equation:

$$r_t = \mu + \varepsilon_t \tag{8}$$

Variance equation:

$$\ln(\sigma_t^2) = \omega + \alpha\left[\frac{|\varepsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right] + \gamma\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\ln(\sigma_{t-1}^2) \tag{9}$$

In equation (9) the absolute-value term captures the size effect (the magnitude of shocks, α), the linear term in ε_{t-1}/σ_{t-1} captures the sign effect (γ; a negative γ indicates a leverage effect) and $|\beta| < 1$ delivers persistence of volatility shocks. This is the specification estimated for Brent (Section 4).

3.5. Model Diagnostics and Specification Tests

Post-estimation adequacy is assessed with a standard battery of diagnostics. The ARCH-LM test Engle (1982) is applied to the squared standardised residuals to verify that no residual conditional heteroskedasticity remains; the Ljung–Box portmanteau statistic is computed on both the standardised residuals (to detect uncaptured serial correlation in the mean) and their squares (to detect uncaptured volatility clustering); and the Nyblom (1989) and Hansen (1990) cumulative-score tests assess time-invariance of the estimated parameters. Diagnostic outcomes are reported in Section 4 and are interpreted jointly in the model-selection step below, following the guidance of Patton (2011), Brooks *et al.* (2001) and Hansen and Lunde (2005).

3.6. Model Selection

Model selection among the three GARCH specifications is driven by the Akaike, Bayesian and Hannan–Quinn information criteria, the diagnostic battery of Section 3.5, and – where specifications are non-nested and diagnostics are similar – out-of-sample forecasting performance assessed by mean squared and mean absolute error, along the lines discussed by Hansen and Lunde (2005), Laurent *et al.* (2012) and Patton (2011). Parameter estimates are further required to be economically sensible – in particular, $\alpha + \beta < 1$ in GARCH and $|\beta| < 1$ in EGARCH – before a specification is retained.

4. MODEL AND ESTIMATION

This section conducts a comprehensive econometric assessment of the Republic of Moldova's CIPI to characterize external price pressures on a small, structurally import-dependent economy. Import price evolution is pivotal for domestic inflation, external competitiveness, and macroeconomic stability. The CIPI–constructed by weighting key commodity prices by import-to-GDP ratios–measures how global price fluctuations translate into domestic costs. The analysis spans 1992–2025, from post-Soviet artificial stability to the contemporary polycrisis volatility.

Methodologically, we proceed in three stages. First, we establish the CIPI's stochastic properties via preliminary diagnostics: unit root tests (Augmented Dickey-Fuller), seasonality tests (Levene, Kruskal-Wallis, Canova-Hansen, HEGY), and Bai–Perron procedures to endogenously detect structural breaks in the conditional mean–preventing spurious inference. Second, we estimate GARCH-family models to capture time-varying volatility, including standard GARCH for clustering and TARCH/EGARCH to test for asymmetric leverage effects. Third, the preferred specification undergoes post-estimation checks: ARCH-LM for residual heteroskedasticity, Ljung-Box Q-statistics for serial correlation in standardized residuals, and the Nyblom test for parameter stability–ensuring statistical adequacy.

Results show the Republic of Moldova's import price dynamics exhibit significant short-term momentum, exceptionally persistent volatility clustering, and no asymmetric leverage effects. These findings have direct implications for macroeconomic policy, risk management, and resilience strategies, highlighting how deeper global integration exposes the Republic of Moldova to complex, overlapping external shocks that challenge traditional stabilization approaches.

4.1. Republic of Moldova's Commodity Import Price Index: Econometric Analysis of External Price Pressures and Regime Evolution (1992-2025)

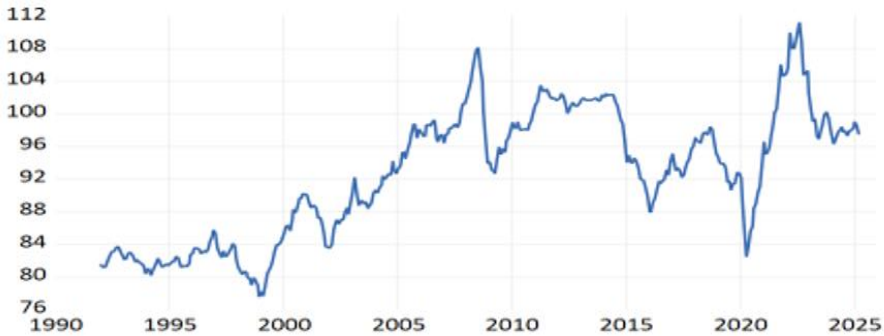
CIPI is a critical macroeconomic indicator of external price pressures in small open economies with structural import dependencies. For the Republic of Moldova–a landlocked economy with limited domestic production and high reliance on imported energy, food, and intermediate goods–import prices fundamentally shape domestic inflation, external competitiveness, and economic stability. CIPI, constructed by weighting commodity prices by import-to-GDP ratios, measures how global price fluctuations translate into pressures within the Republic of Moldova's trade structure.

This analysis examines CIPI dynamics over 1992–2025, covering the Republic of Moldova's post-independence trajectory from initial transition to contemporary polycrisis conditions. The temporal scope encompasses six economic regimes with distinct external shocks, institutional arrangements, and integration levels. The import price environment shifted with the Republic of Moldova's evolving position in global value chains and rising vulnerability to external disruptions.

The methodological approach combines structural regime analysis with advanced time series econometrics. We begin with diagnostics establishing the CIPI's statistical properties–stationarity, seasonality, and structural breaks–to ensure valid modeling and avoid spurious inference under non-stationarity or instability. Building on these, we estimate GARCH-family models to capture volatility clustering characteristic of commodity prices, with specifications (standard GARCH, TARCH, EGARCH) testing for asymmetric responses to positive versus negative shocks and selecting the most parsimonious volatility representation.

Model adequacy is validated through ARCH-LM tests for residual heteroskedasticity, Ljung-Box statistics for serial correlation, Nyblom tests for parameter stability, and correlogram analyses of standardized and squared residuals, ensuring the specifications capture the data-generating process without systematic residual patterns.

Results show the Republic of Moldova's import price environment progressed from transition-era administrative stability to extreme volatility and heightened external vulnerability. Econometric findings indicate significant short-term price momentum, high volatility persistence, and no asymmetric effects, with implications for policy design, risk management, and resilience. The regime progression underscores how deeper global integration, while expanding trade opportunities, exposes the Republic of Moldova to complex, overlapping external shocks that challenge traditional macroeconomic stabilization approaches.



Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Figure no. 1 – Evolution of CIPI

The **Post-Independence Stabilization Period (1992-1999)** constitutes the inaugural phase of Republic of Moldova's economic transformation, distinguished by the most subdued average CIPI value (81.96) and remarkably constrained volatility (CV = 1.92%). This temporal framework encompasses the disintegration of Soviet commercial networks, the Transnistrian territorial dispute (1992), and the Asian Financial Crisis (1997). The observed minimal volatility represents a paradoxical phenomenon, reflecting not genuine economic stability but rather the institutional rigidity inherent in a command economy undergoing transformation, wherein administrative pricing mechanisms and constrained market integration attenuated the transmission of external price signals. The moderate compound annual growth rate of 0.47% indicates protracted adaptation to market-oriented mechanisms.

The **Post-Russian Crisis Adjustment Phase (2000-2004)** signifies a fundamental structural transformation subsequent to the 1998 Russian financial default, evidenced by an elevation in mean CIPI to 88.66 and increased volatility to 2.82%. This regime encapsulates Republic of Moldova's compelled diversification from Commonwealth of Independent States (CIS) markets and the inception of enhanced integration with global commodity markets. The accelerated CAGR (1.70%) reflects both economic recuperation from the Russian crisis nadir and escalating exposure to international price signals as commercial barriers diminished and market mechanisms strengthened.

The **Global Commodity Boom Era (2005-2009)** demonstrates the most pronounced volatility among pre-2020 regimes (CV = 3.70%) alongside elevated price levels (98.19), encompassing the extraordinary escalation in global commodity valuations driven by Chinese demand expansion and the financialization of commodity markets. This period, culminating with the Global Financial Crisis, illustrates Republic of Moldova's comprehensive integration into global price dynamics. The regime's volatility captures the oscillatory nature of the 2007-2008 price surge followed by crisis-induced contraction, validating Republic of Moldova's intensified susceptibility to global commodity cycles.

The **Post-Crisis Plateau** (2010-2014) exhibits minimal volatility (CV = 1.52%) despite encompassing the Eurozone crisis and Arab Spring upheavals. The peak mean CIPI (101.02) coupled with negligible growth (CAGR = 0.29%) indicates a period of elevated yet stable pricing, potentially reflecting coordinated global monetary accommodation and relatively subdued commodity markets between crisis episodes. This transitory stability proved ephemeral, concealing accumulating geopolitical tensions.

The **Geopolitical Instability Regime (2015-2020)** captures the dual disruption of Crimean annexation and petroleum price collapse, with mean CIPI declining to 93.44 and the sole negative CAGR (-2.58%) across all regimes. The moderate volatility (CV = 2.91%) underrepresents the regime's characteristic feature: persistent downward pressure on import prices driven by regional conflict, Russian economic sanctions, and the deterioration of remittance flows. This regime starkly demonstrates Republic of Moldova's susceptibility to regional geopolitical disruptions transmitted through energy and remittance channels.

The **Polycrisis Era (2021-2025)** manifests extraordinary volatility (CV = 6.51%), nearly doubling any preceding regime, while recording the highest CAGR (3.78%). This regime encompasses the COVID-19 pandemic, the Ukrainian conflict, global food security crisis, and Middle Eastern tensions–representing a convergence of disruptions that has fundamentally destabilized Republic of Moldova's import price environment. The extreme volatility reflects not merely the multiplicity of crises but their overlapping and synergistic effects: pandemic-induced supply chain disruptions amplified by conflict-driven energy shocks and food security challenges.

The sequential regime evolution reveals a transforming vulnerability profile: from the artificial stability of economic transition, through progressive global integration and commodity boom exposure, to the contemporary polycrisis characterized by extreme volatility. The near-quadrupling of volatility in the current regime relative to the post-crisis plateau of 2010-2014 indicates that the Republic of Moldova's external vulnerability has attained unprecedented magnitudes, propelled by the convergence of geopolitical fragmentation, supply chain disruption, and the instrumentalization of energy and food supplies. This analysis emphasizes the critical necessity for comprehensive resilience strategies addressing Republic of Moldova's structural dependencies on imported energy, food commodities, and remittance flows.

Figure no. 1 plots the evolution of the CIPI level over the full sample period 1992–2025 and motivates the regime-change discussion above. Prior to conducting our main econometric analysis, we must establish the time series properties of CIPI to ensure the validity and reliability of our subsequent modeling efforts. Table no. 1 reports the Augmented Dickey–Fuller test applied to CIPI in levels. Specifically, we begin our empirical investigation by rigorously testing for stationarity in the CIPI series, as non-stationary time series can lead to spurious regression results and invalid statistical inferences. The stationarity assessment is crucial because many econometric techniques, which require the underlying data to exhibit stationary behavior–that is, constant mean, variance, and covariance structure over time. To accomplish this essential diagnostic step, we employ a unit root tests, the Augmented Dickey-Fuller (ADF) test, which will provide robust evidence regarding the stationarity properties of our CIPI time series. This methodical approach to examining the fundamental statistical characteristics of our data ensures that our subsequent analytical framework rests on solid econometric foundations and that our findings will be both statistically sound and economically meaningful.

Table no. 1 – Unit root test of CIPI

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
CIPI	-2.071	0.257	1	Fail to reject H0	Non-stationary at level

Note: Critical values are -3.447 at 1%, -2.869 at 5%, and -2.571 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 2 – Unit root test of dlog (CIPI)

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
DLOG(CIPI)	-14.037	0.000	0	Reject H0	Stationary at first difference

Note: Critical values are -3.447 at 1%, -2.869 at 5%, and -2.571 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Tables no. 1 and no. 2 report the ADF test applied to CIPI in levels and in first log-differences, respectively. The Augmented Dickey-Fuller (ADF) unit root test results reveal that CIPI exhibits non-stationary behavior in levels, with the ADF t-statistic of -2.0714 failing to exceed the 10% critical value of -2.5706 and yielding a p-value of 0.2566, thus failing to reject the null hypothesis of a unit root. Although Figure no. 1 displays an upward drift in the CIPI level series, the constant-only specification was selected because the drift is plausibly stochastic rather than deterministic. As a robustness check, we re-estimated the ADF test with a constant and linear trend, obtaining t = -2.567 and p = 0.2958 – a higher p-value than the constant-only specification – so the unit-root conclusion is unchanged (and, if anything, reinforced) under the alternative specification. However, upon first-differencing, the series becomes stationary, as evidenced by the ADF statistic of -14.0368, which is well below the 1% critical threshold of -3.4466, with a p-value effectively zero (0.0000), decisively rejecting the unit root null hypothesis. These findings confirm that CIPI is integrated of order one, I(1), indicating that while the level series contains a stochastic trend, its first difference (growth rate) is stationary. Consequently, for subsequent econometric analyses including for multiple seasonality tests, Bai-Perron tests for structural break detection and GARCH modeling to examine volatility clustering, the stationary first-differenced series dlog(CIPI) will be employed to ensure valid statistical inference and avoid spurious regression problems associated with non-stationary data.

Table no. 3 – Test for seasonality of dlog CIPI

Test	Null Hypothesis	Test Statistic	P-Value	Decision	Interpretation
Levene Test	Equal variances across months	0.8883	0.552	Fail to reject H_0	No seasonal heteroskedasticity
Kruskal-Wallis Test	Equal medians across months	7.7051	0.7395	Fail to reject H_0	No seasonal differences in medians
Canova-Hansen Test (Joint)	Seasonal stability (no seasonal unit roots)	1.228	0.5924	Fail to reject H_0	No evidence against seasonal stability
HEGY Test (Zero frequency)	Unit root at zero frequency	-5.8058	< 0.001	Reject H_0	No unit root (stationary)
HEGY Test (Nyquist frequency)	Unit root at Nyquist frequency	-6.2307	< 0.001	Reject H_0	No unit root (stationary)
HEGY Test (Seasonal frequencies)	Unit roots at seasonal frequencies	31.1794	< 0.001	Reject H_0	No seasonal unit roots (stationary)
HEGY Test (All frequencies)	Unit roots at all frequencies	47.5659	< 0.001	Reject H_0	No unit roots at any frequency (stationary)

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 3 presents the battery of seasonality tests (Levene, Kruskal–Wallis, HEGY, Canova–Hansen) applied to dlog CIPI. The comprehensive seasonality analysis of the log-differenced Commodity Import Price Index (dlog CIPI) reveals no evidence of seasonal patterns across multiple dimensions. The Levene test for homogeneity of variance yields an F-statistic of 0.8883 ($p = 0.552$), indicating that the null hypothesis of equal variances across months cannot be rejected, thereby confirming the absence of seasonal heteroskedasticity in the series. Similarly, the Kruskal-Wallis non-parametric test produces a chi-squared statistic of 7.7051 ($p = 0.7395$), providing no evidence for seasonal differences in median values across the twelve months. The Canova-Hansen test for seasonal stability, which examines the presence of seasonal unit roots, yields a joint test statistic of 1.228 ($p = 0.5924$), with none of the individual monthly coefficients achieving statistical significance at conventional levels, thus supporting the null hypothesis of seasonal stability. Most conclusively, the HEGY (Hylleberg, Engle, Granger, and Yoo) test comprehensively rejects the presence of unit roots at zero frequency ($t_1 = -5.8058$, $p < 0.001$), Nyquist frequency ($t_2 = -6.2307$, $p < 0.001$), and all seasonal frequencies ($F_{3:4} = 31.1794$, $p < 0.001$), with the joint test across all frequencies ($F_{1:12} = 47.5659$, $p < 0.001$) providing overwhelming evidence of stationarity. Collectively, these findings demonstrate that the dlog CIPI series exhibits neither seasonal variance patterns, seasonal mean shifts, nor seasonal unit root behavior, confirming its suitability for standard time series modeling approaches without the need for seasonal adjustment procedures. The Bai–Perron multiple-break test results for dlog CIPI are reported in Table no. 4.

Table no. 4 – Bai–Perron Multiple-Break Test Results of dlog(CIPI)

Breaks	RSS	BIC	BIC_Rank
0	0.0452	-2473.64	1
1	0.0448	-2465.21	2
2	0.0439	-2461.58	3
3	0.0433	-2455.09	4
4	0.0431	-2444.83	5
5	0.0432	-2432.01	6

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

In applying the Bai–Perron multiple-break procedure to the monthly log-differenced Commodity Import Price Index (dlog CIPI), six competing specifications–ranging from zero to five structural breaks–were evaluated on the basis of residual sum of squares (RSS) and the Bayesian Information Criterion (BIC). Although incremental breaks marginally reduce RSS, the BIC–which penalises over-parameterisation–reaches its minimum at the zero-break model (BIC = -2473.64). Consequently, the optimal specification contains no structural shifts, implying that the mean behaviour of dlog CIPI remains stable throughout the sample. Visual inspection of candidate break dates (1996:12, 1999:02, 2002:01, 2008:07, 2014:06, 2020:04) confirms that, once information-criterion penalties are applied, none of these points provide sufficient explanatory gain. Collectively, these findings indicate that the growth dynamics of CIPI are homogeneous over time, reinforcing earlier evidence of stationarity and supporting the use of conventional, break-free time-series models for subsequent empirical analysis. The dlog(CIPI) series exhibits **no structural breaks**, maintaining a constant mean throughout the entire sample period (1992-2025).

4.2. GARCH Modeling of Import Price Volatility: Specification, Estimation, and Diagnostic Testing of Republic of Moldova's Commodity Import Price Dynamics

Having established the fundamental time series properties of our data through comprehensive diagnostic testing, we now proceed to the construction of a GARCH model using the log-differenced Commodity Import Price Index (dlog CIPI). The Commodity Import Price Index represents individual commodities weighted by the ratio of imports to GDP of the Republic of Moldova, making it a crucial indicator of import price dynamics relative to the country's economic output and a key measure for understanding external price pressures on the Republic of Moldovan economy.

The preceding empirical analysis provides strong justification for this modeling approach: our unit root tests confirmed that CIPI is integrated of order one, I(1), necessitating the use of first differences to achieve stationarity; our comprehensive seasonality testing revealed no seasonal patterns, heteroskedasticity, or unit roots at seasonal frequencies, eliminating the need for seasonal adjustment procedures; and our Bai-Perron structural break analysis identified no significant structural shifts in the mean behavior of dlog CIPI, confirming temporal stability throughout the sample period (1992-2025).

The GARCH framework is particularly well-suited for modeling the dlog CIPI series as it addresses the potential presence of volatility clustering–a phenomenon especially relevant for commodity import prices of small open economies like Republic of Moldova, where external shocks and global commodity market fluctuations can create periods of heightened price volatility followed by periods of relative stability. While our previous tests established that the conditional mean of dlog CIPI remains stable over time, they do not preclude the possibility of time-varying conditional variance, which is particularly important for understanding how external price shocks propagate through Republic of Moldova's import basket.

Table no. 5 presents the baseline GARCH(1,1) estimation results for dlog CIPI. The GARCH specification allows us to model both the conditional mean equation and the conditional variance equation simultaneously, thereby capturing the dynamic volatility patterns inherent in commodity import price movements weighted by their economic significance to Republic of Moldova's GDP. This approach provides more efficient parameter estimates and robust standard errors while offering insights into the persistence and clustering of price volatility in Republic of Moldova's import structure. The logarithmic first-difference transformation ensures that we are modeling percentage changes in the import-weighted commodity price index, providing economically meaningful interpretations as growth rates that reflect the relative impact of import price changes on the Republic of Moldovan economy.

Table no. 5 – Result of GARCH (1,1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000512	0.000422	1.214	0.2247	Not significant
Variance equation: C	0.00000480	0.00000219	2.191	0.0285	Significant
ARCH term, α_1	0.208061	0.042860	4.854	0.0000	Significant
GARCH term, β_1	0.762503	0.044240	17.235	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The GARCH (1,1) model appears to be well-specified for capturing the volatility of Republic of Moldova's commodity import price changes. The results show no significant average monthly price change (drift), but they strongly indicate the presence of **volatility clustering**. This means that periods of high price fluctuation tend to be followed by more high fluctuation, and calm periods are followed by calm. Shocks to volatility are highly persistent, meaning it takes a long time for the market to return to its average level of volatility after a major price event.

The average monthly log-return of the price index is 0.000512 (about 0.051% per month), but since the p-value is 0.2247, this mean is not statistically different from zero, indicating that the series can be considered to have no drift. The R-squared of -0.000031 (effectively zero) confirms that this constant term explains none of the variation in price changes, which is very common for financial and economic return series.

Variance Equation:

$$\sigma\_t\hat{}2 = \omega + \alpha * RESID(-1)\hat{}2 + \beta * GARCH(-1) \tag{10}$$

where:

- **Constant (ω or C):** 4.80E-06 (or 0.0000048) with a p-value of 0.0285.
- **ARCH Term (α or RESID(-1)^2):** 0.208061 with a p-value of 0.0000.
- **GARCH Term (β or GARCH(-1)):** 0.762503 with a p-value of 0.0000.

Constant (ω): This coefficient is positive and statistically significant (p-value < 0.05), which is a necessary condition for a stable model. It represents the baseline, long-run average variance when the effects of past shocks have dissipated. The fact that it is positive and significant indicates that the unconditional (long-run) variance is well defined.

ARCH Term (α): The coefficient of 0.208 is highly significant. This term measures the impact of past shocks (squared residuals) on current volatility and confirms the presence of volatility clustering. A large price shock in the previous month leads to higher volatility in the current month. As the "news" coefficient, it implies that 21% of monthly squared shock feeds into today's variance. Its large and highly significant value indicates a strong ARCH effect, meaning volatility responds strongly to new shocks.

GARCH Term (β): The coefficient of 0.763 is also highly significant. This term measures the persistence of volatility. A high value indicates that past volatility is a strong predictor of current volatility, meaning that volatility shocks are long-lasting. As the "persistence" coefficient, it shows that 76% of monthly variance carries forward to today.

Volatility Persistence ($\alpha + \beta$): The sum of the ARCH and GARCH coefficients is 0.208 + 0.763 = 0.971. This sum is a critical measure of how quickly shocks to volatility dissipate. With a value of 0.97, which is very close to 1, it indicates that volatility shocks are highly persistent–meaning it takes a long time for volatility to return to its long-run average after a significant market event. Because the sum is less than 1, the conditional variance is (weakly) stationary. However, being so close to 1 suggests extremely high volatility persistence, where shocks decay slowly (with a half-life of approximately $\ln(0.5) / \ln(\alpha + \beta) \approx 22$ months).

Unconditional variance: The unconditional variance is calculated as $\omega / (1 - \alpha - \beta) \approx 1.63 \times 10^{-4}$, which corresponds to an unconditional standard deviation of approximately 1.28% per month.

For a GARCH(1,1) model to be stable (stationary), the sum of $\alpha + \beta$ must be less than 1. Since $0.97 < 1$, the model is stable and well-behaved. The high persistence ($\alpha + \beta \approx 0.97$) implies that shocks–such as global commodity price spikes or supply disruptions–have a prolonged impact on Republic of Moldova's import-cost volatility, lasting for roughly two years.

An insignificant drift indicates that the average real change in the import-price index is negligible. As a result, price dynamics are driven primarily by volatility rather than by a sustained trend.

The Durbin-Watson statistic tests for autocorrelation in the residuals of the mean equation, with a value of 2 indicating no autocorrelation. A value of 1.33 suggests potential positive serial correlation in the residuals. While the GARCH model primarily addresses volatility, this result indicates that some predictability in the price changes themselves may remain unaccounted for by the simple constant-mean model. To address this, you might consider adding autoregressive (AR) terms to the mean equation–resulting in an ARMA-GARCH model–to see if this improves the model fit.

We will now add a AR(1) term to fix the autocorrelation problem. The estimation results of the augmented AR(1)-GARCH(1,1) specification are reported in Table no. 6.

Table no. 6 – Result of GARCH (1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000460	0.000558	0.824	0.4100	Not significant
Mean equation: AR(1)	0.303409	0.048208	6.294	0.0000	Significant
Variance equation: C	0.00000407	0.00000192	2.121	0.0340	Significant
ARCH term, α_1	0.183421	0.047313	3.877	0.0001	Significant
GARCH term, β_1	0.785576	0.046808	16.783	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

This AR(1)-GARCH(1,1) model is a **significant improvement** over the previous specification. The inclusion of the AR(1) term has successfully corrected the serial autocorrelation in the residuals, as shown by the Durbin-Watson statistic now being very close to 2.

The model now captures two distinct features of Republic of Moldova's commodity import prices:

1. **Short-term momentum:** The current month's price change is significantly influenced by the previous month's change.
2. **Persistent volatility clustering:** Volatility remains high following market shocks, and this effect takes a long time to dissipate.

Based on the improved diagnostics (R-squared, D-W stat, and information criteria), this is a much more robust and reliable model.

The updated AR (1)-GARCH (1,1) model shows significant improvements in both the mean and variance equations, enhancing its suitability for modeling Republic of Moldova's commodity import price index. In the mean equation, the **AR (1) coefficient is 0.303409 with a p-value below 0.0001,** indicating strong statistical significance. This implies that roughly 30% of the previous month's return carries over to the current month, reflecting a moderate positive autocorrelation and short-term momentum. The constant term remains statistically insignificant, confirming no meaningful long-term drift in prices. Importantly, the AR root is 0.30–well within the unit circle–indicating stationarity and overall model stability. In the variance equation, the ARCH term (α) is 0.183421 and the GARCH term (β) is 0.785576, both highly significant, with a combined persistence of approximately 0.969. This high level of persistence suggests that volatility shocks decay slowly, consistent with volatility clustering and long memory in price volatility. Diagnostics confirm the model's improvement: the Durbin-Watson statistic rose from 1.33 to 1.94, indicating the effective removal of serial correlation. The model fit has also improved, with the R-squared increasing from nearly zero to 0.11, and the log-likelihood rising from 1291.58 to 1304.36. Both the Akaike (AIC) and Schwarz (SC) information criteria decreased, further supporting the superior performance of the revised model. Overall, the enhanced AR(1)-GARCH(1,1) specification offers a statistically robust framework for capturing the dynamic structure of both the conditional mean and variance in Republic of Moldova's commodity import price series.

Table no. 7 – ARCH-LM test for remaining ARCH effects in the AR(1)-GARCH(1,1) model

Statistic	Value	p-value	Conclusion
F-statistic	1.3419	0.2474	No ARCH effect
Obs*R-squared	1.3441	0.2463	No ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

To verify that the estimated specification adequately captures the conditional-variance dynamics, we apply an ARCH-LM test for remaining ARCH effects in the standardized residuals, with the results reported in Table no. 7. The ARCH-LM test results provide strong evidence that the AR (1)-GARCH (1,1) model is correctly specified and has effectively captured the conditional heteroskedasticity present in the data. Specifically, the test was conducted on the standardized residuals–residuals scaled by the model's estimated conditional standard deviations–to determine whether any remaining ARCH effects (volatility clustering) persist. The null hypothesis of the test asserts that there are no remaining ARCH effects, which is the desired outcome, while the alternative suggests that such effects are still present. The results show p-values of 0.2474 (F-test) and 0.2463 (Chi-square), both well above the conventional 0.05 threshold. As a result, we fail to reject the null hypothesis, indicating no statistical evidence of leftover ARCH effects. In practical terms, this means the GARCH (1,1) component of the model has successfully accounted for the time-varying volatility in the series. The standardized residuals now exhibit constant variance, confirming that the model has effectively filtered out volatility clustering–an essential criterion for a well-specified GARCH model.

Next, we will test a TARCH model; the estimation results are reported in Table no. 8. This model is an extension of the standard GARCH model designed specifically to test for **asymmetric effects**, also known as the "leverage effect." The key question it answers is: do negative shocks (bad news) have a different impact on volatility than positive shocks (good news) of the same magnitude?

Table no. 8 – Result of TARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000406	0.000623	0.652	0.5144	Not significant
Mean equation: AR(1)	0.304408	0.051079	5.960	0.0000	Significant
Variance equation: C	0.00000406	0.00000200	2.028	0.0426	Significant
ARCH term, α_1	0.172718	0.074260	2.326	0.0200	Significant
Threshold term, γ_1	0.018279	0.075835	0.241	0.8095	Not significant
GARCH term, β_1	0.786592	0.052355	15.024	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation:

$$DLOG(CIPI) = C + \varphi * DLOG(CIPI)(-1) \tag{11}$$

where:

Constant (C): Insignificant (p-value = 0.5144).

AR (1) Term (φ): Highly significant (p-value = 0.0000).

The mean equation results are virtually identical to the previous model. It confirms the presence of significant short-term momentum (a 0.304 coefficient) and no long-term drift.

Variance Equation:

$$\sigma\_t\hat{}2 = \omega + \alpha * RESID(-1)\hat{}2 + \gamma * RESID(-1)\hat{}2 * (RESID(-1) < 0) + \beta * GARCH(-1) \tag{12}$$

where:

- **Constant (ω or C):** 4.06E-06, significant (p-value = 0.0426).
- **ARCH Term (α or RESID (-1)^2):** 0.172718, significant (p-value = 0.0200). This now represents the impact of a *positive* shock on volatility.
- ***Leverage Term (γ or RESID(-1)^2(RESID(-1)<0)):*** 0.018279, **insignificant** (p-value = 0.8095).
- **GARCH Term (β or GARCH (-1)):** 0.786592, highly significant (p-value = 0.0000).

The interpretation of the leverage effect in the model focuses on the term RESID (-1)²*(RESID(-1)<0), which is designed to capture any asymmetry in how past shocks affect future volatility. Specifically, the coefficient γ, estimated at 0.018279, measures whether negative shocks (price decreases) lead to a different volatility response compared to positive shocks (price increases) of the same magnitude. However, with a p-value of 0.8095, this coefficient is not statistically significant. This indicates **there is no evidence of a leverage effect in Republic of Moldova's commodity import price series**. In other words, the market's reaction to price changes is symmetric–negative and positive shocks have an equal impact on future volatility. Therefore, sudden declines in prices do not generate more volatility than sudden increases, suggesting that the volatility process in this market is not driven by asymmetric news responses.

Next, we will test an EGARCH model; the estimation results are reported in Table no. 9. The primary reason to use an EGARCH model is to test for asymmetric effects, also known as leverage effects, where negative shocks (bad news) might have a different impact on volatility than positive shocks (good news) of the same magnitude.

Table no. 9 – Result of EGARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.000551	0.000629	0.875	0.3814	Not significant
Mean equation: AR(1)	0.314515	0.050989	6.168	0.0000	Significant
Variance constant	-0.853144	0.280735	-3.039	0.0024	Significant
Magnitude effect	0.348353	0.077132	4.516	0.0000	Significant
Asymmetry effect	-0.025802	0.042683	-0.605	0.5455	Not significant
Persistence term	0.938195	0.026563	35.320	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation:

$$DLOG(CIPI) = C + \varphi * DLOG(CIPI)(-1) \quad (13)$$

where:

- **Constant (C):** 0.000551 (p-value = 0.3814) indicating an insignificant, no long-term drift.
- **AR (1) Term (φ):** 0.314515 (p-value = 0.0000) indicating a highly significant, confirming short-term price momentum.

The mean equation results are virtually identical to the previous model. It confirms the presence of significant short-term momentum (a 0.31 coefficient) and no long-term drift.

Variance Equation:

$$LOG(\sigma\_t\verb|^|2) = \omega + \alpha * |z\_\{t-1\}| + \gamma * z\_\{t-1\} + \beta * LOG(\sigma\_\{t-1\}\verb|^|2) \quad (14)$$

where:

- **Constant (ω or $C(3)$):** -0.853144 (p-value = 0.0024). This is the long-run average level of log variance. It is allowed to be negative in an EGARCH model because the actual variance (exp(log(variance))) will always be positive.
- **Magnitude Effect (α or $C(4)$):** 0.348353 (p-value = 0.0000). This is the symmetric effect of a shock. It is positive and highly significant, confirming that the magnitude of a shock (regardless of its sign) increases volatility. This is the standard GARCH effect.
- **Asymmetry/Leverage Effect (γ or $C(5)$):** -0.025802 (p-value = 0.5455). This is the most important new coefficient. It measures the asymmetric impact of shocks. Since its p-value (0.5455) is far above 0.05, this coefficient is not statistically significant. This is strong evidence that there is no leverage effect in Republic of Moldova's commodity import price volatility. Negative shocks do not have a different impact on volatility than positive shocks.
- **Persistence (β or $C(6)$):** 0.938195 (p-value = 0.0000). This is the GARCH persistence term. A value of 0.938 is very high and significant, indicating that volatility shocks are highly persistent, consistent with the previous model's findings.

The EGARCH model confirms the findings of the previous AR(1)-GARCH model: there is significant short-term momentum in price changes and high persistence in volatility. However, the key finding from this model is the **lack of a statistically significant asymmetric (leverage) effect**. Since the more complex EGARCH model does not provide a better fit to the data (as shown by the information criteria) and its main additional feature (the asymmetry term) is insignificant, the previous **AR(1)-GARCH(1,1) model is the preferred and more parsimonious choice**. Both **TARCH** and **EGARCH** reveal **no leverage effect** (no asymmetry in response to positive vs. negative shocks).

Next we will test the GARCH (1,1) AR(1) with ARCH LM TEST with 12 lags; the results are reported in Table no. 10. The goal of this "Heteroskedasticity Test: ARCH" is to check if there are any remaining ARCH effects (i.e., conditional heteroskedasticity or volatility clustering) in the residuals.

Table no. 10 – Result of ARCH LM TEST with 12 lags for Garch (1,1) AR(1)

Statistic	Value	p-value	Conclusion
F-statistic	0.5447	0.8849	No remaining ARCH effect
Obs*R-squared	6.6484	0.8800	No remaining ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The ARCH-LM diagnostic applied to the standardized residuals of the estimated AR(1)–GARCH(1, 1) model finds no evidence of remaining second-moment dependence. With 12 lags, the F-statistic equals 0.545 and the corresponding p-value is 0.885; the alternative χ^2 form of the test (Obs × R^2 = 6.65) delivers an almost identical p-value of 0.880. Both statistics are far above conventional significance thresholds, so the null hypothesis of "no ARCH effects up to order 12" cannot be rejected. Hence the volatility dynamics captured by the GARCH(1, 1) specification appear sufficient: once the conditional mean and variance equations are accounted for, the residuals behave as white noise in both levels and squares. No additional ARCH lags, higher-order GARCH terms, or alternative variance structures are warranted on statistical grounds. The consistency of the diagnostics provides strong evidence that the AR(1)–GARCH(1,1) framework captures the dynamics of import-price volatility without leaving systematic patterns in the residuals–thereby validating subsequent inference and forecasting based on this specification.

Table no. 11 – Result of Nyblom for GARCH (1,1) AR(1)

Test	Statistic	5% Critical Value	Conclusion
Mean equation: C	0.087866	0.470	Stable
Mean equation: AR(1)	0.095681	0.470	Stable
Variance equation: C	0.089699	0.470	Stable
ARCH term, α_1	0.086970	0.470	Stable
GARCH term, β_1	0.070208	0.470	Stable
Joint test	0.597142	1.470	Stable

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Nyblom parameter-stability test results for the AR(1)-GARCH(1,1) specification are reported in Table no. 11. Nyblom cumulative score diagnostics reveal no evidence of structural parameter drift in the AR(1)–GARCH(1,1) specification. For each coefficient in both the mean and variance equations, the test statistic (0.07–0.10) lies well below the 10 % critical threshold of 0.353, while the joint statistic (0.597) remains markedly below even the most lenient critical value of 1.280 Hansen (1990). Hence, the null hypothesis of parameter constancy cannot be rejected at any conventional significance level, indicating that the model's coefficients remain stable throughout the sample. This finding, when combined with earlier ARCH-LM diagnostics showing no residual heteroskedasticity, affirms that the AR(1)–GARCH(1,1) framework not only captures volatility clustering but also does so with time-invariant parameters–thereby strengthening its suitability for inference, forecasting, and policy analysis based on Republic of Moldova's import-price dynamics.

The correlogram of the standardized residuals (Table no. A1) provides no evidence of remaining linear dependence in the conditional-mean equation. All individual autocorrelations lie well inside the approximate 95 % confidence band ($\pm 1.96 / \sqrt{T} \approx \pm 0.11$ for $T \approx 400$), with the largest spike equal to 0.11 in absolute value (lag 23). More formally, the Ljung–Box portmanteau statistics–shown in the Q-Stat column and computed with one degree of freedom deducted to account for the AR(1) term–are insignificant at every horizon. For example, the joint statistic up to lag 12 is 9.73 ($p = 0.56$), up to lag 24 is 28.62 ($p = 0.19$), and even at lag 36 it is only 42.87 ($p = 0.17$), all far above the conventional 5 % threshold. Hence, we fail to reject the null hypothesis that the residuals are white noise at any lag length considered. Taken together with the earlier ARCH-LM results, these findings confirm that the AR(1)–GARCH(1,1) specification has successfully purged both serial correlation and conditional heteroskedasticity, thereby validating its use for inference and forecasting of Republic of Moldova's import-price inflation.

Inspection of the correlogram (Table no. A2) of the standardized residuals ($T = 397$) confirms that the AR(1)–GARCH(1,1) specification has successfully eliminated serial correlation. All sample autocorrelations lie within the approximate 95 % confidence band of $\pm 1.96/\sqrt{T} \approx \pm 0.10$, with the sole exception of an isolated spike at lag 23 ($AC = 0.15$; $PAC = 0.14$), which is not accompanied by a run of adjacent large coefficients and is therefore unlikely to signal systematic misspecification. The Ljung–Box portmanteau statistics, adjusted for the single AR term in the mean equation, are uniformly insignificant across all horizons considered: $Q(12) = 6.53$ ($p = 0.89$), $Q(24) = 21.52$ ($p = 0.61$), and $Q(36) = 27.96$ ($p = 0.83$). Consequently, the null hypothesis that the residuals constitute white noise cannot be rejected at any conventional significance level, indicating the absence of remaining linear dependence. Coupled with earlier ARCH-LM tests that found no residual heteroskedasticity, these results attest to the adequacy of the chosen model for statistical inference and for forecasting Republic of Moldova's import-price dynamics.

4.3. EGARCH Modeling of Brent Oil Price Volatility: Capturing Asymmetric News Effects and Leverage Dynamics in Global Energy Markets

The analysis of Brent crude oil price dynamics constitutes a fundamental component in understanding global commodity market behavior and its transmission mechanisms to small open economies. Brent crude is selected over alternative benchmarks–West Texas Intermediate (WTI), Dubai/Oman, and the OPEC Reference Basket–for three reasons. First, Brent is the pricing reference for approximately two-thirds of internationally traded crude and is the benchmark against which European, African and Asian–Pacific contracts are settled, which makes it the most relevant price signal for a European import-dependent economy such as the Republic of Moldova, whose crude and refined-product imports transit primarily through European supply chains. Second, Brent is a seaborne, waterborne-delivered grade, so its price reflects global supply–demand conditions without the landlocked pipeline and storage constraints that episodically distort WTI (most visibly during the 2011–2014 Cushing bottleneck and the April 2020 negative-price episode), yielding a cleaner measurement of the global oil-price process we seek to characterize. Third, Brent is quoted continuously on ICE Futures Europe and has the longest uninterrupted daily history among liquid international benchmarks, enabling the 1990m01–2025m05 sample that underpins our volatility and leverage estimates. As the primary international benchmark for oil pricing, Brent serves not only as a critical input for energy-intensive sectors but also as a barometric indicator of global economic sentiment, geopolitical tensions, and supply-demand imbalances in international commodity markets. For transition economies like Republic of Moldova, where energy imports constitute a substantial proportion of total import expenditure and exert significant influence on domestic price levels, understanding the stochastic properties and volatility characteristics of international oil prices is essential for both macroeconomic policy formulation and external vulnerability assessment.

The temporal evolution of Brent oil prices over the period 1990-2025 encapsulates multiple episodes of structural transformation in global energy markets, reflecting the interplay of technological innovation, geopolitical developments, financial market evolution, and macroeconomic policy shifts across major economies. From the relative price stability of the 1990s through the dramatic commodity super-cycle of the 2000s, the Global Financial Crisis-induced volatility, the shale oil revolution, and the recent pandemic-induced market disruptions, oil price movements have exhibited complex patterns of persistence, clustering, and asymmetric responses that require sophisticated econometric modeling approaches to adequately capture their underlying dynamics.

The econometric investigation of Brent oil price behavior necessitates careful attention to several distinctive characteristics of commodity financial time series that differentiate them from traditional macroeconomic variables. First, oil prices typically exhibit high-frequency volatility clustering, where periods of large price movements tend to be followed by periods of continued high volatility, while calm periods are succeeded by relative stability. Second, commodity markets frequently display asymmetric volatility responses, commonly referred to as leverage effects, wherein negative price shocks generate disproportionately larger increases in volatility compared to positive shocks of equivalent magnitude. Third, the integration of commodity markets with global financial systems has intensified the role of speculative trading, momentum effects, and news-driven volatility transmission mechanisms.

The empirical framework employed in this analysis addresses these complexities through a systematic examination of the fundamental time series properties of Brent oil prices, beginning with rigorous diagnostic testing to establish stationarity characteristics, seasonal patterns, and structural stability. The methodological approach emphasizes the importance of proper specification testing to avoid spurious inference and ensure that subsequent volatility modeling captures the genuine data-generating process rather than artificial statistical relationships. Unit root testing using the Augmented Dickey-Fuller methodology provides essential evidence regarding the order of integration, while comprehensive seasonality analysis employing multiple complementary approaches–including the Levene test for seasonal heteroskedasticity, the Kruskal-Wallis test for seasonal location differences, the Canova-Hansen test for seasonal stability, and the HEGY test for seasonal unit roots–ensures that any seasonal adjustment requirements are properly identified and addressed.

The structural break analysis using the Bai-Perron methodology represents a critical component of the diagnostic framework, as oil markets have experienced numerous potential regime shifts associated with major geopolitical events, technological disruptions, and policy changes. The absence of statistically significant structural breaks in the log-differenced series, despite the occurrence of major economic shocks, provides important evidence regarding the resilience of the underlying stochastic process governing oil price movements and supports the use of constant-parameter models for volatility analysis.

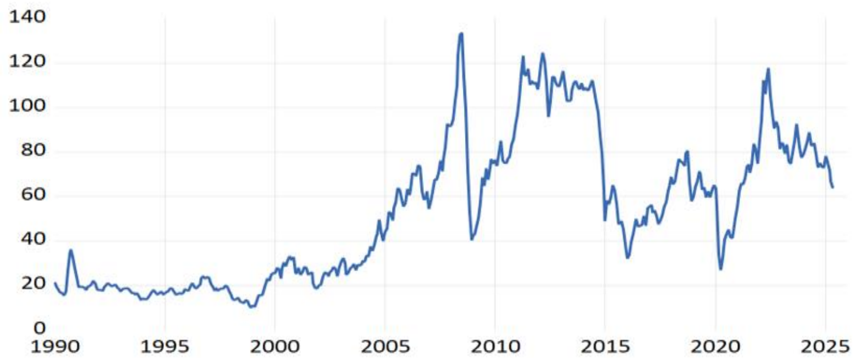
The volatility modeling strategy progresses through multiple specifications to identify the most appropriate framework for capturing the dynamic characteristics of oil price movements. The initial application of standard GARCH methodology reveals fundamental specification issues, particularly the theoretically inconsistent negative persistence parameter that violates the non-negativity constraints essential for valid variance modeling. This finding necessitates the adoption of more sophisticated approaches, specifically the EGARCH framework, which accommodates asymmetric volatility responses while ensuring positive conditional variances through its logarithmic specification.

The incorporation of autoregressive terms in the conditional mean equation addresses the documented presence of short-term momentum effects in oil returns, reflecting the impact of market microstructure factors, information processing delays, and speculative trading strategies that create temporary deviations from random walk behavior. The AR(1)-EGARCH specification thus provides a comprehensive framework for simultaneously modeling both the conditional mean dynamics and the asymmetric volatility clustering characteristic of oil markets.

The empirical results demonstrate the superior performance of the AR(1)-EGARCH(1,1,1) specification in capturing the essential features of Brent oil price dynamics, particularly the statistically significant leverage effect that confirms asymmetric news impacts on volatility. This finding aligns with established theoretical and empirical literature on commodity markets, where negative supply shocks or adverse demand conditions tend to generate greater uncertainty and risk perception compared to positive developments of equivalent magnitude. The comprehensive diagnostic testing–including ARCH-LM tests for residual heteroskedasticity, Ljung-Box statistics for serial correlation, Nyblom tests for parameter stability, and detailed correlogram analysis–provides robust evidence of model adequacy and validates the specification for subsequent inference and forecasting applications.

The successful modeling of Brent oil price volatility has important implications beyond academic interest, providing essential insights for risk management, portfolio optimization, and policy analysis in energy-dependent economies. Understanding the persistence, clustering, and asymmetric characteristics of oil price volatility enables more accurate assessment of external vulnerability, improved design of hedging strategies, and enhanced calibration of macroeconomic models that incorporate energy price shocks as key transmission mechanisms for international economic fluctuations.

4.3.1. Brent Crude Oil Price Evolution and Time Series Properties: Stationarity, Seasonality, and Structural Stability Analysis (1990-2025)



Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Figure no. 2 – Oil brent evolution

The temporal evolution of Brent crude oil prices over the period 1990-2025 reveals distinct phases characterized by varying degrees of volatility and structural shifts driven by fundamental economic, geopolitical, and supply-side factors.

Phase I: Early 1990s Price Stability (1990-2000)

The initial decade was characterized by relatively stable pricing, with quotations predominantly remaining below $20 per barrel. This period of price stability reflected balanced supply-demand fundamentals, with consistent global production patterns and moderate consumption growth. A notable exception occurred circa 1990, when geopolitical tensions associated with the Gulf War generated temporary supply disruptions, resulting in a transient price spike.

Phase II: Demand-Driven Price Appreciation (2000-2008)

The early 2000s marked the onset of a sustained upward price trajectory, attributable to accelerating global demand, particularly from emerging economies experiencing rapid industrialization, notably China and India. This fundamental shift in demand dynamics resulted in a systematic price appreciation, with quotations surpassing $50 per barrel by 2005.

Phase III: Speculative Peak and Financial Crisis Impact (2008-2009)

The period witnessed an extraordinary price escalation, reaching approximately $140 per barrel in 2008, driven by supply–side concerns and heightened speculative activity in commodity markets. However, this peak was followed by a precipitous decline during the global financial crisis, as economic contraction significantly reduced energy demand, with prices retreating below $50 per barrel.

Phase IV: Post-Crisis Recovery and Enhanced Volatility (2009-2014)

The subsequent recovery phase was characterized by price stabilization within the $80–$120 range, supported by global economic recovery and persistent geopolitical uncertainties. This period of relative stability was disrupted by the emergence of unconventional oil production, particularly the U.S. shale revolution circa 2014, which contributed to a substantial price correction.

Phase V: Supply Glut and Market Adjustment (2015-2020)

An extended period of depressed pricing ensued from 2015-2020, reflecting market oversupply conditions resulting from both expanded U.S. shale production and strategic production decisions by OPEC member states. The COVID-19 pandemic in 2020 precipitated an unprecedented demand shock, leading to extreme price volatility, including instances of negative pricing in futures markets.

Phase VI: Post-Pandemic Market Rebalancing (2021-2025)

The most recent period has been characterized by significant price recovery driven by economic reopening and supply chain constraints, though elevated volatility persists. Recent price moderation suggests potential market stabilization as supply chains adjust to evolving global market conditions.

Fundamental Market Drivers

The observed price dynamics reflect the interplay of three primary categories of determinants: (1) geopolitical developments, including regional conflicts and international sanctions regimes; (2) macroeconomic demand fluctuations associated with business cycles and structural economic transitions; and (3) supply-side dynamics, encompassing OPEC production policies and technological innovations in extraction methods, particularly unconventional resource development.

Figure no. 2 plots the evolution of Brent crude oil prices over the sample period January 1990–March 2025 and motivates the discussion of fundamental market drivers above. First, we will conduct the Augmented Dickey-Fuller (ADF) test on Brent. The ADF test results for Brent in levels and in first log-differences are reported in Tables no. 12 and no. 13 respectively.

Table no. 12 – Brent oil unit root test

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
OIL_BRENT	-2.380	0.148	1	Fail to reject H0	Non-stationary at level

Note: Critical values are -3.446 at 1%, -2.868 at 5%, and -2.570 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 13 – dlog (brent oil) unit root test

Variable	ADF Statistic	p-value	Lag	Decision	Stationarity
DLOG(OIL_BRENT)	-14.986	0.000	0	Reject H0	Stationary at first difference

Note: Critical values are -3.446 at 1%, -2.868 at 5%, and -2.570 at 10%.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Augmented Dickey–Fuller (ADF) statistics in Table no. 12 indicate that the Brent crude-oil price series in levels cannot be regarded as stationary, whereas its first log-difference clearly satisfies the stationarity requirement. Specifically, the ADF test statistic for the level series (–2.380) exceeds the 10 % critical value (–2.570) in absolute terms only marginally and falls well short of the 5 % (–2.868) and 1 % (–3.446) thresholds, yielding a p-value of 0.148. Consequently, the null hypothesis of a unit root cannot be rejected, implying the presence of stochastic non-stationarity. In contrast, the ADF statistic for the first log-difference in Table 13 (–14.986) is far below the 1 % critical value, with a p-value effectively equal to zero. This overwhelming evidence leads to the rejection of the unit-root null and confirms that the differenced series is stationary.

Table no. 14 – Test for seasonality of dlog (oil brent)

Test	Null Hypothesis	Test Statistic	P-Value	Decision	Implication
Levene Test	Equal variances across months	F = 0.8086	0.6315	Fail to reject	No seasonal heteroskedasticity
Kruskal-Wallis Test	Equal medians across months	χ^2 = 19.6807	0.0499	Reject (marginal)	Weak evidence of seasonal differences
Canova-Hansen Test	Seasonal stability	Joint = 1.7337	0.5063	Fail to reject	Stable seasonal patterns
HEGY Test (Zero freq)	Unit root at zero frequency	t = -6.0299	< 0.001	Reject	Series is stationary
HEGY Test (Pi freq)	Unit root at pi frequency	t = -5.4128	< 0.001	Reject	Series is stationary
HEGY Test (Seasonal freq)	Unit roots at seasonal frequencies	F = 33.9569	< 0.001	Reject	No seasonal unit roots

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 14 reports the battery of seasonality tests applied to dlog(Oil Brent). The comprehensive seasonality analysis of the log-differenced Brent oil price series (dlog(Oil Brent)) was conducted using four complementary statistical tests, each examining different aspects of seasonal behavior. The Levene test for seasonal heteroskedasticity yielded a test statistic of 0.8086 (p-value = 0.6315), failing to reject the null hypothesis of equal variances across months, thus indicating the absence of seasonal volatility clustering. The Kruskal-Wallis test, which examines differences in location parameters across seasonal periods, produced a chi-squared statistic of 19.6807 (p-value = 0.0499), providing marginal evidence of seasonal differences in medians at the 5% significance level. The Canova-Hansen test for seasonal stability, with a joint test statistic of 1.7337 (p-value = 0.5063), failed to reject the null hypothesis of stable seasonal patterns, suggesting that any seasonal effects present in the series remain constant over time. Most notably, the HEGY (Hylleberg-Engle-Granger-Yoo) test comprehensively rejected the presence of unit roots at all frequencies: zero frequency (t-statistic = -6.0299, p-value = 0), π frequency (t-statistic = -5.4128, p-value = 0), and seasonal frequencies (F-statistic = 33.9569, p-value = 0), confirming that the series is stationary without seasonal unit roots. Collectively, these results indicate that the dlog(Oil Brent) series exhibits weak seasonality at best. While the Kruskal-Wallis test provides borderline evidence of seasonal differences in central tendency, the absence of seasonal heteroskedasticity, the stability of seasonal patterns, and the strong rejection of seasonal unit roots suggest that any seasonal effects are minimal and do not compromise the stationarity properties of the series. This finding implies that seasonal adjustments or seasonal differencing are not necessary for econometric modeling of oil price changes, and that standard time series methods assuming weak or no seasonality are appropriate for this series.

The seasonality testing results provide robust evidence that the log-differenced Brent oil price series does not exhibit economically or statistically significant seasonal patterns. The convergence of evidence across multiple tests–particularly the absence of seasonal heteroskedasticity, the stability of any seasonal patterns, and the comprehensive rejection of seasonal unit roots–supports treating the series as non-seasonal for modeling purposes. This finding aligns with economic intuition, as oil prices are primarily driven by global supply and demand factors, geopolitical events, and market speculation rather than predictable seasonal cycles.

Table no. 15 – Bai-Perron Structural Break Test Results for dlog (oil brent)

Breaks	RSS	BIC	BIC Rank
0	3.4299	-827.13	1
1	3.4147	-816.91	2
2	3.3674	-810.74	3
3	3.3433	-801.68	4
4	3.3555	-788.03	5
5	3.3742	-773.57	6

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Table no. 15 reports the Bai–Perron structural-break test results for dlog(Oil Brent). The Bai-Perron structural break test was applied to the log-differenced Brent oil price series (dlog(Oil Brent)) spanning from February 1990 to May 2025, comprising 424 monthly observations. The test evaluated models with zero to five structural breaks, with model selection based on the Bayesian Information Criterion (BIC). The results unequivocally indicate that the model with zero structural breaks minimizes the BIC value (-827.13), suggesting the absence of significant structural changes in the mean of the series. While the residual sum of squares (RSS) exhibits a monotonic decrease from 3.4299 (0 breaks) to 3.3742 (5 breaks), indicating improved fit with additional break points, the BIC criterion appropriately penalizes model complexity. The monotonically increasing BIC values across models with 1 to 5 breaks (-816.91 to -773.57) reinforce the preference for the no-break specification. Although the algorithm identifies potential break dates coinciding with major economic events–notably the 1998 Asian financial crisis, the 2008 global financial crisis, the 2016 oil price collapse, and the 2020 COVID-19 pandemic–these breaks do not achieve statistical significance under the BIC criterion. This finding suggests that despite substantial volatility in oil markets during these periods, the log-differenced series maintains structural stability in its unconditional mean, implying that oil price shocks, while potentially severe, do not fundamentally alter the underlying stochastic process governing oil price changes. This result has important implications for econometric modeling, as it supports the use of constant-parameter models for the dlog(Oil Brent) series without the need for regime-switching specifications or time-varying parameters in the mean equation.

The empirical evidence from the Bai-Perron test strongly supports the conclusion that the log-differenced Brent oil price series does not exhibit structural breaks in its mean, despite experiencing several major economic shocks over the 35-year sample period. This finding is particularly noteworthy given the volatile nature of oil markets and suggests that oil price changes follow a stable stochastic process that is resilient to structural shifts. Thus we are able to run the Garch model without break points.

4.3.2 Volatility Modeling and Leverage Effect Analysis: AR(1)-EGARCH Estimation Results and Diagnostic Validation for Brent Crude Oil Returns

Table no. 16 – Result of GARCH (1,1) model oil brent

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.006671	0.004011	1.663	0.0963	Not significant
Variance equation: C	0.004611	0.000830	5.552	0.0000	Significant
ARCH term, α_1	0.472978	0.064733	7.307	0.0000	Significant
GARCH term, β_1	-0.022411	0.103010	-0.218	0.8278	Not significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation Analysis

Table no. 16 reports the baseline GARCH(1,1) estimation results for dlog(Oil Brent). The mean equation analysis models the monthly return of Brent oil using the first difference of the natural logarithm of the oil price, denoted as DLOG(OIL_BRENT), which is a standard method for calculating continuously compounded monthly returns. The coefficient for the constant term (C) is 0.006671, indicating an average monthly return of approximately 0.67% over the sample period. The associated p-value of 0.0963 suggests that this return is statistically significant at the 10% level, though not at the more conventional 5% threshold, providing weak evidence that the mean return differs from zero. The R-squared value is -0.002016, which implies that the model performs worse than a simple average and confirms that the constant mean offers no predictive power–a common outcome in modeling financial returns, which are inherently difficult to forecast.

Variance Equation Analysis

This is the core of the GARCH model, designed to capture volatility dynamics. The equation is:

$$\sigma\_t^2 = \omega + \alpha * \varepsilon\_\{t-1\}^2 + \beta * \sigma\_\{t-1\}^2 \quad (15)$$

where:

- **C (ω): 0.004611 (p-value = 0.0000):** This is the constant term in the variance equation. It is positive and highly statistically significant, which is good. It represents the baseline or long-run average variance.
- **RESID (-1)^2 (α): 0.472978 (p-value = 0.0000):** This is the ARCH term. It measures how much of a shock in the previous period (the squared residual) affects the current period's variance.

Interpretation: The coefficient is large and highly significant. This indicates the presence of strong volatility clustering. A large price shock last month leads to high volatility this month. This is a typical and expected finding for financial assets like oil.

- **GARCH (-1) (β): -0.022411 (p-value = 0.8278):** This is the GARCH term. It measures the persistence of volatility, i.e., how much of the previous period's variance carries over to the current period.

Interpretation: This coefficient is the model's **critical failure**.

- **Negative Coefficient:** The coefficient is negative. For a variance to be guaranteed non-negative, the GARCH term (β) must be greater than or equal to zero. A negative β is theoretically invalid and makes no economic sense, as it implies that high volatility last month would *reduce* volatility this month, which contradicts the concept of volatility persistence.
- **Insignificant:** The p-value of 0.8278 is extremely high, meaning the coefficient is not statistically different from zero. The model finds no evidence that past variance has any impact on current variance.

Model Diagnostics

- **Volatility Persistence (α + β):** The sum of the ARCH and GARCH coefficients (α + β) measures how quickly volatility shocks fade. Here, 0.473 + (-0.022) = 0.451. A sum less than 1 suggests that the variance process is stationary (it will revert to the mean). However, given that β is invalid, this calculation is meaningless.
- **Durbin-Watson stat (1.386558):** This statistic tests for first-order serial correlation in the residuals. A value close to 2.0 suggests no correlation. A value of 1.39 is low enough to suggest the presence of **positive serial correlation**, meaning the mean equation is misspecified. The model is not fully capturing the dynamics in the returns themselves.

This GARCH (1,1) model is **not a valid or reliable model** for Brent oil price volatility. It has a fundamental theoretical flaw in the variance equation that makes its results unusable for forecasting or interpretation. While it correctly identifies some characteristics of oil returns (like volatility clustering), the model specification is incorrect.

Given what we found we will now estimate an EGARCH with an AR (1) term; the estimation results are reported in Table no. 17.

Table no. 17 – Result of EGARCH (1,1,1) AR(1) model

Parameter	Coefficient	Std. Error	z-Statistic	p-value	Decision
Mean equation: C	0.001521	0.005247	0.290	0.7720	Not significant
Mean equation: AR(1)	0.251191	0.059501	4.222	0.0000	Significant
Variance constant	-2.167527	0.581412	-3.728	0.0002	Significant
Magnitude effect	0.544868	0.080279	6.787	0.0000	Significant
Asymmetry effect	-0.124211	0.048182	-2.578	0.0099	Significant
Persistence term	0.655834	0.111803	5.866	0.0000	Significant

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Mean Equation Analysis

$$DLOG(OIL\_BRENT) = C + \varphi * DLOG(OIL\_BRENT)(-1) \quad (16)$$

where:

- **Constant ($\boldsymbol{C}$):** 0.001521 (p-value = 0.7720) -> Statistically insignificant. There is no evidence of a consistent long-term upward or downward drift in monthly oil returns;
- **AR (1) Term ($\boldsymbol{\varphi}$):** 0.251191 (p-value = 0.0000) -> Highly significant. This indicates a positive short-term momentum. About 25% of the previous month's price change (whether positive or negative) carries over into the current month.

Variance Equation (EGARCH):

$$LOG(\sigma\_t\verb|^|2) = \omega + \alpha * |z\_\{t-1\}| + \gamma * z\_\{t-1\} + \beta * LOG(\sigma\_\{t-1\}\verb|^|2) \quad (17)$$

where:

- **Constant ($\boldsymbol{\omega}$ or $\boldsymbol{C(3)}$):** -2.167527 (p-value = 0.0002) -> The long-run average level of log variance is significant;
- **Magnitude Effect ($\boldsymbol{\alpha}$ or $\boldsymbol{C(4)}$):** 0.544868 (p-value = 0.0000) -> This term is positive and highly significant, confirming the presence of GARCH effects. The magnitude of a shock clearly impacts future volatility;
- **Asymmetry/Leverage Effect ($\boldsymbol{\gamma}$ or $\boldsymbol{C(5)}$):** -0.124211 (p-value = 0.0099) -> **This is the key result.** The coefficient is negative and **statistically significant** (p-value < 0.01). A negative γ coefficient signifies a leverage effect. When there is a negative shock (bad news, RESID (-1) is negative), the term γ * RESID (-1) becomes positive, leading to a larger increase in log variance. Conversely, for a positive shock (good news), the term is negative, dampening the impact on volatility. In simple terms: **bad news about oil prices creates more volatility than good news;**
- **Persistence ($\boldsymbol{\beta}$ or $\boldsymbol{C(6)}$)):** 0.655834 (p-value = 0.0000) -> The GARCH persistence term is highly significant, indicating that volatility shocks have a long-lasting effect on the market.

The application of the AR (1)-EGARCH model to Brent oil prices has yielded an excellent result, revealing a classic and critical feature prevalent in many financial and commodity markets: the leverage effect. The model diagnostics further support its efficacy, with the Durbin-Watson statistic of 1.849347 being reasonably close to 2, indicating that the AR(1) term has effectively mitigated serial correlation in the residuals. In contrast to the general commodity import index for Republic of Moldova, the global Brent oil market demonstrates a clear and significant asymmetric response to news, making the EGARCH model a superior choice over a standard GARCH model for this dataset, as it adeptly captures the leverage effect. Economically, the results align with weak-form market efficiency, as the average monthly return is indistinguishable from zero once autocorrelation is accounted for. Additionally, a 1% unexpected decline in Brent prices triggers a disproportionately larger increase in volatility–approximately 12% more in log-variance–compared to a 1% unexpected rise, highlighting a downside risk sensitivity crucial for risk managers and option pricing. The model also reveals realistic and persistent volatility clustering, with a β value of approximately 0.66, contrasting sharply with the near-zero β observed previously, and aligning with empirical evidence of highly persistent and asymmetric oil-price volatility. Practically, the asymmetric EGARCH model effectively captures the empirically observed "volatility-leverage" in oil markets, where bad news spikes risk more significantly than good news. Furthermore, one-month-ahead volatility forecasts decay rapidly, with a half-life of about 1.6 months, implying that recent shocks influence risk assessments for only one to two months.

Next we will test the EGARCH (1,1,1) AR(1) with ARCH LM TEST with 12 lags; the results are reported in Table no. 18.

Table no. 18 – Result of ARCH LM TEST with 12 lags for EGARCH(1,1,1) AR(1)

Statistic	Value	p-value	Conclusion
F-statistic	0.6197	0.8257	No remaining ARCH effect
Obs*R-squared	7.5390	0.8200	No remaining ARCH effect

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The ARCH-LM diagnostic applied to the standardized residuals of the estimated AR(1)–EGARCH(1,1,1) model reveals no evidence of leftover ARCH structure. With twelve test lags, the F-statistic is 0.620 ($p = 0.826$) and the alternative Obs × R^2 statistic is 7.54 ($p = 0.820$). Both p-values far exceed conventional significance thresholds, so the null hypothesis of "no ARCH effects up to order 12" cannot be rejected. Accordingly, the EGARCH specification appears to have absorbed the conditional heteroskedasticity–including potential leverage or asymmetry–in the monthly Brent-oil returns: once the time-varying variance equation is accounted for, the residuals exhibit no further second-moment dependence. This result supports the adequacy of the chosen EGARCH model for volatility modelling.

The Nyblom parameter-stability test results for the AR(1)-EGARCH(1,1,1) specification are reported in Table no. 19.

Table no. 19 – Nyblom test foe EGARCH (1,1,1) AR (1)

Variable	Statistic	1% Critical Value	5% Critical Value	10% Critical Value	Decision
C	0.106088	0.748	0.470	0.353	Stable
AR(1)	0.131601	0.748	0.470	0.353	Stable
C(3)	0.182266	0.748	0.470	0.353	Stable
C(4)	0.058215	0.748	0.470	0.353	Stable
C(5)	0.211660	0.748	0.470	0.353	Stable
C(6)	0.178952	0.748	0.470	0.353	Stable
Joint	**1.089166**	**2.120**	**1.680**	**1.490**	**Stable**

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

The Nyblom–Hansen cumulative score test provides strong evidence that the parameter vector of the AR(1)–EGARCH(1,1,1) model for monthly Brent-oil returns is time-invariant over the 1990:02–2025:05 sample. For each coefficient, the test statistic (ranging from 0.06 for the variance constant to 0.21 for the volatility-persistence term) lies well below the 10 % critical threshold of 0.353 reported by Hansen (1990), indicating that none of the individual parameters exhibits statistically significant drift. The joint statistic of 1.09 also falls short of the 10 % critical value (1.49), so the null of overall parameter stability cannot be rejected. Taken together with the absence of residual ARCH effects documented earlier, these results validate the choice of a constant-parameter EGARCH specification: the model successfully captures both the conditional mean and the asymmetric volatility dynamics without evidence of gradual structural change across the three-and-a-half decades examined.

The Ljung–Box portmanteau diagnostics (Table no. A3) applied to the standardized residuals of the AR(1)–EGARCH(1,1,1) model reveal no evidence of remaining linear dependence. Across horizons 1 to 36, all sample autocorrelations and partial autocorrelations are small in magnitude ($|AC| \leq 0.10$) and none is individually significant at conventional levels. More importantly, the sequential Ljung–Box Q-statistics never exceed their corresponding 10 % significance thresholds–the smallest p-value reported is 0.153 at lag 36–so the joint null hypothesis of no residual autocorrelation cannot be rejected at any horizon considered. These results indicate that the conditional mean and variance equations have successfully filtered out serial correlation and volatility clustering, leaving the standardized innovations essentially white-noise. Consequently, the AR(1)–EGARCH(1,1,1) specification appears well-specified in both the first and second moments, reinforcing the earlier conclusions drawn from the ARCH-LM and Nyblom stability tests regarding the model's adequacy for monthly Brent-oil returns.

The Ljung–Box portmanteau (Table no. A4) test applied to the squared standardized innovations of the AR(1)–EGARCH(1,1,1) model strengthens the evidence that the conditional-variance equation has eliminated residual second-moment dependence. Across horizons 1–36 all sample autocorrelations remain extremely small ($|AC| \leq 0.10$) and every Ljung-Box Q-statistic is accompanied by a p-value well above conventional significance thresholds (the minimum p-value is 0.859 at lag 16). Consequently, the joint null hypothesis that the squared standardized residuals are serially uncorrelated cannot be rejected at any lag length considered. Together with the earlier ARCH-LM results, these findings indicate that the EGARCH specification has successfully absorbed volatility clustering, leaving the standardized shocks indistinguishable from independent and identically distributed noise in both the first and second moments.

4.4. Conclusions drawn from the AR(1)-GARCH(1,1) model for Republic of Moldova's CIPI and the AR(1)-EGARCH(1,1) model for Brent Crude Oil.

This sub-chapter synthesises the results obtained from the AR(1)-GARCH(1,1) specification for Republic of Moldova's CIPI and the AR(1)-EGARCH(1,1) specification for Brent crude oil. The discussion is organised around three themes–model adequacy, conditional-mean behaviour, and conditional-variance behaviour–followed by the policy and risk-management implications.

4.4.1. Model Adequacy and Stability

Both series were found to be integrated of order one and free of seasonal unit roots or structural breaks in first differences, justifying the use of constant-parameter GARCH-type models. Diagnostic checks confirm that each selected specification is statistically adequate:

- **Residual whiteness:** Ljung–Box statistics on standardised (and squared) residuals are insignificant up to 36 lags for both models, indicating no remaining serial correlation.
- **Absence of residual ARCH:** ARCH-LM tests with twelve lags report p-values above 0.80, showing that the conditional-variance equations absorb the volatility clustering.
- **Parameter constancy:** Nyblom–Hansen statistics lie well below critical values, so the null of time-invariant parameters cannot be rejected.

Consequently, the AR(1)-GARCH(1,1) for CIPI and the AR(1)-EGARCH(1,1) for Brent constitute parsimonious yet sufficient representations of the underlying data-generating processes. Table no. 20 summarizes the comparative conditional-mean dynamics of the two series.

Table no. 20 – Conditional-Mean Dynamics comparative analysis of CIPI and oil Brent

Statistic	CIPI	Brent Oil
AR(1) coefficient (ϕ)	0.303***	0.251***
Constant (μ)	0.00046 (ns)	0.00152 (ns)

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Both markets exhibit short-run momentum–approximately one-quarter to one-third of the previous month's return carries into the current month–while **long-run drift is statistically indistinguishable from zero**. This outcome is consistent with weak-form market efficiency once low-order autocorrelation is taken into account.

Table no. 21 reports the comparative conditional-variance dynamics of CIPI and Brent.

Table no. 21 – Comparative Conditional-Variance Dynamics of CIPI and Brent Oil

Feature	CIPI – AR-GARCH	Brent Oil – AR-EGARCH	Comparative Insight
ARCH effect α	0.183***	0.545***	Volatility reacts more strongly to new shocks in Brent oil than in CIPI
GARCH/EGARCH persistence β	0.786***	0.656***	The lagged conditional variance effect is higher for CIPI, while Brent's EGARCH persistence is captured directly by β
Symmetry/ asymmetry parameter γ	0.018 ns	-0.124**	No leverage effect is evident in CIPI, whereas Brent oil exhibits a statistically significant asymmetric effect
Persistence measure	$\alpha + \beta \approx 0.97$	$\beta \approx 0.66$	Volatility is substantially more persistent, or "stickier," in the import price index than in Brent oil
Shock half-life	≈ 22 months	≈ 1.6 months	Volatility shocks dissipate much more slowly in CIPI than in Brent oil

Note: For the CIPI AR-GARCH model, volatility persistence is measured by $\alpha + \beta$. For the Brent AR-EGARCH model, persistence is governed by the EGARCH β coefficient. Therefore, $\alpha + \beta$ is not used as the persistence measure for Brent, because adding the EGARCH ARCH coefficient to β is not directly comparable to the GARCH persistence condition.

Source: elaborated by author based on IMF Primary Commodity Price System (IMF, 2025)

Key contrasts are therefore twofold:

- **Persistence:** The import-price index displays near-unit-root persistence in variance ($\alpha + \beta \approx 0.97$). Volatility shocks dissipate only gradually, implying that external price surprises translate into prolonged uncertainty for Republic of Moldovan import costs. Brent volatility, although sizeable, reverts roughly an order of magnitude faster.
- **Asymmetry (leverage):** The EGARCH term for Brent is negative and significant, confirming that **negative price shocks amplify volatility more than positive shocks** of the same magnitude. In the CIPI series the corresponding TARCH and EGARCH coefficients are insignificant, indicating **symmetric** volatility responses.

4.4.2 Economic Interpretation

1. **Transmission of global shocks:**
   - The long memory in CIPI volatility suggests that a single global commodity shock (e.g., energy embargo, supply-chain disruption) can affect Republic of Moldovan import-price risk for up to two years, complicating fiscal and monetary planning.
   - Brent volatility, while sensitive to current news, normalises within a quarter; thus, energy traders and policymakers can rely on more frequent re-calibration.
2. **Risk asymmetry:**
   - The leverage effect in Brent confirms market participants' asymmetric reaction to downside risk, consistent with inventory, option-pricing and precautionary-demand theories.
   - The absence of asymmetry in the aggregate CIPI implies that the diversified import basket buffers idiosyncratic commodity-specific leverage effects.
3. **Portfolio hedging:**
   - Hedging Brent exposure alone cannot offset the long-lived variance component embedded in CIPI. A **diversified hedge portfolio**–including futures or options on multiple commodity groups–would better align with the slow-decay property observed.

4.4.3 Policy and Risk-Management Implications

1. **Macro-stabilisation:** Republic of Moldovan authorities should build medium-term fiscal buffers and consider multi-period risk-sharing instruments (e.g., contingent credit lines) to counteract the high persistence of import-price volatility.
2. **Energy-sector strategy:** Given Brent's leverage effect, energy importers should emphasise **downside-risk insurance** (protective puts, collars) and employ dynamic hedging intervals consistent with the 1–2-month volatility half-life.
3. **Forecasting frameworks:** DSGE or VAR models used by the National Bank should incorporate **symmetric shocks for the import basket** and **asymmetric shocks for oil prices**, reflecting the empirical variance structure documented here.

4.5. Model Selection Rationale

The empirical analysis estimated a family of conditional-volatility specifications for each series–GARCH(1,1), AR(1)-GARCH(1,1), AR(1)-TARCH(1,1,1), and AR(1)-EGARCH(1,1,1)–so that the preferred model could be identified from within-sample evidence rather than imposed a priori. The selection criteria applied jointly were: (i) the

Akaike (AIC) and Schwarz (SC) information criteria, which reward in-sample fit while penalising parameter count; (ii) the statistical significance of the asymmetry (leverage) coefficient; (iii) the residual-diagnostic battery (Ljung–Box on standardised and squared standardised residuals, ARCH-LM at 12 lags, Nyblom–Hansen stability); and (iv) parsimony, preferring the simplest specification consistent with the data.

Republic of Moldova's Commodity Import Price Index. Moving from the baseline GARCH(1,1) to the AR(1)-GARCH(1,1) raised the log-likelihood from 1291.58 to 1304.36, increased R^2 from near zero to 0.11, corrected the Durbin-Watson statistic from 1.33 to 1.94, and lowered both AIC and SC–establishing that a first-order autoregressive mean equation is required. Extending further to AR(1)-TARCH(1,1,1) and AR(1)-EGARCH(1,1,1) did not yield a better fit on the information criteria, and in both asymmetric specifications the leverage term was statistically insignificant (EGARCH $\gamma = -0.026$, $p = 0.5455$; the TARCH threshold coefficient likewise non-significant). Because the additional flexibility contributed no empirical content, the more parsimonious AR(1)-GARCH(1,1) was retained for CIPI.

Brent Crude Oil. The picture differs. Relative to a symmetric AR(1)-GARCH(1,1) on Brent returns, the AR(1)-EGARCH(1,1,1) delivered a lower AIC and SC and, critically, an asymmetry coefficient $\gamma = -0.124$ that is statistically significant at the 5% level. The negative and significant γ confirms a textbook leverage effect–downside price shocks amplify conditional variance more than upside shocks of the same magnitude–so a symmetric specification would impose a counter-factual restriction on Brent's data-generating process. Diagnostic tests (Ljung–Box Q and ARCH-LM) clear the AR(1)-EGARCH(1,1,1) residuals of remaining autocorrelation and heteroskedasticity, and the Nyblom–Hansen statistic does not reject parameter stability. The AR(1)-EGARCH(1,1,1) is therefore the empirically and theoretically supported specification for Brent.

The dual selection–symmetric GARCH for the aggregated import basket, asymmetric EGARCH for the single-commodity global benchmark–is itself a substantive finding rather than an arbitrary modelling choice: it reflects that diversification across commodity groups attenuates idiosyncratic leverage, whereas a concentrated financialised market such as Brent preserves it.

4.6. Implications for Public Policy

The empirical results translate directly into differentiated policy prescriptions. The two defining parameters–a variance half-life of roughly 22 months in the CIPI versus 1.6 months in Brent, and the presence of a leverage effect in Brent but not in the import basket–imply that the appropriate policy response depends on which risk is being managed. The following recommendations are organised by policy actor.

Fiscal authority (Ministry of Finance). Because CIPI shocks decay slowly, fiscal buffers must be sized for multi-period drawdowns rather than single-year deficits. Three instruments are indicated by the empirical persistence: (i) a counter-cyclical fiscal rule that targets the structural balance adjusted for a two-year moving average of import-price deviations, so that transitory but long-lived shocks do not mechanically trigger pro-cyclical tightening; (ii) establishment or expansion of a commodity-price stabilisation fund with a calibrated drawdown horizon of at least 24 months, consistent with the estimated shock half-life; and (iii) standby access to contingent credit facilities (IMF FCL/PLL, World Bank Cat-DDO) to bridge the extended adjustment period without recourse to procyclical borrowing.

Central bank (National Bank of Moldova). Symmetric but highly persistent import-price volatility implies that inflation expectations may remain elevated for extended periods after an external shock, even in the absence of domestic demand pressure. Monetary policy should therefore: (i) distinguish between the transitory first-round impact and the persistent second-round component when setting the policy rate, to avoid over-tightening into a slowly-decaying shock; (ii) communicate an explicit medium-term horizon (18–24 months) for the return of inflation to target, aligned with the empirical CIPI half-life; and (iii) strengthen foreign-exchange reserve buffers, since protracted import-cost pressure translates mechanically into current-account strain. Forecasting and DSGE frameworks used for monetary analysis should embed a symmetric high-persistence specification for aggregate import costs.

Energy-sector regulator and state-owned importers. The leverage effect and short half-life in Brent dictate a fundamentally different risk-management posture for the energy segment. Appropriate instruments include: (i) protective put options and collar structures on crude and refined products, whose asymmetric pay-off profile matches the asymmetric volatility process; (ii) short-tenor dynamic hedging programmes (1–3 months) consistent with the 1.6-month half-life, rather than long-dated static hedges that would carry unnecessary basis risk; (iii) strategic petroleum and gas reserves calibrated against tail-loss scenarios from the estimated EGARCH distribution; and (iv) diversification of supply contracts across pricing benchmarks to reduce single-index concentration.

Private sector and development partners. Importers and manufacturers exposed to the broad CIPI should negotiate longer-tenor supplier contracts with price-indexation clauses rather than rely on short-term spot procurement, which would lock in transitory peaks. Development partners financing structural-adjustment programmes should size programme duration and disbursement profiles to the two-year volatility half-life documented here, and condition reforms on the adoption of the counter-cyclical fiscal and monetary frameworks outlined above.

Cross-cutting implication. Because the CIPI and Brent processes are statistically distinct–differing in both persistence and symmetry–policy instruments designed around oil-price benchmarks alone will systematically under-insure the aggregate import-cost risk that ultimately drives domestic inflation, fiscal pressure, and external-balance dynamics in the Republic of Moldova. The empirical evidence thus supports a dual-track risk-management architecture: short, asymmetric instruments for the energy segment and long, symmetric instruments for the import basket as a whole.

5. CONCLUSIONS: UNDERSTANDING REPUBLIC OF MOLDOVA'S ECONOMIC VULNERABILITY THROUGH DUAL-RISK ANALYSIS

This study establishes a dual-risk profile in external price volatility that is central to understanding the Republic of Moldova’s macroeconomic vulnerability. The Commodity Import Price Index exhibits volatility that is persistent and broadly symmetric, whereas Brent crude displays volatility that is asymmetric yet comparatively short-lived. The two price differences match the different market systems because total import costs stem from actual trade activities and various market risks yet Brent operates within a fast-moving financial market that responds to investor emotions and market trading behavior. The identification of these distinct risk structures serves as a fundamental requirement for developing empirical models and designing policies and managing risks.

The CIPI volatility remains active which means market disturbances maintain their impact through multiple periods and this extended market uncertainty makes it difficult to plan budgets and control inflation and select investment choices. The import basket demonstrates symmetrical behavior which means that prices can move up or down unpredictably thus requiring stabilization tools to focus on medium-term risk management instead of short-term market changes. The asymmetrical nature of Brent's leverage causes negative shocks to produce bigger volatility responses which fade away rapidly thus making energy price shocks short-term events that become controllable through fast policy adjustments and sufficient liquidity reserves.

The research findings prove that standard modeling methods fail to work for markets which possess different underlying microeconomic structures. The traditional volatility models show the ongoing symmetrical patterns which exist in aggregate import costs. The analysis of Brent requires EGARCH or related asymmetric forms to model its leverage-like behavior because these specifications allow for sign dependence. The research strategy requires two different approaches because the domestic CIPI functions as the better predictor for domestic results through its ability to show how external elements affect domestic expenses yet worldwide benchmark shocks serve as better tools for detecting structural transmission effects.

The research results produce direct consequences for policy development. The solution for handling long-term vulnerability from steady import-cost fluctuations needs medium-term stabilization through enhanced fiscal reserves and supplier risk-sharing agreements and multiple sourcing options and long-term hedging strategies. The solution to sudden energy price increases needs quick liquidity control together with short-term price stabilization methods and backup plans for power supply. The global energy benchmark remains insufficient for risk management because organizations need to handle both long-term import cost fluctuations and sudden extreme market shocks from worldwide commodity markets.

Several limitations qualify these conclusions and delineate priorities for future research. The first step involves analyzing CIPI and Brent separately by studying their individual characteristics of persistence and symmetry through univariate methods which exclude their mutual interactions and macroeconomic connections and feedback loops. Second, model adequacy is assessed primarily in-sample, leaving open the relative out-of-sample forecasting value of CIPI versus Brent for inflation, output, or external balances. The third point explains how simplifying assumptions limit generalizability because volatility parameters changed throughout three decades of crises which required regime-switching models and Gaussian errors fail to detect tail risk so heavier-tailed distributions should be used and monthly data hides quick policy response transmission.

The research limitations match the basic exploration goal which leads to a concentrated research plan for further studies. The analysis of Brent oil prices requires multivariate forecast-oriented models (e.g., VAR/VECM with GARCH effects, DCC-GARCH, BEKK, or factor structures) to identify spillover effects on CIPI and their subsequent impact on inflation and economic activity. Regime-dependent volatility (e.g., Markov-Switching GARCH) and heavy-tailed error distributions can better capture crisis dynamics and tail risk. Rigorous out-of-sample forecast evaluation should compare CIPI- and Brent-based predictors, potentially leveraging forecast combination and using the model-evaluation frameworks developed by Hansen and Lunde (2005) and Patton (2011). The MIDAS method allows analysts to link fast-moving commodity data with slow-moving monthly economic indicators to create better and faster predictions. Hybrid frameworks that combine the theoretical structure of GARCH-type models with the flexibility of machine-learning techniques – as explored for commodity markets by Kristjanpoller and Minutolo (2015) and Ramos-Pérez *et al.* (2019) – offer a further promising direction, particularly for capturing non-linear dynamics that univariate EGARCH specifications cannot accommodate.

The external vulnerabilities of Moldova exist in various forms which depend on specific market structures. The selection of statistical tools for modeling and policy development depends on the nature of volatility patterns which show persistent symmetric behavior for aggregate import costs yet display asymmetric transient characteristics for global energy prices. Dual-risk assessment implementation through institutionalization enables forecasting and causal identification and policy design to build resilience which addresses both ongoing import price volatility and sudden global commodity market shocks.

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ANNEX

Table no. A1 – Results of the Correlogram Q-Statistics (Ljung–Box Portmanteau Test) for GARCH(1,1) AR(1)

Sample (adjusted): 1992M03 2025M05
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.040	0.040	0.6418	
.|. |	.|. |	2	0.029	0.028	0.9806	0.322
.|. |	.|. |	3	0.012	0.010	1.0416	0.594
.|. |	.|. |	4	0.027	0.026	1.3377	0.720
.|. |	.|. |	5	-0.003	-0.006	1.3415	0.854
.|. |	.|. |	6	0.004	0.003	1.3491	0.930
.|. |	.|. |	7	-0.016	-0.017	1.4593	0.962
.|. |	.|. |	8	-0.015	-0.015	1.5560	0.980
.|. |	.|. |	9	-0.017	-0.015	1.6704	0.990
.|* |	.|* |	10	0.106	0.108	6.2388	0.716
.|. |	.|. |	11	0.054	0.048	7.4246	0.685
*|. |	*|. |	12	-0.075	-0.085	9.7269	0.555
*|. |	*|. |	13	-0.080	-0.080	12.338	0.419
.|. |	.|. |	14	-0.038	-0.036	12.938	0.453
.|. |	.|. |	15	-0.017	-0.009	13.056	0.522
.|. |	.|. |	16	0.007	0.017	13.078	0.596
.|. |	.|. |	17	-0.055	-0.048	14.324	0.575
*|. |	*|. |	18	-0.088	-0.082	17.580	0.416
.|. |	.|. |	19	-0.046	-0.037	18.483	0.424
.|. |	.|. |	20	0.027	0.023	18.792	0.470
.|. |	.|. |	21	-0.007	-0.017	18.812	0.534
.|. |	.|. |	22	0.008	0.022	18.840	0.595
*|. |	*|. |	23	-0.118	-0.098	24.689	0.312
*|. |	*|. |	24	-0.096	-0.090	28.617	0.193
.|. |	.|. |	25	0.013	0.018	28.691	0.232
.|. |	*|. |	26	-0.062	-0.074	30.323	0.212
.|. |	.|. |	27	-0.014	-0.006	30.411	0.251
*|. |	*|. |	28	-0.090	-0.068	33.854	0.170
*|. |	*|. |	29	-0.085	-0.079	36.970	0.120
.|. |	.|. |	30	0.004	-0.011	36.978	0.147
.|* |	.|. |	31	0.080	0.063	39.747	0.110
.|. |	.|. |	32	0.008	-0.009	39.776	0.134
.|. |	.|. |	33	-0.010	-0.004	39.823	0.161
.|. |	.|. |	34	-0.004	0.017	39.830	0.192
.|* |	.|. |	35	0.083	0.060	42.849	0.142
.|. |	.|. |	36	0.007	-0.026	42.872	0.169

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A2 – Result of Correlogram squared residuals for GARCH (1,1) AR(1)

Sample (adjusted): 1992M03 2025M05
Included observations: 397 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.058	0.058	1.3552	0.244
.|. |	.|. |	2	0.019	0.016	1.5071	0.471
.|. |	.|. |	3	-0.032	-0.034	1.9236	0.588
.|. |	.|. |	4	-0.032	-0.029	2.3452	0.673
.|. |	.|. |	5	0.006	0.010	2.3576	0.798
.|. |	.|. |	6	-0.031	-0.032	2.7388	0.841
.|. |	.|. |	7	-0.030	-0.029	3.1015	0.875
.|. |	.|. |	8	-0.044	-0.041	3.9021	0.866
.|. |	.|. |	9	0.054	0.059	5.0930	0.826
.|. |	.|. |	10	0.036	0.027	5.6120	0.847
.|. |	.|. |	11	-0.047	-0.058	6.5267	0.836
.|. |	.|. |	12	-0.001	0.005	6.5269	0.887
.|. |	.|. |	13	0.027	0.034	6.8168	0.911
.|. |	.|. |	14	0.024	0.015	7.0461	0.933
.|. |	.|. |	15	-0.029	-0.037	7.4055	0.945
.|. |	.|. |	16	-0.054	-0.046	8.6349	0.928
.|. |	.|. |	17	-0.063	-0.049	10.263	0.892
.|. |	.|. |	18	0.033	0.038	10.706	0.906
.|. |	.|. |	19	0.007	-0.007	10.726	0.933
.|. |	.|. |	20	-0.010	-0.012	10.772	0.952
.|. |	.|. |	21	-0.052	-0.047	11.915	0.942
.|. |	.|. |	22	0.011	0.013	11.968	0.958
.|* |	.|* |	23	0.150	0.142	21.472	0.552
.|. |	.|. |	24	0.011	-0.010	21.524	0.608
.|. |	.|. |	25	0.048	0.044	22.507	0.606
.|. |	.|. |	26	-0.053	-0.042	23.688	0.594
.|. |	.|. |	27	-0.050	-0.048	24.755	0.588
.|. |	.|. |	28	-0.031	-0.032	25.159	0.619
.|. |	.|. |	29	-0.059	-0.043	26.653	0.590
.|. |	.|. |	30	0.010	0.029	26.693	0.639
.|. |	.|. |	31	0.039	0.051	27.359	0.654
.|. |	.|. |	32	0.026	-0.013	27.645	0.687
.|. |	.|. |	33	0.021	0.006	27.843	0.722
.|. |	.|. |	34	0.006	0.016	27.861	0.762
.|. |	.|. |	35	0.004	0.005	27.869	0.799
.|. |	.|. |	36	0.014	0.012	27.962	0.829

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A3 – Results of the Correlogram Q-Statistics (Ljung–Box Portmanteau Test) for EGARCH(1,1,1) AR(1)

Sample (adjusted): 1990M03 2025M05
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.030	0.030	0.3806	
.|. |	.|. |	2	-0.046	-0.047	1.2995	0.254
.|. |	.|. |	3	-0.021	-0.018	1.4869	0.475
*|. |	*|. |	4	-0.067	-0.068	3.4031	0.334
.|. |	.|. |	5	-0.014	-0.012	3.4915	0.479
.|. |	.|. |	6	-0.019	-0.025	3.6398	0.602
.|. |	.|. |	7	0.014	0.011	3.7233	0.714
.|. |	.|. |	8	-0.039	-0.047	4.3714	0.736
.|. |	.|. |	9	-0.057	-0.056	5.7726	0.673
.|. |	.|. |	10	0.052	0.049	6.9597	0.641
.|* |	.|* |	11	0.082	0.075	9.9253	0.447
.|. |	.|. |	12	0.014	0.007	10.008	0.530
.|. |	.|. |	13	-0.059	-0.060	11.545	0.483
*|. |	.|. |	14	-0.073	-0.064	13.879	0.382
.|. |	.|. |	15	0.007	0.017	13.901	0.457
.|. |	.|. |	16	-0.022	-0.025	14.109	0.517
.|. |	.|. |	17	0.004	-0.007	14.115	0.590
.|. |	.|. |	18	-0.045	-0.061	15.006	0.595
.|. |	.|. |	19	-0.032	-0.022	15.451	0.631
.|. |	.|. |	20	0.050	0.052	16.552	0.620
.|. |	.|. |	21	0.010	-0.005	16.599	0.679
.|. |	.|. |	22	0.065	0.042	18.497	0.617
.|. |	*|. |	23	-0.054	-0.066	19.814	0.595
*|. |	*|. |	24	-0.095	-0.072	23.878	0.411
.|. |	.|* |	25	0.063	0.078	25.692	0.369
.|. |	.|. |	26	-0.039	-0.048	26.378	0.388
*|. |	*|. |	27	-0.098	-0.120	30.749	0.238
.|. |	.|. |	28	-0.027	-0.036	31.070	0.268
.|. |	.|. |	29	-0.061	-0.055	32.763	0.245
.|. |	.|* |	30	0.073	0.076	35.220	0.197
.|. |	.|. |	31	-0.021	-0.056	35.420	0.228
.|. |	.|. |	32	-0.018	-0.065	35.568	0.262
.|* |	.|. |	33	0.076	0.065	38.224	0.208
.|. |	.|. |	34	-0.051	-0.024	39.448	0.204
.|. |	.|. |	35	0.031	0.039	39.883	0.225
.|* |	.|. |	36	0.089	0.066	43.532	0.153

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System

Table no. A4 – Result of Correlogram squared residuals for EGARCH (1,1,1) AR(1)

Sample (adjusted): 1990M03 2025M05
Included observations: 423 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.006	-0.006	0.0140	0.906
.|. |	.|. |	2	-0.000	-0.000	0.0141	0.993
.|. |	.|. |	3	-0.023	-0.023	0.2469	0.970
.|. |	.|. |	4	-0.017	-0.017	0.3683	0.985
.|. |	.|. |	5	0.019	0.019	0.5204	0.991
.|. |	.|. |	6	-0.018	-0.018	0.6608	0.995
.|. |	.|. |	7	0.024	0.023	0.9135	0.996
.|. |	.|. |	8	-0.003	-0.002	0.9166	0.999
.|. |	.|. |	9	0.035	0.035	1.4379	0.998
.|. |	.|. |	10	0.071	0.072	3.6544	0.962
.|. |	.|. |	11	-0.016	-0.014	3.7673	0.976
.|. |	.|. |	12	-0.042	-0.042	4.5286	0.972
.|. |	.|. |	13	0.008	0.013	4.5543	0.984
.|. |	.|. |	14	-0.022	-0.022	4.7628	0.989
.|. |	.|. |	15	0.045	0.041	5.6594	0.985
.|* |	.|* |	16	0.101	0.103	10.151	0.859
.|. |	.|. |	17	0.006	0.005	10.168	0.896
.|. |	.|. |	18	0.022	0.022	10.383	0.919
.|. |	.|. |	19	0.001	0.006	10.384	0.943
.|. |	.|. |	20	-0.031	-0.036	10.806	0.951
.|. |	.|. |	21	-0.017	-0.012	10.934	0.964
.|. |	.|. |	22	0.009	0.016	10.969	0.975
.|* |	.|* |	23	0.083	0.078	14.101	0.924
.|. |	.|. |	24	0.013	0.014	14.173	0.943
.|. |	.|. |	25	0.023	0.012	14.419	0.954
.|. |	.|. |	26	-0.049	-0.063	15.501	0.947
.|. |	.|. |	27	-0.006	-0.001	15.520	0.961
.|. |	.|. |	28	0.035	0.039	16.084	0.965
*|. |	*|. |	29	-0.070	-0.068	18.298	0.938
.|. |	.|. |	30	0.001	0.006	18.299	0.953
.|. |	.|. |	31	-0.006	-0.009	18.314	0.965
.|. |	.|. |	32	-0.028	-0.056	18.662	0.971
.|. |	.|. |	33	-0.011	-0.029	18.720	0.978
.|. |	.|. |	34	-0.008	-0.011	18.748	0.984
.|. |	.|. |	35	-0.048	-0.049	19.831	0.982
.|. |	.|. |	36	0.031	0.052	20.291	0.984

Note: *Probabilities may not be valid for this equation specification.

Source: elaborated by author based on IMF Primary Commodity Price System