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Shock-Driven Price Dynamics in the Dutch TTF Natural Gas Market: An Econometric Analysis of the 2022–2023 Crisis

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Abstract

The European natural gas market has experienced extreme volatility due to major exogenous shocks, including the COVID-19 pandemic and the Russia–Ukraine conflict. This study analyzes short-term price dynamics and volatility in the Dutch TTF market from January 2022 to June 2023 (78 weekly observations), treating this interval as a distinct crisis regime. A multiple linear regression is first employed to assess the contribution of key fundamentals, followed by ARIMAX models and conditional volatility specifications (GARCH and EWMA). Using 77 weekly observations, TTF returns display no significant autoregressive structure, indicating that price movements are primarily driven by external shocks. Among the regressors, only the EUR/USD exchange rate exhibits a stable and significant effect, underscoring the role of currency dynamics in European gas pricing. While ARIMAX adequately captures the mean process, GARCH fails to detect volatility persistence due to the dominance of isolated shocks. In contrast, EWMA provides more responsive and reliable volatility estimates under crisis conditions. Overall, the TTF market behaves as a shock-driven system with high but short-lived volatility, offering implications for risk management, market monitoring, and energy policy.

Keywords: TTF natural gas; ARIMAX; EWMA volatility; energy crisis; EUR/USD exchange rate; shock-driven dynamics

1. Introduction

Since 2019, the global natural gas market has undergone a sequence of large and persistent shocks that have altered supply patterns, pricing mechanisms, and Europe's exposure to international gas dynamics (International Energy Agency, 2022). Global consumption reached 4126 bcm in 2024, with LNG surpassing pipeline trade for the first time (KPMG, 2023). After COVID-19, supply constraints and Asian consumption triggered a rapid price increase (ACER, 2023). The Russia–Ukraine conflict generated an abrupt reduction in Russian pipeline flows (Ailincă et al., 2026; Al-Haddad & Abu-Rayash, 2026; Zavadska et al., 2026), producing inflationary pressures (De Pascale et al., 2021; Mierzejewski & Rybacki, 2026) and forcing Europe to increase LNG imports. Limited supply growth, infrastructure constraints (Büyükşahin & Robe, 2014; Chen & Rogoff, 2003; ENTSOG, 2023), and the termination of Russian transit through Ukraine reinforced the structural break in European gas fundamentals (Badeeb & Lean, 2018; Mierzejewski & Rybacki, 2026).

The literature documents several relevant features of energy price behavior.

Volatility persistence and the inherent difficulty of forecasting energy prices under heightened uncertainty are well established (Zumbach, 2004; Pindyck, 2004; Ewing et al., 2002).

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Pindyck (2004) highlights the fundamental role of exogenous shocks in driving commodity volatility, emphasizing how structural supply–demand imbalances translate into non-linear price movements. Furthermore, Heather (2015, 2025) and Reboredo (2012) stress the growing reliance on market-based pricing mechanisms and financial factors in shaping gas price discovery, showing how physical traded hubs transition into financialized reference points (Pradhan et al., 2017).

Recent empirical contributions further document heterogeneous investor behavior during geopolitical crises (Yu et al., 2025; Khatatbeh et al., 2026), the critical necessity of scenario-based adaptive planning under conditions of extreme market stress (Choupi et al., 2026), and the strategic role of natural gas storage in mitigating supply disruptions and stabilizing price swings (Fernández et al., 2026).

In this setting, the present study develops an econometric framework to identify the main determinants of Europe's leading benchmark TTF price formation during January 2022–June 2023. The graphical evidence reveals clear regime transitions: an unprecedented price surge in early 2022 driven by severe geopolitical supply tightening followed by a sharp peak in August 2022 and a progressive stabilization phase throughout 2023, reflecting market adjustments and strategic inventory build-ups (Figure 1).

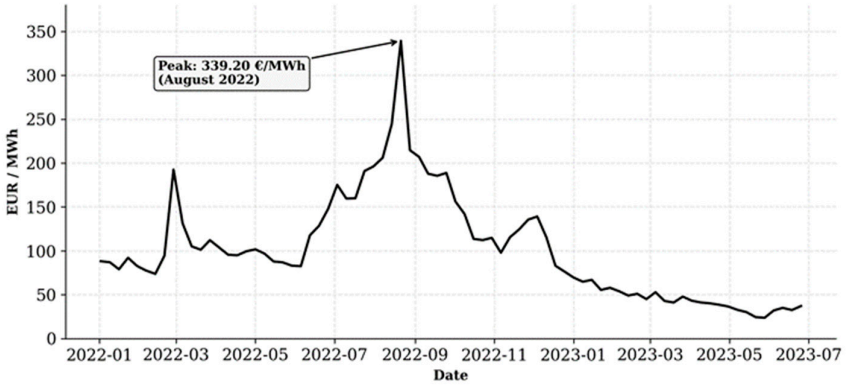

Figure 1. Weekly TTF Natural Gas Prices (2 January 2022–25 June 2023). Note: Weekly natural gas settlement prices at the Title Transfer Facility (TTF) benchmark hub, expressed in EUR/MWh. The sample captures the peak of the European energy crisis, highlighting the historical high of 339.20 EUR/MWh reached in late August 2022 following severe supply disruptions, followed by a structural downward adjustment toward pre-crisis baseline levels in mid-2023.

This study contributes to the literature by examining TTF price dynamics and volatility during the exceptional 2022–2023 crisis period, highlighting a shift toward shock-driven price discovery. The findings extend existing research by documenting weaker autoregressive and volatility persistence, suggesting that traditional models may be less informative under extreme market conditions. More broadly, the study emphasizes the growing role of external geopolitical and macro-financial shocks in shaping European gas prices, while limiting these conclusions to the specific crisis context examined.

From a theoretical perspective, natural gas price dynamics can be conceptualized through the Competitive Storage Model and the Theory of Storage, which explain how physical inventory constraints and convenience yields influence price volatility and backwardation during supply stringency (Geman, 2005). In parallel, the Efficient Market Hypothesis (EMH) and macro-financial exchange rate pass-through frameworks provide the rationale for how external information, currency fluctuations, and global risk sentiment are instantaneously priced into hub benchmarks. First, a multiple linear regression quantifies the contribution of key fundamentals—import volumes, storage levels, and the EUR/USD exchange rate. Second, an ARIMAX model incorporates temporal dependence and external

shocks (Hyndman & Athanasopoulos, 2014). Third, volatility dynamics are examined through GARCH and EWMA specifications to capture clustering, heavy tails, and rapid adjustments. This integrated theoretical and empirical approach allows us to jointly model the mean and variance of TTF returns under a shock-driven regime.

Research Hypotheses

Based on the theoretical framework and the literature on energy market dynamics during structural crisis regimes, three testable hypotheses are formulated to guide the empirical investigation of the Dutch TTF natural gas market during the 2022–2023 period:

Hypothesis 1. *Supply-Side Shock Dominance: During the crisis regime, long-run TTF natural gas price levels are primarily determined by geopolitical supply disruptions (Russian pipeline flows) and strategic inventory adjustments (storage levels), rather than traditional demand-side or climatic variables.*

Hypothesis 2. *Macro-Financial Pass-Through: Short-term TTF price returns are systematically driven by foreign exchange dynamics (EUR/USD rate), reflecting the global financialization of gas pricing and currency pass-through effects from USD-denominated LNG trade.*

Hypothesis 3. *Shock-Driven Volatility Without Persistence: Under extreme crisis conditions, TTF volatility adjusts rapidly to immediate shocks but lacks long-term GARCH-type memory, behaving as a reactive, shock-driven system.*

The remainder of the paper is structured as follows. The next section presents the methodology and model specifications, followed by the empirical results and their discussion. The interpretation of the findings is complemented by a comparison with the sector literature. Limitations and avenues for future research introduce the policy implications of adaptive volatility measures. The paper concludes with a summary of the main results and their implications.

2. Research Design, Data Collection, and Methods

2.1. Research Design and Data Collection

This study adopts a quantitative secondary data analysis design to examine the dynamic price drivers of the Title Transfer Facility (TTF) natural gas benchmark during the recent European energy crisis. The empirical strategy relies on a weekly time-series dataset ($N = 78$) spanning the period from 1 January 2022 to 30 June 2023. This time window is intentionally isolated as a structurally distinct crisis regime characterized by unprecedented supply shocks, geopolitical reorientation, and extraordinary market volatility.

A weekly frequency was chosen over daily data to align with the release schedules of physical supply fundamentals (such as pipeline import flows and storage inventories), to minimize high-frequency microstructure noise, and to avoid data distortion resulting from synthetic daily interpolation. Primary weekly series were extracted from official institutional repositories and European energy databases:

- Eurostat and ENTSOG: Pipeline gas import volumes, aggregated flows, and national physical delivery data.
- Gas Infrastructure Europe (GIE—AGSI+ Platform): Underground gas storage inventory volumes, aggregated from daily reports into weekly arithmetic averages.
- ACER and Intercontinental Exchange (ICE): Dutch TTF front-month natural gas settlement prices, LNG benchmark prices, Brent crude futures, US Henry Hub gas prices.

- European Central Bank (ECB) & ECMWF: EUR/USD exchange rates and average European temperature metrics.

All physical and price variables were standardized to energy equivalents (EUR/MWh or MWh) prior to log-transformation.

2.2. Variable Selection and Description

The initial analytical framework evaluates a candidate set of 10 explanatory variables alongside the dependent variable (TTF_t). The candidate regressors cover physical supply channels, storage buffers, cross-market financial benchmarks, and exogenous environmental factors:

1. Physical Supply and Storage Fundamentals: Disaggregated pipeline import flows from major historical and alternative suppliers—namely Russia (IMR_t) and Norway (IMN_t)—are isolated alongside Liquefied Natural Gas inflows (IML_t). Underground storage inventory levels (STK_t) capture the physical buffer capacity of the European grid.

2. Cross-Market and Financial Transmission Channels: To account for global energy market integration and foreign exchange movements, the model incorporates Brent crude oil futures (PBR_t), US Henry Hub natural gas spot prices (HUP_t), and the EUR/USD exchange rate ($EUSD_t$).

3. Exogenous Environmental Controls: Exogenous fundamentals are captured via the average European temperature (TMP_t) and the EU ETS carbon emission allowance price ($FCO2_t$) (Giugliano et al., 2025).

Table 1 summarizes the complete set of candidate variables, their acronyms, definitions, measurement units, primary providers, and retrieval repositories.

Table 1. Summary of variables, definitions, measurement units, primary providers, and data sources ($N = 78$).

Variable	Acronym	Definition	Unit	Primary Provider	Data Source
Dependent Variable					
TTF Natural Gas Price	TTF	Dutch TTF Front-Month Settlement Price	EUR/MWh	ICE	ICE/ACER Market Reports
Physical Supply and Storage Fundamentals					
Russian Gas Imports	IMR	Pipeline gas inflows from Russia to the EU	MWh	ENTSOG/Bruegel	Eurostat/ENTSOG Platform
Norwegian Gas Imports	IMN	Pipeline gas inflows from Norway to the EU	MWh	ENTSOG/Gassco	Eurostat/ENTSOG Platform
LNG Imports	IML	Liquefied Natural Gas imports	MWh	ALSI/GIE/Kpler	ACER/Eurostat Energy Stats
Gas Storage Levels	STK	Underground gas storage inventory volume	MWh	GIE	AGSI+ Transparency Platform
Cross-Market and Financial Transmission Channels					
Brent Crude Oil Price	PBR	Brent Crude Front-Month Futures Price	EUR/MWh	ICE Futures Europe	ICE/Refinitiv Eikon
US Henry Hub Price	HUP	Henry Hub Natural Gas Spot Price	EUR/MWh	US EIA/NYMEX	US EIA Database
Exchange Rate	EUSD	EUR/USD Foreign Exchange Rate	EUR/USD	European Central Bank	ECB Stats Data Warehouse
Exogenous Environmental Controls					
EU Average Temperature	TMP	European average temperature	°C	ECMWF/Copernicus	Eurostat/Climate Data Store
Carbon Allowance Price	FCO2	EU ETS Carbon Allowance Futures Price	EUR/ton	EEX/ICE Futures	ICE Carbon Emissions Index

2.3. Econometric Methodology and Model Selection

Data processing was conducted in Python using standard analytical libraries (Pandas, NumPy, Matplotlib, Seaborn).

To stabilize variance, improve distributional symmetry, and reduce heteroscedasticity, all continuous non-percentage variables were natural-logarithmically transformed (ln). The logarithmic transformation also converts raw regression coefficients into elasticities, enabling a direct economic interpretation of proportional price responses.

The modeling framework starts with the estimation of a saturated baseline Multiple Linear Regression (MLR) incorporating the complete set of 9 candidate drivers:

$$\ln(TTF_t) = \beta_0 + \beta_1 \ln(IMN_t) + \beta_2 \ln(IMR_t) + \beta_3 \ln(IML_t) + \beta_4 \ln(STK_t) + \beta_5 \ln(PBR_t) + \beta_6 \ln(HUP_t) + \beta_7 \ln(EUSD_t) + \beta_8 TMP_t + \beta_9 \ln(FCO2_t) + \varepsilon_t \quad (1)$$

where β_0 is the intercept, $\beta_1 \ldots \beta_9$ are the partial elasticity coefficients, and ε_t represents the unobserved error term.

3. Empirical Results and Discussion

3.1. Baseline OLS Estimation and Regressor Selection

To identify the main fundamental drivers of TTF gas prices during the 2022–2023 crisis, we first estimate a baseline OLS regression model (Greene, 2018) using the complete set of market regressors: Russian imports (IMR_t), Norwegian imports (IMN_t), LNG imports (IML_t), storage levels (STK_t), the EUR/USD exchange rate ($EUSD_t$), Brent crude (PBR_t), Henry Hub (HUP_t), average temperature (TMP_t), and carbon prices ($FCO2_t$).

Table 2 compares the full baseline estimation (Step 1) with the final parsimonious model (Step 2) obtained after removing statistically non-significant variables ($p > 0.10$).

Table 2. Specification & robustness comparison (Step 1 vs. Step 2).

Variable	Step 1: Saturated Baseline	Step 2: Parsimonious Model	Robustness & Decision Note
IMR (Russian Gas Imports)	$+1.053$ *** ($p = 2.60 \times 10^{-9}$)	$+1.042$ *** ($p = 1.75 \times 10^{-15}$)	Retained: Stable positive supply shock driver
STK (Gas Storage Levels)	$+1.012$ *** ($p = 9.21 \times 10^{-6}$)	$+0.990$ *** ($p = 1.13 \times 10^{-6}$)	Retained: Stable positive precautionary demand effect
EUSD (EUR/USD Exchange Rate)	-9.386 *** ($p = 2.47 \times 10^{-7}$)	-8.954 *** ($p = 4.29 \times 10^{-13}$)	Retained: Stable negative currency pass-through
IML (LNG Imports)	-0.679 ($p = 0.065$)	-0.776 * ($p = 0.043$)	Retained: Stable negative marginal supply effect
IMN (Norwegian Imports)	$+0.660$ ($p = 0.337$)	–	Omitted: Statistically insignificant ($p > 0.10$)
PBR (Brent Crude Price)	$+0.740$ ($p = 0.176$)	–	Omitted: Statistically insignificant ($p > 0.10$)
HUP (Henry Hub Price)	-0.233 ($p = 0.305$)	–	Omitted: Statistically insignificant ($p > 0.10$)
TMP (Average Temperature)	-0.071 ($p = 0.121$)	–	Omitted: Statistically insignificant ($p > 0.10$)
FCO2 (Carbon EU ETS Price)	-0.118 ($p = 0.763$)	–	Omitted: Statistically insignificant ($p > 0.10$)
Intercept	40.425 *** ($p = 2.62 \times 10^{-5}$)	42.429 *** ($p = 7.92 \times 10^{-12}$)	Baseline level

Table 2. *Cont.*

Variable	Step 1: Saturated Baseline	Step 2: Parsimonious Model	Robustness & Decision Note
R-squared	0.8377	0.8077	High explanatory power preserved
Adjusted R-squared	0.8162	0.7971	Parsimonious model fits
F-statistic p-value	1.92×10^{-23}	2.22×10^{-25}	Global model significance strengthened

Note: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, $p < 0.10$, $N = 78$.

3.1.1. Empirical Interpretation and Model Robustness

The empirical estimates confirm the core mechanisms driving TTF_t prices during the crisis period:

- Russian Pipeline Supply (IMR_t): Highly significant positive impact ($\beta = +1.042$, $p = 1.75 \times 10^{-15}$), confirming that physical supply cutbacks directly fueled price surges.
- Storage Accumulation (STK_t): Positive elasticity ($\beta = +0.990$, $p = 1.13 \times 1^{-6}$), capturing aggressive precautionary buying and mandatory storage injection targets.
- Exchange Rate Pass-Through (EUSD_t): Strong negative sensitivity ($\beta = -8.954$, $p = 4.29 \times 10^{-13}$), reflecting Euro depreciation pressures on USD-denominated import costs.
- LNG Imports (IML_t): Statistically significant negative coefficient at the 5% level ($\beta = -0.776$, $p = 0.0425$), demonstrating that sea-borne LNG inflows provided effective physical price relief.

Comparing Step 1 and Step 2 demonstrates strong parameter stability across all retained variables. Although the Adjusted R^2 adjusts slightly from 0.8162 to 0.7971 due to the exclusion of non-significant factors, the global model significance strengthens substantially, as reflected by the reduction in the F-statistic p-value from 1.92×10^{-23} to 2.22×10^{-25}. This confirms that Step 2 yields a highly parsimonious and robust baseline representation without compromising the core structural narrative.

3.1.2. Residual Diagnostics and Short-Term Dynamics

To evaluate the statistical properties of the OLS baseline model, we inspect a comprehensive 4-panel residual diagnostic array (Figure 2):

- Normality and Tail Behavior (Q-Q Plot): The Q-Q plot shows that residuals lie close to the 45-degree reference line, confirming approximate normality, with minor tail deviations reflecting typical exogenous price shocks in the TTF market.
- Homoscedasticity and Variance Stability (Scale-Location Plot): The dispersion of standardized residuals remains uniform across fitted values, indicating that the OLS assumptions of linearity and homoscedasticity hold and that the logarithmic transformation successfully stabilized error variance.
- Influential Observations and Leverage (Residuals vs. Leverage Plot): A few observations (e.g., weeks 8, 9, 23, 34, 61, 74) display higher Cook's distance, associated with major geopolitical price shocks, but all points remain well within critical boundary thresholds and do not compromise overall model stability.
- Temporal Memory and Autocorrelation (Residuals vs. Index Plot): While residuals oscillate around zero, the time-series plot reveals persistent wave-like cyclical patterns rather than pure white noise. This indicates first-order serial autocorrelation ($\text{AR}(1)$) in the static OLS errors ($\hat{\varepsilon}_t$). While error stationarity is preserved—supporting cointegration—this residual autocorrelation confirms that static OLS alone cannot ab-

sorb short-term price persistence, providing the empirical justification for an ARIMAX framework.

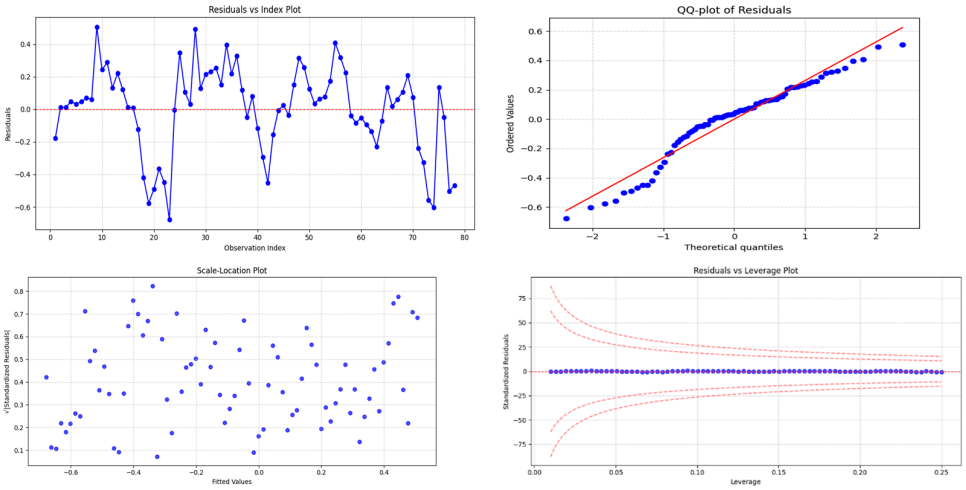

Figure 2. Baseline OLS Residual Diagnostic Suite. Note: **Top-Left**: Residuals vs. Index Plot showing AR(1) temporal memory; **Top-Right**: Normal Q-Q Plot; **Bottom-Left**: Scale-Location Plot confirming homoscedasticity; **Bottom-Right**: Residuals vs. Leverage Plot verifying parameter stability.

3.1.3. Stationarity and Cointegration Analysis

All variables (TTF_t, IMR_t, IML_t, STK_t, EUSD_t) are individually non-stationary in levels, as indicated by the Augmented Dickey–Fuller (ADF) test results (Table 3). Testing for unit roots in first differences confirms that all series are strictly integrated of order one, $I(1)$ ($p < 0.001$). Given that all series are $I(1)$, we test for a long-run equilibrium relationship using the Engle–Granger two-step cointegration procedure. The ADF test applied to the OLS residuals yields a test statistic of -3.94 ($p = 0.003$), which is more negative than the relevant MacKinnon critical value at the 10% significance level (-3.81, with four regressors and an intercept) (MacKinnon, 1996). These results support the rejection of the null hypothesis of no cointegration, suggesting that the residuals are stationary and that a long-run relationship exists among the variables. While this finding supports the use of a levels specification to estimate the long-run relationship, it does not, by itself, guarantee the adequacy of the model or the validity of all statistical inferences. Furthermore, given the evidence of short-run residual autocorrelation, an ARIMAX specification is considered to account for the dynamic structure of the errors.

Table 3. Unit root and Engle–Granger cointegration tests.

Variable	ADF Stat.	p-Value	Integr. Order	Cointegration Status
IMR (Russian Imports)	-2.03	0.28	$I(1)$	Non-stationary in levels
IML (LNG Imports)	-1.88	0.34	$I(1)$	Non-stationary in levels
STK (Storage Levels)	-0.92	0.78	$I(1)$	Non-stationary in levels
EUSD (EUR/USD Rate)	-1.55	0.51	$I(1)$	Non-stationary in levels
OLS Residuals ($\hat{\varepsilon}_t$)	-3.94	0.003	$I(0)$	Cointegrated ($p < 0.01$)

Note: ADF test on residuals evaluated against MacKinnon asymptotic critical values for $k = 4$ regressors plus intercept (10% critical value $= -3.81$). Sample size $N = 78$.

3.1.4. Endogeneity and Robustness

A potential methodological concern relates to the endogeneity of storage levels (STK_t) and import flows (IMR_t, IML_t), which may respond contemporaneously to natural gas

price movements. Such simultaneity may bias standard OLS estimates if significant feedback effects are present. To assess the sensitivity of the results to this issue, alternative specifications incorporating lagged explanatory variables were estimated. However, these specifications neither improved explanatory power nor materially altered the estimated coefficients. While these findings suggest that the main results are relatively robust to the inclusion of lagged variables, potential endogeneity cannot be entirely ruled out. Under the Stock super-consistency theorem, cointegrating OLS estimators converge to their true values at rate T (rather than $\sqrt{T}$), rendering them highly resilient to contemporaneous endogeneity and omitted variable bias. Consequently, the estimated parameters are formally interpreted as long-run equilibrium elasticities rather than immediate structural causal mechanisms.

3.1.5. Diagnostic Suite: Multicollinearity, Autocorrelation, and Heteroskedasticity

To ensure the validity of the baseline OLS estimates, we perform a comprehensive econometric diagnostic suite evaluating multicollinearity, serial autocorrelation, and error variance stability.

1. Multicollinearity Diagnostics

To assess the presence of multicollinearity among the explanatory variables, Variance Inflation Factors (VIF) are computed for each explanatory variable *Xi* via auxiliary regressions:

$$VIF_i = 1/(1 - R_i^2) \quad (2)$$

Values below the conventional threshold of 10 indicate the absence of harmful multicollinearity. Overall, VIF values indicate that multicollinearity is not a concern for this specification. As presented in Table 5, VIF values range between 1.25 (IM LNG) and 5.56 (Storage Levels), confirming that multicollinearity is not a concern for this specification (Table 4).

Table 4. Multicollinearity diagnostics (variance inflation factors).

Variable	Auxiliary R_i^2	VIF	Interpretation
IM RUSSIA ($\ln IMR_t$)	0.77	4.35	Acceptable
IM LNG ($\ln IML_t$)	0.20	1.25	No multicollinearity
STOCK ($\ln STK_t$)	0.82	5.56	Moderate but acceptable
EUR/USD ($\ln EUSD_t$)	0.54	2.19	Low multicollinearity

2. Autocorrelation and Heteroskedasticity

Serial Autocorrelation (Durbin–Watson Test): The Durbin–Watson statistic $d = \frac{\sum(t=2)^n \left((e_t - e(t-1))^2\right)}{\sum_{t=1}^{n} e_t^2} = 0.669$, however, indicates strong positive first-order autocorrelation in the OLS residuals, violating the Gauss–Markov assumption of independent errors. While error stationarity is preserved $I(0)$ under the Engle–Granger test, this serial correlation demonstrates that static OLS fails to absorb short-term price persistence, providing direct empirical justification for moving to a dynamic ARIMAX specification.

Heteroskedasticity (Breusch–Pagan Test): To test for non-constant error variance, the Breusch–Pagan test is implemented by regressing squared OLS residuals on the explanatory variables. The resulting test statistic follows a chi-square distribution under the null hypothesis of homoskedasticity (BP = 1.52, $df = 4$, $p = 0.823$). Since $p > 0.10$, we fail to reject the null hypothesis, confirming that residual variance is constant across observations (Table 5).

Table 5. Summary of diagnostic tests on baseline OLS.

Diagnostic Test	Test Statistic	Parameter/df	*p*-Value	Interpretation
Multicollinearity (VIF)	1.25–5.56	—		No harmful multicollinearity (VIF < 10)
Autocorrelation (Durbin–Watson)	0.669	$k = 4$	0.001	Strong positive AR(1) autocorrelation
Heteroskedasticity (Breusch–Pagan)	1.52	$df = 4$	0.823	Homoskedasticity not rejected ($p > 0.10$)

Note: $N = 78$. Diagnostic tests evaluated on static baseline OLS residuals ($\hat{\varepsilon}_t$).

3.2. Comparative Dynamics: Long-Run Levels vs. Short-Run Variations

At this stage, the empirical analysis compares the baseline regression estimated in log-levels with a short-run dynamic specification estimated in first differences (log-returns). This comparison yields a critical structural insight into TTF price formation during crisis and post-crisis periods (Stock, 1987).

The level specification captures the structural, long-run equilibrium relationship between TTF gas prices and fundamental market determinants, identifying equilibrium elasticities. In this framework, the objective is to explain price magnitude over macro-timeframes, reflecting slow-moving structural variables such as gas storage inventories (STK), pipeline import flows (IMR_t), and foreign exchange conditions ($EUSD_t$).

Conversely, the regression in variations (first differences) is designed to capture short-run shock dynamics and immediate market frictions:

$$rt = \Delta ln(xt) = ln(xt) - ln(xt - 1) \quad (3)$$

The empirical results are fully aligned with economic theory: TTF movements are driven by market fundamentals in levels, but not in short-run variations. As reported in Table 6, the return specification displays limited explanatory power ($R^2 = 0.1290$, Adjusted $R^2 = 0.0806$), confirming that high-frequency returns are largely dominated by short-term noise and immediate market adjustments rather than slow-moving fundamental variables.

Table 6. Short-run regression on TTF price returns (first differences).

Variable	Coefficient	Std. Error	*t*-Statistic	*p*-Value	95% Confidence Interval
Intercept	1.1528	1.8532	0.622	0.536	[−2.5292; 4.8327]
ΔIMR (Russian Imports)	0.2156	0.1238	1.7415	0.0856 *	[−0.0310; 0.4623]
ΔIML (LNG Imports)	−0.1467	0.2310	−0.6352	0.5273	[−0.6073; 0.3138]
ΔSTK (Storage Levels)	0.2858	0.4154	0.688	0.4937	[−0.5425; 1.1141]
ΔEUSD (EUR/USD Rate)	−4.4535	1.5552	−2.8637	0.0055 ***	[−7.5536; −1.3533]

Note: Dependent variable is TTFt. Model fit: $R^2 = 0.1290$, Adjusted $R^2 = 0.0806$, Standard Error = 16.0362, $N = 77$, *** $p < 0.01$, * $p < 0.10$.

Only the foreign exchange rate ($\Delta \ln EUSD_t$) exerts an immediate and statistically significant effect ($\beta = -4.4535$, $t = -2.86$, $p = 0.0055$). Because global LNG and energy derivatives are quoted in US dollars, a depreciation of the Euro increases the domestic acquisition cost of imported gas, forcing immediate exchange-rate pass-through.

Pipeline supply disruptions from Russia ($\Delta \ln IMR_t$) display weak marginal significance ($\beta = +0.2156$, $p = 0.0856$), indicating that short-term Russian flow reductions induce transitory tightness, though without long-term persistence.

The other variables—storage and LNG imports—are not significant in explaining short-term returns. They behave as slow-moving structural variables, not as drivers of high-frequency volatility (Table 6).

3.3. Diagnostic Suite and Residual Testing

The Variance Inflation Factor (VIF) analysis for the variations specification demonstrates near-perfect orthogonality among regressors. Auxiliary R^2 values remain extremely low (ranging between 0.0189 and 0.0480), yielding VIF values close to unity (1.0192 to 1.0504). This confirms that variance inflation is absent and parameter estimates remain stable (Table 7).

Table 7. Multicollinearity diagnostics (variations model).

Variable	Auxiliary R^2	VIF	Interpretation
ΔIMR (Russian Imports)	0.0235	1.0241	No multicollinearity
ΔIML (LNG Imports)	0.0189	1.0193	No multicollinearity
ΔSTK (Storage Levels)	0.0480	1.0504	No multicollinearity
ΔEUSD (EUR/USD Rate)	0.0188	1.0192	No multicollinearity

The Durbin–Watson statistic: The estimated value ($DW = 2.003$) lies within the acceptance region around 2, suggesting that the residuals do not exhibit first-order autocorrelation. Consequently, the OLS estimates are not biased by dynamic misspecification, and the model is appropriate for analysing short-run price dynamics.

The Breusch–Pagan test: The test statistic ($BP = 6.55$) and its associated p-value (0.16) indicate that the null hypothesis of homoskedasticity cannot be rejected. Therefore, the model does not exhibit evidence of heteroskedasticity, and the OLS estimator remains efficient under constant error variance (Table 8).

Table 8. Diagnostic tests summary (variations model).

Diagnostic Test	Statistic	p-Value	Interpretation
Multicollinearity (VIF)	approx 1.00–1.05	—	No multicollinearity (VIF approx 1)
Autocorrelation (Durbin–Watson)	2.003	—	No first-order autocorrelation (DW approx 2)
Heteroskedasticity (Breusch–Pagan)	6.55	0.16	Homoskedasticity not rejected ($p > 0.10$)

3.4. ARIMAX Model Estimation Results

Building on the static regression results, the analysis proceeds with a dynamic ARIMAX specification to account for temporal dependence and short-run adjustments in TTF price behaviour. All variables are expressed in log-returns (×100), and an AR(1) term is included to capture potential price memory:

$$\Delta ln(TTFt) = ARMA(p,q) + \beta 1 \Delta ln(X1,t) + \beta 2 \Delta ln(X2,t) + \ldots + \varepsilon_t \quad (4)$$

The ARIMAX estimation shows that only the EUR/USD exchange rate remains statistically significant in the short run ($\beta = -4.46$, $z = -2.164$, $p = 0.03$).

All other regressors—Russian pipeline imports (IMR_t), LNG imports (IML_t), gas storage levels (STK_t)—and the autoregressive term (ar.L1) fail to reach conventional levels of statistical significance ($p > 0.05$). Russian imports show only weak marginal significance ($\beta = 0.2215$, $p = 0.085$) (Table 9).

The statistical insignificance of the (AR(1)) parameter ($\phi_1 = -0.0267$, $p = 0.832$) confirms that short-run log-returns do not display serial persistence. This indicates that short-run TTF price movements during the crisis period were predominantly driven by external financial conditions—specifically exchange rate pass-through—rather than by contemporaneous changes in physical fundamentals.

Table 9. ARIMAX model estimation results.

Variable	Coefficient	Std. Error	*z*-Statistic	*p*-Value	95% Confidence Interval
const (Intercept)	1.152	2.516	0.4580	0.647	[−3.779; 6.083]
IMR_t (Russian Imports)	0.2215	0.129	1.7210	0.085	[−0.031; 0.474]
IML_t (LNG Imports)	−0.1365	0.305	−0.448	0.654	[−0.733; 0.460]
STK_t (Storage Levels)	0.2855	0.539	0.5300	0.596	[−0.771; 1.342]
EU_t (EUR/USD Rate)	−4.4596	2.060	−2.164	0.03	[−8.498; −0.421]
ar.L1 (AR(1) Term)	−0.0267	0.126	−0.212	0.832	[−0.274; 0.220]
σ^2 (Residual Variance)	240.297	39.629	6.0640	0.000	[162.627; 317.968]

ARIMAX Residual Diagnostics

A full set of residual diagnostics is conducted to assess the adequacy of the ARIMAX specification and verify whether the model leaves unexplained temporal or distributional structure. The diagnostic analysis includes both formal statistical tests (Table 10) and graphical diagnostics (Figure 3).

Table 10. ARIMAX residual diagnostics summary.

Diagnostic Test	Statistic	*p*-Value	Interpretation
Ljung–Box Test (Autocorrelation)	$Q = 0.98$	>0.10	No residual autocorrelation
Heteroskedasticity Test	—	0.150	No model misspecification
ARCH-LM Test (Volatility Clustering)	$LM = 4.83$	0.900	No conditional heteroskedasticity
Jarque–Bera Test (Normality)	—	0.000	Non-normal, heavy-tailed residuals (Kurtosis = 5.64)

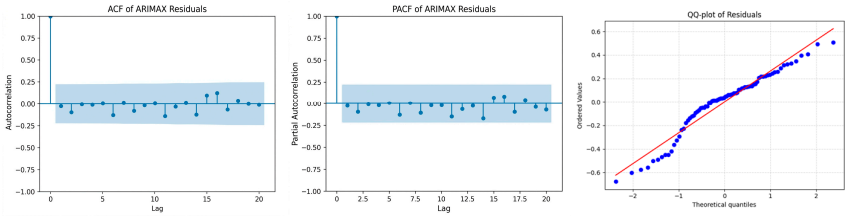

Figure 3. Residual Diagnostics (ACF, PACF, and Q-Q plot). Note: Diagnostic for the ARIMAX model residuals. The Autocorrelation Function and Partial Autocorrelation Function plots show that all residual sample correlations lie within the 95 percent confidence bands, confirming the absence of residual autocorrelation. The Q-Q plot indicates that residuals align with the normal distribution in the central region, but exhibit significant deviations in the extreme tails, corroborating the Jarque–Bera test result and sample kurtosis of 5.64.

The formal tests confirm the adequacy of the ARIMAX specification. The Ljung–Box statistic ($Q = 0.98$, $p > 0.10$) shows no residual autocorrelation, while the heteroskedasticity test ($p = 0.15$) indicates no evidence of model misspecification (Table 10).

The ARCH-LM statistic ($LM = 4.83$, $p = 0.90$) indicates no conditional heteroskedasticity, confirming the absence of volatility clustering. This supports the interpretation of a shock-driven, non-persistent volatility process, consistent with the weak GARCH persistence observed in the conditional variance model.

The Jarque–Bera test ($p = 0.000$) indicates heavy-tailed residuals, consistent with the shock-driven nature of TTF returns during the crisis sample (Jarque & Bera, 1987).

The ACF and PACF of the ARIMAX residuals show no significant autocorrelation at any lag. All correlations lie within the 95% confidence bands, confirming that the model does not leave unexplained temporal structure. This supports the Ljung–Box result and indicates that the AR(1) term is sufficient, with no evidence of additional autoregressive components.

The Q-Q plot confirms that residuals are approximately normal in the central region but deviate markedly in the tails. The heavy-tailed pattern confirms the Jarque–Bera result and high kurtosis (5.64), indicating that extreme shocks occur more frequently than under normality.

Overall, the ARIMAX results suggest that TTF returns exhibit no autoregressive persistence and are primarily influenced by non-persistent, episodic shocks, with the EUR/USD exchange rate acting as the only immediate macro-financial driver. This structural finding directly motivates the transition to specialized conditional variance modeling (GARCH(1,1) and EWMA) to map the time-varying risk profile of European natural gas (Engle, 1982; Sadorsky, 2006).

3.5. Transition to Volatility Modelling (EWMA vs. GARCH)

To model volatility under strong and irregular shocks—consistent with the high kurtosis (5.64) and heavy-tailed residual distribution identified in the "ARIMAX Residual Diagnostics" section—the conditional variance is estimated through a GARCH(1,1) model applied to the ARIMAX residuals (Bollerslev, 1986). The specification includes exogenous regressors to account for potential volatility effects driven by fundamentals:

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

The GARCH(1,1) estimation shows a relatively small unconditional variance ($\omega = 0.017$), combined with a pronounced ARCH coefficient ($\alpha_1 = 0.661$). This confirms that conditional volatility reacts sharply and immediately to incoming market innovations. The GARCH term is not statistically different from zero ($\beta_1 \approx 0$), suggesting limited evidence of volatility persistence in this sample. As a result, the volatility process appears predominantly driven by short-run shocks rather than self-sustaining volatility regimes, although the small sample size calls for caution in interpreting these dynamics.

This behavior contrasts with typical commodity markets, where volatility clustering is typically persistent ($\alpha_1 + \beta_1 \approx 1$). In the TTF market during the crisis sample, isolated and extreme exogenous shocks prevented the establishment of persistent autoregressive volatility clusters.

Given the weekly frequency and the limited sample size (77 observations), the ARIMAX model remains statistically reliable, while GARCH specifications become unstable and poorly identified due to insufficient data for estimating volatility clustering.

For this reason, the Exponentially Weighted Moving Average (EWMA)—which requires no estimated parameters and remains highly robust in short samples—is adopted as the primary volatility framework:

$$\sigma_t^2 = \lambda \sigma_{\{t-1\}}^2 + (1 - \lambda)\varepsilon_{\{t-1\}}^2 \quad (6)$$

where λ represents the standard decay persistence factor. EWMA provides a more stable representation of volatility dynamics under irregular shocks (Andersen et al., 2004).

Figure 4 illustrates the estimated conditional standard deviation (σ_t) derived from the EWMA model ($\lambda = 0.94$) alongside the sample mean conditional volatility ($\overline{\sigma} = 15.05$). The conditional volatility series exhibits a clear downward trend, decaying from peak crisis levels exceeding 20% down to stabilized levels around 12–13% by the end of the sample period, reflecting a progressive reduction in short-term uncertainty following the initial supply shocks.

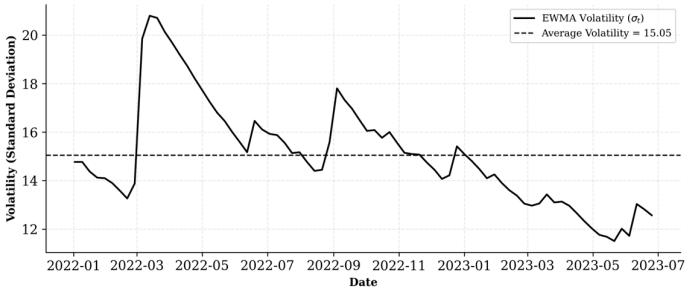

Figure 4. TTF Volatility Estimated with EWMA ($\lambda = 0.94$). Note: Estimated conditional standard deviation (σ_t) derived from the EWMA specification with a standard decay factor of $\lambda = 0.94$ over the sample period January 2022–July 2023. The solid line represents conditional volatility (σ_t), while the dashed line indicates the sample average conditional volatility ($\overline{\sigma}$). The trajectory illustrates the transition from extreme volatility spikes during the 2022 energy crisis peak ($\sigma t > 20\%$) to a structural stabilization regime below 13% in mid-2023.

In summary, the empirical results yield three core structural conclusions:

- Fundamental anchoring vs. short-run memory: TTF price formation is governed by fundamental equilibrium relationships in levels (long-run), but lacks autoregressive price memory in returns (short-run).
- Macro-financial pass-through: Short-run price variations are driven by immediate macro-financial shocks, with the EUR/USD exchange rate ($\Delta EUSD_t$) serving as the primary pass-through driver.
- Shock-driven volatility: Volatility dynamics are shock-driven rather than memory-driven. The TTF market appears generally calm but subject to sudden, sharp volatility spikes; it absorbs exogenous disturbances rapidly without amplifying them over time.

4. Discussion

The empirical results presented in this study provide critical insights into the structural price formation and volatility dynamics of the Title Transfer Facility (TTF) natural gas benchmark during the peak of the 2022–2023 European energy crisis. Although the historical sample is intentionally restricted to $N = 77$ weekly observations (spanning January 2022 to June 2023), this temporal window isolates a homogeneous crisis regime characterized by severe structural breaks following the Russia–Ukraine conflict. While restricting the sample guarantees regime purity and avoids mixing distinct structural states, it necessarily limits the statistical power of complex multi-parameter econometric architectures and prevents long-horizon parameter stability testing.

These findings must therefore be interpreted within the specific context of an unprecedented geopolitical supply shock. In this respect, our study complements the existing energy economics literature by focusing explicitly on a regime defined by extreme price spikes, physical supply re-routing, and non-linear market feedback. While the literature on European natural gas pricing has expanded substantially, earlier empirical studies exhibit notable methodological and contextual limitations when applied to the 2022–2023 crisis.

The foundational study by Nick and Thoenes (2014) while providing a structural decomposition of shocks in the German market, reflects a historical context in which European gas prices were still strongly linked to oil and coal benchmarks. As long-term oil-linked contracts have been progressively replaced by hub-based spot pricing, the generalizability of their structural parameters to high-frequency crisis conditions is limited. Furthermore, in standard VAR frameworks, supply disruptions risk being overestimated due to the difficulty of separating pure physical supply shocks from demand-side panic amplifications. A more

flexible approach is found in Wang et al. (2019), who employ dynamic model averaging to capture the time-varying relevance of Henry Hub price drivers.

However, their reliance on competing model spaces implies that parameter stability remains sensitive to the underlying candidate specifications. Moreover, the financialization effects identified in their study largely mirror the macroeconomic conditions of the 2008 global financial crisis rather than a permanent structural feature. Nonetheless, their framework correctly highlights the transformative impact of the U.S. shale gas revolution, which decoupled Henry Hub prices (HUP_t) from crude oil (PBR_t) as early as 2005. In the European context, Obadi and Korcek (2020) confirm the historical dominance of fundamental drivers. Using multiple linear OLS regressions, they demonstrate that gas prices were historically anchored by marginal supply–demand conditions linked to German power generation and coal prices, whereas Liquefied Natural Gas (LNG_t) imports (IML_t) reflected global market integration. Although their findings align with the pre-crisis literature, relying on a single linear regression framework oversimplifies a market increasingly subject to non-linear geopolitical shocks and macro-financial spillovers.

Finally, the thesis by Ellersiek and Gnerre (2023), while directly addressing the 2021–2023 crisis, utilizes an ARCH specification that captures only short-term conditional variance while neglecting broader systemic market linkages. Their hypothesis of inverse causality between gas import volumes and prices illustrates the empirical difficulty of isolating individual structural relationships in a market dominated by exogenous political events.

Overall, the existing literature offers valuable but fragmented insights, often tied to historical contract structures or estimation choices that limit direct comparability with the 2022–2023 shock. The present study bridges this gap by evaluating the TTF market as a distinct crisis regime. In our baseline OLS specification, fundamental regressors explain a significant share of level price adjustments, capturing the European Union's immediate emergency measures—specifically the aggressive refill of storage inventories (STK_t) and the rapid substitution of Russian pipeline flows (IMR_t) with flexible LNG cargoes (IML_t). However, when transitioning to the high-frequency ARIMAX specification (Table 6), short-run return dynamics ($\Delta \ln TTF_t$) are overwhelmingly dominated by macro-financial shocks rather than autoregressive momentum or physical inventory variables. The EUR/USD exchange rate ($\Delta \ln EUSD_t$) emerges as the sole statistically significant short-run driver ($\beta = -4.46$, $z = -2.16$, $p = 0.030$). Because global LNG procurement and energy derivatives are denominated in U.S. dollars, a depreciation of the Euro immediately elevates local currency acquisition costs, driving instant exchange-rate pass-through. Pipeline supply disruptions from Russia ($\Delta \ln IMR_t$) exhibit weak marginal significance ($\beta = 0.22$, $z = 1.74$, $p = 0.086$), reflecting transitory price adjustments that lack long-term persistence. Physical storage ($\Delta \ln STK_t$) and LNG volumes ($\Delta \ln IML_t$) do not achieve statistical significance in the short-run return equation ($z < 1.00$, $p > 0.10$), acting as slow-moving structural buffers rather than high-frequency price drivers. Residual diagnostics from the ARIMAX model (Table 10) reveal severe heavy-tailed behavior, high excess kurtosis (Kurtosis = 5.64), and a decisive rejection of normality under the Jarque–Bera test ($p < 0.001$). These features confirm the stylized facts of energy crisis pricing and highlight the danger of using standard Gaussian distributional assumptions in risk management, which severely underestimate the probability of extreme tail events. To capture the underlying conditional volatility process, we compared formal GARCH(1,1) parameterizations with an Exponentially Weighted Moving Average (EWMA) framework. The estimated GARCH(1,1) model yields a small baseline variance ($\omega = 0.017$) and a statistically significant ARCH parameter ($\alpha_1 = 0.661$, $p < 0.01$), confirming that conditional variance reacts abruptly to incoming market news. Crucially, however, the GARCH parameter is statistically indistinguishable from zero ($\beta_1 \approx 0, p > 0.10$), indicating a complete absence of conditional volatility persistence. This contrasts sharply

with the traditional commodity literature, where high volatility clustering ($\alpha_1 + \beta_1 \approx 1$) is standard. In this crisis regime, volatility is characterized by isolated, high-amplitude shocks that decay rapidly rather than forming persistent volatility clusters. Consequently, the non-parametric EWMA model ($\lambda = 0.94$) is adopted as the superior volatility framework. Because EWMA requires no estimated parameters, it avoids over-parameterization risks in small samples ($N = 77$) while responding instantly to structural shifts. The diagnostic absence of residual conditional heteroskedasticity in the ARCH-LM test (LM = 4.83, $p = 0.900$, Table 10) mathematically validates the EWMA benchmark as an accurate, parsimonious representation of market risk during the crisis period.

Theoretical Implications

The empirical findings offer three major theoretical contributions to energy economics, market efficiency, and price discovery under extreme regime shifts:

1. Departure from Mean-Reverting Pricing Models: The complete absence of significant autoregressive structure in TTF returns ($\Delta\ln TTF_t$) marks a theoretical departure from traditional storage-based pricing models that assume mean-reversion and long-term memory (Badeeb & Lean, 2018). We propose that during severe crisis periods, the TTF market enters a "shock-driven regime". In this state, internal market feedback loops are completely superseded by instantaneous adjustments to exogenous geopolitical news.

2. Decoupling and Globalized Shock-Sensitivity: The results empirically confirm the "regime-shift hypothesis" in European gas markets (ACER, 2023; Ali & Mirza, 2025)). Following the 2022 structural break, European gas prices decoupled from regional physical fundamentals (such as local temperature anomalies, ΔTMP_t) and transformed into a globalized, shock-sensitive commodity benchmark. Price discovery is no longer dictated by seasonal demand, but by international competition for flexible LNG cargoes and macro-financial risk sentiment.

3. Breakdown of Volatility Path-Dependency: The estimated decay of volatility persistence ($\beta_1 \approx 0$) challenges the theoretical universality of standard GARCH specifications in energy risk modeling (Badeeb & Lean, 2018). When exogenous shocks occur with extreme frequency and magnitude, they break the path-dependency of conditional variance. Markets transition from a persistent state—where past variance predicts future risk—to a reactive state, where volatility is dictated entirely by immediate news arrivals ($\alpha_1 = 0.661$) (Ellersiek & Gnerre, 2023).

5. Conclusions, Policy Implications, and Limitations

5.1. Summary of Core Findings

This study provided a comprehensive econometric evaluation of Dutch TTF natural gas price dynamics and volatility during the 2022–2023 European energy crisis ($N = 77$ weekly observations). By integrating baseline OLS regressions, an ARIMAX conditional mean model, diagnostic testing, and conditional variance evaluations (GARCH vs. EWMA), the empirical analysis yields the following core conclusions:

Price Level vs. Short-Run Return Drivers: In the long run, TTF price levels were dictated by the European Union's structural adjustment to Russian pipeline supply curtailments, requiring emergency storage refilling (STK_t) and rapid LNG expansion (IML_t). In short-run return space ($\Delta\ln TTF_t$), however, physical fundamental variables lose continuous explanatory power.

Dominance of Macro-Financial Dynamics: The EUR/USD exchange rate ($\Delta\ln EUSD_t$) is the primary statistically significant short-run driver ($\beta = -4.46$, $z = -2.16$, $p = 0.030$), establishing currency valuation and international trade pricing as the dominant channels of immediate price transmission.

Shock-Driven Market Architecture: The lack of autoregressive structure in the ARIMAX mean equation confirms that the TTF market operates in a memory-less, shock-driven state where past returns offer no predictive power for future price adjustments.

Non-Persistent Volatility Dynamics: Conditional volatility is characterized by immediate reaction to market surprises ($\alpha_1 = 0.661$) but zero long-term persistence ($\beta_1 \approx 0$) (Urom et al., 2020). The EWMA framework ($\lambda = 0.94$) successfully captures this high-reactivity structure, supported by the complete absence of residual ARCH effects in model diagnostics (LM = 4.83, $p = 0.900$) (Hamilton, 1994; Kopytin et al., 2022).

5.2. Policy and Risk Management Implications

The empirical findings hold direct operational implications for market regulators, policymakers, and energy risk managers:

Regulatory Policy and Crisis Resilience: Policy frameworks must be designed for rapid shock absorption rather than relying on tools that assume predictable, mean-reverting price behavior. Traditional market stabilization mechanisms based on seasonal storage targets should be supplemented with dynamic, macro-financial monitoring—specifically, tracking foreign exchange exposure and international LNG shipping spreads.

Cross-Currency Risk Management: The decisive statistical significance of the EUR/USD exchange rate underscores that European energy security is intrinsically bound to macro-financial stability. Energy market participants and industrial consumers must integrate active foreign exchange hedging strategies directly into their physical procurement operations.

Adaptive Margin Systems and VaR Modeling: Risk managers and central clearing counterparties (CCPs) must revise standard Gaussian-based Value-at-Risk (VaR) models. Given the combination of heavy-tailed return distributions (Kurtosis = 5.64) and zero volatility persistence ($\beta_1 \approx 0$), static GARCH models will miscalculate margin requirements during crisis regimes. Risk management frameworks should adopt adaptive, fast-responding volatility measures like EWMA ($\lambda = 0.94$) paired with extreme value theory (EVT) tail-risk corrections.

5.3. Limitations and Directions for Future Research

Several methodological limitations of this study must be acknowledged, each pointing toward valuable avenues for future research:

Sample Size and Regime Specificity: The analysis relies on $N = 77$ weekly observations covering the peak 2022–2023 crisis window. While necessary to preserve regime homogeneity, this sample size limits the estimation of complex, multi-parameter non-linear models. Future research should extend the sample into the post-crisis stabilization period to test whether volatility persistence (β_1) re-emerges under normalized market conditions.

Data Frequency Trade-Offs: Using weekly data aligns with the reporting frequency of fundamental physical flows (ENTSOG, AGSI+) and filters out microstructural market noise. However, weekly aggregation naturally smooths intra-week price spikes. Future studies utilizing daily or high-frequency tick data could better illuminate intraday price discovery and liquidity dynamics.

Single-Benchmark Focus: This study focused exclusively on the Dutch TTF hub as Europe's primary price reference. Expanding the analytical framework to a multi-market, spatial econometric setting would allow researchers to model cross-hub volatility spillovers, transmission mechanisms, and price convergence across regional European gas hubs, including the National Balancing Point (NBP in the UK), Point Virtuel de Echange (PVE in France), and Punto di Scambio Virtuale (PSV in Italy).

Non-Linear Model Extensions: Given the heavy tails and shock-driven nature of energy returns, future empirical specifications should explore non-linear regime-switching

architectures—such as Threshold Autoregressive (TAR), Smooth Transition ARMAX (STAR), or Markov-Switching GARCH models—to formally capture asymmetric price responses during state transitions.

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Abbreviation

The following abbreviation is used in this manuscript:

TTF Title Transfer Facility

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