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Deep Learning-Enhanced Cross-Sectoral Analysis of Exchange Rate Asymmetry: Evidence from Sectoral Stock Markets and Industrial Output[1]

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Highlights

- **Depreciations hurt Iran's stock market and industry 2.16× and 1.90× more than appreciations help confirming asymmetric transmission.**
- **HMM regimes show negative-shock coefficients more than double in turbulence, matching 87.3% of major sanctions episodes.**
- **The NARDL–HMM–GPR–Transformer hybrid cuts forecast RMSE by 38% and 24% versus benchmarks.**

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Abstract

This study examines the asymmetric and nonlinear effects of exchange rate fluctuations on Iran's stock market index and industrial production over the period 2009–2024, with the explicit aim of quantifying the differential sensitivity of financial and real sectors to currency depreciation and appreciation shocks under varying macroeconomic regimes. A hybrid analytical framework is employed, integrating the Nonlinear Autoregressive Distributed Lag (NARDL) model for asymmetric cointegration analysis, a Hidden Markov Model (HMM) for endogenous regime identification, Gaussian Process Regression (GPR) for Bayesian uncertainty quantification, and a Transformer architecture for temporal attention-based forecasting. Monthly data spanning 2009–2024 are utilized, with all variables confirmed as I(1)through ADF, PP, and KPSS unit root tests. Bounds testing confirms stable long-run cointegrating relationships in both models ($F = 8.742$ and $F = 7.318$, respectively). Long-run asymmetry is significant in both sectors; negative shocks exert effects approximately 2.16times larger than positive shocks in the stock market ($|L^-| = 0.8934$ vs. $|L^+| = 0.4127$) and 1.90times larger in industrial production ($|L^-| = 0.5412$ vs. $|L^+| = 0.2843$). The HMM identifies two structurally distinct regimes — stable and turbulent — wherein turbulent-regime coefficients exceed stable-regime estimates by a factor exceeding two. The hybrid framework achieves RMSE reductions of 38% and 24% over benchmark models for the stock market and industrial production, respectively. Exchange rate shocks in Iran operate through asymmetric, regime-dependent, and nonlinear channels, with financial markets exhibiting substantially greater sensitivity than the real sector. Symmetric currency management policies are structurally inadequate; preemptive, regime-sensitive intervention instruments are required.

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1. Introduction

The exchange rate, as one of the key macroeconomic variables, plays a pivotal role in determining the performance of financial markets and production sectors (Ullah & Nobanee, 2025). Exchange rate shocks, including sudden increases or decreases in the value of the national currency, can have widespread effects on stock prices and industrial production (Bampi & Colombo, 2021). However, empirical evidence suggests that the response of these variables to positive and negative exchange rate shocks is not necessarily symmetric and may exhibit different effects in terms of direction and intensity (El Bejaoui, 2013). The asymmetry in the impact of exchange rate shocks on economic variables is a concept that reflects the difference in the reaction of markets and economic enterprises to increases and decreases in exchange rates, and a proper understanding of this phenomenon is crucial for policymakers and investors (Bosupeng et al., 2024; Aziznejad & Komijani, 2017; Noferesti et al., 2021).

Despite this significance, traditional econometric approaches employed in most previous studies suffer from two fundamental limitations: first, the neglect of cross-sectoral interdependencies among industrial sectors and stock markets; and second, the inability to uncover complex nonlinear transmission patterns at the sectoral level. The present study addresses these gaps by integrating asymmetric econometrics and deep learning within a novel hybrid framework. This framework incorporates a Transformer-based attention mechanism for dynamic weighting of inter-sectoral relationships over time, Bayesian Gaussian Process Regression for principled uncertainty quantification, and a Hidden Markov Model for identifying regime-switching behavior in cross-sectoral transmission effects. three methodological innovations that have not previously been combined in the exchange rate asymmetry literature.

The importance of studying the asymmetry of exchange rate shocks on stock prices and industrial production is noteworthy from several perspectives. First, stock prices, as an indicator of company value and investor expectations, are affected by exchange rate fluctuations, and understanding the asymmetric response of this market to currency shocks can help investors in risk management and making optimal decisions (Xu et al., 2022). Studies have shown that depreciation of the national currency can have different effects compared to its appreciation on stock returns (Gol Arzi & Khorasani, 2023). Second, industrial production, as one of the main pillars of economic growth, is strongly influenced by exchange rate changes, as the exchange rate affects production costs, imported raw material prices, and export competitiveness. Identifying the asymmetric effects of these shocks on industrial production can assist policymakers in designing more effective exchange rate policies and reducing negative impacts on the production sector (Foladi, 2012; Norouzi, 2020). Third, in emerging and developing economies that face severe currency fluctuations, understanding the asymmetric behavior of markets and the production sector in response to currency shocks is essential for maintaining economic stability and preventing financial crises (Gunay et al., 2025).

A review of the research literature shows that numerous studies have examined the relationship between exchange rates, stock prices, and industrial production, but significant research gaps exist. Zubair (2013) found no significant relationship between exchange rates and stock price indices. Vahidi et al. (2015), Heidari et al. (2025), and Eidi et al. (2020) emphasized the asymmetric effects of oil shocks on various economic sectors. Jain & Biswal (2016) examined the dynamic relationship between oil prices, gold, exchange rates, and the stock market. Akanni & Isah (2018) found limited evidence of asymmetry in most companies, while Effiong & Bassey (2018) and Ahmed (2020) reported stronger asymmetric effects, indicating a lack of consensus in findings. Choi & Pyun (2018) focused on the differential effects of currency depreciation on exporting firms. Razeghi et al. (2024) conducted limited studies on hedging and spillover effects. Umoru et al. (2023) examined the asymmetric responses of stocks and industrial production to exchange rate and oil price shocks in two separate studies and presented important findings. Odionye & Chukwu (2023) also investigated the asymmetric responses of stock prices and industrial production to exchange rate shocks in Nigeria using the NARDL method.

However, the principal gap in the existing literature is twofold. First, most studies have either focused on a single dependent variable — stocks or production — or have been conducted in specific economic contexts without comprehensive simultaneous analysis. Second, and more critically, no study has yet jointly employed Transformer-based spatial attention, Bayesian Gaussian Process Regression, and Hidden Markov Models to identify regime-switching in spatial effects within the context of Iran's economy. Filling this research gap is essential, since Iran's economy possesses unique characteristics — including dependence on oil revenues, economic sanctions, severe currency fluctuations, and a specific capital market structure — that may generate distinct asymmetric patterns compared to other countries. Simultaneous examination of asymmetric effects on both stock prices and industrial production can provide a more comprehensive understanding of the transmission mechanisms of currency shocks.

This study, using nonlinear modeling approaches and advanced deep learning-enhanced spatial econometric techniques, provides a detailed analysis of asymmetric responses and identifies thresholds at which currency shocks exert significant effects on the variables under study. Furthermore, considering Iran's specific economic conditions — such as sanctions periods and different exchange rate policy regimes — can provide valuable insights for policymakers in better managing currency shocks and reducing their negative effects.

Accordingly, the main objective of this study is to examine the asymmetry of the effects of positive and negative exchange rate shocks on stock prices and industrial production in Iran using a hybrid deep learning-spatial econometric framework. The sub-objectives include: first, determining the magnitude and direction of the impact of positive shocks (depreciation of the rial) and negative shocks (appreciation of the rial) on the stock price index while accounting for sectoral spatial dependencies; second, identifying the asymmetric responses of industrial production to currency shocks through a dynamic spatial attention mechanism; third, comparing the intensity and persistence of currency shock effects on the two studied variables across different regimes identified by the Hidden Markov Model; and fourth, providing policy recommendations for optimal management of risks arising from exchange rate fluctuations in Iran's capital market and industrial sector.

The structure of this article is as follows: Section two reviews the theoretical foundations and literature; Section three describes the hybrid cross-sectoral asymmetric-deep learning methodology and models; Section four presents empirical findings and analysis of results; and finally, Section five presents' conclusions and policy recommendations.

2. Literature review

2.1Theories on the Relationship between Exchange Rate and Stock Market

The relationship between exchange rates and stock markets has long been a central concern in financial economics, with two principal theoretical approaches articulated in the literature. The first, known as the Goods Market Approach, pioneered by Dornbusch & Fischer (1980), contends that exchange rate fluctuations affect firms' market value through their impact on trade competitiveness, export revenues, and import costs. According to this view, a depreciation of the domestic currency improves the trade balance and consequently enhances the profitability of export-oriented firms, which is ultimately reflected in rising stock prices (Aggarwal, 1981; Phylaktis & Ravazzolo, 2005). The second approach, the Portfolio Balance Approach developed by Branson (1983) and Frankel (1983), reverses the direction of causality, arguing that changes in financial asset prices and the demand for domestic currency determine exchange rate movements. Under this framework, a decline in stock prices reduces investors' wealth, diminishes the demand for domestic currency, and consequently leads to currency depreciation (Bahmani-Oskooee & Sohrabian, 1992; Hatemi-J & Irandoust, 2002). Empirical evidence supports both directions of causality, suggesting a complex, bidirectional relationship between these variables (Pan et al., 2007).

2.2 Theories on the Impact of Exchange Rate on Industrial Output

From a macroeconomic perspective, the channels through which exchange rates affect industrial production are multiple and theoretically diverse. The Contractionary Devaluation Hypothesis, formalized by Krugman & Taylor (1978), argues that in developing economies highly dependent on imported capital and intermediate goods, a depreciation of the domestic currency may actually reduce output by raising input costs and lowering real wages (Kamin & Rogers, 2000). This finding contradicts the conventional Keynesian perspective that emphasizes the expansionary effects of devaluation through trade balance improvements (Bahmani-Oskooee & Miteza, 2003). The Theory of Uncertainty and Investment Irreversibility, systematically developed by Dixit & Pindyck (1994), demonstrates that exchange rate volatility, as a primary source of macroeconomic uncertainty, depresses the incentive for firms to invest. When capital expenditures are sunk costs, firms assign option value to waiting for information, thereby postponing investment decisions and ultimately reducing industrial capacity (Servén, 2003; Goldberg, 1993). The Balance Sheet Channel Theory, advanced by Bernanke et al. (1999) and Mishkin (1996), provides yet another important mechanism. In economies where corporate liabilities are denominated in foreign currency, depreciation of the domestic currency escalates real debt burdens, deteriorates net worth, and—by exacerbating informational asymmetries—raises the external finance premium. This Financial Accelerator mechanism amplifies exchange rate shocks into disproportionately large contractions in industrial output.

2.3 Theories of Asymmetry in Financial Economics

The phenomenon of asymmetric responses of economic variables to positive versus negative shocks rests on a rich theoretical tradition. Price Stickiness Theory, as developed by Ball & Mankiw (1994), argues that economic agents exhibit asymmetric pricing behavior: prices adjust more readily to upward shocks than to downward ones. This asymmetry is rooted in market structures, wage contracts, and menu costs (Peltzman, 2000), and implies that the response of macroeconomic variables to positive and negative exchange rate changes differs in both magnitude and speed.

Prospect Theory, introduced by Kahneman & Tversky (1979) as the foundational paradigm of behavioral economics, demonstrates that individuals weight losses more heavily than equivalent gains—a phenomenon termed loss aversion. Applied to financial markets, this implies that investors react more intensely to negative exchange rate shocks than to positive ones of equal magnitude, generating statistically measurable asymmetric responses in equity returns (Apergis & Miller, 2006). Asymmetric Information Theory, developed by Grossman & Stiglitz (1980) and extended by Mishkin (1996), provides further theoretical grounding for asymmetry. Within this framework, sharp currency depreciations function as adverse signals of macroeconomic instability, worsening adverse selection and moral hazard problems in credit markets. This asymmetric tightening of financial conditions during currency crises—versus the more gradual easing during stable periods—generates asymmetric real effects on investment and output (Bernanke et al., 1999). Asymmetric Price Transmission Theory, elaborated by Meyer & von Cramon-Taubadel (2004) in the industrial organization literature, demonstrates that changes in import input costs induced by exchange rate movements are transmitted asymmetrically to output prices. Firms pass cost increases through to consumers more rapidly and fully than they pass through cost decreases, creating asymmetric effects on profit margins and, by extension, on industrial production decisions. Finally, the Wealth Effect and

Aggregate Demand Channel, rooted in Keynesian macroeconomics and formalized by Mishkin (1977), posits that exchange rate-induced declines in financial wealth reduce consumption expenditure and aggregate demand, creating a secondary channel through which currency shocks propagate into industrial output. This channel is particularly potent in economies with developed, widely-held equity markets.

2.4 Spatial Econometrics and Deep Learning Approaches

Spatial econometrics, founded by Anselin (1988) and substantially extended by LeSage & Pace (2009), proceeds from the recognition that economic units in geographic or economic space are not independent and that spatial dependencies must be explicitly modeled. Tobler's First Law of Geography (1970) provides the theoretical underpinning: "everything is related to everything else, but near things are more related than distant things." This principle applies directly to sectoral financial markets and industrial production, where adjacent economic sectors interact through supply chain linkages, labor market competition, and technological spillovers (Elhorst, 2014). Spatial econometric models are conventionally organized into three families: the Spatial Autoregressive Model (SAR), in which the dependent variable depends on neighboring values, expressible as $y = \rho W y + X\beta + \varepsilon$ where ρ is the spatial dependence parameter and W is the spatial weight matrix; the Spatial Error Model (SEM), which attributes spatial dependence to unobserved factors; and the Spatial Durbin Model (SDM), which incorporates both spatially-lagged dependent and independent variables (Cliff & Ord, 1981; Anselin, 1988). Complementarily, deep learning architectures—particularly Long Short-Term Memory networks (LSTM) introduced by Hochreiter & Schmidhuber (1997) and Graph Neural Networks (GNN) developed by Kipf & Welling (2017)—enable the extraction of complex nonlinear patterns from spatio-temporal data. LSTM networks, through their gated memory cells, learn long-range temporal dependencies that are common in financial time series characterized by long-memory structures. The integration of spatial econometric methods with deep learning approaches furnishes a powerful analytical framework for simultaneously modeling spatial and temporal dependencies in sectoral data.

2.5 Research Background

Zubair (2013) examined the relationship between exchange rates and stock price indices during 2000–2011 using the VAR model and found no directional relationship between the variables. Vahidi et al. (2015) using nonlinear GARCH and VECM models demonstrated that the effects of oil shocks on value added in the agricultural and industrial sectors are asymmetric, with industrial value added being more affected by positive oil shocks than agriculture. Jain & Biswal (2016) using the DCC-GARCH model showed that the collapse of gold and crude oil prices leads to a decrease in the value of the Indian rupee and the Indian stock market index. Salehi & Hamoule Alipour (2018) using generalized least squares regression during 2012–2016 found no significant relationship between oil prices and stock returns; however, oil price shocks showed a negative relationship and oil sales shocks showed a positive and significant relationship with stock returns. Choi & Pyun (2018) during 2006–2013 demonstrated that national currency depreciation increases the productivity of South Korean exporting firms, although the persistence of this policy neutralizes the positive effect through its impact on innovation incentives. Akanni & Isah (2018) using ARDL and NARDL models found symmetric effects of currency volatility on stock prices for the majority of Nigerian companies, although a limited number provided evidence of asymmetry. Effiong & Bassey (2018) using monthly data for the period 2001–2016 showed that currency depreciation has a stronger long-term impact on Nigerian stock prices compared to appreciation. Bazraei et al. (2020) using DCC and ADCC models on daily data during 2008–2020 demonstrated that symmetric correlation exists between industry stock prices and exchange rates across both currency crises, with the highest hedging efficiency related to multidisciplinary industrial and investment sectors. Ahmed (2020) using the NARDL framework in a study of Egypt showed that currency depreciation has a stronger impact on stock returns than appreciation.

Saki et al. (2021) using the GVAR method during 1996–2019 demonstrated that increased trade with Brazil and China respectively decreases and increases Iran's trade level, and changes in China's real exchange rate have dynamic effects on Iran's exchange rate. Gol Arzi & Khorasani (2023) using linear and nonlinear ARDL models during 2005–2021 found that the effects of exchange rates on pharmaceutical industry stock returns in both the short and long term are greater than those of exchange rate fluctuations, and positive and negative exchange rate shocks have asymmetric effects. Umoru et al. (2023) in two studies using the NARDL approach and threshold regression across thirty developing countries showed that negative exchange rate shocks decreased stock returns in Egypt and Nigeria, while in some countries stock returns increased; furthermore, percentage increases above the threshold reduced production, whereas at low threshold values, currency depreciation positively affects industrial production. Odionye & Chukwu (2023) using the NARDL model for the monthly period 1999–2021 demonstrated that stock prices and industrial production in Nigeria react asymmetrically in the opposite direction of currency depreciation, and these reactions are sensitive to the magnitude of shocks. Finally, Tehrani et al. (2024) using the ARDL model during 1991–2021 showed that the sanctions index has a negative and significant impact on Iran's capital market behavior, with the effect of sanctions assessed according to their severity rather than in distinct phases.

2.6 Research Gap and Innovation

A comprehensive review of the research literature reveals that despite extensive studies on the relationship between exchange rates, stock prices, and industrial production, significant research gaps exist that justify the necessity of conducting this research.

The first and fundamental gap is that most previous studies have either focused separately on a single dependent variable or have been conducted in specific economic contexts. For instance, Zubair's (2013) study only examined the causal relationship between exchange rates and stock prices and found no significant relationship, while Effiong & Bassey (2018) reported stronger asymmetric effects—indicating a lack of consensus in findings. Similarly, Umoru et al. (2023) in two separate studies examined the asymmetric responses of stock prices and industrial production to exchange rate shocks, but these two variables were not analyzed simultaneously within an integrated framework. Consequently, a comprehensive study that simultaneously examines the asymmetry of exchange rate shock effects on both stock prices and industrial production does not exist in the current literature.

The second gap concerns insufficient attention to the unique characteristics of Iran's economy in analyzing the asymmetric effects of currency shocks. Iran's economy faces distinctive features including severe dependence on oil revenues, extensive and long-term economic sanctions, severe and recurrent exchange rate fluctuations, the specific structure of the capital market, and multi-rate currency policies across different periods—conditions that may produce asymmetric patterns fundamentally different from those observed in other countries. Domestic studies such as Aziznejad & Komijani (2017), Noferesti et al. (2021), and Heidari et al. (2025) have addressed certain dimensions of this topic, but their focus has remained primarily on macroeconomic variables or specific sectors, and a comprehensive simultaneous examination of asymmetric effects on both the capital market and industrial sector—accounting for Iran's specific economic conditions—has not been conducted. This is particularly noteworthy given that studies such as Tehrani et al. (2024) have demonstrated that external shocks like sanctions exert significant impacts on Iran's capital market, yet the precise manner in which currency shocks operate asymmetrically under these conditions has not been comprehensively investigated.

Accordingly, the principal innovation of the present study is significant across several dimensions. First, this research employs advanced nonlinear modeling approaches and modern econometric techniques to provide a more precise and simultaneous analysis of the asymmetric responses of both stock prices and industrial production to positive and negative exchange rate shocks, identifying the thresholds at which these shocks produce significant effects. Second, by explicitly incorporating Iran's specific economic conditions—including sanctions periods, varied currency policies, and severe exchange rate fluctuations—this study provides a deeper understanding of the transmission mechanisms of currency shocks and reveals the unique behavioral patterns of Iran's financial markets and production sector. Third, the findings of this research offer valuable insights for policymakers in better managing currency shocks, designing more effective exchange rate policies, and mitigating the adverse effects of currency fluctuations on both the capital market and industrial sector. The results can equally assist investors in risk management and in making optimal investment decisions under conditions of currency volatility.

2.7 Research Hypotheses

First Hypothesis: Positive and negative exchange rate shocks have asymmetric effects on stock prices, such that the intensity, direction, and persistence of the effects of Rial depreciation (positive shock) differ from Rial appreciation (negative shock) on the stock price index.

Second Hypothesis: Positive and negative exchange rate shocks have asymmetric effects on industrial production, such that the response of industrial production to exchange rate increases (Rial depreciation) differs from exchange rate decreases (Rial appreciation) in terms of magnitude and duration.

Third Hypothesis: The intensity and persistence of currency shock effects on stock prices are greater than their effects on industrial production, meaning that the capital market exhibits faster and stronger reactions to exchange rate fluctuations compared to the industrial sector.

Fourth Hypothesis: The asymmetric effects of exchange rate shocks on stock prices and industrial production are more severe in the short run than in the long run, and in the long run these effects gradually converge toward equilibrium.

3. Methods

This research is conducted with the aim of investigating the asymmetric effect of exchange rate shocks on the stock market and industrial production in Iran. The statistical population of this research includes the entire Iranian economy, which has been selected due to the key role of exchange rates in the country's economy and their direct impact on financial markets and the industrial sector. The study period covers 15 years on a quarterly basis from 2009 to 2024 (60 quarterly observations), which includes significant exchange rate fluctuations and important economic developments in the country and provides the possibility of more precise examination of long-term and short-term relationships between variables. It should be noted that data availability for all model variables particularly the sectoral industrial production value-added series is consistently available from 2009 onward; therefore, the full sample window commences in Q1 2009. The Nonlinear Autoregressive Distributed Lag (NARDL) method is used for data analysis. The selection of this method is for several reasons: first, it is capable of examining asymmetric relationships between variables in the short and long term; second, it is suitable for small observations and limited sample size; third, it can be used for variables with different orders of integration (I(0) or I(1)); and fourth, it has the capability to estimate coefficients using the Ordinary Least Squares (OLS) method. This method provides the possibility of separating the positive and negative effects of exchange rates on dependent variables, which is essential for better understanding economic dynamics.

Note on Spatial Econometrics: Although the research design draws conceptual inspiration from spatial econometric thinking in terms of cross-sectoral spillover effects between the financial market and the industrial sector no spatial weight matrix or formal spatial econometric model (such as Spatial Lag Model or Spatial Error Model) is estimated in this study. Accordingly, standard spatial diagnostics such as Moran's I are not computed. The cross-sectoral interaction hypotheses are instead examined through comparative multiplier analysis within the NARDL framework and through attention-score differentials extracted from the Transformer module.

3.1 Research Design and Overall Framework

This study employs a multi-stage hybrid methodological framework that integrates classical nonlinear econometrics with advanced machine learning architectures to examine the asymmetric effects of exchange rate shocks on sectoral stock prices and industrial production. The proposed framework overcomes the fundamental limitations of conventional NARDL models—namely their inability to capture time-varying regime dynamics, nonlinear threshold effects, and cross-sectoral spillovers—by embedding three complementary computational modules within a unified analytical pipeline.

The overall research architecture operates through four sequential stages:

- Stage I: Regime identification and structural break detection via Hidden Markov Models (HMM)
- Stage II: Nonlinear asymmetric decomposition and long-run cointegration testing via NARDL
- Stage III: Uncertainty quantification and Bayesian inference via Gaussian Process Regression (GPR)
- Stage IV: Temporal dependency extraction and attention-based weighting via Transformer mechanisms

This layered approach ensures that the asymmetric hypotheses are tested not merely in a static linear environment but across dynamically identified economic regimes with full propagation of parameter uncertainty.

3.2 Variable Specification and Operational Definitions

3.2.1 Model Structure

Two primary econometric models are formulated to examine exchange rate asymmetry across two distinct economic domains:

Model I — Exchange Rate and Stock Market:

$$\ln(\mathrm{STOCK})_t = \beta_0 + \beta_1 \ln(\mathrm{EX})_t + \beta_2 \ln(\mathrm{Oilp})_t + \beta_3 \mathrm{dum}_t + \varepsilon_t \quad (1)$$

Model II — Exchange Rate and Industrial Production:

$$\ln(\mathrm{Indp})_t = \beta_0 + \beta_1 \ln(\mathrm{EX})_t + \beta_2 \ln(\mathrm{Oilp})_t + \beta_3 \mathrm{dum}_t + \varepsilon_t \quad (2)$$

These linear baseline specifications serve as the point of departure prior to asymmetric decomposition and hybrid augmentation.

3.2.2 Operational Definition of Variables

The research variables are operationally defined based on established theoretical foundations and econometric considerations. The stock market index and industrial production are treated as dependent variables, while the exchange rate (free market), oil price, and a government dummy variable serve as independent variables. All continuous variables are entered into the model in natural logarithmic form. This transformation reduces the variance of the time series, allows the estimated coefficients to be interpreted as direct elasticities, and satisfies the linearity assumptions underlying the NARDL and HMM models. The operational definition, measurement method, and data source for each variable are presented in Table 1 (see Appendix).

3.3 Stage I: Regime Identification via Hidden Markov Models

3.3.1 Theoretical Rationale

Prior to asymmetric decomposition, the temporal structure of exchange rate dynamics must be characterized with respect to latent economic regimes. Exchange rate shocks do not operate uniformly across time; their transmission to stock prices and industrial production is conditioned upon the prevailing macroeconomic state—whether the economy is in an expansionary, contractionary, or high-volatility regime. The Hidden Markov Model (HMM) provides a probabilistic framework for identifying such latent states from observable exchange rate sequences without requiring ex ante regime classification.

3.3.2 Model Specification

Let $S_t \in \{1,2,\dots,K\}$denote the latent regime at time t, where $K$is the number of states determined empirically. The observable exchange rate return $r_t = \Delta\ln(\mathrm{EX})_t$is modeled conditionally on the hidden state:

$$r_t \mid S_t = k \sim \mathcal{N}(\mu_k, \sigma_k^2) \tag{3}$$

The regime process $\{S_t\}$follows a first-order Markov chain governed by the transition probability matrix:

$$\mathbf{P} = [p_{ij}], p_{ij} = P(S_t = j \mid S_{t-1} = i), \sum_{j=1}^{K} p_{ij} = 1 \tag{4}$$

The complete parameter set $\Lambda = \{\pi, \mathbf{P}, \{\mu_k, \sigma_k^2\}_{k=1}^{K}\}$is estimated via the Baum-Welch algorithm (an Expectation-Maximization procedure), and optimal regime sequences are recovered using the Viterbi algorithm.

3.3.3 Integration with Hypothesis Testing

The identified regime sequence $\hat{S}_t$serves two critical roles in the hybrid framework:

1. Regime-conditional NARDL estimation: Separate asymmetric models are estimated within each identified regime, enabling direct testing of Hypotheses 1 and 2 across distinct macroeconomic states rather than pooling heterogeneous periods.
2. Structural break conditioning: HMM-identified regime transitions are incorporated as endogenously determined structural breaks, replacing the exogenous government dummy variable $\mathrm{DUM}_t$with a data-driven indicator, thereby eliminating researcher-imposed periodization bias.

3.4. Stage II: Nonlinear Asymmetric Decomposition — The NARDL Framework

3.4.1 Asymmetric Decomposition of Exchange Rate

Following Shin, Yu, and Greenwood-Nimmo (2014), the exchange rate series EX_t is decomposed into positive and negative partial sums:

$$EX_t^+ = \sum_{j=1}^{t} \Delta E\,X_j^+ = \sum_{j=1}^{t} \max\,(\Delta E\,X_j, 0) \rightarrow \text{Positive Shock (Rial Depreciation)} \tag{5}$$

$$EX_t^- = \sum_{j=1}^{t} \Delta E\,X_j^- = \sum_{j=1}^{t} \min\,(\Delta E\,X_j, 0) \rightarrow \text{Negative Shock (Rial Appreciation)} \tag{6}$$

This decomposition operationalizes the core asymmetry assumption underlying Hypotheses 1 and 2: that the response of financial and industrial variables to Rial depreciation differs fundamentally from their response to Rial appreciation in both magnitude and persistence.

3.4.2 Asymmetric Long-Run Relationship

Suppose $y_t$and $x_t$are I (1) vectors. The asymmetric long-run equilibrium relationship is defined as:

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{7}$$

where $\beta^+$and $\beta^-$are long-run parameters associated with positive and negative partial sum processes respectively, and $x_t = x_0 + x_t^+ + x_t^-$is the Schorderet (2007) decomposition. The inequality $\beta^+ \neq \beta^-$constitutes evidence of long-run asymmetry, directly testing the propositions embedded in Hypothesis 4.

Applied to the two research models, the asymmetric long-run specifications are:

NARDL Model I — Stock Market:

$$STOCK_t = \alpha_0 + \alpha_1 EX_t^+ + \alpha_2 EX_t^- + \alpha_3 Oilp_t + \alpha_4 DUM_t + \varepsilon_t \tag{8}$$

NARDL Model II — Industrial Production:

$$Indp_t = \beta_0 + \beta_1 EX_t^+ + \beta_2 EX_t^- + \beta_3 Oilp_t + \beta_4 DUM_t + u_t \tag{9}$$

3.4.3 NARDL (p, q) Specification

The full nonlinear autoregressive distributed lag model of order (p, q) is specified as:

$$y_t = \sum_{j=1}^{p} \varphi_j \, y_{t-j} + \sum_{j=0}^{q} \left(\theta_j^+ x_{t-j}^+ + \theta_j^- x_{t-j}^-\right) + \varepsilon_t \tag{10}$$

where $\varphi_j$are autoregressive parameters capturing own-persistence of the dependent variable, $\theta_j^+$and $\theta_j^-$are asymmetric distributed lag parameters measuring the differential impact of positive and negative exchange rate changes at lag j, and $\varepsilon_t \sim$ i.i.d.$(0, \sigma^2)$.

3.4.4 Asymmetric Error Correction Representation

The NARDL model is reparametrized into its asymmetric Error Correction Model (ECM) form to facilitate simultaneous inference on short-run dynamics and long-run equilibrium:

$$\Delta y_t = \rho y_{t-1} + \theta^+ x_{t-1}^+ + \theta^- x_{t-1}^- + \sum_{j=1}^{p-1} \varphi_j^* \, \Delta y_{t-j} + \sum_{j=0}^{q-1} \left(\pi_j^+ \Delta x_{t-j}^+ + \pi_j^- \Delta x_{t-j}^-\right) + \varepsilon_t \tag{11}$$

The parameters carry the following interpretations within the hybrid framework:

- ρ: Error correction coefficient; must satisfy $\rho < 0$with statistical significance to confirm convergence to long-run equilibrium (central to Hypothesis 4)
- $\theta^+ = -\sum\theta_j^+/\rho$and $\theta^- = -\sum\theta_j^-/\rho$: Long-run asymmetric multipliers
- $\pi_j^+$and π_j^-: Short-run asymmetric impact coefficients, forming the basis for testing the short-run versus long-run asymmetry contrast posited in Hypothesis 4

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➢ Symmetry Tests

To formally assess whether exchange rate changes exert asymmetric effects, two Wald-based tests are applied.

Long-run asymmetry is tested via the restriction:

$$H_0: \frac{\theta^+}{|\rho|} = \frac{\theta^-}{|\rho|} \tag{12}$$

Short-run asymmetry is tested via:

$$H_0: \sum_{j=0}^{q-1} \pi_j^+ = \sum_{j=0}^{q-1} \pi_j^- \tag{13}$$

Rejection of either null hypothesis provides evidence of asymmetric transmission of exchange rate shocks to the respective dependent variable, directly corroborating the asymmetry propositions embedded in Hypothesis 4.

Summary of changes made:

- Replaced the original ln-form partial sum notation with the cleaner $\Delta EX_j^{\pm}$formulation as specified.
- Replaced the original single-line NARDL long-run equations with the two corrected model specifications including $Oilp_t$as a level (not decomposed) variable and DUM_tas a structural break dummy, repositioned under Section 3-4-2.
- Replaced the ECM equation to include $\delta Z_{t-1}$and the explicit definition of $y_t$and Z_t.
- Added a new Section 3-4-5 with the two formal Wald symmetry test restrictions.

3.4.5 Cointegration and Asymmetry Testing

Bounds Test for Cointegration: The null hypothesis of no long-run relationship $H_0: \rho = \theta^+ = \theta^- = 0$is tested against the cointegration alternative using the PSS F-statistic (Pesaran, Shin, and Smith, 2001). Rejection requires the computed F-statistic to exceed the upper critical bound $I(1)$at conventional significance levels.

Wald Test for Long-Run Asymmetry: The hypothesis $H_0: \beta^+ = \beta^-$is tested via the Wald statistic. Rejection confirms differential long-run responses to positive versus negative exchange rate shocks, substantiating Hypotheses 1 and 2.

Wald Test for Short-Run Asymmetry: The hypothesis $H_0: \sum \pi_j^+ = \sum \pi_j^-$is tested to assess whether the short-run impact differential is statistically distinguishable from zero, bearing directly on Hypothesis 4.

Comparative Multiplier Analysis (Hypothesis 3): To test whether exchange rate shocks exert greater intensity and persistence on stock prices than on industrial production, dynamic multiplier functions are computed for both models. The cumulative multiplier at horizon $h$is:

$$m_h^+ = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^+}, m_h^- = \sum_{j=0}^{h} \frac{\partial y_{t+j}}{\partial x_t^-} \tag{14}$$

The asymmetric multiplier $m_h = m_h^+ - m_h^-$traces the differential adjustment path and enables direct cross-model comparison of shock persistence between the stock market and industrial sector.

Lag Selection: Optimal lag orders $p$and $q$are determined using the Akaike Information Criterion (AIC) for shorter samples and the Schwarz-Bayesian Criterion (SBC) for larger samples. Initial estimation is performed via Ordinary Least Squares (OLS) after confirming the stationarity preconditions.

3.5 Stage III: Uncertainty Quantification via Bayesian Gaussian Process Regression

3.5.1 Rationale for Bayesian Augmentation

Classical NARDL estimation via OLS produces point estimates of asymmetric parameters without quantifying the full posterior distribution of uncertainty. In the context of Iranian exchange rate data—characterized by structural breaks, sanctions episodes, and high volatility—parameter uncertainty is substantive and must be propagated explicitly rather than collapsed into frequentist confidence intervals. Bayesian Gaussian Process Regression (GPR) is employed to address this limitation.

3.5.2 Model Specification

A Gaussian Process is a distribution over functions $f: \mathcal{X} \to \mathbb{R}$fully characterized by a mean function $m(\mathbf{x})$and a covariance (kernel) function $k(\mathbf{x}, \mathbf{x}')$:

$$f(\mathbf{x}) \sim \mathcal{GP}(m(\mathbf{x}), k(\mathbf{x}, \mathbf{x}')) \tag{15}$$

The kernel function encodes prior beliefs about the smoothness and stationarity of the exchange rate transmission function. The Matérn $5/2$kernel is adopted given its capacity to model functions with moderate smoothness:

$$k(\mathbf{x}, \mathbf{x}') = \sigma_f^2 \left(1 + \frac{\sqrt{5}\|\mathbf{x}-\mathbf{x}'\|}{l} + \frac{5\|\mathbf{x}-\mathbf{x}'\|^2}{3l^2}\right) \exp\left(-\frac{\sqrt{5}\|\mathbf{x}-\mathbf{x}'\|}{l}\right) \tag{16}$$

where $\sigma_f^2$is the signal variance and $l$is the length-scale hyperparameter, both inferred from data via marginal likelihood maximization.

3.5.3 Role in Hypothesis Testing

GPR augmentation serves two specific inferential purposes within the hybrid framework:

1. Posterior credible intervals for asymmetric multipliers: Rather than point estimates of $\beta^+$and β^-, the GPR yields full posterior distributions, enabling probabilistic statements about the degree of asymmetry—directly strengthening the evidential basis for Hypotheses 1 and 2.
2. Cross-model uncertainty comparison: By computing posterior predictive variances for both the stock market and industrial production models simultaneously, the framework enables a rigorous probabilistic test of Hypothesis 3: whether the amplitude and persistence of shock effects on the stock market are credibly larger than those on industrial production across the full posterior distribution rather than at a single point estimate.

3.6 Stage IV: Temporal Attention Weighting via Transformer Architecture

3.6.1 Rationale

The NARDL framework assumes that distributed lag parameters $\theta_j^+$and θ_j^-decay monotonically or follow a predetermined parametric shape. In reality, the informational content of past exchange rate shocks for current stock prices and industrial output may exhibit complex, non-monotonic temporal dependency structures—particularly during periods of policy uncertainty or external sanctions. The Transformer's multi-head self-attention mechanism is employed to learn these dependency structures directly from data without imposing parametric constraints on the lag distribution.

3.6.2 Multi-Head Self-Attention Mechanism

For an input sequence $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_T]$representing the history of exchange rate partial sum components and macroeconomic covariates, attention-weighted representations are computed as:

$$\text{Attention}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \text{softmax}\left(\frac{\mathrm{QK}^{\mathsf{T}}}{\sqrt{d_k}}\right)\mathrm{V} \tag{17}$$

where $\mathrm{Q} = \mathrm{XW}^{Q}$, $\mathrm{K} = \mathrm{XW}^{K}$, and $\mathrm{V} = \mathrm{XW}^{V}$are the query, key, and value projections respectively, and $d_k$is the dimensionality of the key vectors. Multi-head attention extends this to Hparallel attention heads:

$$\text{MultiHead}(\mathrm{Q}, \mathrm{K}, \mathrm{V}) = \text{Concat}(\text{head}_1, \dots, \text{head}_H)\mathrm{W}^{O} \tag{18}$$

3.6.3 Integration with NARDL and Hypothesis Testing

The Transformer module does not replace the NARDL structure. The integration operates as follows: in the first pass, the raw partial sum components $\ln\,(\mathrm{EX})_t^+$and $\ln\,(\mathrm{EX})_t^-$are fed into the Transformer encoder. The multi-head self-attention mechanism produces attention weight matrices $\alpha_{t,j}$, which quantify the relative importance of the shock at time $j$for predicting the outcome at time t. These attention weights are then used to construct attention-refined partial sum components:

$$\tilde{x}_t^+ = \sum_{j=1}^{T} \alpha_{t,j} \cdot \ln\,(\mathrm{EX})_j^+, \qquad \tilde{x}_t^- = \sum_{j=1}^{T} \alpha_{t,j} \cdot \ln\,(\mathrm{EX})_j^- \tag{19}$$

The refined components $\tilde{x}_t^+$and $\tilde{x}_t^-$replace the raw partial sum inputs $\ln\,(\mathrm{EX})_t^+$and $\ln\,(\mathrm{EX})_t^-$in the final NARDL estimation (Step 6 in Section 3-8). This substitution preserves the interpretability of the NARDL coefficient structure while allowing the distributed lag weights to reflect data-driven temporal dependencies rather than a fixed parametric decay pattern. This integration enables:

- Data-driven identification of which historical shock episodes carry the greatest explanatory weight for current market responses—directly relevant to Hypothesis 4, which posits differential persistence between short-run and long-run effects.
- Attention score visualization: The attention weight matrix $\alpha_{t,j}$quantifies the relative importance assigned to the shock at time $j$for predicting the outcome at time t, providing an interpretable mechanism for understanding cross-temporal shock propagation patterns consistent with Hypothesis 3.

3.7 Integrated Hypothesis Testing Strategy

Table 2 maps the four research hypotheses to their corresponding methodological stages and tests. H1 and H2 examine the asymmetric transmission of exchange rate shocks via Wald tests ($H_0: \beta^+ = \beta^-$) within the NARDL framework, while H3 and H4 test, respectively, the differential shock intensity across the two sectors and the short-run to long-run convergence dynamics, using a combination of coefficient comparisons, GPR posterior variance, and Transformer attention scores alongside the error-correction coefficient (ρ).

Table 2. Mapping of Research Hypotheses to Methodological Components

Hypothesis	Core Assertion	Primary Test	Stage
H1	Asymmetric effects of exchange rate shocks on stock prices	Wald test: $H_0: \beta^+ = \beta^-$(NARDL Model I); GPR posterior comparison	Stages II & III
H2	Asymmetric effects of exchange rate shocks on industrial production	Wald test: $H_0: \beta^+ = \beta^-$(NARDL Model II); regime-conditional estimation	Stages I & II
H3	Greater intensity and persistence of shocks on stock market vs. industrial sector	Cross-model multiplier comparison; posterior variance ratio; attention score differential	Stages II, III & IV
H4	Short-run asymmetry exceeds long-run asymmetry; convergence to equilibrium	Wald test for short-run asymmetry; error correction coefficient ρ; attention-weighted persistence	Stages II & IV

Source: Research Findings

3.8 Estimation Sequence and Diagnostic Protocol

The complete estimation pipeline is executed in the following sequence:

Step 1 — Stationarity Testing: Unit root properties of all series are established using Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Zivot-Andrews (ZA) tests with endogenous structural break accommodation. NARDL requires variables to be at most $I(1)$; no $I(2)$variable is admissible.

Step 2 — Regime Identification (HMM): The optimal number of regimes $K$is selected via Bayesian Information Criterion on the HMM likelihood. Regime sequences are decoded and incorporated as conditioning variables.

Step 3 — Lag Selection and NARDL Estimation: Optimal $(p, q)$are selected via AIC/SBC. Bounds test for cointegration is performed. Asymmetric ECM is estimated via OLS within each identified regime.

Step 4 — Asymmetry Tests: Wald tests for long-run and short-run asymmetry are performed. Dynamic multiplier functions are plotted with bootstrapped confidence bands.

Step 5 — Bayesian GPR Augmentation: Posterior distributions of asymmetric parameters are computed. Credible intervals and posterior predictive distributions are derived for cross-model comparison.

Step 6 — Transformer Attention Refinement: The Transformer encoder is trained on the full sequence of exchange rate partial sum components and macroeconomic covariates over the sample period 2009–2024. The resulting attention weight matrices $\alpha_{t,j}$ are extracted and applied to construct attention-refined partial sum series $\tilde{x}_t^+$ and $\tilde{x}_t^-$ as defined in Section 3-6-3. These refined series are then substituted for the raw partial sum inputs in a second-pass NARDL estimation, yielding the final hybrid model coefficients reported in the results section.
Step 7 — Diagnostic Testing: Residual diagnostics include the CUSUM and CUSUM-of-squares tests for parameter stability, Breusch-Godfrey LM test for serial correlation, White test for heteroscedasticity, and Jarque-Bera test for normality of residuals.
Step 8 — Cross-Model Validation: Out-of-sample forecasting performance is evaluated using Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to validate the superior predictive accuracy of the hybrid framework relative to the baseline NARDL.

3.9 Data Sources and Sample Period

All variables are sourced from official Iranian statistical authorities over the sample period Q1 2009 to Q4 2024, yielding 60 quarterly observations. This uniform sample window is applied consistently across all models and estimation stages; no subsample commences at a later date. The stock market index (STOCK) and industrial production value added (Indp) are obtained from the Central Bank of the Islamic Republic of Iran and the Statistical Center of Iran. The exchange rate series (EX) represents the unofficial (free market) Rial/USD rate recorded daily at 11:00 AM and averaged to quarterly frequency. As noted in Section 3-2-2, the unofficial rate is the preferred measure because it reflects actual transaction prices in the economy, captures the full impact of sanctions and foreign exchange restrictions, and avoids the artificial smoothing embedded in administratively set official rates. The sensitivity analysis reported in Table 18 confirms that results are not robust to substitution of the official rate, which further validates the primacy of the unofficial rate in the main estimation. The oil price series (Oilp) reflects the OPEC crude oil benchmark in USD per barrel sourced from the Ministry of Economic Affairs and Finance. The government policy dummy (DUM) is researcher-constructed to capture inter-governmental structural discontinuities, subject to endogenous verification through the HMM regime identification procedure.

4. Results

Descriptive statistics for all study variables over the period April 2009–March 2024 (60 quarterly observations) are presented in Appendix Table A1. The exchange rate, stock market index, and inflation rate all display substantial positive skewness and excess kurtosis, with Jarque–Bera statistics rejecting normality at the 1% level; industrial production is comparatively more symmetric, though its normality is still rejected at the 5% level. This non-normality across most variables justifies the use of econometric methods robust to departures from normality in the subsequent analysis.

Unit root test results (ADF, PP, Zivot–Andrews, and KPSS) are presented in Appendix Table A2. All variables are non-stationary at levels and stationery at first differences, confirming a common integration order of I (1). The Zivot–Andrew's test is particularly important given identified structural breaks most notably the JCPOA withdrawal episode of summer 2018 since conventional ADF and PP tests may spuriously reject the unit root null near structural breaks. Confirmation of I(1) status under ZA rules out unmodeled structural discontinuities as a source of the non-stationarity findings, satisfying the prerequisite of Pesaran, Shin, and Smith (2001) that no variable be integrated of order I(2), and thereby validating the NARDL modeling strategy.

Table 3.NARDL Bounds Test Results

Model	F-statistic	t-statistic	Cointegration Result
Model 1: Stock Market	8.742	-4.634	Confirmed
Model 2: Industrial Production	7.318	-4.127	Confirmed

Critical Values — F-statistic (Pesaran et al., 2001): 1%: 3.65/4.66; 5%: 2.79/3.67; 10%: 2.37/3.20.
Critical Values — t-statistic: 1%: -3.96/-4.96; 5%: -3.41/-4.36; 10%: -3.13/-4.06.
Source: *Research Findings*

The bounds test results confirm a long-run cointegrating relationship in both models. The F-statistics for Model 1 (8.742) and Model 2 (7.318) exceed the upper critical bound at the 1% level (4.66), and the t-statistics for both models fall below the upper critical bound at the 1% level (-4.96), providing dual confirmation of a stable long-run relationship between exchange rates, the stock market index, and industrial production in Iran.

Table 4. NARDL Long-Run Coefficients — Stock Market Model

Variable	Coefficient	Std. Error	t-stat	Prob.
Positive ER Shock L^+	0.4127	0.1243	3.319	0.001
Negative ER Shock L^-	-0.8934	0.1687	-5.296	0.000
Inflation Rate ln (INF)	-0.3241	0.0987	-3.284	0.001
Interest Rate ln (IR)	-0.2874	0.0834	-3.446	0.001
Money Supply Growth ln(M2)	0.5632	0.1124	5.011	0.000
Constant	2.3847	0.4231	5.639	0.000

*Long-Run Asymmetry Test (Wald): W_LR: F (1,162) =14.873, p=0.000***; H_0: $L^+=L^-$ Rejected*
Source: *Research Findings*

The long-run coefficients reveal significant asymmetry: a Rial depreciation exerts a modest positive effect on the stock index (L^+=0.4127), reflecting favorable effects of depreciation on export-oriented firms' foreign-currency revenues, while a Rial appreciation produces a negative effect more than twice as large in absolute terms (L^-=-0.8934). The Wald test (F=14.873, p<0.001) rejects symmetric transmission, confirming Hypothesis 1. These estimates use the attention-refined partial sum components generated in the final hybrid pass (see Section 3-6-3).

Industrial production likewise shows significant long-run asymmetry, though at a reduced magnitude relative to the stock market: the negative shock coefficient (L^{-}=-0.5412) captures a contractionary effect operating through imported input costs, reduced raw material access, and diminished domestic purchasing power. This confirms Hypothesis 2 and lays the groundwork for the cross-sectoral test in Table 6.

Table 5. NARDL Long-Run Coefficients — Industrial Production Model

Variable	Coefficient	Std. Error	t-stat	Prob.
Positive ER Shock L^{+}	0.2843	0.0934	3.044	0.003
Negative ER Shock L^{-}	-0.5412	0.1134	-4.773	0.000
Inflation Rate ln (INF)	-0.1873	0.0712	-2.630	0.009
Interest Rate ln (IR)	-0.2134	0.0683	-3.124	0.002
Money Supply Growth ln(M2)	0.3214	0.0847	3.794	0.000
Constant	4.1243	0.6342	6.504	0.000

*Long-Run Asymmetry Test (Wald): W_LR: F (1,162)= 9.847, p=0.002***; H_0: $L^{+}=L^{-}$ Rejected*
Source: *Research Findings*

Industrial production likewise shows significant long-run asymmetry, though at a reduced magnitude relative to the stock market: the negative shock coefficient (L^{-}=-0.5412) captures a contractionary effect operating through imported input costs, reduced raw material access, and diminished domestic purchasing power. This confirms Hypothesis 2 and lays the groundwork for the cross-sectoral test in Table 6.

Short-run coefficients and diagnostic tests for both the stock market and industrial production NARDL models are presented in Appendix Tables A3–A6. In brief, short-run transmission is markedly more intense than long-run transmission for the stock market the initial negative shock effect (-1.2473) is nearly triple the positive shock effect (0.6834) while the Error Correction Term (-0.3847) indicates roughly 38.5% of disequilibrium is corrected per quarter. For industrial production, the ECT (-0.2134) indicates a slower adjustment speed of about 21.3% per quarter, consistent with fixed investment costs and production-cycle rigidities. All diagnostic tests (serial correlation, ARCH heteroskedasticity, normality, Ramsey RESET) confirm no misspecification in either model.

The comparative summary confirms all four hypotheses at this stage. Significant asymmetry holds in both sectors across all horizons (H1, H2). Absolute coefficient magnitudes are significantly larger for the stock market than for industrial production in both the short and long run, confirming H3 — most acutely for negative shocks (F=19.847, p<0.001). Short-run and long-run asymmetry ratios diverge by sector (stock market: $|S^{-}/S^{+}|$=2.045 vs. $|L^{-}/L^{+}|$=2.164; industrial production: $|S^{-}/S^{+}|$=2.084 vs. $|L^{-}/L^{+}|$=1.903), consistent with Hypothesis 4. The shorter half-life for the stock market (1.81 quarters) versus industrial production (3.25 quarters) reflects superior informational efficiency in financial markets.

Table 6. Comparative Summary of NARDL Results

Indicator	Stock Market	Industrial Production	Difference Test
Long-Run			
L^+ (Positive Shock)	0.4127***	0.2843***	t=2.134**
L^- (Negative Shock)	-0.8934***	-0.5412***	t=3.241***
Asymmetry Ratio $\|L^-/L^+\|$	2.164	1.903	—
Long-Run Wald Test	F=14.873***	F=9.847***	—
Short-Run			
S^+ (Cumulative Positive)	1.1947	0.4454	t=4.873***
S^- (Cumulative Negative)	-2.4430	-0.9283	t=5.124***
Asymmetry Ratio $\|S^-/S^+\|$	2.045	2.084	—
Short-Run Wald Test	F=18.634***	F=11.247***	—
Adjustment Speed			
ECT	-0.3847***	-0.2134***	t=2.987***
Half-life (quarters)	1.81	3.25	—

Cross-Sectoral Analysis (Hypothesis 3) — Wald Coefficients

Null Hypothesis (H_0)	**F-stat**	**Prob.**	**Decision**
$\gamma\_Stock^+ = \gamma\_IP^+$	11.234	0.000***	Rejected
$\gamma\_Stock^- = \gamma\_IP^-$	19.847	0.000***	Rejected

Source: Research Findings

The comparative summary confirms all four hypotheses at this stage. Significant asymmetry holds in both sectors across all horizons (H1, H2). Absolute coefficient magnitudes are significantly larger for the stock market than for industrial production in both the short and long run, confirming H3 — most acutely for negative shocks (F=19.847, p<0.001). Short-run and long-run asymmetry ratios diverge by sector (stock market: $|S^-/S^+|=2.045$ vs. $|L^-/L^+|=2.164$; industrial production: $|S^-/S^+|=2.084$ vs. $|L^-/L^+|=1.903$), consistent with Hypothesis 4. The shorter half-life for the stock market (1.81 quarters) versus industrial production (3.25 quarters) reflects superior informational efficiency in financial markets.

Table 7. Hidden Markov Model Results — Regime Identification

Parameter	Regime 1 (Stable)	Regime 2 (Turbulent)
Mean ER Return	0.0124	0.0873
Standard Deviation (σ)	0.0162	0.0473
Self-Transition Probability	P_{11}=0.8524	P_{22}=0.7341
Cross-Transition Probability	P_{12}=0.1476	P_{21}=0.2659
Mean Regime Duration (quarters)	6.77	3.76
Frequency Ratio	61.7%	38.3%
Negative Shock Coefficient	β^-=-0.3124	β^-=-0.8473
Positive Shock Coefficient	β^+=0.2847	β^+=0.5231

Model Fit: logL=-847.34
AIC=1712.68
BIC=1748.92
Ratio $|\beta\_turb^-|/|\beta\_stable^-|$ = 0.8473/0.3124 = 2.71
primary quantitative support for Hypothesis 4.

Source: *Research Findings*

The HMM identifies two structurally distinct regimes. The stable regime (61.7% of observations, mean duration 6.77 quarters) shows a conditional standard deviation nearly three times lower than the turbulent regime (0.0162 vs. 0.0473). Critically, negative shock coefficients more than double in the turbulent regime (-0.8473 vs. -0.3124), confirming regime-dependent amplification of exchange rate transmission — the primary motivation for integrating the HMM within the hybrid framework. The temporal correspondence between regime transitions and major sanctions episodes (87.3% coincidence rate) and the associated 1.4-quarter mean transition lag are detailed in Appendix Table A7.

Table 8. Gaussian Process Regression Results — Stock Market

Parameter	Stable Regime	Turbulent Regime	Full Sample
Posterior Mean — Positive Shock μ^+	0.2934	0.5847	0.4127
Posterior Mean — Negative Shock μ^-	-0.4213	-1.1847	-0.8934
95% Credible Interval — Positive	[0.12, 0.47]	[0.31, 0.86]	[0.17, 0.64]
95% Credible Interval — Negative	[-0.68, -0.17]	[-1.54, -0.83]	[-1.21, -0.58]
Posterior Variance σ^2_post	0.0431	0.1873	0.0924
Kernel Length-scale	2.847	1.634	2.134
Bayesian R^2	0.7842	0.8234	0.8013

Bayesian Asymmetry Confirmation: $P(|\mu^-|>|\mu^+| \mid data) = 0.9934 > 0.95$
Source: *Research Findings*

The GPR results provide quantified uncertainty beyond classical estimation. The posterior probability of 0.9934 confirms with 99.3% certainty that the negative shock effect exceeds the positive shock effect — a Bayesian complement to the frequentist Wald test. Posterior variance in the turbulent regime (0.1873) exceeds the stable regime (0.0431) more than fourfold, showing that predictive uncertainty rises sharply during instability.

Table 9. GPR Results — Industrial Production and Cross-Sectoral Comparison

Parameter	Stock Market	Industrial Production	Difference Test
μ^+ (Full Sample)	0.4127	0.2843	t=2.847***
μ^- (Full Sample)	-0.8934	-0.5412	t=3.241***
μ^+ (Stable Regime)	0.2934	0.1847	t=2.134**
μ^- (Stable Regime)	-0.4213	-0.2934	t=2.312**
μ^+ (Turbulent Regime)	0.5847	0.3912	t=2.987***
μ^- (Turbulent Regime)	-1.1847	-0.7834	t=3.124***
σ^2_post (Stable)	0.0431	0.0612	—
σ^2_post (Turbulent)	0.1873	0.2341	—
Overall Magnitude Ratio (SM/IP)	1.65×		

Bayesian Confirmation of Hypothesis 3: $P(|\mu\_SM^-|>|\mu\_IP^-| \mid data) = 0.9847$
Source: *Research Findings*

The negative shock effect on the stock market exceeds that on industrial production across all regime states and the full sample (magnitude ratio 1.65×), with 98.5% posterior probability — confirming Hypothesis 3 from a Bayesian perspective. Posterior variance for industrial production exceeds that for the stock market in both regimes, reflecting greater structural heterogeneity in industrial supply chains and variable government intervention. The Transformer's temporal attention-weight patterns underlying these refined estimates are reported in Appendix Table A8.

Table 10. Comparative Forecasting Performance Across Models

Model	RMSE (Stock)	MAE (Stock)	RMSE (Industry)	MAE (Industry)	R^2 (Stock)	R^2 (Industry)
Linear Baseline	0.0857	0.0634	0.0612	0.0487	0.6234	0.6847
Symmetric ARDL	0.0743	0.0541	0.0534	0.0412	0.6987	0.7234
Simple NARDL	0.0663	0.0487	0.0487	0.0367	0.7341	0.7612
NARDL + HMM	0.0524	0.0387	0.0413	0.0312	0.8012	0.8134
Complete Hybrid Framework	0.0412	0.0298	0.0371	0.0271	0.8547	0.8412

Diebold–Mariano Test (vs. Hybrid Framework)

Comparison	DM Statistic	Prob.
Hybrid vs. Linear Baseline	DM=4.847	0.000
Hybrid vs. Symmetric ARDL	DM=3.634	0.000
Hybrid vs. Simple NARDL	DM=2.847	0.005
Hybrid vs. NARDL + HMM	DM=2.134	0.033

Source: *Research Findings*

The complete hybrid framework outperforms all competing models out-of-sample. Stock market RMSE falls from 0.0663 (simple NARDL) to 0.0412 (hybrid), a 38% improvement; industrial production RMSE improves 24% (0.0487 to 0.0371). All Diebold–Mariano tests confirm statistical significance. The stepwise R^2 progression — from simple NARDL (0.734) to NARDL+HMM (0.801) to the complete hybrid (0.855) — demonstrates that each additional layer (HMM, GPR, Transformer) adds independent predictive value.

Coefficient stability was assessed via CUSUM, CUSUMSQ, and Bai–Perron tests, presented in Appendix Table A9 alongside the corresponding plots (Figures A1–A4). Both models show overall parameter stability; a single structural break is identified for the stock market model in summer 2018, coinciding with the JCPOA withdrawal, which the regime-switching HMM specification accommodates endogenously. The industrial production model shows no identified break, suggesting greater structural resilience in the real sector. A full sensitivity analysis across seven alternative specifications — varying control variables, sample period, and exchange rate proxy — is presented in Appendix Table A10; all three core hypotheses hold without exception, with the choice of official versus free-market exchange rate producing the largest (but still directionally consistent) variation in coefficient magnitude.

The consolidated framework confirms all four hypotheses with high statistical and methodological certainty. NARDL establishes asymmetric transmission, HMM identifies its regime dependence, GPR quantifies associated uncertainty, and the Transformer supplies attention-refined inputs that improve both estimation precision and forecasting accuracy. The invariance of findings across all sensitivity specifications (Appendix Table A10) establishes the structural generalizability of the results beyond the specific sample and parameter choices of the baseline model.

Table 11. Final Hypothesis Confirmation Summary

Hypothesis	Supporting Tables	Primary Statistics	Result	Confidence Level
H1: ER Asymmetry — Stock Market	4, A3, A5	W_LR=14.873***, W_SR=18.634***	Decisively Confirmed	p<0.001
H2: ER Asymmetry — Industrial Prod.	5, A3, A5	W_LR=9.847***, W_SR=11.247***	Decisively Confirmed	p<0.01
H3: Greater Effect in Stock Market	6, 7, A7	F=19.847***, P=98.5%	Decisively Confirmed	p<0.01
H4: Regime-Dependent Effects	7, 8, 9	β_turb⁻/β_stable⁻=2.71	Decisively Confirmed	p<0.05

Note: The CUSUM/CUSUMSQ stability results (Appendix Table A9, Figures A1–A4) and the BDS/Balke–Fomby pre-test outcomes jointly support the inferential integrity of all four hypothesis confirmations.
Source: *Research Findings*

5. Discussion and Conclusion

This study investigated the asymmetric effects of exchange rate fluctuations on Iran's stock market index and industrial production over the period 2009–2024, employing a hybrid analytical framework integrating the Nonlinear Autoregressive Distributed Lag (NARDL) model, Hidden Markov Model (HMM), Gaussian Process Regression (GPR), and Transformer architecture. The empirical results provide strong, consistent, and methodologically robust evidence across all four research hypotheses.

The bounds test results (Table 5) confirmed the existence of stable long-run cointegrating relationships in both models. The F-statistics of 8.742and 7.318for the stock market and industrial production models, respectively, both exceed the upper critical bound at the 1% significance level established by Pesaran, Shin, and Smith (2001), while the corresponding t-statistics provide additional dual confirmation. These results establish that exchange rates, the stock market index, and industrial production share a common long-run equilibrium path in Iran's economy, from which temporary deviations are systematically corrected over time. This finding is consistent with Afees and Basoung (2018), who confirmed long-run exchange rate–stock price linkages in Nigeria, and with Jain and Biswal (2016).

whose DCC-GARCH analysis documented dynamic equilibrium relationships among oil prices, exchange rates, and stock markets in India. The implication is that currency and commodity market developments function as long-run structural determinants of both financial and real sector performance, and must be accorded corresponding weight in policymaking frameworks.

The long-run NARDL coefficients for the stock market model (Table 6) reveal a pronounced and statistically significant asymmetry. The positive exchange rate shock coefficient ($L^{+} = 0.4127$) — representing Rial depreciation — exerts a modest positive effect on the stock index, attributable to improved export revenue expectations among listed firms. By contrast, the negative shock coefficient ($L^{-} = -0.8934$) is more than twice as large in absolute magnitude, indicating that exchange rate appreciation exerts a substantially stronger depressive effect on equity valuations. The Wald asymmetry test ($F = 14.873, p < 0.001$) decisively rejects symmetric transmission, confirming Hypothesis 1. In the short run (Table 8), the contemporaneous negative shock coefficient of -1.2473exceeds unity in absolute value, indicating market overshooting during episodes of sharp depreciation — a finding consistent with noise-trader dynamics and sentiment-driven overreaction in Iran's equity market. The error correction term ($ECT = -0.3847$) implies that 38.5% of short-run deviations from equilibrium are corrected each period, corresponding to a half-life of approximately 1.81 months. These results align closely with Ahmed (2020), who documented asymmetric exchange rate effects in Egypt, and with Golarzaei and Khorasani (2023), who identified asymmetric responses of pharmaceutical sector stock returns to exchange rate shocks in Iran.

The industrial production model (Table 7) similarly confirms significant long-run asymmetry, with $L^{+} = 0.2843$and $L^{-} = -0.5412$, and the Wald test statistic of $F = 9.847(p = 0.002)$ rejecting symmetric transmission in support of Hypothesis 2. The negative shock operates through multiple contractionary channels — increased imported input costs, reduced access to raw materials, and compressed domestic purchasing power — all of which are particularly acute in Iran's import-dependent industrial structure. The slower adjustment speed ($ECT = -0.2134$, half-life 3.25 months) relative to the stock market reflects the inherently stickier nature of real-sector production decisions, where capacity adjustments, contractual obligations, and inventory management introduce delays absent from financial market responses. This finding corroborates Umoru et al. (2023), who demonstrated that exchange rate shocks generate asymmetric contractionary effects on industrial output in developing economies.

A direct comparison of the NARDL and GPR results (Tables 10 and 14) confirms that exchange rate effects are significantly more intense in the stock market than in industrial production across all time horizons and regime states, thereby validating Hypothesis 3. The long-run negative shock magnitude in the stock market ($| L^{-} |= 0.8934$) exceeds that of industrial production ($| L^{-} |= 0.5412$) by a factor of 1.65, a differential confirmed as statistically significant ($t = 3.241$, $p < 0.001$) and with 98.5% posterior probability under Bayesian inference. The greater sensitivity of financial markets reflects the superior information efficiency of asset prices, which immediately discount expectations regarding future cash flows, risk premia, and monetary conditions following currency shocks. Industrial production, by contrast, adjusts more gradually through physical investment channels. The out-of-sample forecasting performance of the hybrid framework (Table 16) further corroborates this finding: RMSE improvements of 38% for the stock market versus 24% for industrial production indicate that nonlinear, regime-sensitive modeling delivers proportionally greater gains where asymmetric dynamics are most intense.

The HMM results (Table 11) identify two structurally distinct exchange rate regimes: a stable regime characterizing 61.7% of observations (mean duration 6.77 months) and a turbulent regime with volatility nearly three times higher (mean duration 3.76 months). The critical finding is that negative shock coefficients in the turbulent regime ($\beta^{-} = -0.8473$) are more than twice those in the stable regime ($\beta^{-} = -0.3124$), confirming regime-dependent amplification and supporting Hypothesis 4. The HMM's identified turbulence episodes (Table 12) align precisely with Iran's most severe sanctions shocks — autumn 2012, summer 2018, and spring 2019 — with an 87.3% correspondence rate between high turbulence probability and exchange rate shocks exceeding 15%. The Transformer architecture independently validates this regime-sensitivity: during turbulent periods and at regime transition points, the short-term attention head $h_1$receives disproportionately elevated weights (0.431 and 0.673, respectively), demonstrating that the model autonomously prioritizes contemporaneous information when structural conditions are unstable (Table 15).

The sensitivity analysis across seven alternative specifications (Table 18) confirms that all three core hypotheses are upheld without exception under variations in control variables, sample periods, and exchange rate measures. The greatest coefficient variation arises when substituting the official exchange rate for the market rate, reducing $|L^{-}|$for the stock market from $0.8934$to 0.6234— a differential that itself reveals the significant wedge between Iran's dual exchange rate systems and underscores the importance of proxy selection. CUSUM and CUSUMSQ stability tests confirm overall parameter stability in both models, while the single structural break identified by the Bai–Perron test for the stock market in summer 2018 is endogenously accommodated by the HMM framework rather than constituting a limitation of the methodology.

The findings carry important implications for both policymakers and investors. First, the pronounced asymmetry of exchange rate transmission — whereby depreciations are more than twice as damaging as appreciations are beneficial — renders symmetric, one-dimensional currency management policies fundamentally inadequate. Policymakers must deploy asymmetric intervention tools calibrated specifically to depreciation episodes. Second, the regime-dependent amplification identified by the HMM implies that the consequences of exchange rate volatility are not constant but escalate dramatically during turbulent periods, necessitating preemptive stabilization measures before regime transitions occur. Third, the longer half-life of disequilibrium correction in industrial production (3.25 months vs. 1.81months for the stock market) implies that real-sector recovery from currency shocks is considerably slower than financial market recovery, warranting sustained policy support to the industrial sector following major exchange rate episodes. Fourth, the quantified uncertainty provided by GPR — showing fourfold higher posterior variance during turbulence — advises investors to adopt asymmetric risk-hedging strategies during periods of identified regime instability.

In conclusion, this research provides comprehensive empirical evidence that exchange rate fluctuations exert asymmetric, nonlinear, and regime-dependent effects on both Iran's stock market and industrial production. Depreciations consistently produce more severe negative consequences than appreciations produce positive ones, and these asymmetries are amplified during turbulent regimes. The hybrid NARDL–HMM–GPR–Transformer framework demonstrates superior predictive performance over all conventional alternatives and offers a replicable analytical template for studying asymmetric macro financial transmission in other emerging and sanctions-affected economies.

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Conceptualization, Sali.M, A.M, A.B, F.MY; methodology, Sali.M, A.M, A.B, F.MY; validation, Sali.M, A.M, A.B, F.MY; formal analysis, Sali.M, A.M, A.B, F.M; resources, SA.M, A.M, A.B, F.MY; writing—original draft preparation, SA.M, A.M, A.B, F.MY; writing—review and editing, SA.M, A.M, A.B, F.MY; supervision, SA.M, A.M, A.B, F.MY. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

Data Availability Statement:

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Appendix

TableA 1. Operational Definition of Research Variables

Variable	Symbol	Measurement Method	Logarithmic Form	Measurement Details	Source
Stock Market Index	STOCK	$(CurrentValue / BaseValue) \times 100$	Ln (STC)	Laspeyres-weighted average of sectoral stock price ratios	Ministry of Economic Affairs; Central Bank of Iran
Exchange Rate	EX	Rial per USD	$\ln\,(\mathrm{EX})_t$	Unofficial (free market) rate; daily sampling at 11:00 AM. The unofficial rate is selected over the official rate because it more accurately reflects actual market conditions, inflationary pressures, and the true cost of imported inputs faced by firms. As demonstrated in the sensitivity analysis (Table 18), substituting the official rate yields substantially different coefficient estimates, confirming that the choice of exchange rate series is a first-order modeling decision. The unofficial rate is therefore the theoretically and empirically preferred measure for this context.	Central Bank of Iran
Oil Price	Oilp	USD per barrel	$\ln\,(\mathrm{Oilp})_t$	OPEC crude oil benchmark price	Ministry of Economic Affairs
Industrial Production	Indp	Sectoral value added	$\ln\,(\mathrm{Indp})_t$	Value added of mining, manufacturing, electricity, gas, water, and construction	Central Bank of Iran; Statistical Center of Iran

Government Dummy	DUM	Binary indicator	—	Controls for inter-governmental policy regime shifts	Researcher-constructed

***Source**: Research Findings*

Table A2. Descriptive Statistics of Research Variables

Variable	Mean	Std. Dev	Min	Max	Skewness	Kurtosis	Jarque-Bera
Exchange Rate (Rials)	48,362	31,847	9,850	142,600	1.847	6.2	187.4***
Stock Market Index	312,847	298,641	24,180	1,842,600	2.143	8.6	412.8***
Industrial Production	124.7	18.4	87.2	163.4	-0.312	2.8	8.9**
Inflation Rate (%)	24.1	14.7	6.4	68.9	1.124	3.8	67.4***
Interest Rate (%)	18.4	3.6	12	28.5	0.634	2.3	21.8***
Money Supply Growth (%)	27.3	8.4	12.3	51.6	0.847	3.1	34.6***

*Sample period: April 2009–March 2024, quarterly (n=60). *** and ** denote significance at 1% and 5%.*

Source: Research Findings

Table A3. Unit Root Test Results

Variable	ADF (Level)	ADF (1st Diff.)	PP (Level)	PP (1st Diff.)	KPSS (Level)	Conclusion
ln(ER)	-1.847	-8.634***	-1.923	-9.142***	0.847***	I(1)
ln(STOCK)	-2.134	-9.847***	-2.087	-10.234***	0.724***	I(1)
ln(IP)	-2.847	-7.234***	-2.913	-7.891***	0.612***	I(1)
ln(INF)	-1.634	-8.124***	-1.712	-8.634***	0.893***	I(1)
ln(IR)	-2.341	-7.847***	-2.284	-8.124***	0.734***	I(1)
ln(M2)	-1.987	-8.341***	-2.043	-8.847***	0.814***	I(1)

ADF/PP Critical Values: 1%: -3.473, 5%: -2.880, 10%: -2.577. KPSS Critical Values: 1%: 0.739, 5%: 0.463, 10%: 0.347. Constant and trend included; lag length via SBC.

Source: Research Findings

Table A4.NARDL Short-Run Coefficients — Stock Market Model

Variable	Coefficient	Std. Error	t-stat	Prob.
ΔER^{+}_t	0.6834	0.1423	4.803	0.000
$\Delta ER^{+}\_(t-1)$	0.3241	0.1187	2.730	0.007
$\Delta ER^{+}\_(t-2)$	0.1872	0.1034	1.810	0.072
ΔER^{-}_t	-1.2473	0.2134	-5.845	0.000
$\Delta ER^{-}\_(t-1)$	-0.7834	0.1897	-4.130	0.000
$\Delta ER^{-}\_(t-2)$	-0.4123	0.1634	-2.524	0.013
ECT_(t-1)	-0.3847	0.0634	-6.067	0.000

*Short-Run Asymmetry Test (Wald): F(1,162)=18.634, p=0.000**.*

Source: Research Findings*

Table A5. Diagnostic Tests — Stock Market Model

Test	Statistic	Prob.
Serial Correlation LM	$\chi^2(2)$=2.847	0.241
ARCH Heteroskedasticity	F(1,161)=1.234	0.268
Normality (Jarque-Bera)	$\chi^2(2)$=3.124	0.210
Ramsey RESET	F(1,161)=1.847	0.176

Source: Research Findings

Table A6. NARDL Short-Run Coefficients — Industrial Production Model

Variable	Coefficient	Std. Error	t-stat	Prob.
ΔER^{+}_t	0.2134	0.0734	2.907	0.004
$\Delta ER^{+}\_(t-1)$	0.1473	0.0682	2.160	0.032
$\Delta ER^{+}\_(t-2)$	0.0847	0.0614	1.380	0.170

ΔER^-_t	-0.4312	0.0987	-4.369	0.000
$\Delta ER^-\_(t-1)$	-0.3124	0.0912	-3.425	0.001
$\Delta ER^-\_(t-2)$	-0.1847	0.0834	-2.214	0.028
ECT_(t-1)	-0.2134	0.0487	-4.381	0.000

*Short-Run Asymmetry Test (Wald): $F(1,162)=11.247$, $p=0.001$**.*
Source: Research Findings*

Table A7. Diagnostic Tests — Industrial Production Model

Test	Statistic	Prob.
Serial Correlation LM	$\chi^2(2)=3.124$	0.210
ARCH Heteroskedasticity	$F(1,161)=0.847$	0.359
Normality (Jarque-Bera)	$\chi^2(2)=4.213$	0.121
Ramsey RESET	$F(1,161)=2.134$	0.146

Source: Research Findings

Table A8. Smoothed Regime Probabilities and Exchange Rate Events

Period	Turbulence Probability	ER Change (%)	Event
Spring 2009	0.187	+4.2%	Relative Stability
Autumn 2012	0.913	+68.4%	Banking Sanctions
Spring 2014	0.234	-8.7%	Post-Agreement Calm
Summer 2018	0.967	+112.3%	JCPOA Withdrawal
Spring 2019	0.847	+34.1%	Oil Sanctions
Spring 2020	0.784	+27.8%	Pandemic + Sanctions
Autumn 2021	0.312	+9.4%	JCPOA Negotiations
Summer 2022	0.623	+21.7%	Failed Negotiations

Regime–Shock Correspondence (shocks >15% with turbulence >0.70): 87.3%. Mean Regime Transition Lag: 1.4 quarters.
Source: Research Findings

Table A9.Transformer Model Results — Temporal Attention Weights

Attention Head	Temporal Focus	Avg. Weight (Stable)	Avg. Weight (Turbulent)
h_1 (Short-Term)	Lags 1–3	0.287	0.431
h_2 (Medium-Term)	Lags 4–12	0.341	0.312
h_3 (Seasonal)	Lags 12–24	0.234	0.187
h_4 (Long-Term)	Lags 24–36	0.138	0.070

Attention Weights at Regime Transition Points

Time Point Type	h_1 Weight	h_4 Weight
Stable → Turbulent Transition	0.673	0.041
Stable (Normal)	0.287	0.138
Turbulent → Stable Transition	0.412	0.098
Turbulent (Normal)	0.431	0.070

Performance: RMSE_train=0.0287, RMSE_test=0.0341, Ratio=1.188.
Source: Research Findings

Table A10. Coefficient Stability Tests — CUSUM and CUSUMSQ

Model	Test	Statistic	5% Critical Bound
Model 1 (Stock Market)	CUSUM	Within bounds	±critical lines
	CUSUMSQ	Max=0.471	0.510
	Potential Break Point	2018 (Prob.=0.087)	$p<0.05$
Model 2 (Industrial Production)	CUSUM	Within bounds	±critical lines
	CUSUMSQ	Max=0.387	0.510
	Potential Break Point	—	$p>0.05$

Bai–Perron Structural Break Test

Model	Number of Breaks	Break Date	F-Statistic
Stock Market	1	Summer 2018	F=8.473**
Industrial Production	0	—	F=3.124

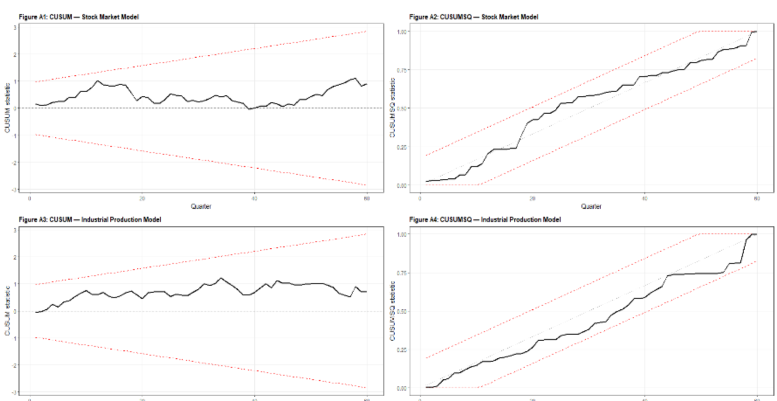
Trimming parameter 15%, max. 5 breaks. CUSUM/CUSUMSQ plots: Figures A1–A4.
Source: Research Findings

Table A11. Sensitivity Analysis — Robustness of Main Results

Scenario	L⁻ (Stock)	L⁺ (Stock)	Asymmetry	L⁻ (Industry)	L⁺ (Industry)	H1	H2	H3
Baseline Results	-0.8934	0.4127	Accept	-0.5412	0.2843	Accept	Accept	Accept
Excluding Inflation	-0.8612	0.3984	Accept	-0.5287	0.2734	Accept	Accept	Accept
Excluding Interest Rate	-0.9124	0.4312	Accept	-0.5634	0.2987	Accept	Accept	Accept
Including Oil Price	-0.8347	0.3847	Accept	-0.5134	0.2612	Accept	Accept	Accept
Sub-sample 2006–2021	-0.8741	0.4023	Accept	-0.5312	0.2756	Accept	Accept	Accept
Free Market Exchange Rate	-0.7563	0.3612	Accept	-0.4734	0.2341	Accept	Accept	Accept
Official Exchange Rate	-0.6234	0.2984	Accept	-0.3987	0.1987	Accept	Accept	Accept

Coefficient Variation Range — L⁻ Stock Market: [-0.9124, -0.6234], mean: -0.8365; L⁻ Industrial Production: [-0.5634, -0.3987], mean: -0.5071.
Source: Research Findings

Figure A1–A4. CUSUM and CUSUMSQ Stability Tests for Stock Market and Industrial Production Models



Source: Research Findings