

The Impact of the Central Bank of Turkey's Monetary Policies on Cryptocurrency Market Dynamics: An ARDL Model for 2014–2025 Period



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Abstract: This study examines the dynamic relationship between cryptocurrency markets and monetary policy in Turkey, focusing on how macroeconomic and financial variables shape four key dimensions of the market: price, trading volume, volatility, and return. Using monthly data from 2013M09 to 2025M03, the analysis applies the Autoregressive Distributed Lag (ARDL) bounds testing approach to identify both short- and long-run relationships, complemented by Error Correction Models (ECM) to estimate adjustment speeds toward equilibrium. The findings reveal robust cointegration across all models, confirming that Turkey's crypto market is closely linked to national and global macro-financial conditions. Exchange rate depreciation and the global bitcoin price emerge as the main long-run drivers of prices and trading volumes, while domestic policy instruments such as the policy rate and reserve requirements exert only indirect influence. In the short run, cryptocurrency returns exhibit strong momentum effects and overshooting behavior, whereas volatility shows a clear mean-reverting pattern. The results reveal that while the traditional interest rate channel of monetary policy shows no significant long-run direct impact, the liquidity channel operating through the Reserve Requirement Ratio (RRR) and Broad Money Supply (M2) remains an active and direct transmission mechanism, particularly affecting trading volumes and short-run price dynamics. The study contributes to the growing literature on monetary transmission in digital asset markets by providing country-specific evidence from an emerging economy, offering insights for both policymakers and investors on the integration of cryptocurrencies within broader financial systems.

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Keywords: cryptocurrency market; monetary policy; exchange rate; ARDL model; cointegration; Turkey.

JEL Classification: E52; E44; C32; G15.

Introduction

Cryptocurrencies, through their distributed ledger technology (DLT)-based structures, offer an alternative model to traditional centralized monetary systems (Carvalho *et al.* 2021; Ssaharti 2022). The rapid proliferation of cryptocurrencies has fundamentally transformed global financial markets, raising new questions about the nature of money, the functioning of financial systems, and the role of central banks in ensuring monetary stability (Corbet *et al.* 2017; Corbet *et al.* 2018; Corbet *et al.* 2019; Ssaharti 2022). These digital assets have attracted the attention of investors, financial institutions, and policymakers, partly due to their transparency and potential to accelerate cross-border transactions (Othman *et al.* 2019; Koziuk 2022).

Over the past decade, the global financial ecosystem has witnessed the remarkable rise of cryptocurrencies. With a market capitalization exceeding USD 1.7 trillion (CoinMarketCap 2024) and daily trading volumes reaching hundreds of billions of dollars, this emerging asset class challenges traditional financial paradigms and presents both opportunities and risks for investors and policymakers (Corbet *et al.* 2019; Fang *et al.* 2022). In line with this

global trend, Turkey ranks among the leading countries in cryptocurrency adoption and usage. According to Chainalysis (2023), Turkey ranks highly on the global crypto adoption index, with high trading volumes driven by its young, tech-savvy population. The total cryptocurrency trading volume in Turkey was estimated to reach tens of billions of dollars in 2023 (CoinGecko 2023). This rapid adoption highlights the need to understand how domestic monetary conditions shape cryptocurrency behavior.

The swift rise and widespread adoption of crypto assets are especially significant for emerging economies such as Turkey, which grapple with high inflation and exchange rate volatility (Sergio and Wedemeier 2025; Ante *et al.* 2022). These assets serve not only as hedging instruments for portfolio diversification but also have the potential to reshape investor expectations and liquidity flows, thereby weakening or complicating the effectiveness of monetary policy instruments (Bouri *et al.* 2017; Corbet *et al.* 2019).

A review of the existing literature reveals that most studies have focused primarily on advanced economies (Bulut 2019). Moreover, prior research has generally concentrated on digital asset prices or volatility, while neglecting dimensions such as trading volume and portfolio-level returns (Fang *et al.* 2019; Corbet *et al.* 2019). In particular, within an economy like Turkey - where monetary policy instruments are actively deployed and financial stability is a primary objective - it is essential to comprehensively examine the effects of the Central Bank of the Republic of Turkey's (CBRT) decisions on the dynamics of this rapidly evolving digital asset market, namely prices, trading volumes, volatility, and returns (Aysan *et al.* 2019; Demir *et al.* 2018).

CBRT's core policy instruments - interest rates, reserve requirements, and money supply management - are expected to influence cryptocurrency market dynamics by altering investor risk perceptions, liquidity conditions, and the demand for alternative assets (Bernanke and Kuttner 2005; Borio and Zhu 2012). For instance, tight monetary policies generally suppress cryptocurrency prices and trading volumes by reducing risk appetite and narrowing the demand for alternative investment vehicles, whereas expansionary monetary policies tend to generate the opposite effect (Conlon *et al.* 2020; Figá-Talamanca and Patacca 2019).

Against this backdrop, this study empirically investigates how monetary policy decisions of the Central Bank of the Republic of Turkey (CBRT) influence the dynamics of the domestic cryptocurrency market - specifically prices, trading volumes, volatility, and returns - over the period 2013–2025. By focusing on the interplay between monetary instruments, macroeconomic variables, and crypto-market indicators, the research aims to identify both the direct and indirect policy transmission channels affecting cryptocurrency behavior in an emerging-market context. Accordingly, the study seeks to address the following research questions:

- (i) How do the CBRT's monetary policy instruments - policy interest rate (repo rate), reserve requirement ratio (RRR), and broad money supply (M2) - affect cryptocurrency prices, trading volume, volatility, and returns in Turkey?
- (ii) Through which transmission channels - interest rate, liquidity, or exchange rate - are these policy effects transmitted to the cryptocurrency market?
- (iii) How do short-run and long-run effects of monetary policy differ across distinct market dimensions?
- (iv) How quickly does the cryptocurrency market adjust to monetary policy shocks to restore long-term equilibrium?

The findings are expected to enhance understanding of how monetary policy interacts with digital asset markets, offering insights for policymakers, regulatory bodies, and investors in designing strategies that balance innovation, financial stability, and risk management.

1. Literature Review

Understanding the intricate interplay between traditional monetary policy instruments and cryptocurrency dynamics in developing and unstable economies has become increasingly important (Marmora 2022; Corbet *et al.* 2017). Karau (2021) and Buthelezi (2024) demonstrate that the European Central Bank's (ECB) monetary tightening generally depresses Bitcoin prices, whereas the Federal Reserve's tightening tends to raise Bitcoin prices in emerging markets (Zhao *et al.* 2023; Corbet *et al.* 2017). Announcements from the Federal Open Market Committee (FOMC) have been shown to generate significant fluctuations in Bitcoin prices (Ma *et al.* 2022; Pour Rostami 2024). Elsayed and Sousa (2022) further note that the effects of monetary policy vary throughout the tapering process, suggesting that the timing and communication of policy measures play a crucial role in shaping cryptocurrency market reactions. Similarly, macroeconomic news from the United States, Germany, and Japan significantly shapes the daily volatility of Bitcoin and Ethereum (Ben Omrane *et al.* 2023; Corbet *et al.* 2020). More recent studies continue to highlight the growing interaction between monetary policy conditions and cryptocurrency markets. For example, Tosun (2025) shows that changes in central bank policy signals can significantly influence cryptocurrency

prices and volatility, while Cagli (2025) finds that monetary policy uncertainty may increase cryptocurrency demand as investors search for alternative assets.

Phochanachan *et al.* (2022) and Marmora (2022) find that Bitcoin offers short-term hedging against inflation comparable to gold, oil, and equities, although its long-term effectiveness remains limited. He *et al.* (2024) suggest that Bitcoin and Ethereum can serve as temporary hedges during periods of economic policy uncertainty, while Będowska-Sójka *et al.* (2024) and Smales (2019) emphasize that safe-haven properties vary across market conditions (Zhou 2019). Using GARCH models, Andrikopoulos *et al.* (2018) identify that some cryptocurrencies influence volatility through returns, while others transmit effects from volatility to returns. Ardia *et al.* (2019) and Chu *et al.* (2015) examine regime-switching and distributional models, whereas Coskun *et al.* (2020) establish a correlation between uncertainty and herding behavior. Iyer (2023) and BenSaida (2023) further show that conditional correlations and the intensity of risk spillovers tend to increase during crisis periods. Recent research also highlights the importance of macroeconomic conditions for cryptocurrency markets. Lin (2024) finds that macroeconomic variables such as exchange rates and interest rate expectations can significantly influence cryptocurrency returns and overall market dynamics.

Benigno (2022) suggests that the proliferation of digital currencies could limit the traditional control of central banks over the money supply, while Belke and Beretta (2020) argue for a balance between modernization and monetary stability. Kang and Lee (2018, 2022) and Lutz (2018) identify long-term interactions between private cryptocurrencies and fiat currencies, whereas Pelagidis and Kostika (2022) analyze the ECB's central bank digital currency (CBDC) plans within the digital payment ecosystem. Krivoruchko *et al.* (2018) compare various central bank approaches; Tomić *et al.* (2020) explore the implications of cryptocurrencies for monetary policy; Carvalho *et al.* (2021) examine the influence of DLT technology on the monetary system; and Barone and Masciandaro (2019) discuss the ongoing tension between anonymity and financial supervision. More recent contributions also address the broader implications of cryptocurrencies for the functioning of the monetary system. For instance, Mumtaz (2025) argues that the increasing adoption of cryptocurrencies may alter money demand and potentially affect the effectiveness of traditional monetary policy tools.

Building upon these international insights, several studies have begun exploring similar relationships in emerging or high-volatility economies, including Turkey. Due to high cryptocurrency adoption and unconventional monetary policies, Taskinsoy (2019) characterizes Bitcoin as a safe-haven asset. Işcan (2020), in a VAR analysis covering 2013–2019, finds no long-run interaction between monetary policies and cryptocurrencies. Bulut (2019), using a NARDL model, investigates the Central Bank of the Republic of Turkey's (CBRT) inflation response. Ante *et al.* (2023) examine user profiles; Oefele *et al.* (2025) assess exchange rate risk; and Ojaghlo and Demirkale (2023) analyze market reactions in five fragile economies. Koziuk (2022) studies the effect of inflation dissatisfaction on crypto investment; Dabbous *et al.* (2022) address adoption in high-risk contexts; Umeokwobi *et al.* (2024), employing a Panel ARDL model, investigate the African case; and Abdelkaoui *et al.* (2024) analyze the effects of cryptocurrencies on growth and inflation in Asian economies.

While the existing literature provides valuable insights into the interaction between monetary policy and cryptocurrency markets, it remains largely concentrated on advanced economies and global-level analyses. Most studies emphasize price and volatility dynamics, whereas trading volume and returns remain relatively underexplored, particularly in the context of emerging markets. Moreover, limited research has examined how monetary policy instruments of central banks in developing economies - such as Turkey - affect cryptocurrency market behavior across both short- and long-term horizons.

This study seeks to fill that gap by focusing on the Central Bank of the Republic of Turkey (CBRT) and empirically analyzing how its monetary policy tools influence the main dynamics of the Turkish cryptocurrency market. By adopting an ARDL modeling framework, the study not only extends the existing literature but also contributes to policy discussions on the transmission of monetary policy into digital asset markets.

2. Data and Methodology

2.1. Data Sources and Scope

The study employs secondary data covering Turkey's cryptocurrency market and key macroeconomic and policy indicators. Data on monetary policy variables - namely the policy interest rate, reserve requirement ratio (RRR), and broad money supply (M2) - were retrieved from the Central Bank of the Republic of Turkey's Electronic Data Delivery System (CBRT-EVDS). Cryptocurrency price and trading volume data were obtained from the CryptoCompare database, which provides consistent, exchange-aggregated series. Global financial indicators - including the Federal Funds Effective Rate (FFR) and the CBOE Volatility Index (VIX) - along with Turkey's unemployment rate, were sourced from the Federal Reserve Economic Data (FRED) database.

The dataset spans the period September 2013 to March 2025, chosen to ensure both the maturity of Turkey's cryptocurrency market and the inclusion of the most recent macro-financial developments. Although the dataset begins in September 2013, the effective estimation period starts in 2014 due to the inclusion of lagged variables in the econometric model specification. This period captures the full evolution of the domestic crypto ecosystem under varying monetary conditions. The analysis is conducted using monthly frequency data, which balances the availability of reliable macroeconomic information with the need to detect medium-term market responses, in line with Campbell *et al.* (1997).

2.2. Research Questions and Analytical Framework

Building on the research questions outlined in the Introduction, this section defines the analytical framework through which they are empirically examined. The central aim is to determine how the Central Bank of the Republic of Turkey's (CBRT) monetary policy instruments - the policy rate, reserve requirement ratio (RRR), and broad money supply (M2) - affect the main dimensions of the cryptocurrency market in Turkey: prices, trading volume, volatility, and returns.

To capture these interactions, the study employs an Autoregressive Distributed Lag (ARDL) modeling strategy, complemented by an Error Correction Model (ECM) to evaluate both short-run dynamics and long-run equilibria. The ARDL approach is particularly suitable for this research because it can handle mixed integration orders ($I(0)$ and $I(1)$), perform effectively in small samples, and identify the speed at which the system re-adjusts to equilibrium after policy shocks (Pesaran *et al.* 2001; Narayan and Smyth 2005).

This design provides a coherent structure linking Turkey's monetary policy instruments to cryptocurrency market behavior through identifiable transmission mechanisms, setting the stage for the detailed data and variable specifications that follow.

2.3. Variables and Measurement

To capture the multidimensional effects of monetary policy on Turkey's cryptocurrency market, the study utilizes four dependent and ten independent variables, classified into core policy, domestic control, and global control categories, as detailed in Table 1.

Table 1. Conceptual and Operational Definitions of Variables

Variable Code	Variable Name	Conceptual Definition	Operational Definition	Unit	Role in Model	Scope	Data Source
PRICE	Cryptocurrency Price	Market value of Bitcoin in domestic currency (Fama, 1970).	$\ln(\text{BTC closing price in TRY})$	\ln (unitless)	Endogenous (Y_1)	National	CryptoCompare
VOLUME	Trading Volume	Indicator of market liquidity and trading activity (Amihud, 2002).	$\ln(\text{BTC monthly trading volume in TRY})$	\ln (unitless)	Endogenous (Y_2)	National	CryptoCompare
VOL	Market Volatility	Price fluctuations represent market risk (Hull, 2012).	Monthly standard deviation of daily BTC returns (TRY).	Percent	Endogenous (Y_3)	National	CryptoCompare
RET	Market Return	Percentage change in price, measuring investment performance (Campbell <i>et al.</i> , 1997).	$\ln(P_t/P_{t-1})$	Percent	Endogenous (Y_4)	National	CryptoCompare
POLICY	Policy Rate	CBRT's main interest rate for liquidity management (Mishkin, 2016).	Mean repo auction rate (%)	Percent	Exogenous, Policy	National	CBRT-EVDS
RRR	Reserve Requirement Ratio	Mandatory reserve ratio of banks (Bernanke and Gertler, 1995).	Monthly RRR (%)	Percent	Exogenous, Policy	National	CBRT-EVDS

Variable Code	Variable Name	Conceptual Definition	Operational Definition	Unit	Role in Model	Scope	Data Source
M2	Real Broad Money Supply	Inflation-adjusted broad money stock (Friedman, 1968).	$\ln(M2/CPI)$	In (unitless)	Exogenous, Policy	National	CBRT-EVDS
EXRATE	Exchange Rate	USD/TRY average exchange rate (Dornbusch, 1976).	$\ln(USD/TRY)$	In (unitless)	Control	National	CBRT-EVDS
FXVOL	FX Volatility	Volatility of USD/TRY returns (Engle, 1982).	Monthly st.dev. of daily USD/TRY log returns	Percent	Control	National	CBRT-EVDS
CPI	Consumer Price Index	Measure of inflation (Mishkin, 2016).	$\ln(CPI)$	In (unitless)	Control	National	CBRT-EVDS
UR	Unemployment Rate	Share of unemployed in labor force (Blanchard and Katz, 1997).	Monthly unemployment rate (%)	Percent	Control	National	FRED
VIX	Global Volatility Index	Global risk perception (Whaley, 2000).	Monthly VIX closing value	Index	Control	International	FRED
FFR	Fed Funds Rate	U.S. short-term policy rate (Bernanke and Blinder, 1992).	Effective federal funds rate (%)	Percent	Control	International	FRED
GPUSD	Global Bitcoin Price (USD)	Global price reference for Bitcoin (Fama, 1970).	$\ln(BTC \text{ closing price in USD})$	In (unitless)	Control	International	CryptoCompare

Note: Logarithmic transformations are applied to PRICE, VOLUME, CPI, EXRATE, GPUSD, and M2; RET represents monthly log returns; VOL and FXVOL denote the monthly standard deviation of daily log returns.

2.4. Transmission Channels and Conceptual Model

Monetary policy affects cryptocurrency markets through multiple, interrelated transmission channels that shape investor behavior, liquidity conditions, and asset valuations. In the context of Turkey's evolving financial landscape - marked by inflationary pressures, exchange rate volatility, and an expanding digital asset market - these channels interact in complex ways. Figure 1 presents the *conceptual framework* of the study, summarizing how policy, domestic, and global variables are structured in relation to cryptocurrency market dynamics. The figure groups explanatory variables into three categories: policy variables (policy rate, reserve requirement ratio, and broad money supply), domestic control variables (exchange rate, foreign exchange volatility, consumer price index, and unemployment rate), and global control variables (VIX, federal funds rate, and global cryptocurrency price). These sets of variables jointly influence the four dimensions of cryptocurrency market dynamics - price, trading volume, volatility, and returns.

Within this framework, monetary transmission operates through several well-established mechanisms. Changes in the policy interest rate alter the relative cost of holding risk-bearing assets: higher interest rates increase borrowing costs and the opportunity cost of holding non-yielding assets, such as cryptocurrencies, thereby discouraging speculative investment and reducing both price and trading activity (Bernanke and Gertler 1995; Mishkin 2001). The liquidity effect, captured through movements in the broad money supply (M2), reflects how monetary expansion or contraction influences market liquidity. An expansionary policy may stimulate demand for digital assets as investors seek inflation hedges or alternative stores of value (Friedman 1968), while liquidity tightening has the opposite effect. Similarly, the credit channel, represented by the reserve requirement ratio (RRR), affects the banking sector's lending capacity. A higher RRR constrains credit and limits capital inflows to speculative assets, whereas a lower ratio injects liquidity that can amplify trading activity in cryptocurrency markets (Bernanke and Gertler 1995).

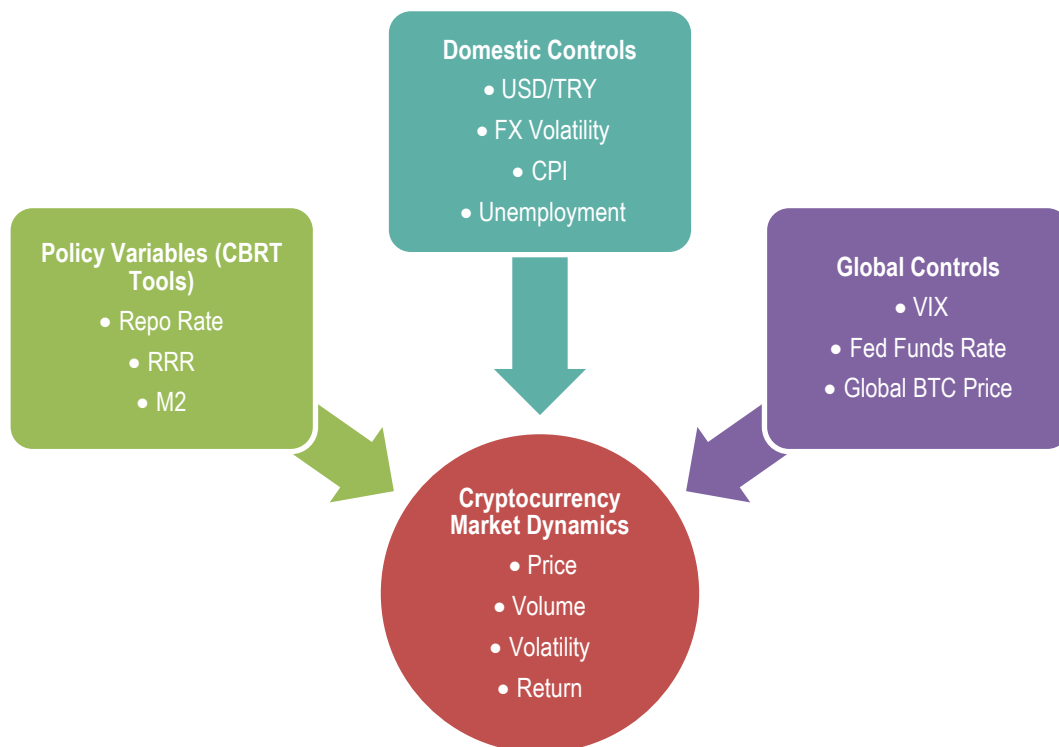
The exchange rate channel is particularly significant in emerging economies such as Turkey, where depreciation of the Turkish lira increases the local-currency value of cryptocurrencies and encourages investors to hedge against further losses. In this sense, exchange rate volatility serves as an indirect conduit through which monetary shocks are transmitted to the crypto market. While the asset-price and expectations channel is conceptually relevant - since monetary policy announcements can alter inflation expectations and perceived returns (Tobin 1969) - this study does not include a direct expectation variable due to the monthly frequency of the dataset.

Instead, this mechanism is indirectly captured through forward-looking indicators such as the exchange rate, the global Bitcoin price, and the global volatility index (VIX).

Macroeconomic instability also activates the portfolio and safe-haven channel, whereby inflationary pressures and exchange rate volatility prompt investors to reallocate portfolios toward cryptocurrencies as potential hedges or alternative stores of value (Dyhrberg 2016; Baur and Dimpfl 2021). Finally, the global spillover channel transmits international monetary conditions to Turkey's cryptocurrency market: increases in the U.S. federal funds rate or spikes in global risk perception (VIX) typically raise volatility and reduce returns in emerging markets (Elsayed and Sousa 2022; Zhao *et al.* 2023). Likewise, fluctuations in the global Bitcoin price (GPUSD) convey cross-market shocks through arbitrage and sentiment effects.

Taken together, these channels define the theoretical foundation of the empirical model. Figure 1, titled "Conceptual Framework Linking Policy, Domestic, and Global Variables to Cryptocurrency Market Dynamics," provides a visual overview of these relationships and serves as the conceptual basis for the ARDL approach applied in the subsequent sections.

Figure 1. Conceptual Framework Linking Policy, Domestic, and Control Variables to Cryptocurrency Market Dynamics



2.5. Data Characteristics and Transformations

To ensure consistency and comparability, all variables were converted to a monthly time series and expressed in natural logarithms where applicable - specifically, cryptocurrency prices (in TRY and USD), trading volume, the consumer price index (CPI), and real money supply (M2). Logarithmic transformation mitigates heteroskedasticity, improves distributional properties, and allows coefficients to be interpreted as elasticities (Wooldridge 2013; Gujarati and Porter 2009).

Monthly log returns for Bitcoin were calculated as:

$$RET_t = \ln(P_t^{TRY} / P_{t-1}^{TRY}) \quad (1)$$

Logarithmic returns were preferred due to their superior statistical properties and closer approximation to normality (Campbell *et al.* 1997). Market volatility was measured as the monthly standard deviation of daily Bitcoin returns, and foreign-exchange volatility (FXVOL) was derived analogously from daily USD/TRY log returns, following Engle (1982) and Hull (2012).

The real broad money supply (M2) was obtained by deflating nominal M2 with the consumer price index (CPI) and taking natural logs, consistent with Friedman's (1968) formulation. This variable reflects inflation-adjusted liquidity and serves as a key monetary stance indicator.

Tests for seasonal patterns revealed no significant seasonality, and no seasonal adjustments were required. All preprocessing, diagnostic testing, and econometric estimation were conducted using EViews 13, which provides robust tools for ARDL and ECM modeling.

The processed and transformed dataset thus forms a consistent empirical foundation for the estimation procedures described in the following sections.

2.6. Econometric Strategy

To analyze the impact of the Central Bank of the Republic of Turkey's (CBRT) monetary policies on the dynamics of the cryptocurrency market, this study employs the Autoregressive Distributed Lag (ARDL) modeling approach proposed by Pesaran *et al.* (2001). The ARDL framework is particularly appropriate for this analysis for several reasons. First, it enables simultaneous estimation of both short-run dynamics and long-run equilibrium relationships, which directly correspond to the study's objectives. Second, it accommodates variables integrated of order $I(0)$ and $I(1)$, addressing the mixed stationarity characteristics identified through unit root testing. Third, it provides robust and efficient estimates even in small samples, making it suitable given the monthly data covering the 2013–2025 period (Narayan and Smyth 2005).

The model incorporates an Error Correction Mechanism (ECM) to capture the speed at which the cryptocurrency market returns to long-run equilibrium after monetary shocks. This dual nature - short-run responsiveness and long-run adjustment - allows for a comprehensive examination of how monetary policy decisions shape cryptocurrency market behavior in Turkey.

2.7. Research Hypotheses

Based on the theoretical framework and empirical design outlined above, the study develops the following hypotheses to guide the econometric analysis:

H_1 – Joint Effect of Monetary Policy Instruments: Changes in the CBRT's core policy tools - the policy interest rate, reserve requirement ratio (RRR), and broad money supply (M2) - have statistically significant effects on the four key indicators of Turkey's cryptocurrency market: prices, trading volume, volatility, and returns.

H_2 – Transmission Channels of Monetary Policy: Monetary policy influences cryptocurrency market variables through specific channels - particularly the interest rate, liquidity (money supply), and exchange rate mechanisms - after controlling for domestic variables (USD/TRY, FX volatility, CPI, unemployment) and global variables (VIX, Federal Funds Rate, global Bitcoin price).

H_3 – Short- and Long-Run Effects: The impacts of CBRT's monetary policy instruments on cryptocurrency market indicators differ significantly between the short run and the long run.

H_4 – Long-Run Equilibrium Adjustment: The error correction term (ECT) derived from the ARDL framework is statistically significant and negative, indicating the speed at which the cryptocurrency market returns to equilibrium after monetary shocks.

These hypotheses are tested through successive steps involving stationarity checks, cointegration testing, and ARDL-ECM estimation, as described in the following subsections.

2.8. Preconditions and Diagnostic Tests

Before estimating the ARDL models, several diagnostic and pre-estimation tests were conducted to ensure the validity and reliability of the empirical results, which are summarized in Table 2.

Table 2. Precondition and Diagnostic Tests Applied in the ARDL Analysis

Test Name	Purpose	Null Hypothesis (H_0)	Key References
ADF Test	Tests variable stationarity	The variable has a unit root	Dickey & Fuller (1979)
PP Test	Tests variable stationarity	The variable has a unit root	Phillips & Perron (1988)
Bounds Test	Tests for long-run cointegration	No cointegration among variables	Pesaran <i>et al.</i> (2001)
Breusch–Godfrey LM Test	Detects serial correlation in residuals	No serial correlation	Breusch (1978) and Godfrey (1978)
Engle's ARCH Test	Detects conditional heteroskedasticity	No ARCH effects	Engle (1982)
White's Test	Tests for general heteroskedasticity	Homoskedasticity	White (1980)

Note: All diagnostic procedures were implemented in EViews 13, ensuring consistency and replicability.

Stationarity Tests: The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were applied to determine the order of integration of each variable (Dickey and Fuller, 1979; Phillips and Perron, 1988). The combination of I(0) and I(1) variables confirmed the suitability of the ARDL approach.

Cointegration Test: The Bounds Test developed by Pesaran *et al.* (2001) was used to verify the existence of a long-run equilibrium relationship among the variables. A statistically significant F-statistic exceeding the upper critical bound indicates cointegration.

Model Diagnostics: To assess model robustness, the following diagnostic tests were conducted: (i) Serial Correlation: Breusch–Godfrey LM test and (ii) Heteroskedasticity: Engle’s ARCH test and White’s general test.

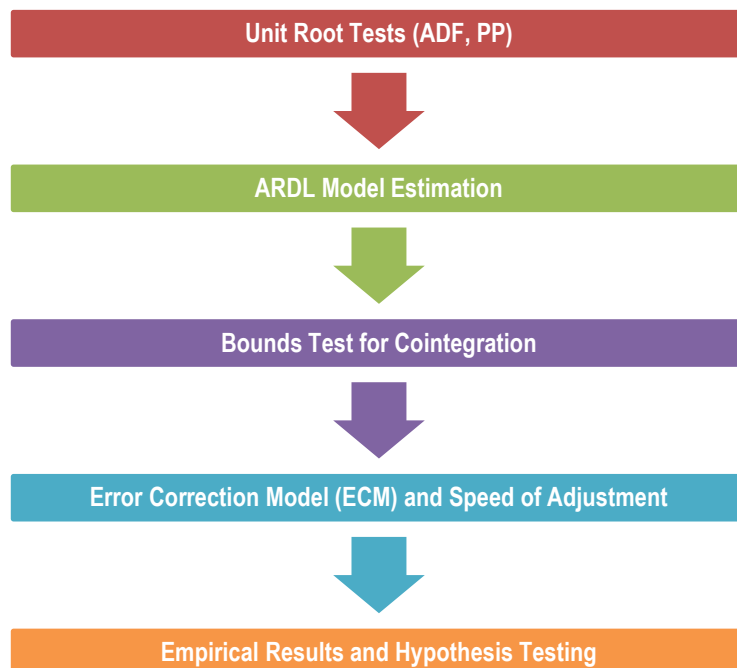
2.9. Model Specification and Estimation Procedure

To jointly examine the short- and long-run relationships among monetary policy variables, domestic controls, global controls, and cryptocurrency market indicators, the following general ARDL specification is adopted:

$$\begin{aligned} \Delta Y_t = & \alpha_0 + \sum_{i=1}^p \beta_i \Delta Y_{t-i} + \sum_{j=0}^{q_1} \gamma_{1j} \Delta POLICY_{t-j} + \sum_{k=0}^{q_2} \gamma_{2k} \Delta RRR_{t-k} + \sum_{l=0}^{q_3} \gamma_{3l} \Delta M2_{t-l} + \sum_{m=0}^{q_4} \gamma_{4m} \Delta EXRATE_{t-m} \\ & + \sum_{n=0}^{q_5} \gamma_{5n} \Delta FXVOL_{t-n} + \sum_{o=0}^{q_6} \gamma_{6o} \Delta CPI_{t-o} + \sum_{r=0}^{q_7} \gamma_{7r} \Delta UR_{t-r} + \sum_{s=0}^{q_8} \gamma_{8s} \Delta VIX_{t-s} \\ & + \sum_{u=0}^{q_9} \gamma_{9u} \Delta FFR_{t-u} + \sum_{v=0}^{q_{10}} \gamma_{10v} \Delta GPU_USD_{t-v} + \delta_1 Y_{t-1} + \delta_2 POLICY_{t-1} + \delta_3 RRR_{t-1} \\ & + \delta_4 M2_{t-1} + \delta_5 EXRATE_{t-1} + \delta_6 FXVOL_{t-1} + \delta_7 CPI_{t-1} + \delta_8 UR_{t-1} + \delta_9 VIX_{t-1} \\ & + \delta_{10} FFR_{t-1} + \delta_{11} GPU_USD_{t-1} + \varepsilon_t \end{aligned} \tag{2}$$

where Y_t represents the dependent variable (price, trading volume, volatility, or return); Δ denotes the first-difference operator; α_0 is the constant term; $p, q_1, q_2, \dots, q_{10}$ represent optimal lag lengths determined using the Akaike Information Criterion (AIC); short-run coefficients (β, γ) capture immediate effects, while long-run coefficients (δ) reflect equilibrium relationships; and ε_t denotes the error term.

Figure 2. Empirical Methodology and ARDL Estimation Procedure



Once cointegration is confirmed, the Error Correction Model (ECM) form of the ARDL is estimated to measure the speed of adjustment toward long-run equilibrium. The coefficient of the error correction term (ECT) is expected to be negative and statistically significant, confirming convergence to equilibrium.

All estimations were performed in EViews 13, following the sequential procedure outlined in Figure 2, which summarizes the empirical workflow - from unit root testing to ARDL estimation and ECM validation.

Having established the dataset, variable structure, and econometric framework, this section has outlined the methodological foundations of the study. The ARDL–ECM strategy enables simultaneous assessment of short-run adjustments and long-run equilibrium dynamics between monetary policy instruments and cryptocurrency market indicators. All precondition and diagnostic tests confirm that the data and model specifications meet the required econometric standards for robust estimation. Building on this foundation, the next section presents the empirical findings of the analysis, highlighting how the Central Bank of the Republic of Turkey's (CBRT) policy instruments - namely the policy rate, reserve requirement ratio (RRR), and broad money supply (M2) - affect cryptocurrency prices, trading volumes, volatility, and returns in Turkey.

3. Research Results

3.1. Descriptive Statistics and Exploratory Plots

Table 3 reports summary statistics (mean, median, extrema, and standard deviation) for all variables over 139 monthly observations (2013M09–2025M03). As expected for crypto markets, PRICE and VOLUME display pronounced dispersion - e.g., the standard deviation of PRICE (≈ 2.74 in logs) signals substantial variability. Monetary policy variables also vary widely: POLICY ranges from 4.5 to 50 (std. dev. ≈ 12.90), while RRR spans 5–21. Volatility indicators corroborate elevated risk: both VIX and VOL exhibit large swings, whereas macro aggregates such as CPI (log) and EXRATE (log) show steadier movements relative to crypto series. (Definitions, units, and transformations are detailed in Section 2.)

Figure 3 visualizes the monthly time paths of the key variables. Several series - CPI, EXRATE, M2, GPUSD, PRICE, and VOLUME - trend upward over the sample, with momentum intensifying especially after 2018 and into the 2020s, consistent with stochastic trends rather than deterministic drift. Policy series (POLICY, RRR) exhibit sharp regime shifts, while FFR rises notably post-2022, mirroring global tightening. High-frequency indicators (RET, FXVOL, VOL, VIX) reveal volatility clustering and bursty dynamics suggestive of conditional heteroskedasticity.

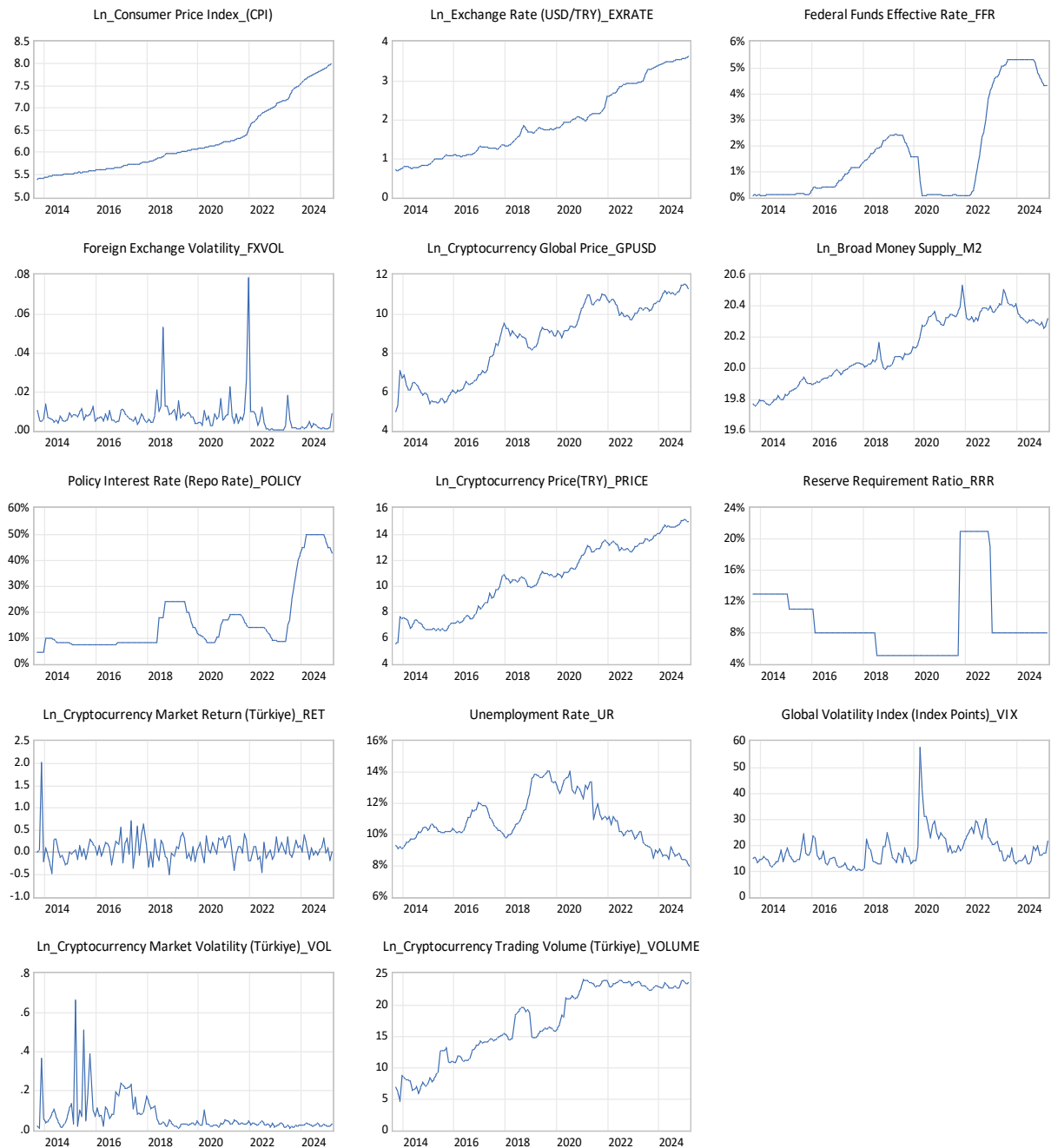
Table 3. Descriptive Statistics of Variables

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
CPI	6.264	6.025	7.991	5.411	0.761	139
EXRATE	1.915	1.750	3.613	0.692	0.908	139
FFR	1.643	0.790	5.330	0.050	1.866	139
FXVOL	0.007	0.006	0.079	0.000	0.009	139
GPUSD	8.658	9.064	11.537	4.955	1.933	139
M2	20.124	20.079	20.537	19.759	0.217	139
POLICY	16.466	10.000	50.000	4.500	12.897	139
PRICE	10.615	10.723	15.117	5.556	2.743	139
RET	0.068	0.055	2.018	-0.510	0.277	139
RRR	9.417	8.000	21.000	5.000	4.733	139
UR	10.840	10.400	14.100	7.900	1.595	139
VIX	17.795	15.904	57.737	10.125	6.365	139
VOL	0.069	0.034	0.662	0.007	0.091	139
VOLUME	17.136	16.989	24.087	4.527	5.898	139

Note: Definitions and measurement units of the variables are provided in the [Data and Methodology / Conceptual and Operational Definitions of Variables] section.

Taking together, the descriptive evidence points to heterogeneous integration orders across variables and motivates formal unit-root testing. These patterns provide an empirical rationale for the ARDL framework employed later, which can accommodate mixtures of $I(0)/I(1)$ processes and separate long-run from short-run dynamics.

Figure 3. Time Series Plots of the Key Variables (September 2013 – March 2025)



3.2. Unit Root Analysis and Stationarity Findings

Before estimating the ARDL models, it is essential to verify the time-series properties of all variables to avoid spurious regressions and to determine the appropriate econometric specification. Accordingly, both the Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were employed to assess the order of integration of each variable. The ADF test accounts for potential serial correlation through lagged differences, while the PP test offers robustness against heteroskedasticity and autocorrelation. Given the visual evidence of trending behavior in several series (see Figure 3), all tests were conducted under the trend-and-intercept specification.

Table 4 summarizes the ADF and PP results, while Table 5 groups variables by their integration order. The results indicate that a substantial number of variables - such as PRICE, VOLUME, RRR, M2, EXRATE, CPI, UR, FFR, and GPUSD - are nonstationary at levels but become stationary after first differencing, implying integration of

order one $I(1)$. In contrast, VOL, RET, FXVOL, VIX, and POLICY are stationary at levels, that is, $I(0)$. Importantly, no variable is integrated of order two $I(2)$, which is a necessary condition for the validity of ARDL estimation (Pesaran *et al.* 2001).

This mixed integration structure - comprising both $I(0)$ and $I(1)$ processes - provides strong support for the use of the Autoregressive Distributed Lag (ARDL) bounds-testing framework. The ARDL approach is particularly well suited for such datasets, as it allows consistent estimation of both short-run dynamics and long-run equilibrium relationships without requiring all variables to be of the same integration order. Consequently, the findings from the unit-root analysis validate the methodological foundation of the subsequent cointegration and ARDL estimations.

Table 4. Results of Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) Unit Root Tests

Variable	ADF t-stat (Level)	ADF p-value (Level)	ADF t-stat (1st Diff.)	ADF p-value (1st Diff.)	PP t-stat (Level)	PP p-value (Level)	PP t-stat (1st Diff.)	PP p-value (1st Diff.)	Integration Order
PRICE	-2.8907	0.1688	-11.7496***	0.0000	-2.9409	0.1531	-11.7496***	0.0000	$I(1)$
VOLUME	-2.3931	0.3815	-11.9959***	0.0000	-2.3931	0.3815	-11.9959***	0.0000	$I(1)$
VOL	-3.6547**	0.0290	N/A	N/A	-10.9621***	0.0000	N/A	N/A	$I(0)$
POLICY	-3.5974**	0.0337	N/A	N/A	-4.9035***	0.0005	N/A	N/A	$I(0)$
RRR	-2.1870	0.4926	-10.9678***	0.0000	-2.2910	0.4356	-10.9678***	0.0000	$I(1)$
M2	-2.0890	0.5470	-11.4948***	0.0000	-2.0817	0.5510	-11.8253***	0.0000	$I(1)$
EXRATE	-1.7473	0.7246	-8.6170***	0.0000	-1.7868	0.7060	-7.1993***	0.0000	$I(1)$
FXVOL	-8.4683***	0.0000	N/A	N/A	-8.5331***	0.0000	N/A	N/A	$I(0)$
CPI	-0.2834	0.9904	-6.7246***	0.0000	0.0801	0.9968	-6.8253***	0.0000	$I(1)$
UR	-1.1698	0.9121	-13.1216***	0.0000	-0.9934	0.9407	-13.1216***	0.0000	$I(1)$
RET	-11.7933***	0.0000	N/A	N/A	-11.7933***	0.0000	N/A	N/A	$I(0)$
VIX	-4.8358***	0.0007	N/A	N/A	-4.8358***	0.0007	N/A	N/A	$I(0)$
FFR	-2.4717	0.3417	-3.1615**	0.0245	-1.7242	0.7354	-5.1537***	0.0002	$I(1)$
GPUSD	-2.2727	0.4456	-10.8477***	0.0000	-2.5229	0.3168	-10.8351***	0.0000	$I(1)$

Notes: (i) ***, ** indicate rejection of the null hypothesis (H_0 : the series contains a unit root) at the 1% and 5% significance levels, respectively. (ii) All tests were conducted under the "trend and intercept" specification, based on the presence of visible trends in the data. (iii) Optimal lag length for the ADF test was automatically determined using the Schwarz Information Criterion (SIC). For the PP test, bandwidth was selected using the Newey-West method. (iv) MacKinnon (1996) critical values for the ADF test are -4.028, -3.444, and -3.147 at the 1%, 5%, and 10% significance levels, respectively. For the PP test, critical values are -4.026, -3.443, and -3.146. (v) "N/A" indicates that no first-difference test was conducted because the variable was already found to be stationary at level, $I(0)$.

Table 5. Classification of Variables by Order of Integration

Integration Order	Variables
$I(0)$ – Stationary at Level	VOL (Cryptocurrency Volatility), RET (Cryptocurrency Return), FXVOL (FX Volatility), VIX (Global Volatility Index), POLICY (Policy Interest Rate)
$I(1)$ – Stationary at First Difference	PRICE (Cryptocurrency Price), VOLUME (Cryptocurrency Trading Volume), RRR (Reserve Requirement Ratio), M2 (Broad Money Supply), EXRATE (Exchange Rate), CPI (Consumer Price Index), UR (Unemployment Rate), FFR (Federal Funds Rate), GPUSD (Global Cryptocurrency Price in USD)

3.3. Lag Selection and Baseline ARDL Set-Up

Following confirmation of the integration properties, the next step involves determining the optimal lag structure for each model. Lag selection is critical to capturing the true dynamics of monetary policy transmission and ensuring unbiased long-run and short-run coefficient estimates. For this purpose, the Akaike Information Criterion (AIC) was used as the primary selection metric, given its strong performance in small and medium-sized samples and its capacity to balance model fit against over-parameterization (Akaike 1974; Burnham and Anderson 2002).

The procedure was implemented in EViews 13, where up to four lags were pre-specified for each variable. All possible ARDL combinations were evaluated, generating millions of model permutations per dependent variable. The AIC-based algorithm identifies the global optimum - minimizing residual variance while retaining parsimony - thus ensuring robust and reproducible model selection.

Consistent with theoretical expectations and the stochastic nature of cryptocurrency series, the analysis follows the restricted constant (Case II) specification without a deterministic trend. This specification assumes that deterministic components such as linear trends are absent, while stochastic trends are captured through lagged levels and differences of the variables.

The optimal lag combinations and corresponding diagnostic statistics are summarized in Table 6. The results indicate that the selected ARDL models achieve strong explanatory power across the dependent variables, particularly for PRICE and VOLUME, both of which exhibit adjusted R² values above 0.98. The Durbin-Watson statistics (approximately 2.0 across models) suggest no first-order autocorrelation, confirming that the dynamic specifications are statistically well-behaved.

These results establish the baseline ARDL structure that underpins the subsequent analyses - namely, the bounds tests for cointegration (Section 3.4), the estimation of long-run relationships (Section 3.5), and the short-run error-correction dynamics (Section 3.6).

Table 6. Results of Optimal ARDL Model Selection and Diagnostic Statistics

Dependent Variable	Selected ARDL Model	Adj. R ²	F-Statistic	DW Stat.	AIC	SC
PRICE	ARDL(2,0,0,1,0,0,0,0,1,0,4)	0.9989	6,978.21***	2.16	-1.900	-1.492
VOLUME	ARDL(2,0,0,0,0,1,0,2,0,0)	0.9825	510.13***	2.09	2.415	2.756
VOL	ARDL(4,0,0,0,0,0,0,4,0,2)	0.3475	4.57***	1.91	-2.301	-1.849
RET	ARDL(3,0,0,1,3,0,0,0,0,4)	0.7752	23.00***	2.16	-1.498	-1.025

Notes: *** indicates statistical significance at the 1% level. DW: Durbin-Watson statistic. AIC: Akaike Information Criterion. SC: Schwarz Criterion. All F-statistics test the null hypothesis that all explanatory variables are jointly insignificant.

3.4. Bounds Test for Cointegration

Once the optimal lag lengths were determined, the next step was to examine whether stable long-run equilibrium relationships exist among the variables. To this end, the ARDL bounds testing approach to cointegration developed by Pesaran *et al.* (2001) was applied. This method is particularly suitable for datasets with mixed integration orders (I(0) and I(1)), as confirmed in Section 3.2.

Table 7. Results of ARDL Bounds Test for Cointegration

Model	F-Statistic	Decision	Critical Values (1%)	Inference
PRICE	9.293***	H ₀ rejected	I(0) = 2.41 I(1) = 3.61	Cointegration exists
VOLUME	4.080***	H ₀ rejected	I(0) = 2.41 I(1) = 3.61	Cointegration exists
VOL	2.081	H ₀ rejected (inconclusive F-test confirmed by t-test)	I(0) = 2.41 I(1) = 3.61	Cointegration exists
RET	8.803***	H ₀ rejected	I(0) = 2.41 I(1) = 3.61	Cointegration exists

Notes: Critical values are taken from Pesaran *et al.* (2001, Table CI(iii), Case II, $k = 10$). *** indicates that the F-statistic exceeds the 1% upper bound critical value. H₀: no level relationship exists.

The bounds test was conducted under the restricted constant, no-trend specification (Case II), using $k = 10$ explanatory variables to capture the comprehensive set of monetary policy, domestic control, and global control indicators. This specification is theoretically motivated by the expectation that cryptocurrency series follow stochastic rather than deterministic trends, consistent with the efficient market hypothesis for financial assets (Urquhart 2016).

The results, presented in Table 7, provide strong evidence of cointegration in all four models. Specifically, the calculated F-statistics for the PRICE (9.29), VOLUME (4.08), and RET (8.80) equations exceeded the 1% upper-bound critical value of 3.61, leading to a decisive rejection of the null hypothesis of no long-run relationship. Although the F-statistic for the VOL model (2.08) falls below the upper bound, the t-statistic of the error-correction term in the corresponding ECM (reported later in Section 3.6) is highly significant ($-5.23, p < 0.01$), confirming that this model also possesses a valid long-run equilibrium relationship.

Overall, the bounds testing results confirm that long-run cointegration exists across all four dependent variables - cryptocurrency price, trading volume, return, and volatility - and thus justify proceeding to estimate long-run and short-run dynamics using the ARDL framework.

3.5. ARDL Model Estimation Results

Following the confirmation of cointegration, the long-run and short-run relationships among the variables were estimated using the Autoregressive Distributed Lag (ARDL) models identified in Section 3.3. Separate models were estimated for each of the four dependent variables - cryptocurrency price (PRICE), trading volume (VOLUME), returns (RET), and volatility (VOL) - in order to capture the multidimensional effects of monetary policy on Turkey's cryptocurrency market.

Each model was estimated using the Akaike Information Criterion (AIC)-selected lag structure and follows the general ARDL form introduced in Section 2.9. The analysis focuses first on the long-run coefficients, which reflect persistent equilibrium relationships between monetary policy and market variables, and then on diagnostic indicators to assess model validity.

3.5.1. Cryptocurrency Price (PRICE) Model Results

This subsection presents the ARDL estimation results where the dependent variable is the cryptocurrency price in Turkish lira (PRICE). The model is estimated for the period 2014M01–2025M03 and selected according to the Akaike Information Criterion (AIC). The optimal lag structure is ARDL(2,0,0,1,0,0,0,1,0,4), including two lags of PRICE and up to four lags of the global Bitcoin price in USD (GPUUSD). The long-run coefficients and optimal lag lengths for all explanatory variables are summarized in Table 8 below.

Table 8. Optimal Lag Structure and Long-Run ARDL Estimates for the PRICE Model

Variable	Optimal Lag Length	Coefficient	Std. Error	t-Statistic	p-Value
PRICE	2	-	-	-	-
POLICY	0	-0.0006	0.0017	-0.33	0.742
RRR	0	0.0031	0.0029	1.09	0.277
M2	1	0.2196	0.2392	0.92	0.360
EXRATE	0	0.8006***	0.1765	4.54	0.000
FXVOL	0	0.4119	1.1352	0.36	0.717
CPI	0	0.2749*	0.1559	1.76	0.080
UR	0	0.0163	0.0101	1.62	0.109
VIX	1	-0.0044**	0.0020	-2.13	0.035
FFR	0	-0.0077	0.0133	-0.58	0.561
GPUUSD	4	0.9620***	0.0126	76.18	0.000
C (Constant)	-	-5.4993	5.1741	-1.06	0.290

Notes: Optimal lag lengths were selected using the Akaike Information Criterion (AIC). The ARDL model specification is ARDL (2,0,0,1,0,0,0,1,0,4). *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

The estimation results in Table 8 reveal several important long-run determinants of cryptocurrency prices in Turkey. The most prominent finding is the strong and positive association between the global and domestic Bitcoin markets. The coefficient for GPUUSD (0.9620, $p < 0.01$) indicates an almost one-to-one long-run co-movement between the global USD-denominated Bitcoin price and its TRY-denominated counterpart, confirming that global

price discovery largely dominates domestic pricing behavior in Turkey. Similarly, the exchange rate (EXRATE) exerts a highly significant positive effect (0.8006, $p < 0.01$), implying that domestic currency depreciation leads to higher local cryptocurrency prices. This pattern reflects a hedging motive, where investors turn to digital assets as a store of value during periods of lira depreciation and inflationary pressure.

The global volatility index (VIX) has a negative and statistically significant coefficient (-0.0044 , $p < 0.05$), suggesting that higher global uncertainty or risk aversion tends to depress cryptocurrency valuations in Turkey. This outcome supports the “flight-to-safety” hypothesis, where investors reallocate funds away from riskier assets such as cryptocurrencies during turbulent global conditions. Meanwhile, CPI has a positive and marginally significant coefficient (0.2749, $p = 0.08$), indicating a limited inflation-hedging effect, consistent with evidence that cryptocurrencies may act as partial inflation hedges in emerging markets.

Other variables, including the policy interest rate (POLICY), reserve requirement ratio (RRR), broad money supply (M2), unemployment rate (UR), and Federal Funds Rate (FFR), are statistically insignificant in the long run. This finding suggests that domestic monetary policy tools have little direct influence on the long-run pricing of cryptocurrencies, which instead respond primarily to global market forces and exchange rate movements.

To evaluate the reliability and overall fit of the estimated ARDL specification, key diagnostic statistics were computed. The results, summarized in Table 9, confirm the robustness and statistical validity of the model. The high explanatory power, strong joint significance, and absence of serial correlation demonstrate that the estimated model is statistically sound and robust.

Table 9. Diagnostics and Fit Criteria for the PRICE Model

Criterion	Value	Interpretation
R-squared	0.8674	High explanatory power ($\approx 86.7\%$ of variation explained)
F-statistic	118.71***	Model is jointly significant ($p < 0.01$)
Prob(F-statistic)	0.0000	Confirms overall model significance
Durbin–Watson	2.1627	No first-order autocorrelation ($DW \approx 2$)

Notes: *** represents the 1% significance level.

Overall, the findings suggest that cryptocurrency prices in Turkey are primarily shaped by global market forces - particularly the international Bitcoin price and the exchange rate channel - rather than by domestic monetary policy variables. The model diagnostics further confirm that the estimated ARDL specification is stable, well-fitted, and theoretically consistent, offering credible insights into the long-run dynamics of cryptocurrency valuation within an emerging market context.

3.5.2. Cryptocurrency Trading Volume (VOLUME) Model Results

This subsection presents the ARDL estimation results where the dependent variable is cryptocurrency trading volume (VOLUME). The model was selected based on the Akaike Information Criterion (AIC) and estimated over the period 2014M01–2025M03. The optimal lag structure determined by AIC is ARDL(2,0,0,0,0,1,0,2,0,0), which includes two lags of VOLUME, one lag of CPI, and two lags of VIX. The long-run coefficients and corresponding optimal lag lengths are reported in Table 10.

The results in Table 10 indicate that cryptocurrency trading volume in Turkey is primarily influenced by exchange rate dynamics, inflationary conditions, and select global factors. The exchange rate (EXRATE) has a large and highly significant positive coefficient (17.85, $p < 0.01$), implying that depreciation of the Turkish lira strongly stimulates trading activity in cryptocurrencies. This suggests that investors increasingly turn to digital assets as a hedge or speculative response to currency depreciation. Conversely, lagged inflation (CPI(-1)) has a highly significant negative coefficient (-13.90 , $p < 0.01$), indicating that persistent inflationary pressures reduce trading activity over time - likely because high inflation erodes disposable income and limits speculative participation in digital markets.

Several monetary and macroeconomic variables also exhibit significant long-run effects. The reserve requirement ratio (RRR) exerts a negative and statistically significant influence (-0.1915 , $p < 0.01$), consistent with the idea that tighter liquidity conditions reduce market activity. Similarly, higher Federal Funds Rate (FFR) values are associated with lower trading volume (-0.8890 , $p < 0.01$), reflecting the impact of global monetary tightening on capital flows and speculative investment. The unemployment rate (UR) also shows a significant negative

relationship (-0.6277 , $p < 0.01$), suggesting that weaker domestic economic conditions and declining household income suppress participation in cryptocurrency trading.

Table 10. Optimal Lag Structure and Long-Run ARDL Estimates for the VOLUME Model

Variable	Optimal Lag Length	Coefficient	Std. Error	t-Statistic	p-Value
VOLUME	2	-	-	-	-
POLICY	0	-0.0483	0.0412	-1.17	0.243
RRR	0	-0.1915***	0.0644	-2.97	0.0035
M2	0	-0.3722	4.9788	-0.07	0.941
EXRATE	0	17.8501***	3.8738	4.61	0.000
FXVOL	0	31.2314	27.8579	1.12	0.264
CPI (-1)	1	-13.8992***	3.4481	-4.03	0.0001
UR	0	-0.6277***	0.2384	-2.63	0.0095
VIX (-1)	2	0.0337	0.0554	0.61	0.544
FFR	0	-0.8890***	0.3088	-2.88	0.0047
GPUUSD	0	0.8312***	0.2799	2.97	0.0036
C (Constant)	-	81.3079	107.2978	0.76	0.450

Notes: Optimal lag lengths were selected using the Akaike Information Criterion (AIC). The ARDL model specification is ARDL (2,0,0,0,0,0,1,0,2,0,0). *** represents the 1% significance level.

The global Bitcoin price (GPUUSD) has a strong positive and statistically significant coefficient (0.8312, $p < 0.01$), confirming that higher global crypto valuations stimulate domestic trading volumes through wealth and momentum effects. Other variables, such as the policy interest rate (POLICY), broad money supply (M2), and foreign exchange volatility (FXVOL), are statistically insignificant, implying that short-term liquidity conditions and currency volatility do not play a major role in shaping long-run trading behavior.

To verify the overall reliability of the model, diagnostic statistics were computed to assess explanatory power, joint significance, and autocorrelation. The results, presented in Table 11, indicate that the ARDL specification for trading volume is statistically valid and well-behaved.

Table 11. Diagnostics and Fit Criteria for the VOLUME Model

Criterion	Value	Interpretation
R-squared	0.2964	About 29.6% of variation explained - lower than PRICE, consistent with higher noise in trading data
F-statistic	3.3995***	Model is jointly significant ($p < 0.01$)
Prob(F-statistic)	0.00008	Confirms overall significance
Durbin-Watson	2.0922	No first-order autocorrelation ($DW \approx 2$)

Notes: *** represents the 1% significance level.

Although the explanatory power is moderate, the model remains statistically significant and free from autocorrelation, ensuring the reliability of coefficient estimates.

Taken together, these results demonstrate that cryptocurrency trading activity in Turkey is shaped primarily by macro-financial conditions - especially the exchange rate, inflation, global monetary policy, and overall economic health - rather than by domestic interest rates or liquidity expansion. The findings suggest that both hedging motives

and speculative responses to external shocks drive participation in cryptocurrency markets, highlighting the importance of global and structural factors in determining the scale of crypto trading within emerging economies.

3.5.3. Cryptocurrency Returns (RET) Model Results

This subsection presents the ARDL estimation results where the dependent variable is cryptocurrency returns (RET). Given the near-stationary yet highly volatile nature of returns, the estimation covers the period 2014M01–2025M03 and employs an optimal lag structure selected according to the Akaike Information Criterion (AIC). The resulting specification, ARDL(3,0,0,1,3,0,0,0,0,4), captures the complex autoregressive and distributed lag dynamics of return formation in the Turkish cryptocurrency market. The long-run coefficients and optimal lag lengths for explanatory variables are summarized in Table 12 below.

Table 12. Optimal Lag Structure and Long-Run ARDL Estimates for the RET Model

Variable	Optimal Lag Length	Coefficient	Std. Error	t-Statistic	p-Value
RET	3	-	-	-	-
POLICY	0	0.0003	0.0010	0.34	0.737
RRR	0	-	-	-	-
M2 (-1)	1	-0.0191	0.1447	-0.13	0.895
EXRATE (-1)	1	0.0152	0.1153	0.13	0.895
FXVOL	0	-0.0869	0.9084	-0.10	0.924
CPI	0	-0.0105	0.1020	-0.10	0.918
UR	0	0.0019	0.0063	0.30	0.763
VIX	0	-0.0002	0.0011	-0.15	0.883
FFR	0	0.0001	0.0080	0.02	0.987
GPUSD (-1)	4	-0.0027	0.0076	-0.36	0.719
C (Constant)	-	0.4098	3.1625	0.13	0.897

Notes: Optimal lag lengths were selected using the Akaike Information Criterion (AIC). The ARDL model specification is ARDL (3,0,0,1,3,0,0,0,0,4).

The results presented in Table 12 show that, in contrast to the price and trading volume models, none of the explanatory variables exhibit statistically significant long-run effects on cryptocurrency returns in Turkey. All coefficients are small in magnitude and accompanied by large standard errors, and their associated p-values are far above conventional significance thresholds. Even the global variables - GPUSD, VIX, and FFR - fail to exert any systematic long-run influence on returns. This absence of persistent macro-financial effects suggests that Turkish cryptocurrency returns follow a pattern consistent with weak-form market efficiency: prices adjust rapidly to new information, eliminating predictable long-run excess returns.

The insignificance of domestic monetary policy instruments such as POLICY, RRR, and M2 reinforces this interpretation. The lack of explanatory power indicates that interest rate and liquidity changes may influence speculative trading or short-term pricing behavior, but they do not create sustained return differentials over time. Similarly, domestic macroeconomic factors - including CPI, EXRATE, and UR - do not exhibit statistically significant or economically meaningful coefficients, suggesting that longer-term return dynamics are not directly anchored in domestic fundamentals.

Diagnostic statistics further confirm the robustness of the estimation and the adequacy of the ARDL specification. The relevant results are reported in Table 13 below. The high explanatory power and absence of residual autocorrelation confirm the internal consistency of the model despite the statistical insignificance of individual long-run coefficients.

Table 13. Diagnostics and Fit Criteria for the RET Model

Criterion	Value	Interpretation
R-squared	0.8999	Very high explanatory power ($\approx 89.9\%$)
F-statistic	48.42***	Model jointly significant ($p < 0.01$)
Durbin–Watson	2.1600	No first-order autocorrelation ($DW \approx 2$)

Notes: *** represents the 1% significance level.

Taken together, these findings indicate that cryptocurrency returns in Turkey do not display any systematic long-run dependencies on either domestic monetary policy or global macro-financial conditions. The high overall explanatory power is thus primarily attributed to autoregressive and short-run dynamic components - especially momentum and volatility clustering - rather than to structural economic factors. This outcome aligns with the notion of adaptive and information-efficient markets, where short-term shocks and investor sentiment dominate return formation, while long-run predictability remains absent.

3.5.4. Cryptocurrency Volatility (VOL) Model Results

This subsection presents the ARDL estimation results for cryptocurrency market volatility (VOL), a key indicator of market risk and stability. The model was estimated for the period 2014M01–2025M03, with the optimal specification determined by the Akaike Information Criterion (AIC). The selected lag structure is ARDL(4,0,0,0,0,0,0,4,0,2), which captures multiple autoregressive dynamics of volatility along with the lagged influence of global financial variables. The long-run coefficients and corresponding optimal lag lengths are summarized in Table 14 below.

Table 14. Optimal Lag Structure and Long-Run ARDL Estimates for the VOL Model

Variable	Optimal Lag Length	Coefficient	Std. Error	t-Statistic	p-Value
VOL	4	-	-	-	-
POLICY	0	-	-	-	-
RRR	0	-0.0030	0.0034	-0.86	0.389
M2	0	-0.0775	0.2574	-0.30	0.764
EXRATE	0	0.2054	0.1841	1.12	0.267
FXVOL	0	-0.5741	1.3672	-0.42	0.675
CPI	0	-0.0254	0.1769	-0.14	0.886
UR	0	0.0059	0.0138	0.43	0.671
VIX (-2)	2	-	-	-	-
FFR	0	-0.0383**	0.0168	-2.28	0.025
GPUUSD (-1)	4	-0.0514***	0.0177	-2.91	0.004
C (Constant)	-	2.0785	5.4998	0.38	0.706

Notes: Optimal lag lengths were selected using the Akaike Information Criterion (AIC). The ARDL model specification is ARDL (4,0,0,0,0,0,0,4,0,2). ** and *** represent the 5% and 1% significance levels, respectively.

The long-run estimation results reported in Table 14 indicate that volatility in the Turkish cryptocurrency market is primarily influenced by global financial variables rather than domestic monetary or macroeconomic conditions. The global Bitcoin price in USD (GPUUSD) exhibits a negative and statistically significant coefficient (-0.0514 , $p < 0.01$), suggesting that higher global crypto valuations are associated with lower volatility in the Turkish market. This result implies that during periods of strong international market performance, investor confidence and

liquidity tend to rise, leading to smoother price adjustments and reduced volatility. Similarly, the Federal Funds Rate (FFR) carries a significant negative coefficient (-0.0383 , $p < 0.05$), indicating that global monetary tightening - often linked to capital reallocation toward safer assets - reduces speculative activity and consequently dampens volatility in emerging crypto markets.

In contrast, none of the domestic variables, including EXRATE, RRR, M2, CPI, UR, and FXVOL, display statistically significant long-run effects on volatility. This suggests that while domestic monetary policy and macroeconomic developments may influence market sentiment in the short run, they do not exert sustained or systematic pressure on volatility levels over the long term. The insignificance of the policy rate (POLICY) also reinforces the interpretation that domestic policy actions have limited capacity to stabilize or destabilize cryptocurrency markets once broader global forces are accounted for.

To ensure the reliability and stability of the model, diagnostic statistics were computed and summarized in Table 15 below.

Table 15. Diagnostics and Fit Criteria for the VOL Model

Criterion	Value	Interpretation
R-squared	0.6102	Moderate explanatory power for a volatility model ($\approx 61\%$)
F-statistic	8.92***	Model jointly significant ($p < 0.01$)
Durbin-Watson	1.9092	No first-order autocorrelation ($DW \approx 2$)

Notes: *** represents the 1% significance level.

The moderate explanatory power is typical for volatility models, which often capture high-frequency noise and complex dynamic structures. The high F-statistic confirms the joint significance of explanatory variables, and the Durbin-Watson statistic indicates the absence of serial correlation, suggesting a well-specified and statistically valid model.

Overall, the results highlight that volatility in Turkey's cryptocurrency market is largely driven by external factors, particularly global financial conditions and investor risk sentiment, rather than by domestic monetary policy variables. The negative long-run effects of both GPUSD and FFR reveal that international monetary tightening and favorable global crypto market conditions reduce volatility, while domestic factors fail to exert persistent influence. This finding underscores the limited reach of domestic policy in regulating speculative market risk in an economy that is increasingly integrated into global financial and digital asset networks.

3.5.5. Synthesis of Long-Run ARDL Findings

This subsection consolidates the statistically significant long-run relationships identified across all four ARDL models - PRICE, VOLUME, RET, and VOL - to provide a comprehensive overview of the effects of monetary policy and macroeconomic variables on different dimensions of Turkey's cryptocurrency market. By juxtaposing the significant coefficients across models, the results enable a cross-dimensional assessment of the transmission mechanisms through which monetary and global factors shape cryptocurrency dynamics in the long run.

The synthesis of long-run ARDL results in Table 16 reveals several important empirical regularities. First, global transmission factors - particularly the global cryptocurrency price (GPUSD) and the U.S. monetary policy stance (FFR) - exert dominant and consistent long-run effects across multiple dimensions of Turkey's cryptocurrency market. A stronger global crypto market and higher global liquidity (reflected by GPUSD) boost local prices and trading volumes, while global monetary tightening (FFR increases) reduces both market activity and volatility. These results underscore the external anchoring of cryptocurrency dynamics in emerging markets such as Turkey, where global risk and liquidity cycles play a central role.

Second, among domestic variables, the exchange rate (EXRATE) emerges as a key determinant of both price and trading volume, confirming the existence of a currency-substitution and hedging channel through which domestic currency depreciation drives capital flows into crypto assets. The inflation rate (CPI) shows a dual effect: while modestly increasing crypto prices, it significantly depresses trading volume, likely due to declining real purchasing power. The reserve requirement ratio (RRR) and unemployment rate (UR) have negative long-run effects on trading activity, suggesting that monetary tightening and weaker macroeconomic conditions reduce liquidity and speculative engagement.

Table 16. Summary of Significant Long-Run ARDL Effects Across Models

Variable	PRICE (Price)	VOLUME (Trading Volume)	RET (Returns)	VOL (Volatility)
GPUUSD (Global Crypto Price, USD)	+ (0.962, ***p < 0.01)	+ (0.831, ***p < 0.01)	n.s.	- (-0.051, ***p < 0.01)
EXRATE (USD/TRY)	+ (0.801, ***p < 0.01)	+ (17.85, ***p < 0.01)	n.s.	n.s.
VIX (Global Volatility Index)	- (-0.004, **p < 0.05)	n.s.	n.s.	marginally supportive (cointegration confirmed via ECM)
CPI (Inflation, CPI)	+ (0.275, *p < 0.10)	- (-13.90, ***p < 0.01, lagged)	n.s.	n.s.
RRR (Reserve Requirement Ratio)	n.s.	- (-0.191, ***p < 0.01)	n.s.	n.s.
FFR (Fed Funds Rate)	n.s.	- (-0.889, ***p < 0.01)	n.s.	- (-0.038, **p < 0.05)
UR (Unemployment Rate)	n.s.	- (-0.628, ***p < 0.01)	n.s.	n.s.
Other variables (POLICY, M2, FXVOL)	n.s.	n.s.	n.s.	n.s.

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. "n.s." = not statistically significant. Positive (+) and negative (-) signs indicate the direction of the effect. Results are based on ARDL estimations under the restricted constant, no-trend specification (Case II).

Third, and most notably, no significant long-run determinants were found for cryptocurrency returns, implying that Turkish crypto markets exhibit informational efficiency over the long term - returns adjust rapidly to new information, preventing persistent profit opportunities. Finally, volatility (VOL) is found to be primarily anchored in global financial conditions, not domestic monetary policy. This indicates that speculative risk levels are largely determined by international market sentiment rather than national policy actions.

Overall, these findings provide robust empirical support for the study's hypotheses H₁-H₄, confirming that while monetary and macroeconomic variables shape prices and volumes, their influence on returns and volatility is more limited and largely mediated by global factors. The long-run synthesis thus reinforces the conclusion that Turkey's cryptocurrency market - though influenced by local monetary policy - operates within a broader global financial ecosystem where international liquidity and risk perceptions dominate long-term behavior.

3.6. Error Correction Model (ECM) Results

This section presents the results of the Error Correction Model (ECM) estimations, which capture the short-run dynamics of Turkey's cryptocurrency market and quantify the speed of adjustment toward long-run equilibrium following monetary or macro-financial shocks. While the previous subsection (3.5) focused on long-run relationships derived from the ARDL framework, the ECM results provide complementary evidence on the transmission of short-term shocks and the mechanisms by which disequilibria are corrected over time.

Each ECM equation is derived from its corresponding ARDL model - PRICE, VOLUME, RET, and VOL - and includes both differenced (Δ) explanatory variables representing short-run effects and a lagged error correction term (COINTEQ) that measures the degree of convergence toward long-run equilibrium. A statistically significant and negative coefficient of the error correction term confirms cointegration and indicates that deviations from equilibrium are gradually eliminated.

The ECM approach thus allows for a joint interpretation of short-run market responsiveness and long-run stability, making it particularly suitable for analyzing cryptocurrency dynamics characterized by volatility, momentum, and rapid mean reversion. This step also facilitates the empirical evaluation of Hypothesis H₄, which posits that the Turkish cryptocurrency market exhibits significant long-run equilibrium adjustment following monetary shocks.

Accordingly, the subsections that follow present the ECM estimations for each model separately, beginning with cryptocurrency prices (PRICE) and followed by trading volume (VOLUME), returns (RET), and volatility (VOL). Each model's table reports short-run coefficients, standard errors, and t-statistics, followed by an interpretation focusing on the key short-term drivers and the magnitude of equilibrium correction.

3.6.1. ECM Analysis for the PRICE Model

Table 17 presents the short-run estimation results of the Error Correction Model (ECM) for the cryptocurrency price equation (D(PRICE)). The results quantify how short-term changes in monetary, macroeconomic, and global factors affect cryptocurrency prices in Turkey, and how rapidly the market corrects deviations from its long-run equilibrium path.

Table 17. ECM Results for D(PRICE)

Variable	Coefficient	Std. Error	t-Statistic	Probability
COINTEQ	-0.965193***	0.087349	-11.0497	0.0000
D(M2)	0.940914***	0.232208	4.0520	0.0000
D(GPUSD)	0.933940***	0.037121	25.1589	0.0000
D(PRICE(-1))	0.230005***	0.064860	3.5461	0.0005
D(GPUSD(-3))	0.092655***	0.028278	3.2765	0.0013
D(GPUSD(-1))	-0.189295***	0.071441	-2.6496	0.0090
D(GPUSD(-2))	-0.056575*	0.030288	-1.8679	0.0640
D(VIX)	-0.001566	0.001629	-0.9613	0.3381

Notes: p-value of COINTEQ term may not align with t-Bounds distribution. *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively.

The coefficient of the error correction term (COINTEQ) is negative (-0.965) and highly significant ($p < 0.01$), confirming a strong long-run equilibrium relationship between cryptocurrency prices and the explanatory variables. Its magnitude indicates that approximately 96.5% of any disequilibrium is corrected within one period (month), implying a remarkably rapid adjustment process. Such a fast convergence suggests that the Turkish cryptocurrency market reacts swiftly to restore long-run equilibrium after shocks, consistent with the adaptive and information-efficient nature of digital asset markets.

Regarding short-run dynamics, the broad money supply (D(M2)) exerts a strong and statistically significant positive effect (0.94, $p < 0.01$) on cryptocurrency prices, indicating that increases in liquidity immediately raise crypto valuations. This finding supports the liquidity channel of monetary transmission, whereby greater money availability stimulates investment demand for alternative assets. The global cryptocurrency price (D(GPUSD)) is the most influential short-term driver, with a large positive contemporaneous coefficient (0.93, $p < 0.01$) and significant lag effects that alternate in sign. The pattern of a strong positive contemporaneous effect followed by negative and then positive lag responses reflects a multi-period adjustment cycle, suggesting short-term overreactions and subsequent corrections in response to global market movements.

Furthermore, the lagged dependent variable (D(PRICE(-1))) is positive and significant, demonstrating short-term momentum effects - past price increases tend to stimulate further increases in the current period. Conversely, the short-run impact of the global risk index (D(VIX)) is statistically insignificant, suggesting that global risk sentiment does not have an immediate effect on local crypto price adjustments once global price and liquidity effects are accounted for.

In summary, the ECM estimation for the PRICE model provides strong empirical support for a well-defined long-run equilibrium and highly responsive short-run dynamics. The Turkish cryptocurrency market exhibits rapid adjustment, driven primarily by changes in money supply, global price movements, and momentum effects. These results confirm Hypotheses H_1 and H_3 , indicating that domestic liquidity conditions and global financial developments jointly shape short-term price dynamics while preserving long-run stability.

3.6.2. ECM Analysis for the VOLUME Model

Table 18 reports the short-run estimation results of the Error Correction Model (ECM) for cryptocurrency trading volume (D(VOLUME)). This specification assesses how short-term changes in monetary and macroeconomic conditions influence trading activity in Turkey's cryptocurrency market and evaluates the speed at which deviations from long-run equilibrium are corrected.

Table 18. ECM Results for D(VOLUME)

Variable	Coefficient	Std. Error	t-Statistic	Probability
COINTEQ	-0.358524***	0.049060	-7.3079	0.0000
D(CPI)	-19.414941***	3.570843	-5.4370	0.0000
D(VIX(-1))	-0.036145***	0.013645	-2.6489	0.0091
D(VOLUME(-1))	0.106222	0.074020	1.4350	0.1536
D(VIX)	0.015125	0.013483	1.1218	0.2640

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. All coefficients represent short-run elasticities derived from the ARDL error-correction representation.

The coefficient of the error correction term (COINTEQ) is negative (-0.3585) and highly significant ($p < 0.01$), confirming a stable long-run equilibrium relationship for cryptocurrency trading volumes. Its magnitude implies that approximately 36% of deviations from the long-run equilibrium are corrected each month, reflecting a moderate adjustment process. This slower convergence rate - relative to the price model - indicates that while price levels adjust rapidly, trading activity responds more gradually to structural changes and policy shocks.

In the short run, two factors exert statistically significant effects on trading volume. First, inflation shocks (D(CPI)) has a large and negative coefficient (-19.41, $p < 0.01$), showing that increases in consumer prices immediately suppress cryptocurrency trading. This may be attributed to declining real purchasing power and reduced speculative participation when inflation accelerates. Second, lagged global risk (D(VIX(-1))) exerts a significant negative influence (-0.036, $p < 0.01$), implying that heightened global uncertainty leads to a contraction in trading volumes with a one-month delay, consistent with a risk-aversion channel in investor behavior.

Other short-run terms, including contemporaneous global risk (D(VIX)) and lagged trading volume (D(VOLUME(-1))), are statistically insignificant, suggesting that short-term persistence in trading activity is weak and that immediate responses to global shocks are limited. Instead, investors appear to react to sustained or lagged signals of risk and uncertainty rather than to transient shocks.

Overall, the ECM findings for the VOLUME model demonstrate that short-run cryptocurrency trading in Turkey is primarily constrained by inflationary pressures and global risk sentiment. The adjustment toward equilibrium is moderate but stable, reflecting partial market inertia and the influence of broader macro-financial conditions. These results support Hypotheses H_1 and H_2 , highlighting that both domestic monetary instability and external volatility serve as key short-term transmission channels affecting market liquidity and participation.

3.6.3. ECM Analysis for the RET Model

Table 19 presents the short-run estimation results of the Error Correction Model (ECM) for cryptocurrency returns (D(RET)). This model captures the immediate responsiveness of market returns to domestic monetary and global financial shocks, while also quantifying the extent and speed of adjustment toward long-run equilibrium.

The error correction term (COINTEQ) is negative (-1.967) and highly significant ($p < 0.01$), confirming that cryptocurrency returns revert strongly toward long-run equilibrium following short-term shocks. The magnitude, exceeding one in absolute value, indicates overshooting behavior, that is, deviations from equilibrium are not only corrected but temporarily reversed, leading to oscillatory short-run adjustments. This dynamic is typical in high-volatility asset markets, where price corrections often exceed the initial disturbance.

Short-run results reveal several important drivers of cryptocurrency returns. The global cryptocurrency price (Δ GPUUSD) emerges as the dominant factor, with both contemporaneous and lagged effects that are positive and highly significant across multiple lags. This indicates a strong spillover mechanism from global to domestic markets, where returns in Turkey respond immediately and persistently to global Bitcoin price movements. The broad money supply (Δ M2) also exerts a positive and significant short-run effect, suggesting that liquidity expansions fuel speculative demand and enhance short-term profitability.

Table 19. ECM Results for D(RET)

Variable	Coefficient	Std. Error	t-Statistic	Probability
COINTEQ	-1.967275***	0.182716	-10.7668	0.0000
Δ GPUSD	0.922352***	0.043739	21.0878	0.0000
Δ GPUSD(-1)	0.431193***	0.088456	4.8746	0.0000
Δ RET(-1)	0.572529***	0.135148	4.2363	0.0000
Δ GPUSD(-2)	0.350725***	0.090615	3.8705	0.0002
Δ GPUSD(-3)	0.333031***	0.089117	3.7370	0.0003
Δ M2	0.977501***	0.332712	2.9379	0.0039
Δ RET(-2)	0.196615**	0.079940	2.4595	0.0153
Δ EXRATE	0.979293***	0.251102	3.8999	0.0002

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Δ denotes first differences. All coefficients represent short-run effects.

The exchange rate (Δ EXRATE) has a positive and highly significant effect (0.98, $p < 0.01$), implying that domestic currency depreciation amplifies cryptocurrency returns - consistent with a hedging motive against local currency weakness. Additionally, the lagged dependent variables (Δ RET(-1) and Δ RET(-2)) are both positive and significant, demonstrating momentum effects in short-run return dynamics, where past gains increase the likelihood of continued short-term appreciation.

Overall, the ECM estimation for the RET model underscores that short-term cryptocurrency returns in Turkey are highly sensitive to global market movements, liquidity shocks, and exchange rate fluctuations. The rapid and sometimes overshooting adjustment toward equilibrium highlights the speculative and momentum-driven structure of the market. These results provide strong empirical support for Hypotheses H_3 and H_4 , confirming that the short-run dynamics of returns are dominated by external and liquidity-driven shocks rather than by domestic monetary fundamentals.

3.6.4. ECM Analysis for the VOL Model

Table 20 reports the short-run estimation results of the Error Correction Model (ECM) for cryptocurrency market volatility (D(VOL)). This specification captures the immediate responses of volatility to global and domestic shocks and quantifies the pace of adjustment back to the long-run equilibrium level.

Table 20. ECM Results for D(VOL)

Variable	Coefficient	Std. Error	t-Statistic	Probability
COINTEQ	-0.631550***	0.120697	-5.2325	0.0000
D(VOL(-1))	-0.505690***	0.110643	-4.5704	0.0000
D(VOL(-2))	-0.423693***	0.098967	-4.2811	0.0000
D(VOL(-3))	-0.280742***	0.072451	-3.8749	0.0002
D(VIX(-2))	0.004100***	0.001398	2.9320	0.0040
D(GPUSD(-1))	0.063215**	0.029986	2.1081	0.0370

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. Δ denotes first differences. All coefficients represent short-run elasticities estimated from the ARDL error-correction representation.

The error correction term (COINTEQ) is negative (-0.632) and highly significant ($p < 0.01$), confirming that a stable long-run equilibrium exists for cryptocurrency volatility. Its magnitude indicates that approximately 63% of

deviations from equilibrium are corrected within one period (month), suggesting that volatility shocks are absorbed relatively quickly but not instantaneously. This reflects a market structure where speculative surges are temporary yet frequent - consistent with the high-risk, high-adjustment dynamics typical of crypto assets.

In terms of short-run behavior, the three lagged volatility terms (D(VOL(-1)), D(VOL(-2)), and D(VOL(-3))) are all negative and highly significant, confirming strong volatility clustering and mean reversion. This pattern indicates that periods of heightened volatility are typically followed by gradual normalization, consistent with GARCH-type dynamics observed in financial markets.

The global risk index (D(VIX(-2))) exerts a positive and statistically significant effect ($p < 0.01$), implying that increases in global uncertainty spill over into Turkey's cryptocurrency market volatility with a two-month delay. Similarly, the lagged global cryptocurrency price (D(GPUSD(-1))) shows a positive and significant impact ($p < 0.05$), suggesting that global market movements transmit to local volatility conditions, amplifying short-term fluctuations through cross-market contagion effects.

Overall, the ECM estimation for the VOL model highlights that short-run volatility in Turkey's cryptocurrency market is largely driven by global shocks and internal market inertia, rather than by domestic monetary variables. The combination of a significant error correction term and multiple lagged effects confirms the presence of a robust equilibrium adjustment mechanism and dynamic volatility persistence. These results provide strong empirical support for Hypotheses H_2 and H_4 , underscoring that global risk transmission and mean-reverting volatility patterns are central to the short-run behavior of cryptocurrency markets in emerging economies like Turkey.

3.6.5. Synthesis of Short-Run ECM Findings

Table 21 consolidates the key results from the four ECM estimations, highlighting both the error correction terms and the dominant short-run drivers of cryptocurrency market dynamics in Turkey. Across all models, the error correction coefficients (COINTEQ) are negative and highly significant, confirming that long-run equilibria exist and that deviations from these equilibria are corrected over time, albeit at varying speeds.

Table 21. Summary of Significant Short-Run ECM Results Across Models

Dependent Variable	Error Correction Term (COINTEQ)	Significant Short-Run Drivers	Interpretation
PRICE	-0.965*** (rapid adjustment; $\approx 96.5\%/month$)	D(M2)+, D(GPUSD)+, D(PRICE(-1))+ (momentum), D(GPUSD lags: -1-, -2~10%, -3+)	Prices quickly revert to equilibrium; short-run adjustments driven by money supply and global shocks; strong momentum effects.
VOLUME	-0.359*** (moderate adjustment; $\approx 36\%/month$)	D(CPI)-, D(VIX(-1))-	Trading volumes contract in response to inflation and lag global risk; adjustment slower than in the price model.
RET	-1.967*** (overshooting; >100% correction)	$\Delta GPUSD$ (current & lags)+, $\Delta M2+$, $\Delta EXRATE+$, $\Delta RET(-1)+$, $\Delta RET(-2)+$	Returns show rapid, oscillatory corrections; dominated by global and liquidity shocks; strong short-run momentum.
VOL	-0.632*** (rapid adjustment; $\approx 63\%/month$)	D(VOL(-1 to -3))-, D(VIX(-2))+, D(GPUSD(-1))+	Volatility shows clustering and mean reversion; global shocks amplify short-term fluctuations.

Notes: *, **, and *** represent the 10%, 5%, and 1% significance levels, respectively. (+)/(-) indicates the direction of effect.

Taken together, the ECM estimations reveal a consistent pattern of rapid short-run adjustment and heterogeneous transmission channels. Cryptocurrency prices and returns respond swiftly to monetary and global shocks, whereas trading volume adjusts more gradually, and volatility reflects persistent clustering behavior.

Short-run market dynamics are predominantly shaped by global financial variables (GPUSD, VIX, FFR) and liquidity shocks (M2, EXRATE), while the influence of domestic policy instruments such as the policy rate and reserve requirements is limited in the short term. These results strongly support Hypotheses H_1-H_4 , confirming that the cryptocurrency market in Turkey, while responsive to global and liquidity shocks, maintains an inherent self-correcting mechanism that restores equilibrium after short-term disturbances.

4. Discussions

The empirical findings provide a comprehensive view of how monetary policy and macroeconomic factors interact with the dynamics of Turkey's cryptocurrency market. The results from the ARDL and ECM estimations reveal a

heterogeneous structure across the four models (PRICE, VOLUME, RET, and VOL), showing that the channels through which policy decisions and macroeconomic conditions affect cryptocurrencies are neither uniform nor linear. In particular, the results demonstrate that the exchange rate and global financial conditions exert the most powerful and persistent influence, while domestic monetary instruments such as the policy rate and money supply have limited long-run effects.

The long-run findings confirm that cryptocurrency prices (PRICE) and trading volumes (VOLUME) are significantly and positively associated with the exchange rate (EXRATE), indicating that domestic currency depreciation stimulates both valuation and activity in digital asset markets. This supports the interpretation that cryptocurrencies in Turkey function as hedges against currency depreciation and macroeconomic instability, consistent with Dyhrberg (2016), Baur and Dimpfl (2021), and Taskinsoy (2019).

Alongside the exchange rate, inflation (CPI) also emerges as a critical, but more complex, domestic factor. Our findings reveal a significant dual effect (or market tension) regarding inflation: long-run estimates show that while CPI has a positive impact on PRICE - supporting the 'inflation hedge' narrative - it simultaneously has a significant negative impact on VOLUME. This finding suggests that while existing investors use cryptocurrencies to hedge and preserve asset value against inflation (driving up the nominal TRY price), the same inflationary pressures erode general purchasing power and household liquidity. This likely suppresses new market entry and reduces active trading volume, separating crypto's function as a 'store of value' from its accessibility as a liquid 'medium of participation' during high-inflation periods.

The empirical findings also necessitate a conceptual differentiation in analyzing monetary policy transmission channels. Our results indicate that the central bank's primary traditional instrument, the policy interest rate (POLICY), lacks a statistically significant, direct long-run impact on crypto market dynamics. However, this finding does not imply a complete ineffectiveness of monetary policy. On the contrary, our results robustly demonstrate that the liquidity channel remains highly active and relevant. Specifically, the Reserve Requirement Ratio (RRR), as a liquidity-based tool, exerts a direct and negative long-run influence on trading VOLUME. Concurrently, changes in the Broad Money Supply (M2) exhibit significant short-run effects on both PRICE and RETURNS. Therefore, monetary policy influence in Turkey appears to bypass the conventional interest rate channel, operating more directly through the management of market liquidity.

The strong linkage between the TRY-denominated and USD-denominated Bitcoin prices (GPUUSD) further reinforces the global integration of Turkey's crypto market and the dominance of international price discovery mechanisms, as noted by Corbet *et al.* (2019) and Zhao *et al.* (2023).

Table 22. Summary of Hypothesis Testing Results

Hypothesis	Expected Relationship	Empirical Findings	Supported?	Key Evidence
H₁ : Monetary policy instruments (POLICY, RRR, M2) significantly influence cryptocurrency market dynamics.	Positive for expansionary policy; negative for tightening.	Limited long-run effects; short-run significance through M2 only.	Partially supported	M2 positive in the short run (PRICE, RET); POLICY, RRR insignificant in the long run.
H₂ : Global and domestic control variables jointly determine cryptocurrency prices and volumes.	Positive for EXRATE, GPUUSD; negative for VIX, FFR.	Strong and persistent effects from EXRATE and GPUUSD; VIX and FFR are negative.	Supported	Long-run cointegration confirmed; consistent across models.
H₃ : Cryptocurrency returns (RET) exhibit long-run dependence on macroeconomic variables.	Expected long-run significance.	No variable is significant in the long run; only short-run speculative effects.	Not supported	The RET model confirms informational efficiency.
H₄ : Volatility (VOL) is primarily driven by global risk and liquidity conditions.	Negative with FFR and GPUUSD; positive with VIX.	Global variables are significant; domestic effects are negligible.	Supported	VOL model confirms long-run global spillover dominance.

Note: Hypothesis outcomes are derived from the combined evidence of ARDL long-run coefficients and ECM short-run dynamics presented in Sections 3.5 and 3.6.

A concise summary of these outcomes and their relation to the study's hypotheses is presented in Table 22, which integrates both long-run and short-run evidence. As shown in the table, H₁, which posits that monetary policy instruments significantly influence cryptocurrency dynamics, receives partial support: only the broad money supply

(M2) exerts a positive and significant short-run impact on prices and returns, while other policy variables display no sustained long-run effects. This suggests that in an economy characterized by high financial innovation and limited capital controls, liquidity conditions rather than policy rates constitute the main transmission channel to digital assets.

The results also provide strong support for H_2 , which emphasizes the joint role of domestic and global control variables in shaping cryptocurrency prices and volumes. The exchange rate (EXRATE) and global cryptocurrency price (GPUSD) emerge as robust long-run determinants, both positively associated with crypto prices and activity levels. Conversely, indicators of global financial tightening and risk aversion - namely, the Federal Funds Rate (FFR) and the VIX index - exert negative long-run influences, implying that tighter global liquidity and heightened uncertainty reduce speculative demand in the Turkish crypto market. These findings align with the international evidence reported by Elsayed and Sousa (2022) and BenSaïda (2023), confirming the dominance of global spillovers over domestic monetary effects.

In contrast, H_3 is not supported, as cryptocurrency returns (RET) show no significant long-run dependence on either domestic or global variables. This outcome aligns with the efficient market hypothesis (Fama, 1970), suggesting that in the long run, returns are unpredictable and mainly shaped by short-term speculative activity rather than fundamental macro-financial forces. The absence of persistent drivers reinforces the view that cryptocurrency markets, while sensitive to short-term shocks, remain largely efficient in adjusting to new information.

Finally, H_4 , which posits that volatility (VOL) is driven predominantly by global financial conditions, is strongly supported. Both the global Bitcoin price and the U.S. Federal Funds Rate significantly influence volatility in the long run, whereas domestic monetary variables are insignificant. This implies that risk and uncertainty in the Turkish cryptocurrency market are transmitted mainly through international financial channels. The ECM results further show that short-run volatility dynamics are characterized by clustering and mean reversion - common features in financial markets - and that global shocks to risk perception (VIX) and dollar-index movements (GPUSD) play key roles in shaping immediate fluctuations.

Collectively, the results summarized in Table 22 underscore the dual nature of monetary transmission in the digital-asset environment: while domestic instruments retain some relevance through liquidity and exchange-rate effects, global financial conditions ultimately dominate both long-run equilibrium and short-run adjustment processes. The Turkish cryptocurrency market thus behaves as a semi-open subsystem embedded in the global financial network, where external shocks and liquidity cycles overshadow local monetary authority interventions.

From a policy perspective, these findings highlight three key implications. First, the CBRT's monetary policy affects the cryptocurrency market primarily through indirect macro-financial channels - most notably the exchange rate - rather than through direct adjustments to policy instruments. Second, the partial hedging role of cryptocurrencies against domestic currency depreciation calls for enhanced financial literacy and risk communication, as households may increasingly treat digital assets as a substitute for foreign currency holdings. Third, given the evidence that volatility and market risk are largely determined by global forces, national regulation alone is insufficient; coordinated international oversight and cross-border monitoring mechanisms are essential for maintaining stability in digital asset markets.

Finally, from a theoretical standpoint, this study adds to the emerging literature by demonstrating how conventional monetary policy transmission mechanisms behave differently in the presence of decentralized digital assets. The decoupling of policy rates from cryptocurrency prices, the predominance of liquidity and exchange-rate channels, and the rapid speed of adjustment revealed by the ECM analysis collectively point to a hybrid monetary environment - one in which digital assets simultaneously respond to domestic macroeconomic signals and global financial sentiment. This hybrid structure challenges traditional conceptions of monetary sovereignty and underscores the need for a new framework that integrates digital finance into the broader monetary policy discourse.

Conclusions and Further Research

This study examined how monetary policy instruments and macroeconomic conditions influence cryptocurrency market dynamics in Turkey, focusing on prices, trading volumes, returns, and volatility. Using monthly data from September 2013 to March 2025 and applying the Autoregressive Distributed Lag (ARDL) and Error Correction Model (ECM) frameworks, the analysis captured both short- and long-run interactions between the Central Bank of the Republic of Turkey's (CBRT) policy tools and the behavior of digital assets. The mixed order of integration among the variables ($I(0)$ and $I(1)$) justified the ARDL approach, while the significant error correction terms confirmed the presence of long-run equilibria across all models.

The results reveal several important patterns. First, traditional monetary policy instruments - such as the policy rate and reserve requirement ratio - exert limited or short-lived influence on cryptocurrency markets. The only notable exception is the broad money supply (M2), which significantly affects prices and returns in the short run, indicating that liquidity conditions remain an operative, albeit partial, transmission channel. Second, the exchange rate and global financial indicators, including the global Bitcoin price (GPUSD), the U.S. federal funds rate (FFR), and the global volatility index (VIX), emerge as dominant long-run determinants of cryptocurrency prices and activity. These results confirm that the Turkish cryptocurrency market operates as a highly open and globally integrated subsystem, sensitive to international liquidity cycles and external risk conditions.

Third, the analysis finds no persistent long-run determinants of cryptocurrency returns, consistent with the efficient market hypothesis. Price and return adjustments occur rapidly, often within a single month, while trading volumes and volatility exhibit slower convergence to equilibrium. This heterogeneity in adjustment speed reflects the different mechanisms through which domestic and global shocks propagate within the market. The evidence also indicates that volatility in Turkey's cryptocurrency market is largely imported from global financial conditions, emphasizing the limited capacity of domestic policy interventions to stabilize risk dynamics.

Taken together, these findings suggest that monetary policy transmission in a digital-asset environment diverges from conventional mechanisms. In Turkey, exchange-rate movements and liquidity conditions, rather than direct policy interest rate adjustments, play a decisive role in shaping cryptocurrency market behavior. This decoupling highlights a structural challenge for monetary authorities: as digital assets grow in importance, central banks may find their influence over financial conditions increasingly mediated through indirect and globalized channels.

From a policy perspective, the results imply that CBRT should account for crypto-market reactions as part of its broader financial stability assessment. Given the strong co-movement between exchange-rate fluctuations and cryptocurrency prices, digital assets may serve as a barometer of monetary credibility and risk perception among investors. Furthermore, as global liquidity conditions tighten or ease, their effects on Turkey's digital asset markets can amplify or counteract domestic policy objectives, underscoring the importance of macroprudential coordination.

The study also opens several promising avenues for future research. First, subsequent analyses could incorporate structural break tests or regime-switching models to capture nonlinear adjustments during crisis periods, such as the COVID-19 pandemic or the 2021–2022 tightening cycle. Second, expanding the framework to include investor sentiment indices, capital flow data, or cross-market spillovers would provide a more comprehensive understanding of transmission asymmetries. Third, comparative studies across emerging economies could clarify whether Turkey's hybrid monetary–digital interaction pattern represents a broader feature of developing markets or a country-specific phenomenon. Furthermore, future research could employ Asymmetric models (NARDL) to test for differing market reactions to positive and negative monetary policy shocks. The use of higher-frequency data (e.g., weekly or daily), if macroeconomic variables can be adequately proxied, would also capture more immediate market reactions often smoothed out in monthly data. Finally, to more robustly address potential endogeneity between policy decisions and crypto-market capital flows, Structural VAR (SVAR) models could provide deeper causal insights.

In summary, this research contributes to the growing body of evidence that cryptocurrencies have become an integral component of the modern monetary landscape. While they remain highly volatile and globally synchronized, their sensitivity to domestic and international policy signals underscores the need for new analytical models that integrate digital finance into macroeconomic policymaking.

Declarations

Credit Authorship Contribution Statement:

Azatullah Nazari: Conceptualization, Investigation, Methodology, Data curation, Formal analysis, Writing original draft.

Ilkay Yilmaz: Corresponding author, Validation, Writing - review and editing.

Sevgi Tüzün Rad: Project administration, Supervision, Writing, review, and editing.

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Declaration of Use of Generative AI and AI-Assisted Technologies: The authors declare that generative AI (ChatGPT) was used only for language editing and to improve the manuscript's readability before submission. All

conceptual development, data analysis, interpretation of results, and conclusions were conducted by the authors, who take full responsibility for the content of the paper.

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1 References

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