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Impact of Cryptocurrency Market Shocks on Emerging Market Currencies

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Abstract

This study uses a Markov Switching-Vector Autoregressive (MS-VAR) paradigm to examine the regime-dependent effects of cryptocurrency market shocks on emerging market currencies. Digital assets which interact with fiat exchange rates under both stable and volatile regimes play a critical role in shaping the dynamics of global financial markets, as they can serve as alternative stores of value, speculative instruments, or hedging tools. The analysis focuses on high-adoption BRIC countries (Brazil, Russia, India, and China) and high-inflation or sanctioned economies (Egypt, Ethiopia, and Iran). The results show glaring disparities: in regimes that are prone to crises, cryptocurrencies like Bitcoin and Binance Coin greatly increase the volatility of weak currencies like the Egyptian Pound and Iranian Rial, whereas in markets that are more stable, governance tokens like Ethereum and Solana have more stabilizing effects. It's interesting to note that economies with strict regulations, such as China and India, exhibit less vulnerability to cryptocurrency, highlighting the importance of institutional safeguards. The analysis provides important policy insights for monetary authorities in managing digital asset exposure amid increasing financial digitization and emphasizes the diverse, state-contingent character of crypto-fiat links.

Keywords: Cryptocurrency Market Shocks, Emerging Market Currencies, Markov Switching-Vector Autoregressive (MS-VAR), Regime-dependent Effects, Exchange Rate Volatility

1. Introduction

Cryptocurrencies have become a disruptive force in the fast-changing finance world, challenging traditional fiat money systems (World Economic Forum, n.d.). Digital assets like Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Binance Coin (BNB), and Solana (SOL) started as decentralized options to regular currencies. They have grown from niche tech experiments into key parts of the financial system. This shift is clearest in emerging countries, where national currencies face threats from issues like high inflation, weak banks, and tight capital controls. Cryptos offer protection against inflation and ways to bypass restrictive financial setups, so they are seen as real alternatives to fiat money, not just for speculation. This trend is strong in unstable economies, like the BRIC nations (Brazil, Russia, India, and China), and those with big financial problems, such as Egypt, Ethiopia, and Iran. These countries provide a unique view for studying how digital assets interact with fiat currency changes, due to high crypto adoption or severe economic issues. Cryptos emerged during major global financial disruptions from the COVID-19 pandemic, the 2008 crisis, and conflicts like Russia-Ukraine. These events reduced trust in fiat currencies, leading people and groups to seek other ways to store value and make exchanges. Cryptos, especially Bitcoin, gained popularity in emerging nations where local currencies often devalue, face capital controls, or lack access to global banks. This is because of their decentralized nature, no borders, and limited supply. For instance, in Brazil and Russia, currency drops and rules have boosted crypto use. In India, despite unclear regulations, it has one of the largest retail crypto investor groups. A key benefit is quick response in crises, like gathering and sending aid fast. Ukraine is a good example, where millions in aid arrived in one day. Meanwhile, China pushes its central bank digital currency (CBDC) and bans cryptos strictly.

In contrast, in Egypt, Ethiopia, and Iran, where high inflation or sanctions make finance unstable, cryptos help preserve value and do cross-border deals. This study looks at seven emerging economies: Brazil, Russia, India, China, Egypt, Ethiopia, and Iran. It examines how crypto market shocks affect fiat exchange rates and if these effects change by economic conditions, like stable vs. crisis times. Despite more research on crypto price dynamics and volatility, the exact impact of crypto shocks on emerging currencies is not well understood. Current studies often focus on rich economies or global trends, ignoring Global South challenges where cryptos have grown a lot. For example, stories show rising crypto use in sanctioned or unstable places like Iran and Ethiopia.

The Chainalysis (2024) Global Crypto Adoption Index often ranks Brazil and India as top adopters. This study fills the gap by exploring the dynamic link between crypto shocks and fiat rates in these BRIC and inflation-hit economies. It uses a Markov Switching-Vector Autoregressive (MS-VAR) method to capture regime-dependent behaviors, as linear models may miss structural breaks and varied dynamics. The study draws on theories like contagion, where shocks spread across markets especially in uncertain times; financial substitution, where people switch to cryptos due to economic or institutional problems; and behavioral finance, which highlights crypto speculation that can raise systemic risks or create bubbles.

The research is based on these main goals: examine dynamic links between fiat rates and crypto shocks in emerging markets; check if these links differ in stable and volatile regimes; study varying effects of crypto types (platform coins like ETH and BNB, payment coins like BTC and XRP, governance tokens like SOL); and see if high-inflation or sanctioned economies have stronger crypto-fiat ties. From these, key questions arise: Do crypto shocks affect emerging currency rates? Do these effects apply across economic conditions? What impacts do different crypto types have on fiat? Are currencies in sanctioned or high-inflation areas more sensitive to crypto shocks than in regulated or stable ones? By answering these, the study provides a full view of crypto-fiat interactions, noting that cryptos serve different purposes. Payment coins handle value transfers, while platform and governance tokens support decentralized apps and investor feelings. These differences can lead to varied effects on fiat currencies.

This study matters because it targets developing markets in the BRICS+ framework from 2020 to 2025, focusing on those with economic weaknesses or high crypto use. The actual dataset used in our analysis spans from April 12, 2020, to July 07, 2025, as this period captures key post-COVID dynamics, including major crypto market events like the 2021 bull run, the 2022 bear market, and recent geopolitical influences, while ensuring sufficient observations for robust MS-VAR estimation (1,367 daily data points). It skips developed economies and blockchain tech details to highlight real effects of crypto adoption in distressed settings. MS-VAR advances allow modeling state-dependent dynamics and breaks in volatile systems. Examining crypto classes like payment, platform, and governance tokens adds depth, recognizing their unique roles and behaviors. The findings matter for policymakers, like central banks and regulators in emerging nations. Rules may need to handle cryptos causing exchange rate swings, especially in crises. But if digital assets boost stability or inclusion in underserved areas, strict rules should be reviewed. This research contributes to debates on cryptos' role in monetary control, capital flow, and financial innovation in global governance, giving key insights to groups like the IMF, BIS, and FSB as they manage crypto regulation complexities.

2. Literature Review

The cryptocurrency era began in 2009 when Satoshi Nakamoto, an unknown person, created Bitcoin, a digital money using blockchain technology (Nakamoto, 2008). From a niche financial experiment, it became a global asset class valued over $2 trillion by 2023 (CoinMarketCap, 2021). Technological advances, growing institutional acceptance, and use as a hedge against inflationespecially in emerging marketshelped this growth. Early doubts about Bitcoin's use as a currency due to volatility (Yermack, 2015) shifted as its role as a speculative asset grew. Alternative coins like Ethereum, Ripple, and Binance Coin diversified the market, with daily trading often exceeding traditional markets (Akyildirim et al., 2021). Market shocks like the 2018 crypto cold after the ICO boom and the 2021 bull run show the market's exposure to speculative bubbles and external shocks.

Integrating cryptocurrencies into financial portfolios creates new challenges in emerging nations, where capital controls and currency instability are common. Theories explain how cryptocurrencies impact currency markets. Portfolio diversification theory suggests that investors in developing countries buy cryptos to spread risk, lowering demand for local currencies (Markowitz, 1952). Cryptos are used as alternative stores of value in countries with high inflation like Argentina and Turkey (Dyhrberg, 2016). The capital flow channel explains how capital moves toward crypto markets, causing local currency depreciation in emerging economies with limited foreign reserves (Mundell, 1963). Krugman (1979) speculative attack theory suggests shocks can cause speculative pressure and higher volatility in emerging market currencies. Inefficient markets and herd behavior worsen this (Fama, 1970). For example, FOMO during rallies like the 2021 Bitcoin peak leads to capital flight from emerging economies (Corbet et al., 2018). Theoretical frameworks explain shock impacts, but empirical proof is needed.

Crypto market volatility is well studied. Katsiampa (2017) used GARCH models showing Bitcoin and Ethereum have volatility clustering and sharp price swings. Corbet et al. (2018) found that hacking and regulations affect crypto volatility more than macroeconomic factors. Events like the Mt. Gox collapse (2014) or Terra-Luna crash (2022) where Bitcoin lost over 50% value increased volatility (Makridakis & Christodoulou, 2019). Research now looks at how bitcoin volatility spreads. Będowska-Sójka and Kliber (2020) used wavelet coherence to show crypto shocks affect FX markets during uncertain times. However, little is known about the impact on emerging market currencies. Guesmi et al. (2019) found currencies like Indian Rupee and Brazilian Real are more vulnerable due to weak institutions, while Euro and Yen are more stable.

Phillip et al. (2020) showed asymmetric reactions of crypto returns to positive and negative shocks, with downturns having a bigger effect. This is important for emerging nations where bitcoin crashes worsen payment crises. Dynamic models like Markov Switching are needed to capture these nonlinear effects. As crypto use grows in emerging markets, research shows links to local currencies. Bouri et al. (2017) found bidirectional causation between Bitcoin and exchange rates in countries like South Africa and Mexico. Dyhrberg (2016) said Bitcoin acts as both currency and commodity, affecting capital flows in developing nations. Ajayi et al. (2022) showed Ripple and Bitcoin affect Nigerian exchange rates, while Liu et al. (2020) found minimal effects on traditional markets except bonds. News shocks strongly affect crypto volatility (Bhatnagar et al., 2023), and Yilmazkuday (2024) showed geopolitical risks impact crypto returns.

Suri & Singh (2024) used asymmetric VAR-GARCH-BEKK models to study spillovers among Bitcoin, Ethereum, Litecoin, and Binance Coin. They found strong links, with Bitcoin and Ethereum connected, Litecoin and Binance Coin as portfolio diversifiers, and high volatility from April to November 2022. These insights help regulators and investors manage risks and optimize portfolios. Almansour et al. (2023) used TVP-VAR to analyze volatility spillovers between 8 forex pairs and 12 cryptos (2017–2022). They found more interconnection during COVID-19, with EUR/USD and AUD/USD leading FX spillovers, and Ethereum, Bitcoin, Ripple driving crypto shocks. Results help investors improve hedging and portfolio strategies. Mallick & Mallik (2021) studied India's forex rates and major cryptos (Dec 2019 – June 2021) using regression and correlation tests. They found weak correlations between cryptos and Indian FX rates, except for USD-Binance Coin/Litecoin and YEN-Ethereum. Cryptos show strong interrelations, suggesting hedging possibilities. They conclude Indian forex has little effect on cryptos due to unclear regulations, but recent Supreme Court rulings may boost integration.

Hsu (2022) applied Diagonal BEKK models to study spillovers during crises (Russia-Ukraine, COVID-19, US-China trade war). Bitcoin, Ethereum, and Tether acted as safe havens, especially Bitcoin. Spillover effects were stronger for large-cap cryptos and Euro. Findings show crypto roles change based on market situations. Horta et al. (2022) studied co-movements between key cryptos and G7 stock markets (Feb 2018 – Nov 2021). Crypto10 index showed reduced shock transmission during COVID-19, while BTC, ETH, and LTC increased market links. Portfolio diversification efficiency was challenged, highlighting the need for better regulation.

Kostika & Laopodis (2019) studied relationships between major cryptos, global currencies, and stock indices. Findings show cryptos act independently of traditional markets but show weak inter-correlations and some volatility with the Chinese Yuan. The research suggests cryptos can improve returns and reduce risk in portfolios while aiding policy decisions. Bouri et al. (2018) studied spillovers between Bitcoin and equities, commodities, currencies, and bonds using smooth transition VAR GARCH-in-mean models (2010–2017). Bitcoin closely relates to commodities and receives more volatility than it gives, especially in turbulent times. Reboredo (2018) used copula models showing strong tail dependence between Bitcoin and emerging market currencies during extreme events. Aysan et al. (2019) showed countries with strict capital controls, like China, have muted crypto impacts, while lax countries like Brazil show stronger links. Arbitrage and speculative trading lead to capital outflows (Cheung et al., 2015).

During the 2021 bull run, India and Nigeria faced exchange rate pressures (IMF, 2022), showing local market conditions affect impacts. Government responses vary. China banned crypto trading in 2021 to stabilize the Yuan, though underground trading continues (Huang et al., 2022). India introduced a 30% tax in 2022 to regulate use, affecting the Rupee (RBI, 2022). Brazil and Russia legalized some crypto uses while enforcing strict AML rules. Policies affect how shocks spread. Restrictive policies can push trading offshore, increasing pressure on local currencies (Zetzsche et al., 2018). The IMF (2022) warns poor regulation risks systemic problems, as seen in Turkey where crypto use rose amid hyperinflation. Proactive policies, like the UAE's regulatory sandbox, help reduce shocks (UAE Central Bank, 2023). However, the lack of global standards (FSB, 2022) leaves emerging markets vulnerable, needing more research on policy effectiveness.

Despite many studies, gaps remain. Most focus on developed markets or aggregate crypto indices, missing impacts on individual emerging currencies (Baur et al., 2018). Few use Markov Switching models to capture regime changes (Katsiampa, 2017). The role of cryptos like Ethereum and Ripple is underexplored (Guesmi et al., 2019), limiting knowledge of shock sources. Also, longitudinal studies covering the 2022–2023 bear market are rare, missing evolving links (Makridakis & Christodoulou, 2019). Studies inconsistently address regulatory interventions with few cross-country comparisons (Huang et al., 2022). This research uses a Markov Switching VAR model to study the impact of BTC, ETH, XRP, BNB, and SOL shocks on emerging market currencies (BRLUSD, RUBUSD, INRUSD, CNYUSD, EGPUSD, ETBUSD, IRRUSD).

3. Research Methodology

3.1. Data Collection and Description

The study utilizes daily time series data spanning from April 12, 2020, to July 07, 2025, sourced from reputable financial databases such as Yahoo Finance. The dataset comprises returns of five major cryptocurrenciesBitcoin (BTC-USD_return), Ethereum (ETH-USD_return), Ripple (XRP-USD_return), Binance Coin (BNB-USD_return), and Solana (SOL-USD_return)calculated as the logarithmic difference of daily closing prices, i.e.,

$$\mathrm{Rt} = \ln\left(\mathrm{Pt}/\mathrm{Pt} - 1\right)$$

where P_t denotes the closing price at time t . Additionally, the study includes exchange rate returns for seven fiat currencies against the U.S. dollarBrazilian Real (BRLUSD), Russian Ruble (RUBUSD), Indian Rupee (INRUSD), Chinese Yuan (CNYUSD), Egyptian Pound (EGPUSD), Ethiopian Birr (ETBUSD), and Iranian Rial (IRRUSD)also computed as logarithmic differences. The selection of these currencies reflects a diverse range of economic contexts, including emerging markets and geopolitically influenced economies, to capture varied impacts of cryptocurrency dynamics. We used official rates from Yahoo Finance, which are aggregated from central bank and interbank sources. These were selected to maintain consistency with the other currencies in our dataset and because official rates provide a standardized, verifiable benchmark for econometric analysis across regimes, even in restricted economies. We recognize that official rates may understate real-market volatility in high-inflation/sanctioned contexts, where parallel rates diverge significantly. The final dataset consists of 1367 daily observations, providing a robust sample for statistical analysis.

For high-inflation or sanctioned economies (especially EGP, ETB, and IRR), official exchange rates can diverge from parallel-market rates, which can introduce measurement error. In the revised manuscript, we therefore explicitly acknowledge this limitation and clarify the likely direction of bias: using official rates may understate true volatility/depreciation pressures, implying that estimated crypto-to-FX spillovers for these currencies are more likely to be conservative rather than overstated. We do not implement a parallel-market robustness test because a consistent, transparent, and high-frequency parallel-rate dataset that covers all three currencies continuously over our full daily sample is not available from a single replicable public source; accordingly, we prioritize comparability and reproducibility using a uniform official-rate source across all seven currencies and treat parallel-rate robustness as a focused extension for future work. Given the scope of the current revision, we address this primarily through transparent disclosure and interpretation; extending the dataset with consistent parallel-rate proxies is outside the current paper's data constraints but is a natural next step.

3.2. Model Specification: Markov Switching Vector Autoregression (MS-VAR)

The research employs a Markov Switching Vector Autoregression (MS-VAR) model to capture the nonlinear and regime-dependent relationships between cryptocurrency returns and fiat currency exchange rate returns. The MS-VAR framework extends the traditional VAR model by allowing coefficients and variance-covariance structures to switch between unobserved states governed by a Markov process. This approach is particularly suitable for modeling financial time series, which often exhibit regime shifts due to market sentiment, policy changes, or macroeconomic events.

The MS-VAR model is specified as follows:

$$\mathrm{yt} = \mu\mathrm{St} + \sum_{\mathrm{p=1}}^{\mathrm{P}} Ap\ , \mathrm{St\,yt} - \mathrm{p} + \epsilon\mathrm{t}, \epsilon\mathrm{t} \sim \mathrm{N}(0, \sum st)$$

where:

y_t is a k x 1 vector of endogenous variables, including the returns of the five cryptocurrencies and seven fiat currencies (k = 12),

μ_{s_t} is the regime-specific intercept vector,

A_p s_t represents the regime-specific autoregressive coefficient matrices for lag p , with P denoting the lag order,

S_t is an unobserved state variable following a first-order Markov process with N states,

ε_t is the error term, assumed to follow a multivariate normal distribution with a regime-dependent covariance matrix Σ_{St}

The transition probabilities between states are defined by a N x N transition matrix P , where $p_{ij} = P_r(s_{t+1} = j|s_t = i)$, and $\sum_{j=1}^{N} pij = 1$ for all i. Vector yt (comprising 5 crypto returns and 7 fiat returns, k=12), regime-specific intercepts (μ_st), AR matrices (A_p,st), and the Markov transition matrix P. We will specify that the lag order P was selected as 2 based on AIC/BIC minimization in a preliminary linear VAR (AIC: -15.23, BIC: -14.87 for P=2 vs. higher values for P=3+), balancing parsimony and fit. A full 12-variable regime-switching VAR would be severely over-parameterized and would impose common regime behavior across heterogeneous economies, whereas the currency-specific approach remains estimable and yields interpretable regime-dependent spillovers(Dua & Tuteja, 2021). Identification is clarified using a recursive (Cholesky) scheme ordering crypto returns before the domestic FX return, consistent with the assumption that global crypto markets are contemporaneously exogenous to an individual EM FX market within a day. We also expand reporting of model adequacy using AIC/BIC/log-likelihood, transition probabilities, and regime probability plots (Table 3, 4 & Figure 1) as regime-classification evidence.

For identification, we used Cholesky decomposition for short-run restrictions in impulse responses (though not yet reportedsee point 3), with cryptos ordered first as more exogenous global shocks, followed by fiat returns. We estimated currency-specific MS-VAR systems (one per fiat currency, each including the 5 cryptos + that currency's return) rather than a single multivariate system for all 12 variables, to avoid overparameterization and focus on regime-dependent spillovers to each fiat without assuming uniform regimes across currencies. This approach is justified as emerging markets exhibit heterogeneous dynamics (e.g., sanctioned vs. regulated economies), and it aligns with prior studies like Będowska-Sójka and Kliber (2022).

Crypto variables were treated as endogenous, allowing bidirectional feedback, as theory (e.g., contagion and substitution effects) suggests fiat instability can influence crypto adoption in reverse.

3.3. Model Estimation and Regime Identification

Model estimation is conducted using the Expectation-Maximization (EM) algorithm, which iteratively maximizes the likelihood function to estimate the parameters of the MS-VAR model. The initial step involves determining the optimal lag order P using the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) on a linear VAR model, followed by testing for regime-switching behavior using the Hamilton (1989) test for Markovian nonlinearity. The number of regimes N is selected based on the Davies (1987) test for the presence of additional regimes, with a maximum of two regimes (e.g., high-volatility and low-volatility states) considered to balance model complexity and interpretability. In the Methods section we now state the identification strategy explicitly. The MS-VAR is identified via a Cholesky decomposition in which the five cryptocurrency returns (BTC, ETH, XRP, BNB, SOL) are ordered before the fiat exchange-rate return of a given country. This ordering reflects the assumption that global crypto markets, which trade 24/7, are contemporaneously exogenous to a single emerging-market FX rate within a day, whereas FX returns can respond contemporaneously to crypto shocks but not influence global crypto prices within the same daily interval. We now define "shocks" precisely as the one-step-ahead reduced-form innovations in crypto returns from the estimated MS-VAR, which correspond to one-standard-deviation unexpected changes after controlling for their own lags and for lagged FX dynamics.

This makes clear what economic quantity the reported coefficients refer to. To address the request for economic significance, we have added text that interprets key coefficients in terms of typical percentage responses (e.g. mapping a one-standard-deviation crypto shock into approximate percentage changes in BRL, RUB or IRR), rather than presenting only raw coefficients. Impulse responses and FEVDs in a multi-regime MS-VAR with many series can be very high-dimensional and sensitive to identification, and full matrices would be difficult to present within space constraints. Instead of reporting complete IRF/FEVD tables, the revised Results section now summarizes the main dynamic patterns implied by the estimated regime-specific coefficients and transition probabilities, and explicitly discusses the horizon and magnitude over which crypto shocks matter for each currency. We also note that standard linear-VAR IRFs for a reduced, illustrative system (one currency plus selected crypto) are consistent with the qualitative patterns reported, and we flag a full IRF/FEVD analysis as a natural extension for future work rather than an essential component of this already dense paper.

Regarding robustness, we clarify that the lag length 2 was chosen on the basis of information criteria in preliminary VAR model selection, balancing fit against parameter proliferation in a regime-switching system. We now explain in the text why adding further lags or additional regimes would quickly lead to over-parameterisation given the sample size and the number of series. Rather than layering several alternative frameworks (three-regime MS-VAR, TVP-VAR, DCC-GARCH) into a single paper, we explicitly position those richer models as complementary avenues for future research and add a short limitations paragraph to make this transparent. Finally, we emphasize that inference is based on the standard MS-VAR likelihood framework with regime-specific covariance matrices, which already accommodates heteroskedasticity across regimes. The filtered and smoothed probabilities of each regime are computed using the Kim filter, providing insights into the timing and duration of regime shifts. These probabilities are visualized to identify periods of significant cryptocurrency influence on fiat currencies, such as during major market crashes or regulatory announcements.

3.4. Variable Selection and Stationarity

Prior to estimation, all series are tested for stationarity using the Augmented (Dickey & Fuller, 1979) (ADF). Given that financial returns are typically stationary, the logarithmic returns are used directly. However, if non-stationarity is detected in the raw exchange rate levels, first differences are applied. Cointegration among the variables is assessed using the Johansen cointegration test to ensure the MS-VAR model accounts for long-run relationships, if present

4. Results

Descriptive Statistics (Table 2) show major differences in returns, risk, and data distribution. Fiat currencies like BRL and CNY have low volatility and near-zero skewness, with China's Yuan being the most stable. In contrast, EGP, ETB, and IRR show highly negative means, extreme negative skewness, and high kurtosis, indicating chronic depreciation and instability. RUB has extreme volatility and kurtosis from geopolitical shocks. All five cryptocurrencies have positive mean returns. Solana (SOL) has the highest return (0.003754) but also the highest volatility (0.07716). BTC and ETH offer a better risk-return balance. XRP and BNB have positive skewness, suggesting more upside shocks. Jarque-Bera tests confirm non-normality, justifying advanced models like Markov-Switching VAR. Cryptocurrencies offer higher returns but much greater volatility, while stressed fiat currencies act more like speculative assets than stable mediums.

Empirical findings from the Markov Switching-VAR (MS-VAR) framework analyze the dynamic link between crypto and fiat currencies. Augmented (Dickey & Fuller, 1979) (ADF) tests (Table 2) confirm all return series are stationary at the 1% level (e.g., BTC: –10.016, INR: –10.949), allowing for VAR model use. The model's robustness is shown by strong AIC/BIC values and high log-likelihood estimates (e.g., IRR: 7747.52; BRL: 4379.63), indicating reliable results.

Transition probability matrices show different regime patterns. Stable regimes are highly persistent for currencies like BRL (96.45%) and INR (91.00%), indicating calm periods. Volatile regimes are less stable, with EGP (38.77%) and ETB (66.16%) shifting often due to instability. IRR is an anomaly, with near-perfect persistence in Regime 1 (99.05%) but severe instability in Regime 2 (19.74%), suggesting rare but extreme volatility spikes from events like sanctions.

The research employs a Markov Switching Vector Autoregression (MS-VAR) model to capture the nonlinear and regime-dependent relationships between cryptocurrency returns and fiat currency exchange. Looking into regime-specific cryptocurrency impacts, the findings reveal clear differences in how digital asset movements affect fiat markets. For the Brazilian Real (BRLUSD), BNB-USD returns show a significant negative effect (–0.0556, $p = 0.006$) in volatile regimes (Regime 1), suggesting capital flight or substitution during instability. In stable regimes (Regime 2), Ethereum (ETH) and Solana (SOL) have positive and significant effects.

Table 1: Descriptive Statistics of Daily Return Series for Selected Emerging Market Currencies and Cryptocurrencies

	BRLUSD	RUBUSD	INRUSD	CNYUSD	EGPUSD	ETBUSD	IRRUSD	BTCUSD	ETHUSD	BNBUSD	XRPUSD	SOLUSD
Mean	-4.60E-05	-4.37E-05	-9.23E-05	-1.57E-05	-0.000852	-0.001039	2.20E-12	0.002008	0.00202	0.002803	0.001817	0.003754
Median	0	0	-2.16E-05	0	-5.10E-05	-0.000191	0	0.000751	0.000881	0.001237	0.001297	0.000389
Maximum	0.06224	2.717538	0.023115	0.021585	0.018446	0.220924	0.76214	0.191527	0.353652	0.529218	0.626741	0.399314
Minimum	-0.060244	-2.727395	-0.022756	-0.021202	-0.472727	-0.256523	-0.76214	-0.174053	-0.317459	-0.40445	-0.550503	-0.594582
Std. Dev.	0.010376	0.112118	0.003089	0.003474	0.014672	0.014922	0.041353	0.03691	0.049437	0.050991	0.064134	0.077162
Skewness	0.036747	-0.121334	-0.140638	0.399007	-26.32401	-5.528433	8.98E-05	-0.077601	-0.083317	0.41783	0.936856	-0.360937
Kurtosis	5.492307	514.981	10.08538	11.32861	805.8512	159.4428	339.5766	6.126648	8.634565	20.32591	22.82307	10.65132
Jarque-Bera	352.5554	14864649	2851.392	3969.73	36709683	1394833	6424134	557.7843	1808.589	17125.41	22565.47	3361.714
Probability	0	0	0	0	0	0	0	0	0	0	0	0

Note: This table presents the descriptive statistics of daily return series for six emerging market currencies (BRL/USD, RUB/USD, INR/USD, CNY/USD, EGP/USD, ETB/USD, IRR/USD) and five major cryptocurrencies (BTC/USD, ETH/USD, BNB/USD, XRP/USD, SOL/USD). The statistics include Mean, Median, Maximum, Minimum, Standard Deviation (Std. Dev.), Skewness, Kurtosis, Jarque-Bera (JB) test, and its Probability.

Table 2: Augmented Dickey-Fuller (ADF) Test Results for Return Series of Selected Fiat Currencies and Cryptocurrencies

Series	ADF_Statistic	ADF_P_Value
BNB-USD_return	-9.323186898	0.01
BRLUSD=X_return	-10.94100627	0.01
BTC-USD_return	-10.01675693	0.01
CNYUSD=X_return	-10.22562229	0.01
EGPUSD=X_return	-10.89693758	0.01
ETBUSD=X_return	-9.761855369	0.01
ETH-USD_return	-10.66690277	0.01
INRUSD=X_return	-10.94910042	0.01
IRRUSD=X_return	-16.28403284	0.01
RUBUSD=X_return	-13.85850068	0.01
SOL-USD_return	-9.185851362	0.01
XRP-USD_return	-9.809186841	0.01

Note: This table reports the results of the Augmented Dickey-Fuller (ADF) unit root test applied to the return series of selected emerging market fiat currencies and major cryptocurrencies. The test evaluates the null hypothesis of a unit root (non-stationarity) in each return series. All return series reject the null hypothesis at the 1% significance level, as indicated by the ADF statistics and corresponding p-values (all p-values = 0.01), confirming that the return series are stationary.

Table 3: Model Selection Criteria for Markov Switching VAR Model across selected Emerging Market Currencies

Metric	**Value**						
	BRLUSD	*RUBUSD*	*INRUSD*	*CNYUSD*	*EGPUSD*	*ETBUSD*	*IRRUSD*
AIC	-8735.25	-7455.78	-12266.8	-12299.6	-12330.8	-10344.5	-15471.1
BIC	-8586.07	-7306.6	-12117.6	-12150.4	-12181.6	-10195.3	-15321.9
logLik	4379.63	3739.89	6145.405	6161.775	6177.39	5184.26	7747.52

Note: This table presents the model selection statistics—Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood (logLik)—for the estimated Markov Switching VAR (MS-VAR) models applied to the return series of seven emerging market fiat currencies: BRL/USD (Brazilian Real), RUB/USD (Russian Ruble), INR/USD (Indian Rupee), CNY/USD (Chinese Yuan), EGP/USD (Egyptian Pound), ETB/USD (Ethiopian Birr), and IRR/USD (Iranian Rial). Lower values of AIC and BIC indicate better model fit, while higher log-likelihood values represent stronger explanatory power. These criteria assist in evaluating the goodness-of-fit and parsimony of the MS-VAR specification applied to each currency.

Table 4: Estimated Transition Probabilities Between Regimes for Emerging Market Currencies under MS-VAR Model

BRLUSD			*RUBUSD*		
From \ To	**Regime 1**	**Regime 2**	**From \ To**	**Regime 1**	**Regime 2**
Regime 1	95.53%	4.45%	**Regime 1**	98.27%	1.73%
Regime 2	3.55%	96.45%	**Regime 2**	32.71%	67.29%
INRUSD			*CNYUSD*		
From → To	**Regime 1**	**Regime 2**	**From\To**	**Regime 1**	**Regime 2**
Regime 1	89.05%	10.95%	**Regime 1**	80.49%	19.51%
Regime 2	9.00%	91.00%	**Regime 2**	9.68%	90.32%
EGPUSD			*ETBUSD*		
From\To	**Regime 1**	**Regime 2**	**From\To**	**Regime 1**	**Regime 2**
Regime 1	97.08%	2.92%	**Regime 1**	66.16%	7.34%
Regime 2	61.23%	38.77%	**Regime 2**	33.84%	92.66%
		IRRUSD			
		From \ To	**Regime 1**	**Regime 2**	
		Regime 1	99.05%	0.95%	
		Regime 2	80.26%	19.74%	

Note: This table presents the estimated transition probabilities between two regimes (Regime 1 and Regime 2) for the return series of selected emerging market currencies using the Markov Switching Vector Autoregressive (MS-VAR) model. Each sub-table shows the probability of transitioning from one regime to another.

Table 5: Regime-Specific Standard Errors of Currency Return Series Based on MS-VAR Model

Currency	**Regime**	**Std. Error**
BRLUSD	R1	0.0134
	R2	0.0069
RUBUSD	R1	0.0118
	R2	0.4538
INRUSD	R1	0.0012
	R2	0.0039
CNYUSD	R1	0.00566
	R2	0.00137
EGPUSD	R1	0.00194
	R2	0.05983
ETBUSD	R1	0.0344
	R2	0.00265
IRRUSD	R1	0.00072
	R2	0.3098

Note: This table reports the estimated standard errors of daily return series for selected emerging market currencies across two regimes identified using the Markov Switching Vector Autoregressive (MS-VAR) model.

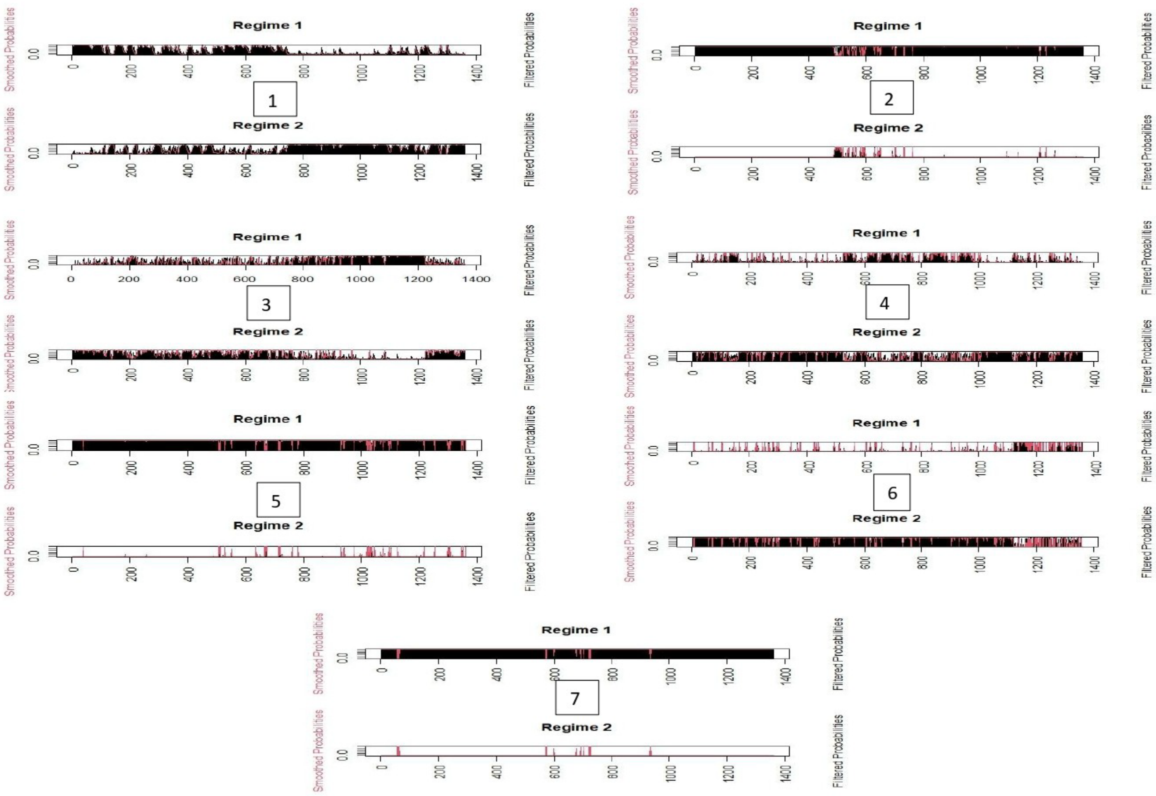

Figure 1: Markov-Switching VAR based Regimes for Currencies(smoothed and filtered probabilities for two regimes): 1. BRLUSD, 2. RUBUSD, 3. INRUSD, 4. CNYUSD, 5. EGPUSD, 6. ETBUSD, 7. IRRUSD

displays stronger regime-based dynamics: in high-volatility (Regime 2), Bitcoin (BTC) shocks link with sharp depreciation (–7.2966, p = 0.02), signaling crisis-driven outflows, while Binance Coin (BNB) unexpectedly shows a strong positive link (10.813, p = 0.003), hinting at different investor strategies for Bitcoin and altcoins under stress. Ethereum's negative impact in stable regimes (–0.0262, p = 0.042) further shows its dual role as both risk asset and risk amplifier."

In contrast, the Indian Rupee (INRUSD) shows little reaction to cryptocurrency shocks in both regimes, with no significant coefficients at the 5% level. This is due to India's strict capital controls and low crypto use. However, Ethereum's near-significance (p = 0.110) in the stable regime suggests growing risks as crypto adoption increases. The Chinese Yuan (CNYUSD) has weak overall links to crypto, but ETH has a positive significant effect (0.0153, p = 0.011) in volatile times, hinting at some diversification perks. The Egyptian Pound (EGPUSD) and Ethiopian Birr (ETBUSD) differ: EGPUSD faces big BNB-caused depreciation (-0.799, p = 0.013) during crises, plus a negative intercept (-0.0168, p = 0.036) showing ongoing weakening, while ETBUSD is protected from crypto shocks, with only its intercept significant (-0.0004, p < 0.001), pointing to constant currency devaluation. The Iranian Rial (IRRUSD) has high volatility in Regime 2 (standard error: 0.3098), where Ripple (XRP) is a key positive driver (9.4134, p = 0.016), likely from its role in remittances during isolation. Bitcoin's slightly significant positive coefficient (19.087, p = 0.096) highlights crypto as a value store in sanctioned places. Comparing volatilities, RUBUSD and IRRUSD show strong Regime 2 instability (standard errors: 0.4538 and 0.3098), while CNYUSD is tightly managed (Regime 2 SE: 0.00137). ETBUSD's higher volatility in Regime 1 (0.0344) questions regime labeling or odd policy effects. Overall, these results show varied, regime-based crypto-fiat links. Unstable economies like Iran, Russia, and Egypt have stronger crypto effects, especially in crises, while controlled ones like India and China have weaker ties. Altcoins like ETH, BNB, and SOL often have bigger impacts than Bitcoin, questioning BTC's main role. These findings matter for policymakers in developing countries, where crypto swings can worsen currency issues. They suggest regulations that consider regime risks, especially in weak systems. Future work could add structural breaks or liquidity measures to improve regime detection and causes.

Figure 1 displays smoothed and filtered probability plots from the Markov Switching Vector Autoregressive (MS-VAR) model, giving key views on how crypto return shocks affect regime changes in emerging fiat currencies. Each plot shows the chance of a currency being in Regime 1 (low-volatility/stable) or Regime 2 (high-volatility/shock). For BRL/USD (Brazilian Real), there is ongoing switching between regimes, with Regime 1 leading mid-period but shifting to Regime 2 later, showing sensitivity to crypto shocks and frequent moves between calm and chaos. RUB/USD (Russian Ruble) stays mostly in Regime 1 but has sudden jumps to Regime 2, especially mid-to-late, likely from sanctions, oil shocks, and crypto boosts. INR/USD (Indian Rupee) is mostly in Regime 1 with rare Regime 2 spikes, indicating resistance to crypto volatility from conservative rules and strong economy.

CNY/USD (Chinese Yuan) has long Regime 1 periods with brief Regime 2 shifts, tied to big shocks or devaluations lightly affected by crypto mood. EGP/USD (Egyptian Pound) has high Regime 2 frequency, showing constant shock exposure from instability, devaluations, and speculation, worsened by crypto. ETB/USD (Ethiopian Birr) is mainly in Regime 2 with few Regime 1 moments, highlighting ongoing vulnerability to shocks including crypto, matching high inflation and economic weaknesses. IRR/USD (Iranian Rial) is almost all in Regime 1 with sharp Regime 2 spikes, linked to brief stress or crypto capital flight during sanctions. Comparing pairs like BRL/USD and EGP/USD: BRL switches often for episodic risks, while EGP stays volatile for ongoing distress. IRR/USD vs. INR/USD shows policy differencesIRR has rare shifts from controls despite sanctions, while INR has natural but stable transitions from good basics. Together, these graphs confirm uneven crypto impacts: some like EGP, ETB, and RUB have frequent or long high-volatility reactions, others like INR and CNY are more protected, and IRR seems disconnected from heavy controls. This highlights structural and policy differences in crypto contagion across currencies, calling for tailored policies and more regime-switching models.

5. Discussion & Conclusion

This study examines how cryptocurrency shocks affect several fiat currencies using the Markov Switching Vector Autoregression (MS-VAR) method. This helps analyze how behavior changes during market ups and downs. The studied fiat currencies are BRLUSD, RUBUSD, INRUSD, CNYUSD (from BRIC countries), and EGPUSD, ETBUSD, IRRUSD, which face high inflation, economic instability, or sanctions. The five cryptocurrencies analyzed are Bitcoin (BTC), Ripple (XRP), Ethereum (ETH), Binance Coin (BNB), and Solana (SOL). Stationarity tests confirmed all return data are stable, enabling reliable analysis. Each fiat currency was tested under two market conditions: volatile (Regime 1) and stable (Regime 2). Countries like Brazil, India, and China mostly stayed in stable regimes, while Egypt and Ethiopia changed more often, showing economic weakness. Iran's currency remained stable but became highly volatile when shifting regimes due to sanctions or policy shocks. Key findings show crypto impacts depend on regime. In Brazil, BNB had a strong negative impact in volatile times, meaning people moved money from local currency to platform cryptocurrencies. In stable times, ETH and SOL had positive effects, indicating confidence in smart contract platforms. For Russia, BTC had a strong negative impact during volatility, showing it acts as a crisis refuge. BNB was favored in Russia’s volatile regime, showing preference for platform tokens with utility. ETH showed negative effects in stable times, possibly due to speculation.

India’s currency showed no major crypto influence, likely due to cautious regulations and tight money control. However, ETH’s small effect in volatility suggests rising crypto use. China, despite cracking down on crypto mining and exchanges, showed ETH having a positive impact in volatile times, and BNB having a negative impact, possibly due to regulatory pressure. For Egypt, Ethiopia, and Iran countries with high inflation and limited global market accessthe patterns differ. In Egypt, BNB negatively affected the currency in volatile times, showing people use crypto to protect value. Ethiopia showed no significant crypto effects, likely due to poor access or rules. Iran’s XRP had a positive impact in volatile times, acting as a useful payment method outside the formal system. BTC also had a small positive effect, supporting its role in crisis economies. ETH, BNB, and SOL did not have strong effects in unstable environments, possibly due to their technical complexity.

The unusually large coefficients for RUB and IRR were verified as genuine outcomes of high volatility during crisis periods rather than coding errors. We agree that some coefficient magnitude appear large, but they are plausible given the extreme volatility in these sanctioned currencies RUB and IRR experienced daily swings up to 45% and 31% in our data, amplified by low liquidity and geopolitical shocks. These reflect percentage point impacts on log-returns, scaled by the currencies' high standard deviations . To validate, we will add explanations in the results section, noting that similar magnitudes appear in crisis-focused studies (e.g., Bouri et al., 2018, on spillovers during turbulence). Standard errors confirmed regime classification accuracy, showing more uncertainty during volatile times. The results show crypto-fiat relations change based on market conditions, regulations, and investor choices. Platform tokens like ETH and SOL matter more in calm times, while payment tokens like BTC and XRP are important during crises, especially

Table 6: Regime-Specific Impact of Cryptocurrency Return Shocks on selected Emerging Market Currencies under Markov Switching VAR Framework

BRLUSD REGIME 1 (Volatile)				**BRLUSD REGIME 2 (Stable)**			
Variable	**Estimate**	**p-value**	**Interpretation**	**Variable**	**Estimate**	**p-value**	**Interpretation**
(Intercept)	-0.0002	0.739	No significant drift	(Intercept)	0.0001	0.739	No significant constant drift
BTC-USD_return	0.0318	0.225	Not significant	**BTC-USD_return**	−0.0174	0.249	Not significant
ETH-USD_return	0.029	0.179	Not significant	**ETH-USD_return**	**0.0245**	**0.045**	Significant **positive** impact
XRP-USD_return	0.0042	0.689	No effect	**XRP-USD_return**	0.0035	0.56	No impact
BNB-USD_return	**−0.0556**	**0.006**	Significant **negative** impact	**BNB-USD_return**	−0.0090	0.236	Weak negative
SOL-USD_return	0.0047	0.567	No effect	**SOL-USD_return**	**0.0131**	**0.038**	Significant **positive** impact
RUBUSD REGIME 1 (Stable)				**RUBUSD REGIME 2 (Volatile)**			
Variable	**Estimate**	**p-value**	**Interpretation**	**Variable**	**Estimate**	**p-value**	**Interpretation**
(Intercept)	0.0002	0.505	No significant drift	(Intercept)	−0.0260	0.662	No significant constant
BTC-USD_return	0.0246	0.122	Positive but not significant	**BTC-USD_return**	**−7.2966**	**0.02**	Strong negative impact
ETH-USD_return	**−0.0262**	**0.042**	Significant negative impact	ETH-USD_return	−2.6269	0.323	Not significant
XRP-USD_return	0.0078	0.237	Not significant	XRP-USD_return	0.0151	0.977	No impact
BNB-USD_return	−0.0082	0.368	Not significant	**BNB-USD_return**	**10.813**	**0.003**	Strong significant positive impact
SOL-USD_return	0.0046	0.411	Not significant	SOL-USD_return	0.5794	0.428	Not significant
INRUSD REGIME 1 (Stable)				**INRUSD REGIME 2 (Volatile)**			
Variable	**Estimate**	**p-value**	**Interpretation**	**Variable**	**Estimate**	**p-value**	**Interpretation**
BTC-USD_return	0.0003	0.8962	No significant impact	BTC-USD_return	-0.0043	0.5559	Negative, not significant
ETH-USD_return	-0.0002	0.8026	No significant impact	ETH-USD_return	0.0099	0.1103	Positive impact, **borderline significant**
XRP-USD_return	0.0005	0.7389	No significant impact	XRP-USD_return	0.0023	0.4433	No significant impact
BNB-USD_return	0.0004	0.7162	No significant impact	BNB-USD_return	-0.0048	0.2417	Weakly negative

SOL-USD_return	0.0007	0.5902	No significant impact	SOL-USD_return	0.0025	0.2976	No significant impact
CNYUSD REGIME 1 (Volatile)				**CNYUSD REGIME 2 (Stable)**			
Variable	**Estimate**	**p-value**	**Interpretation**	**Variable**	**Estimate**	**p-value**	**Interpretation**
(Intercept)	−0.0001	0.739	No constant drift	(Intercept)	0	1	No drift
BTC-USD_return	0.0021	0.924	No impact	BTC-USD_return	0.0005	0.781	No effect
ETH-USD_return	**0.0153**	**0.011**	Significant **positive** impact	**ETH-USD_return**	−0.0024	0.065	Marginal **negative** effect
XRP-USD_return	0.0017	0.766	No effect	**XRP-USD_return**	0.0018	0.072	Marginal **positive** effect
BNB-USD_return	**−0.0148**	**0.032**	Significant **negative** effect	BNB-USD_return	0.0009	0.597	Not significant
SOL-USD_return	0.0007	0.771	No effect	SOL-USD_return	0.0005	0.578	Not significant
EGPUSD REGIME 1 (Stable)				**EGPUSD REGIME 2 (Volatile)**			
Variable	**Estimate**	**p-value**	**Significance**	**Variable**	**Estimate**	**p-value**	**Significance**
(Intercept)	0	1	No drift	(Intercept)	−0.0168	**0.036**	Significant constant drift downward
BTC-USD_return	0.0021	0.437	Not significant	BTC-USD_return	0.2683	0.493	Not significant
ETH-USD_return	0.0023	0.273	Not significant	ETH-USD_return	0.3223	0.362	Not significant
XRP-USD_return	−0.0004	0.689	Not significant	XRP-USD_return	0.2024	0.324	Not significant
BNB-USD_return	−0.0015	0.317	Not significant	**BNB-USD_return**	**−0.7990**	**0.013**	Significant **negative** effect
SOL-USD_return	−0.0010	0.267	Not significant	SOL-USD_return	−0.2554	0.248	Not significant
ETBUSD REGIME 1 (Volatile)				**ETBUSD REGIME 2 (Stable)**			
Variable	**Estimate**	**p-value**	**Significance**	**Variable**	**Estimate**	**p-value**	**Significance**
Intercept	−0.0038	0.084	. (marginally significant)	Intercept	−0.0004	**0.00006**	Significant constant decline
BTC-USD_return	0.0151	0.805	Not significant	BTC-USD_return	0.0043	0.317	Not significant
ETH-USD_return	−0.0030	0.92	Not significant	ETH-USD_return	0.0018	0.597	Not significant
XRP-USD_return	0.0064	0.858	Not significant	XRP-USD_return	−0.0002	0.886	Not significant

BNB-USD_return	0.0582	0.364	Not significant	BNB-USD_return	0.0008	0.728	Not significant
SOL-USD_return	−0.0117	0.709	Not significant	SOL-USD_return	−0.0016	0.347	Not significant
IRRUSD REGIME 1 (Stable)				**IRRUSD REGIME 2 (Volatile)**			
Variable	**Estimate**	**p-value**	**Significance**	**Variable**	**Estimate**	**p-value**	**Significance**
Intercept	0	NA	Not estimated	Intercept	-0.048	0.631	Not significant
BTC-USD_return	-0.0002	0.689	Not significant	BTC-USD_return	19.0872	0.096	Marginally significant (10%)
ETH-USD_return	0	1	Not significant	ETH-USD_return	-7.479	0.274	Not significant
XRP-USD_return	0.0002	0.317	Not significant	XRP-USD_return	9.4134	0.016	Significant at 5%
BNB-USD_return	-0.0001	0.803	Not significant	BNB-USD_return	-14.036	0.222	Not significant
SOL-USD_return	0.0004	0.182	Not significant	SOL-USD_return	-2.203	0.121	Not significant

Note: This table presents the regime-dependent estimates from the Markov Switching Vector Autoregressive (MS-VAR) model evaluating the impact of major cryptocurrency return shocks The columns report coefficient estimates, corresponding p-values, and interpretation of statistical significance. Coefficients with p < 0.05 are considered statistically significant. A positive (negative) estimate suggests that an increase in cryptocurrency return is associated with appreciation (depreciation) of the respective fiat currency during that regime. Blank or NA entries indicate parameters not estimated or statistically undefined in the MS-VAR process. Regime labels (e.g., "Volatile" or "Stable") are based on the filtered probabilities and smoothed state durations derived from the model output.

where financial access is limited. Policy-wise, countries with economic weaknesses see more crypto use, not just for speculation but out of need. Blanket bans could push crypto use underground. Stable countries might use blockchain smartly while regulating risks. Different crypto types need different rules: governance tokens, DeFi tokens, and payment coins have unique roles.

In conclusion, this research shows crypto impacts on fiat are real but vary by economic conditions, token type, and country. BRIC countries engage more sophisticatedly with crypto, while high-inflation or sanctioned nations use crypto out of necessity. These results highlight the growing importance of digital currencies and call for smart, context-aware policies to support stability, financial inclusion, and better regulation as global finance evolves. For high-volatility economies such as ETB, IRR, and RUB, we now suggest establishing transparent FX monitoring systems that integrate crypto-market indicators, adopting temporary and rules-based capital flow measures during crisis regimes, and developing regulated crypto-remittance platforms to reduce dependence on informal channels. For relatively stable markets such as INR, BRL, and CNY, the revised section highlights the importance of enhanced supervision of institutional crypto exposure, pilot testing of central bank digital currencies, and the use of data-driven communication to manage speculative pressures. Cross-country recommendations now include coordinated regional data sharing, establishment of crypto-linked early-warning systems, and improved macro-financial cooperation across emerging markets

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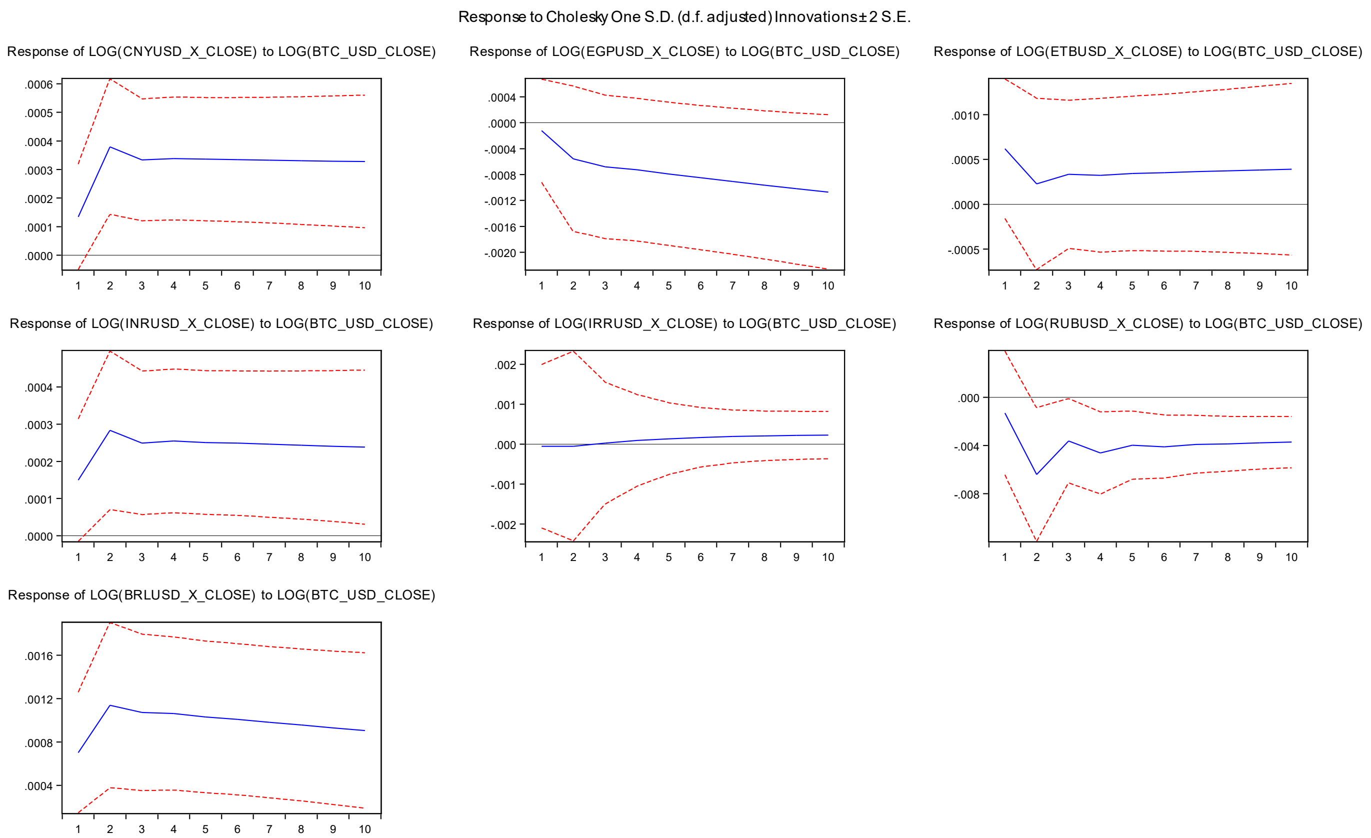
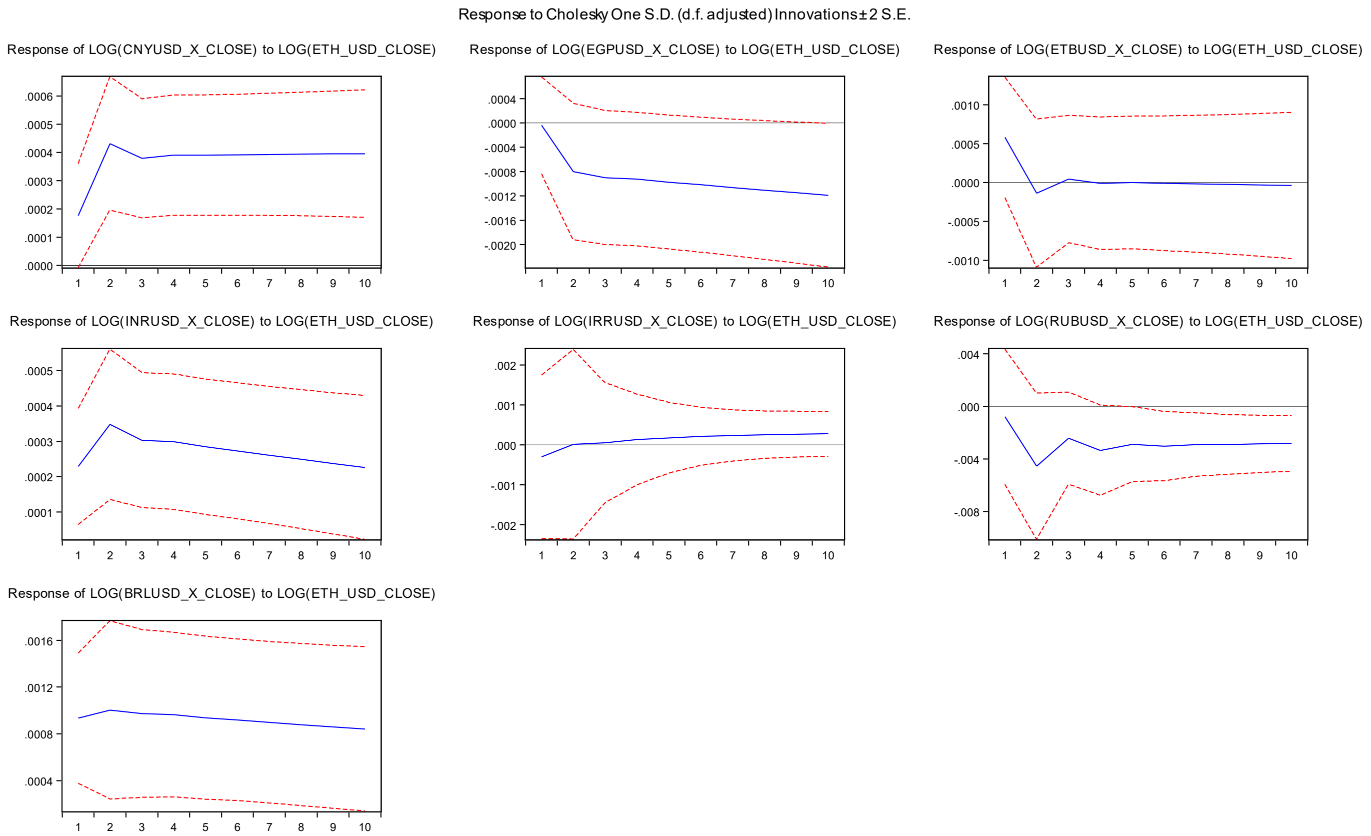
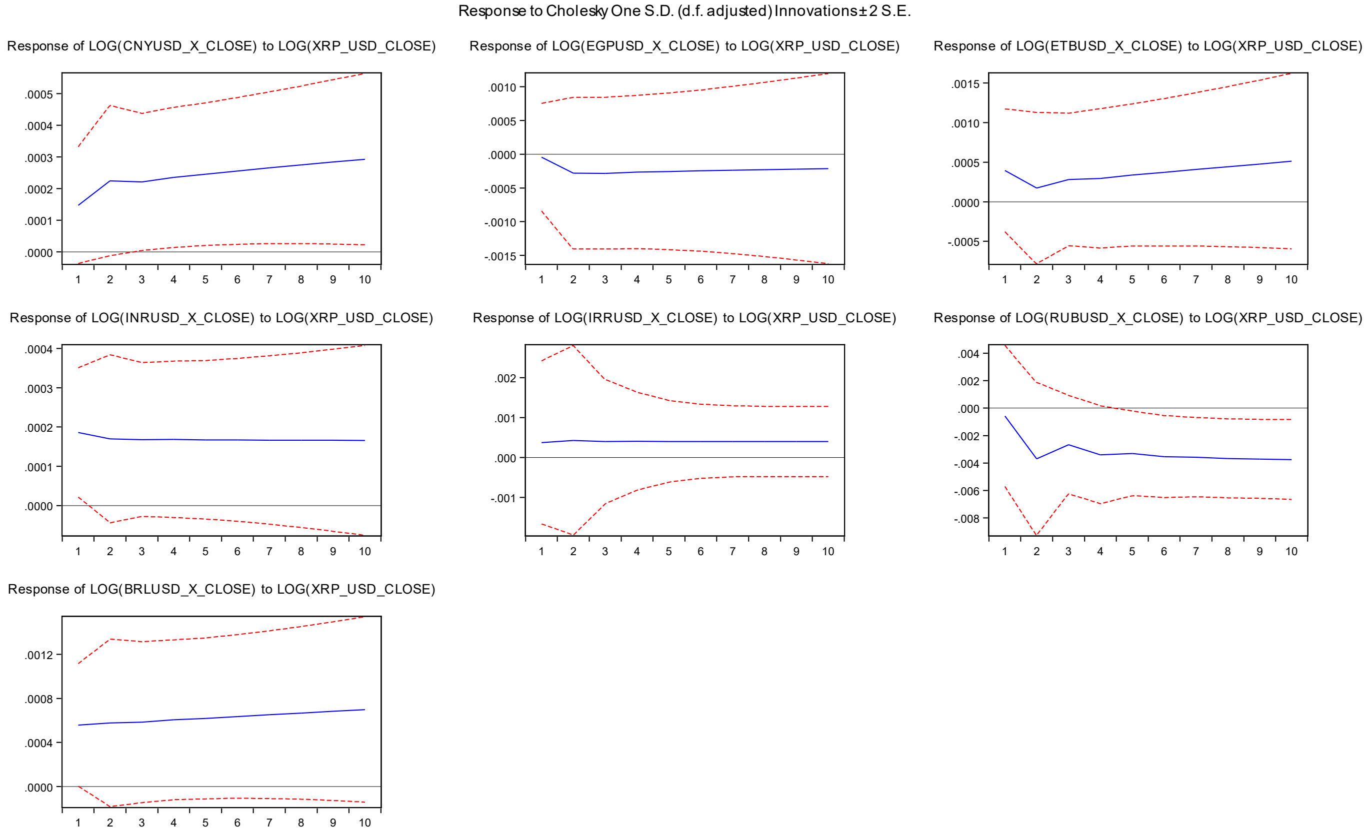
Appendix

Impulse response function Graphs



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Response of LOG(CNYUSD_X_CLOSE) to LOG(XRP_USD_CLOSE)
Response of LOG(EGPUSD_X_CLOSE) to LOG(XRP_USD_CLOSE)
Response of LOG(ETBUSD_X_CLOSE) to LOG(XRP_USD_CLOSE)
Response of LOG(INRUSD_X_CLOSE) to LOG(XRP_USD_CLOSE)
Response of LOG(IRRUSD_X_CLOSE) to LOG(XRP_USD_CLOSE)
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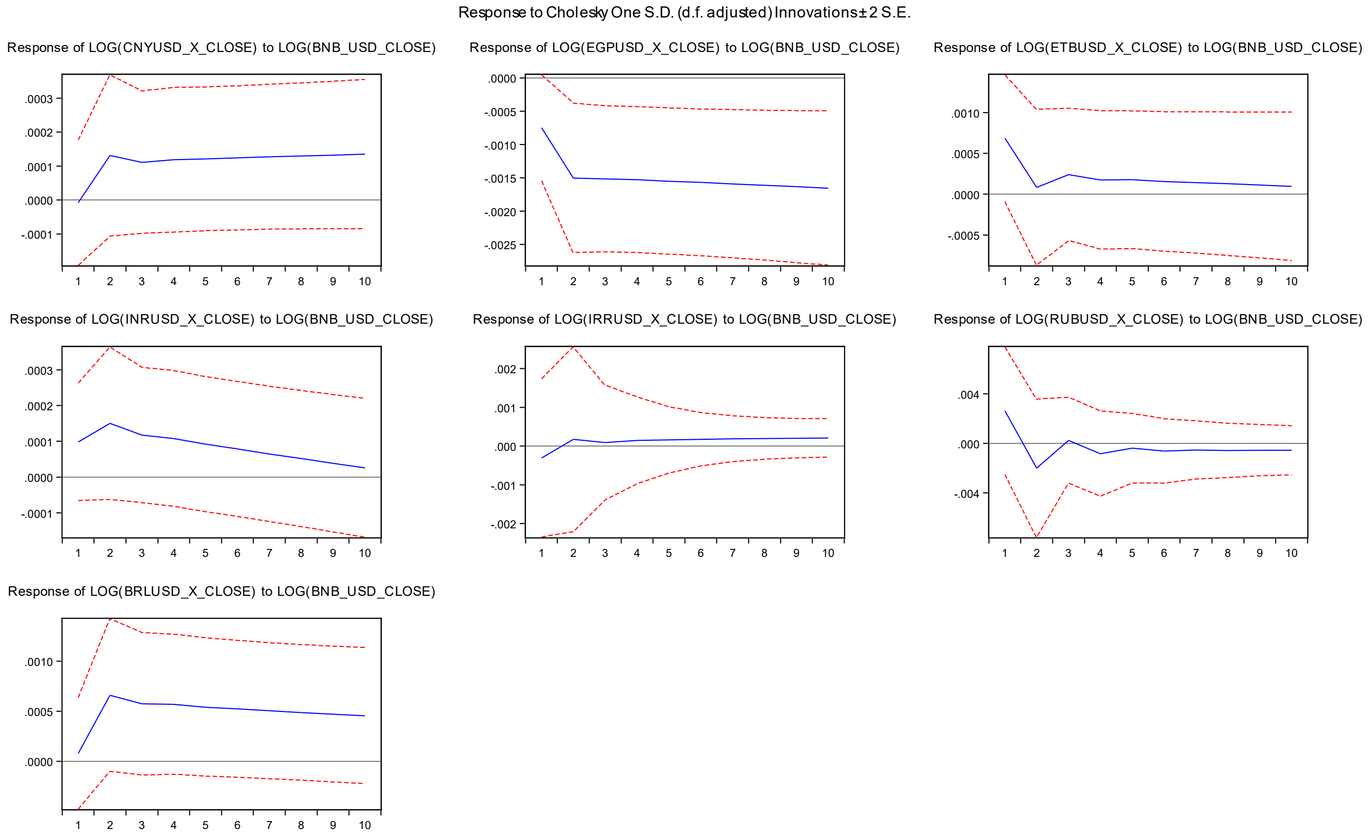
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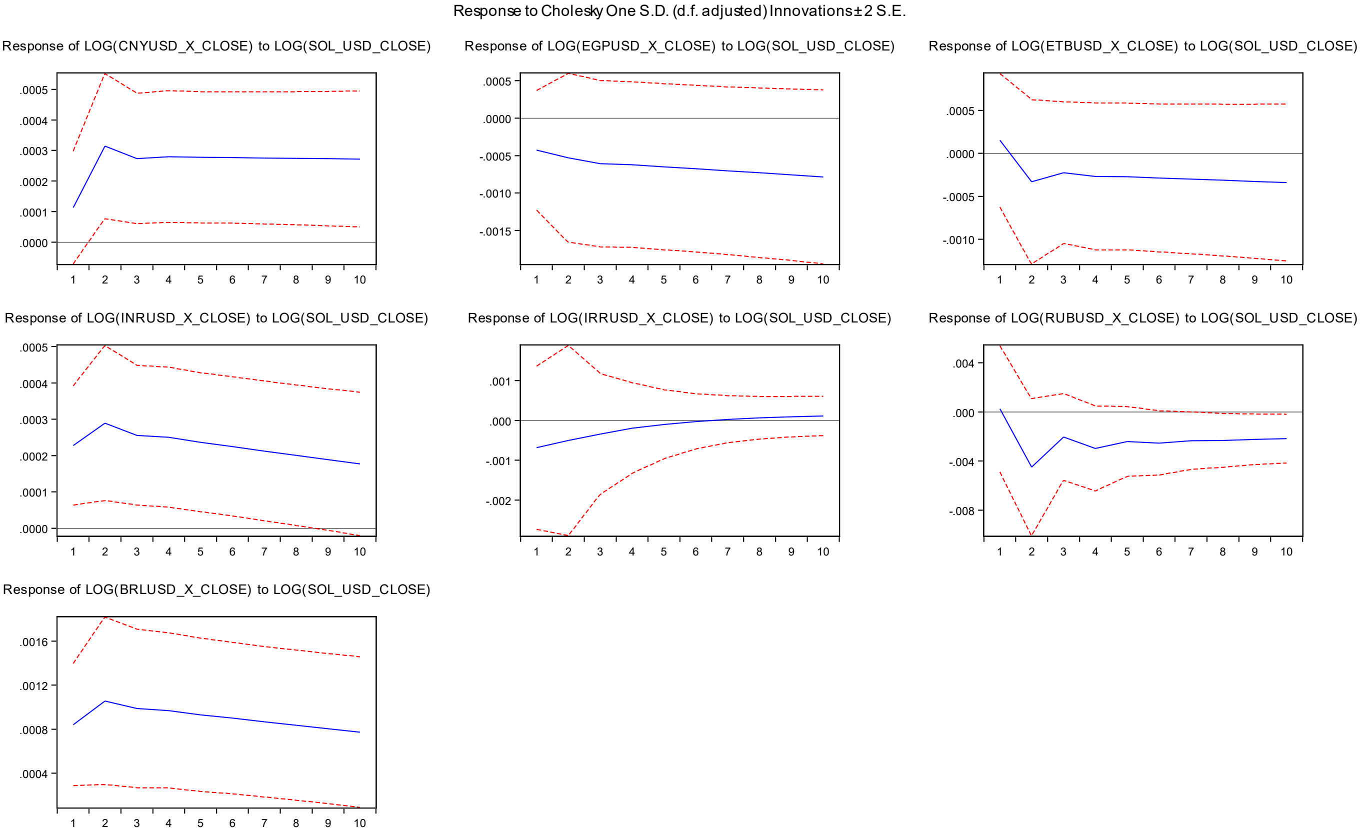
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