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The Implication of Cryptocurrency Volatility on the Financial System Stability of the Five Largest MENA Financial Markets: Evidence from Diagonal BEKK-GARCH and DCC-GARCH Models

Hicham Es-Saadi[1*], Zakariae Bel Mkaddem[2], Mohammed Amine[3], Imane Tesse[3]

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ABSTRACT

The rapid integration of cryptocurrencies into the East and North Africa (MENA) financial landscape has raised concerns about domestic financial systems' exposure to crypto-market turbulence. This paper investigates the implications of cryptocurrency volatility for the financial system stability of the five largest MENA financial markets: Saudi Arabia, the United Arab Emirates, Qatar, Egypt and Morocco. Using daily data on Bitcoin, Ethereum and the benchmark stock indices of the five markets (TASI, DFMGI, QE General, EGX 30 and MASI) from January 2018 to December 2025, we estimate bivariate diagonal and full BEKK-GARCH(1,1) models for each cryptocurrency–stock-index pair, complemented by DCC-GARCH(1,1) models that trace time-varying conditional correlations. Own-volatility persistence is high in all markets (0.88–1.00). Volatility spillovers are bidirectional but asymmetric: transmission from MENA equity markets to cryptocurrencies is significant in all ten pairs, whereas crypto-to-equity spillovers are significant for Saudi Arabia, the UAE and Qatar, marginal for Egypt, and absent for Morocco. Dynamic conditional correlations are low on average (0.04–0.13) but increase significantly during crisis episodes, notably for the Gulf markets, indicating contagion rather than pure interdependence. MENA financial systems' exposure to crypto-induced instability therefore remains moderate but is rising, and is highest in the more open Gulf markets. These findings call for the integration of crypto-market indicators into the macroprudential surveillance frameworks of MENA central banks and for differentiated, risk-based regulatory responses.

INTRODUCTION

Over the past decade, cryptocurrencies have evolved from a marginal technological experiment into a globally traded asset class held by retail investors, institutional portfolios and, increasingly, financial intermediaries. This rapid expansion has been accompanied by extreme price volatility: the crypto market has repeatedly experienced drawdowns exceeding fifty percent within a few weeks, as illustrated by the collapse of the 2017 bubble, the liquidity crisis of March 2020, and the succession of shocks that hit the ecosystem in 2021 and 2022, culminating in the failure of the FTX exchange. Because volatility is the primary channel through which crypto-assets may transmit stress to the conventional financial system, the question of whether, and to what extent, cryptocurrency turbulence spills over to domestic financial markets has moved to the center of the financial stability agenda of regulators and central banks (Farroukh *et al.*, 2025; Adelopo & Luo 2025).

The literature identifies several channels through which crypto-asset volatility may impinge on financial stability: direct balance-sheet exposure of banks and investment funds to digital assets; wealth and confidence effects on households that hold crypto alongside traditional securities; the growing use of stablecoins in payments and remittances; and the leverage embedded in crypto derivatives, which can force fire sales of conventional assets during market stress (Mathias & Sahoo 2026; Minarni 2025). When the two markets become integrated, a crisis originating in the cryptocurrency sphere no longer remains confined to it: it propagates to equity prices, undermines portfolio diversification and may ultimately threaten the resilience of the domestic financial system (Joseph *et al.*, 2024; Niyitegeka & Zhou 2023).

The Middle East and North Africa (MENA) region offers a particularly relevant, and largely understudied, setting in which to examine these questions. Cryptocurrency adoption has expanded rapidly across the region, driven by a young and highly connected population, substantial remittance flows and national strategies aimed at financial diversification (Allen, 2021; Grossman, 2022). Several jurisdictions, most notably the United Arab Emirates and Saudi Arabia, have explicitly positioned themselves as regional hubs for digital assets (Aysan, 2025; Alrawashdeh *et al.*, 2024), while others maintain restrictive or prohibitive regulatory stances (Hassib & Ayad, 2026; Youssef *et al.*, 2025). Morocco illustrates this paradox: despite a restrictive official position, it consistently ranks among

[1] National School of Business and Management- El Jadida, Study and Research Laboratory in Economics and Manage-ment, University Chouaib Doukkali, El Kelaa Des Sraghnas, Morocco
[2] Research Professor, National School of Business and Management- El Jadida, Study and Research Laboratory in Eco-nomics and Management, University Chouaib Doukkali,El Jadida, Morocco
[3] Doctoral Researcher, National School of Business and Management- El Jadida, Study and Research Laboratory in Eco-nomics and Management, University Chouaib Doukkali,El Jadida, Morocco
[*] Corresponding author's e-mail: es-saadi.hicham@ucd.ac.ma

the leading countries in terms of grassroots crypto adoption. This coexistence of rapid adoption, regulatory heterogeneity and bank-dominated financial systems makes the stability implications of crypto volatility a first-order policy question for the region.

Yet the empirical evidence on crypto-to-equity volatility transmission in MENA remains fragmented. Existing studies typically focus on a single country (Sajeev and Afjal 2022), on Islamic financial segments (Trichilli and Boujelbène 2023; Mezghani *et al.* 2024), on oil–stock interactions rather than crypto–stock linkages (Guenichi 2022; Soltani and Abbes 2025a, 2025b), or on the COVID-19 episode alone (Chkili 2026; Al-Nassar and Makram 2022). In a closely related contribution, Joseph *et al.* (2024) examined the five largest African financial systems and documented significant spillovers from cryptocurrency volatility to these markets. To date, however, no comprehensive multi-country assessment has been conducted for the largest MENA financial markets within a unified multivariate GARCH framework.

This paper fills that gap. It investigates three research questions: (RQ1) Are there significant return and volatility spillovers between the cryptocurrency market and the five largest MENA equity markets, and in which direction do they run? (RQ2) How do conditional correlations between the two markets evolve over time, and do they intensify during crisis episodes in a way that signals contagion rather than mere interdependence? (RQ3) What do these spillover patterns imply for the financial system stability of Saudi Arabia, the United Arab Emirates, Qatar, Egypt and Morocco? To answer these questions, we estimate bivariate BEKK-GARCH(1,1) models, in diagonal and full form, which capture the direction and persistence of volatility transmission, together with DCC-GARCH(1,1) models, which trace the dynamic evolution of conditional correlations. Three hypotheses are tested:

- **H1:** There exist significant volatility spillovers between the cryptocurrency market and the five largest MENA equity markets, with the dominant direction running from cryptocurrencies to equities.
- **H2:** Conditional correlations between cryptocurrency and MENA equity returns increase significantly during crisis periods, indicating contagion effects.
- **H3:** The intensity of spillovers is heterogeneous across the five countries and is stronger in markets characterized by higher crypto adoption and greater regulatory openness.

The contribution of the paper is threefold. First, it provides the first systematic multi-country evidence on crypto-to-equity volatility transmission for the five largest MENA financial markets, extending the African analysis of Joseph *et al.* (2024) to a region that combines rapid crypto adoption with bank-centered financial systems. Second, methodologically, it combines BEKK-GARCH and DCC-GARCH approaches in a single framework, so that spillover direction and persistence (BEKK) are assessed jointly with the time path of market integration (DCC), and the two sets of results cross-validate each other. Third, it derives concrete policy implications for MENA regulators and central banks regarding macroprudential monitoring, regulatory design and cross-border coordination.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the data and the econometric methodology. Section 4 reports and discusses the empirical results. Section 5 presents the robustness checks. Section 6 concludes with policy implications, limitations and avenues for future research.

LITERATURE REVIEW

Cryptocurrency Volatility and Financial Stability

Cryptocurrency returns exhibit the stylized facts that motivated the development of ARCH and GARCH models: volatility clustering, leptokurtic distributions and asymmetric reactions to shocks (Engle 1982; Bollerslev, 1986). What distinguishes crypto-assets, however, is the amplitude and persistence of their volatility, which far exceeds that of conventional asset classes. As institutional adoption has deepened, this idiosyncratic volatility has increasingly been viewed as a potential source of systemic risk rather than a curiosity confined to a niche market (Mpanza 2026; Farroukh *et al.* 2025). Systematic reviews of the interconnectedness literature converge on the conclusion that growing adoption tightens the link between crypto and traditional markets and can amplify systemic risk during stress episodes (Adelopo & Luo 2025; Adekunle, 2024). In emerging markets, where supervisory capacity and investor sophistication are more limited, the financial stability implications are potentially more severe (Minarni, 2025).

Volatility Spillovers Between Cryptocurrencies and Equity Markets in Emerging Economies

A growing body of work documents volatility transmission between cryptocurrency and equity markets in developing regions. For the five largest African financial systems, Joseph *et al.* (2024) applied diagonal BEKK-GARCH and DCC-GARCH models and found evidence of volatility spillovers from the cryptocurrency market to African equities, with correlations that strengthen during turbulent periods, a pattern they interpret as a threat to financial stability as market integration deepens. Kumah and Odei-Mensah (2021) similarly report increasing integration between cryptocurrencies and African stock markets, while Kumah (2021) shows that the COVID-19 pandemic intensified contagion within African financial markets. Evidence from developed and emerging markets more broadly confirms that contagion episodes between crypto and equity markets are recurrent and economically meaningful (Niyitegeka & Zhou 2023; Bawa, 2026). For South Africa, Mudiangombe and Muteba Mwamba (2025) document significant risk transmission between Bitcoin, currency pairs and traditional financial assets, and Korsah *et al.* (2026) show that the hedging and safe-haven properties of cryptocurrencies vis-à-vis African

stock markets deteriorate precisely when they are most needed.

Evidence from the MENA Region

MENA-focused studies remain comparatively scarce and fragmented. Sajeev and Afjal (2022), the closest antecedent to the present paper, applied diagonal BEKK and DCC-GARCH models to examine the contagion effect of Bitcoin on selected securities markets, including MENA markets, and found significant volatility spillovers. Chkili (2026) combined DCC-GARCH with Diebold–Yilmaz measures to assess risk transmission from COVID-19 to MENA stock markets and to evaluate the hedging effectiveness of Bitcoin and precious metals. Al-Nassar and Makram (2022) employed BEKK-GARCH and asymmetric DCC-GARCH specifications to study risk–return spillovers between main and SME stock markets in the region during the pandemic. Other contributions examine the comovement between cryptocurrencies and Islamic financial instruments (Trichilli and Boujelbène 2023; Mezghani *et al.* 2024), regime-specific spillovers involving GCC markets, oil and gold (Soltani and Abbes 2025a, 2025b), correlations between cryptocurrencies and regional stock markets during the COVID-19 and Russia–Ukraine episodes (Abdelmalek and Ben Abdallah 2025), and contagion across emerging markets more generally (Neifar and HarzAllah 2025). On the adoption and regulatory side, Aysan (2025), Hassib and Ayad (2026), Alrawashdeh *et al.* (2024) and Youssef *et al.* (2025) document the rapid rise of cryptoasset adoption in the region and the diversity of regulatory responses, from hub strategies to conditional legalization. What is missing is a unified, multi-country quantification of crypto-to-equity volatility transmission for the largest MENA financial markets, explicitly linked to financial system stability, the gap this paper addresses.

Multivariate GARCH Modeling of Volatility Transmission

The econometrics of volatility spillovers relies heavily on multivariate GARCH models. The BEKK specification of Engle and Kroner (1995) guarantees the positive definiteness of the conditional covariance matrix and allows shocks and volatility in one market to affect the conditional variances and covariances of others; its diagonal version, widely used in the spillover literature, retains this property at a tractable computational cost. The constant conditional correlation model of Bollerslev (1990) assumes fixed correlations, an assumption rejected in most financial applications, which motivated the dynamic conditional correlation (DCC) model of Engle (2002) and the related specification of Tse and Tsui (2002), in which correlations evolve over time in response to standardized innovations. Combining BEKK with DCC is now standard practice in contagion studies: the BEKK model identifies the direction, significance and persistence of spillovers, while the DCC model describes the time-varying degree of co-movement and makes it possible to distinguish contagion, a significant rise in correlation during crises, from stable interdependence (Sajeev and Afjal 2022; Joseph *et al.* 2024).

Research Gap and Hypotheses

Three gaps emerge from this review. First, no study provides a systematic, multi-country assessment of cryptocurrency volatility transmission to the five largest MENA financial markets; regional evidence is confined to single countries, specific episodes or specific market segments. Second, the few MENA studies that use multivariate GARCH models rarely combine the BEKK and DCC specifications, so that spillover direction and correlation dynamics are not examined jointly. Third, the link between estimated spillover patterns and country-level financial system stability, the central policy question for the region's regulators, is rarely made explicit. The present paper addresses these three gaps and tests hypotheses H1 to H3 formulated in Section 1.

MATERIALS AND METHODS

Data and Variable Construction

The empirical analysis uses daily closing prices of the two leading cryptocurrencie, Bitcoin (BTC) and Ethereum (ETH), and the benchmark stock indices of the five largest MENA financial markets: the Tadawul All Share Index (TASI) for Saudi Arabia, the Dubai Financial Market General Index (DFMGI) for the United Arab Emirates, the QE General Index for Qatar, the EGX 30 for Egypt, and the Moroccan All Shares Index (MASI) for Morocco. Cryptocurrency prices are sourced from Yahoo Finance (BTC-USD, ETH-USD) and cross-checked against CoinMarketCap; stock indices are obtained from Investing.com and the Saudi Exchange. The sample spans the period from 2 January 2018 to 31 December 2025, covering the 2018 crypto correction, the COVID-19 turmoil of March 2020, the 2021 bull market, the 2022 crypto winter (Terra-Luna collapse, FTX failure) and the subsequent recovery. Because cryptocurrency markets trade continuously while stock exchanges close on weekends and public holidays, with different holiday calendars across the five countries, the analysis is conducted on a pairwise basis: for each cryptocurrency–stock-index pair, the sample consists of the trading days of the corresponding stock exchange, so that no artificial price imputation is required. This yields between 1,940

$$r_{i,t} = 100 \times \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \qquad (1)$$

and 2,000 daily return observations per pair. Continuously compounded daily returns are computed as:

where Pi,t denotes the closing price of asset i on day t. Table 1 summarizes the variables.

Preliminary Analysis

Before estimating the multivariate models, the return series are subjected to a standard battery of preliminary tests: descriptive statistics (mean, standard deviation,

Table 1: Variables, definitions and data sources

Symbol	Market / Asset	Description	Source
BTC/USD	Cryptocurrency	Bitcoin daily closing price (USD)	Yahoo Finance / CoinMarketCap
ETH/USD	Cryptocurrency	Ethereum daily closing price (USD)	Yahoo Finance / CoinMarketCap
TASI	Saudi Arabia	Tadawul All Share Index	Saudi Exchange / Yahoo Finance
DFMGI	United Arab Emirates	Dubai Financial Market General Index	Investing.com / DFM
QE	Qatar	QE General Index	Investing.com / QSE
EGX 30	Egypt	Egyptian Exchange benchmark index	Investing.com / EGX
MASI	Morocco	Moroccan All Shares Index	Investing.com / Casablanca SE

skewness, kurtosis) and the Jarque–Bera normality test; augmented Dickey–Fuller and Phillips–Perron unit-root tests to confirm stationarity; Ljung–Box tests on returns and squared returns to detect serial correlation and volatility clustering; and Engle's (1982) ARCH-LM test to verify the presence of conditional heteroscedasticity, which legitimizes the GARCH specification.

Mean Equation

To purge the returns of linear dependence, each series is filtered through an autoregressive structure of order one:

$$r_t = \mu + \Phi\, r_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim (0, Ht) \qquad (2)$$

where rt is the (2 × 1) vector of returns of the cryptocurrency–stock-index pair, μ a vector of constants, Φ the matrix of autoregressive coefficients, εt the vector of innovations conditional on the information set Ωt−1, and Ht the conditional covariance matrix modeled below.

Diagonal and full BEKK-GARCH(1,1) Models

The BEKK model of Engle and Kroner (1995)

$$H_t = C'C + A'\varepsilon_{(t-1)\varepsilon'_{t-1}A} + B'H_{(t-1)B} \qquad (3)$$

parameterizes Ht in a way that guarantees its positive definiteness:

where C is a lower-triangular matrix of constants and A and B are (2 × 2) matrices of ARCH and GARCH coefficients. In the diagonal version, A and B are restricted to be diagonal; the full version frees the off-diagonal elements, which measure cross-market transmission. For a pair (i, j), the conditional variance and covariance equations implied by the BEKK(1,1) are:

$$h_{ii,t} = c_{ii} + \left(a_{(ii)\varepsilon_{i,t-1}} + a_{(ji)\varepsilon_{j,t-1}}\right)^2 + b_{ii}^2 h_{ii,t-1} + \ldots \qquad (4)$$

$$h_{ij,t} = c_{ij} + \left(a_{(ii)\varepsilon_i} + a_{(ji)\varepsilon_j}\right)\left(a_{(ij)\varepsilon_i} + a_{(jj)\varepsilon_j}\right) + \left(b_{(ii)b_{jj}} + \ldots\right)h_{ij,t-1} \qquad (5)$$

The coefficient aji (resp. bji) captures the impact of past shocks (resp. past volatility) in market j on the conditional variance of market i. Taking market 1 as the cryptocurrency and market 2 as the stock index, a12 and b12 measure shock and volatility transmission from the stock market to the cryptocurrency, while a21 and b21 measure transmission from the cryptocurrency to the stock market. Wald tests of the restrictions aij = bij = 0 are used to establish the direction and significance of spillovers, and likelihood-ratio tests compare the diagonal and full specifications. Own-volatility persistence is measured by a2ii + b2ii: values close to unity indicate that volatility shocks are long-lived and therefore more threatening to financial stability.

DCC-GARCH(1,1) Model

The DCC model of Engle (2002) is estimated in two steps. In the first step, univariate GARCH(1,1) models are fitted to each return series:

h_{i,t}=\omega_i+\alpha_i\varepsilon_{i,t-1}^{2}+\beta_i h_{i,t-1} (6)

and the standardized residuals zi,t = εi,t / √hii,t are extracted. In the second step, the conditional correlation matrix Rt is obtained from:

Q_t=(1-\alpha-\beta)\bar{Q}+\alpha z_{t-1}z_{t-1}^{\prime}+\beta Q_{t-1} (7)

$$R_t = diag\left(Q_t\right)^{-\frac{1}{2}} Q_t diag\left(Q_t\right)^{-\frac{1}{2}} \qquad (8)$$

where Q is the unconditional covariance matrix of the standardized residuals and the scalars α and β satisfy $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$. The resulting series ρij,t of dynamic conditional correlations between each cryptocurrency and each MENA stock index is then examined around four crisis windows, the COVID-19 crash (February–April 2020), the May–June 2021 crypto correction, the Terra-Luna collapse (May–June 2022) and the FTX failure (November–December 2022). A significant increase in ρij,t during these episodes, assessed by a Welch mean-difference test between crisis and non-crisis periods, is interpreted as contagion.

Estimation Strategy and Diagnostics

All models are estimated by maximizing the Gaussian log-likelihood; the resulting quasi-maximum likelihood estimators remain consistent for the parameters of the conditional mean and covariance even when standardized innovations are non-normal. Standard errors are obtained from the numerically evaluated Hessian at the optimum. Model adequacy is assessed by Ljung–Box tests on standardized and squared standardized residuals, which confirm that the GARCH filters remove the dynamics of the first two conditional moments. Estimations were implemented in Python (custom BEKK and DCC

likelihoods validated on simulated data, with the arch package for univariate GARCH steps); bivariate pairs are preferred to a single seven-variable system in order to respect the different trading calendars of the five exchanges, following the pairwise strategy of Sajeev and Afjal (2022) and Joseph *et al.* (2024).

From Spillover Estimates to Financial Stability Assessment

The translation of econometric results into financial stability implications follows the framework used by Joseph *et al.* (2024) for African markets. Three criteria are applied to each country: (i) the significance and sign of the crypto-to-equity spillover coefficients, which indicate whether the domestic equity market is exposed to crypto shocks; (ii) the persistence of conditional volatility, which measures how long a shock continues to affect the domestic market; and (iii) the behavior of dynamic conditional correlations during crisis episodes, which reveals whether diversification benefits collapse precisely when they are most needed. A country whose market exhibits significant incoming spillovers, high persistence and crisis-period correlation surges is classified as highly exposed to crypto-induced instability.

RESULTS AND DISCUSSION

Descriptive statistics and preliminary tests

Table 2 reports the descriptive statistics and preliminary tests for the seven return series. Three stylized facts emerge. First, cryptocurrencies are several times more volatile than MENA equities: the daily standard deviation reaches 3.47% for Bitcoin and 4.58% for Ethereum, against 0.78%–1.34% for the five stock indices. Second, all series display significant negative skewness and large excess kurtosis (from 5.25 for the EGX 30 to 20.63 for the MASI), and the Jarque–Bera test rejects normality at the 1% level in every case. Third, the ADF and Phillips–Perron tests confirm that all return series are stationary, while the highly significant ARCH-LM statistics and Ljung–Box tests on squared returns establish strong volatility clustering. These properties jointly justify the multivariate GARCH approach adopted below.

Table 2: Descriptive statistics and preliminary tests on daily returns

Series	N	Mean	Std. dev.	Skewness	Ex. kurtosis	Jarque–Bera	ADF (p)	ARCH-LM (p)
BTC	2805	0.063	3.468	−0.964	14.43	24 774***	0.000	0.000
ETH	2805	0.043	4.576	−0.846	10.66	13 616***	0.000	0.000
TASI	1941	0.019	0.979	−1.164	11.95	11 995***	0.000	0.000
DFMGI	2000	0.029	0.991	−0.926	13.68	15 876***	0.000	0.000
QE	1992	0.011	0.880	−0.871	11.75	11 709***	0.000	0.000
EGX 30	1941	0.053	1.344	−0.537	5.25	2 326***	0.000	0.000
MASI	1986	0.021	0.779	−1.549	20.63	36 001***	0.000	0.000

*Note: returns in percent. *** denotes significance at the 1% level. ADF (p) and ARCH-LM (p) are p-values of the augmented Dickey–Fuller test (with constant) and of Engle's ARCH test with 10 lags; Phillips–Perron tests (not reported) lead to identical conclusions.*

BEKK-GARCH Results: Direction and Persistence of Spillovers

Table 3 reports the estimates of the full bivariate BEKK-GARCH(1,1) for the ten cryptocurrency–stock-index pairs, and Table 4 summarizes the associated Wald tests, persistence measures and likelihood-ratio (LR) tests against the diagonal specification. Three results stand out. First, own-market dynamics are well captured: the own ARCH (aii) and GARCH (bii) coefficients are significant at the 1% level in all twenty variance equations, and volatility persistence is high everywhere, ranging from 0.88 (MASI) to 0.96 (QE) for stock indices and from 0.94 to 1.00 for the cryptocurrencies. Shocks to volatility therefore die out slowly, which mechanically lengthens the duration of any instability episode transmitted across markets.

Second, the cross-market coefficients reveal a clear asymmetry in the direction of transmission. Spillovers running from the stock market to the cryptocurrency (a21, b21) are significant in all ten pairs, mostly at the 1% level, indicating that shocks and volatility in MENA equity markets systematically feed into crypto-market volatility. By contrast, spillovers running from the cryptocurrency to the stock market (a12, b12) are smaller in magnitude and significant only for a subset of pairs: Bitcoin transmits significantly to the DFMGI (both ARCH and GARCH terms) and, at the 10% level, to the EGX 30 (GARCH term), while Ethereum transmits significantly to the TASI, DFMGI and QE (ARCH terms) and to the DFMGI (GARCH term). For the MASI, no crypto-to-equity coefficient is significant.

Third, the Wald tests in Table 4 formalize this asymmetry. The null of no transmission from the stock market to the cryptocurrency is rejected at the 5% level in all ten pairs, whereas the null of no transmission from the cryptocurrency to the stock market is rejected at the 5% level for five pairs (BTC–DFMGI, BTC–QE, ETH–TASI, ETH–DFMGI, ETH–QE), at the 10% level for three additional pairs (BTC–TASI, BTC–EGX 30, ETH–EGX 30), and cannot be rejected for the two Moroccan pairs. The LR tests further show that the full BEKK

specification significantly dominates the diagonal one in every pair, confirming that cross-market terms carry genuine information. Hypothesis H1 is therefore only partially supported: significant volatility spillovers do

Table 3: Full BEKK-GARCH(1,1) estimates for the cryptocurrency–stock-index pairs

Pair	a11	a12	a21	a22	b11	b12	b21	b22
BTC–TASI	0.2045***	0.0059	0.2959***	0.5050***	0.9696***	0.0037	−0.3348***	0.8009***
BTC–DFMGI	0.2430***	0.0107**	−0.2068**	0.3748***	0.9421***	−0.0102**	0.2619***	0.8949***
BTC–QE	0.2086***	−0.0033	0.4303***	0.3190***	0.9536***	−0.0026	−0.1552***	0.9260***
BTC–EGX 30	0.2361***	0.0017	0.2834***	0.3324***	0.9425***	−0.0061*	−0.1070***	0.9154***
BTC–MASI	0.2378***	−0.0041	0.4594***	0.4388***	0.9483***	0.0007	−0.2159***	0.8296***
ETH–TASI	0.1734***	0.0061*	0.3449***	0.4516***	0.9864***	0.0017	−0.2911***	0.8473***
ETH–DFMGI	0.2215***	0.0082**	−0.2436*	0.3875***	0.9515***	−0.0070***	0.3135***	0.8851***
ETH–QE	0.1649***	−0.0051*	0.4273***	0.3323***	0.9742***	−0.0007	−0.1544**	0.9206***
ETH–EGX 30	0.1924***	−0.0063	0.2708***	0.3498***	0.9673***	−0.0016	−0.1111***	0.9047***
ETH–MASI	0.1953***	−0.0024	0.6148***	0.4608***	0.9721***	0.0012	−0.3517***	0.8190***

*Note: market 1 = cryptocurrency, market 2 = stock index. a12, b12: transmission from the stock market to the cryptocurrency (shock and volatility terms); a21, b21: transmission from the cryptocurrency to the stock market. ***, ** and * denote significance at the 1%, 5% and 10% levels. Constant terms C are significant and omitted for brevity.*

Table 4: Wald tests of no-spillover, persistence and specification tests

Pair	Wald crypto→ equity	p-value	Wald equity→ crypto	p-value	Persist. crypto	Persist. equity	LR diag. vs full (p)
BTC–TASI	5.09	0.078*	13.53	0.001***	0.982	0.896	15.36 (0.004)
BTC–DFMGI	6.60	0.037**	32.66	0.000***	0.947	0.941	32.84 (0.000)
BTC–QE	6.26	0.044**	14.51	0.001***	0.953	0.959	19.79 (0.001)
BTC–EGX 30	4.84	0.089*	17.55	0.000***	0.944	0.948	21.99 (0.000)
BTC–MASI	0.79	0.674	17.99	0.000***	0.956	0.881	19.48 (0.001)
ETH–TASI	8.22	0.016**	16.19	0.000***	1.003	0.922	19.40 (0.001)
ETH–DFMGI	8.93	0.012**	24.35	0.000***	0.954	0.934	26.23 (0.000)
ETH–QE	6.29	0.043**	7.13	0.028**	0.976	0.958	17.46 (0.002)
ETH–EGX 30	5.69	0.058*	12.74	0.002***	0.973	0.941	22.21 (0.000)
ETH–MASI	0.73	0.693	18.62	0.000***	0.983	0.883	18.76 (0.001)

Note: Wald statistics test the joint restrictions a12 = b12 = 0 (crypto→equity) and a21 = b21 = 0 (equity--crypto), chi-squared with 2 degrees of freedom. Persistence = $a^2ii + b^2ii$. LR: likelihood-ratio test of the diagonal against the full BEKK, chi-squared with 4 degrees of freedom (p-value in parentheses).

exist between the two markets, but — contrary to our prior, the dominant direction runs from MENA equity markets toward cryptocurrencies rather than the reverse, except for the Gulf markets where the crypto-to-equity channel is clearly active.

DCC-GARCH Results: Time-Varying Correlations and Crisis Behavior

Table 5 reports the DCC-GARCH(1,1) estimates and the behavior of dynamic conditional correlations across the four crisis windows, and Fig. 1 plots the correlation paths. Average correlations between cryptocurrencies and MENA equities are positive but low, ranging from 0.042 (BTC–QE and BTC–MASI) to 0.125 (ETH–TASI). Over the full sample, the two markets are therefore only weakly integrated, limiting the systematic exposure of MENA financial systems to crypto-market turbulence. Correlation persistence varies across pairs: it is high for ETH–DFMGI and ETH–MASI ($\beta \approx 0.81$–0.86), but low for the remaining pairs, where correlations respond to innovations without strong smoothing.

The crisis-window analysis nonetheless reveals a pattern

consistent with contagion in the more open markets. Mean correlations rise significantly during crisis episodes for BTC–TASI (from 0.104 to 0.110, p = 0.032), BTC–DFMGI (from 0.080 to 0.090, p = 0.009), BTC–QE (from 0.042 to 0.046, p = 0.018) and most strongly ETH–DFMGI (from 0.113 to 0.132, p < 0.001), with

Table 5: DCC-GARCH(1,1) estimates and dynamic correlations across crisis windows

Pair	α	β	Mean ϱ	COVID-19	Crash 2021	Terra-Luna	FTX	Crisis vs calm (t, p)
BTC–TASI	0.028	0.000	0.105	0.110	0.102	0.120	0.109	2.16 (0.032**)
BTC–DFMGI	0.033	0.028	0.081	0.096	0.086	0.097	0.079	2.64 (0.009***)
BTC–QE	0.016	0.000	0.042	0.049	0.047	0.045	0.041	2.39 (0.018**)
BTC–EGX 30	0.041	0.000	0.055	0.077	0.049	0.061	0.050	1.35 (0.180)
BTC–MASI	0.000	0.000	0.043	0.043	0.043	0.043	0.043	1.52 (0.130)
ETH–TASI	0.003	0.000	0.125	0.125	0.125	0.127	0.125	1.73 (0.085*)
ETH–DFMGI	0.012	0.814	0.115	0.141	0.122	0.160	0.104	6.19 (0.000***)
ETH–QE	0.002	0.000	0.062	0.063	0.063	0.063	0.062	1.78 (0.076*)
ETH–EGX 30	0.042	0.000	0.065	0.083	0.056	0.073	0.062	1.06 (0.292)
ETH–MASI	0.005	0.858	0.069	0.082	0.061	0.076	0.064	1.60 (0.111)

Note: crisis windows — COVID-19: 15 Feb–30 Apr 2020; Crash 2021: 1 May–30 Jun 2021; Terra-Luna: 1 May–30 Jun 2022; FTX: 1 Nov–31 Dec 2022. The last column reports the Welch t-test of equal mean correlations in crisis versus non-crisis days (p-value in parentheses).

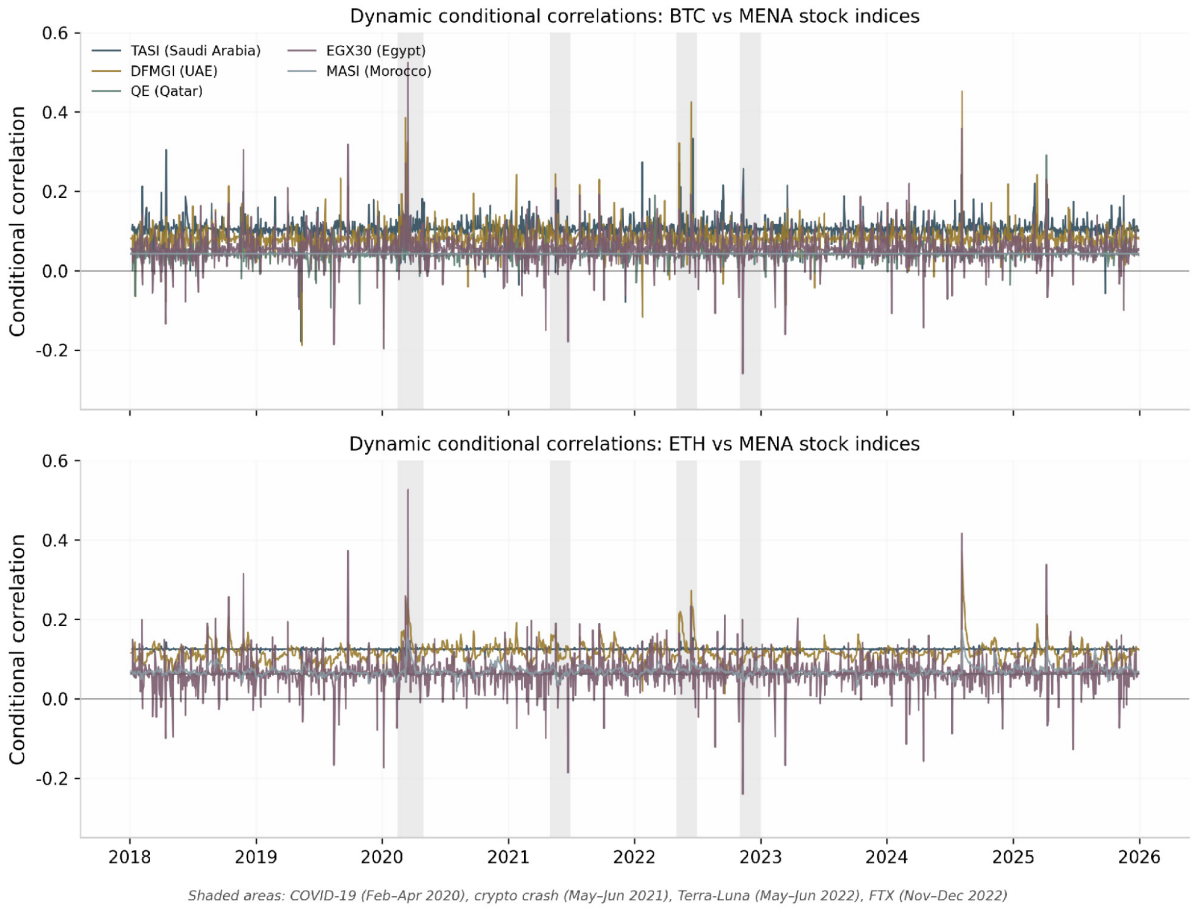


Figure 1: Dynamic conditional correlations between BTC (top panel), ETH (bottom panel) and the five MENA stock indices. Shaded areas mark the crisis windows: COVID-19 (February–April 2020), crypto crash (May–June 2021), Terra-Luna (May–June 2022) and FTX (November–December 2022).

visible spikes around March 2020 and mid-2022 in Fig. 1. For the EGX 30 and MASI pairs, by contrast, crisis-period increases are small and statistically insignificant. Hypothesis H2 is thus supported for the Gulf markets, where correlations strengthen precisely when markets are under stress, but not for Egypt or Morocco.

Discussion: Implications for the Stability of the Five Financial Systems

Applying the three criteria of the assessment framework yields a differentiated picture of crypto-induced vulnerability across the region. The United Arab Emirates emerges as the most exposed market: it is the only country for which the crypto-to-equity channel is significant for both cryptocurrencies in both the ARCH and GARCH terms, its correlations are the highest among the five markets together with Saudi Arabia, and they strengthen markedly during crises, consistent with its deliberate positioning as a regional digital-asset hub (Aysan 2025; Alrawashdeh *et al.* 2024). Saudi Arabia and Qatar display an intermediate profile: significant crypto-to-equity spillovers for Ethereum (and for Bitcoin in Qatar), high volatility persistence, and significant crisis-period correlation increases. Egypt shows weaker exposure: incoming spillovers are only marginally significant and crisis-period correlations do not rise significantly. Morocco is the least exposed market: no significant crypto-to-equity transmission, the lowest average correlations, and no contagion pattern,a profile consistent with a more segmented market, a restrictive regulatory stance and limited institutional crypto exposure (Hassib and Ayad 2026). Hypothesis H3 is therefore supported: spillover intensity is heterogeneous across the five countries and increases with the openness of the market and the depth of crypto adoption.

Compared with the African evidence of Joseph *et al.* (2024), who found substantial cryptocurrency-to-equity spillovers for the five largest African financial systems, our results indicate that the direct threat of crypto volatility to MENA equity markets is real but more contained and concentrated in the Gulf. The strong and systematic reverse channel, from MENA equities to cryptocurrencies, suggests that, in this region, crypto markets behave more as receivers than as emitters of volatility, reflecting the relatively small weight of MENA investors in global crypto markets and the sensitivity of crypto prices to regional macro-financial conditions. For financial stability, the main near-term risk is therefore less a generalized contagion from crypto to equities than a growing two-way integration in the Gulf markets, where rising correlations during crises progressively erode the diversification benefits that currently protect these financial systems.

Robustness Checks

Four exercises assess the robustness of these findings. First, the sample is split at the onset of the COVID-19 crisis (15 February 2020): mean conditional correlations are higher in the post-COVID period for all ten pairs, and the increase is statistically significant for eight of them (e.g., from 0.077 to 0.082 for BTC–DFMGI, $p = 0.002$; from 0.108 to 0.118 for ETH–DFMGI, $p < 0.001$), confirming that the integration between the two markets has deepened over time rather than being driven by a single episode. Second, the likelihood-ratio tests reported in Table 4 show that the full BEKK specification, which allows cross-market transmission, significantly outperforms the restricted diagonal specification in every pair, the spillover estimates are therefore not an artifact of model restriction. Third, post-estimation diagnostics indicate that the models are well specified: Ljung–Box tests on squared standardized residuals from the univariate GARCH steps fail to reject the null of no remaining ARCH effects in all series (p-values between 0.21 and 0.99), so the volatility dynamics are adequately captured; residual autocorrelation in levels largely disappears once an AR(1) filter is applied, with marginal significance remaining only for a few index series. Fourth, the results are consistent across the two cryptocurrencies: the direction, significance and ranking of spillovers obtained with Bitcoin are replicated with Ethereum, whose transmission coefficients are, if anything, slightly stronger, indicating that the findings reflect market-level linkages rather than the choice of a particular crypto proxy.

CONCLUSION

This paper has examined the implications of cryptocurrency volatility for the financial system stability of the five largest MENA financial markets, Saudi Arabia, the United Arab Emirates, Qatar, Egypt and Morocco, by estimating bivariate BEKK-GARCH(1,1) and DCC-GARCH(1,1) models on daily data on Bitcoin, Ethereum and the five benchmark stock indices over 2018–2025. Three main findings emerge. First, volatility spillovers between the two markets are significant and bidirectional, but asymmetric: transmission from MENA equities to cryptocurrencies is systematic, while crypto-to-equity transmission is concentrated in the Gulf markets, significant for the UAE, Saudi Arabia and Qatar, marginal for Egypt and absent for Morocco. Second, conditional correlations between the two markets remain low on average (0.04–0.13), but rise significantly during crisis episodes in the Gulf markets, a contagion pattern that erodes diversification benefits precisely when they are most valuable. Third, exposure to crypto-induced instability is heterogeneous and increases with market openness and crypto adoption: it is highest in the UAE, intermediate in Saudi Arabia and Qatar, low in Egypt and minimal in Morocco.

These findings carry several policy implications. First, central banks and market authorities in the Gulf, the Saudi Central Bank, the Central Bank of the UAE and the Qatar Central Bank, should incorporate crypto-market indicators into their macroprudential surveillance, since the two-way integration of their equity markets

with cryptocurrencies is already statistically visible and strengthens during stress episodes. Second, the crisis-period correlation surges argue for stress-testing scenarios that incorporate crypto-market crashes and for explicit guidance on the crypto exposure of regulated financial institutions, in line with the emerging regulatory frameworks documented by Youssef *et al.* (2025). Third, the heterogeneity of results supports differentiated, risk-based regulatory responses rather than uniform regional rules: hub strategies such as those of the UAE and Saudi Arabia call for stronger prudential safeguards, whereas the more restrictive stance of countries like Morocco appears, for now, to have effectively contained direct spillovers, although continued grassroots adoption may gradually erode this insulation (Hassib and Ayad 2026). Fourth, given the importance of Islamic finance in the region, supervisory attention should extend to the interaction between crypto volatility and Sharia-compliant instruments (Trichilli and Boujelbène 2023; Mezghani *et al.* 2024).

The study has limitations that open avenues for future research. The analysis is restricted to the two largest cryptocurrencies and to daily frequency; extending it to stablecoins, high-frequency data, asymmetric or regime-switching specifications (e.g., ADCC or Markov-switching BEKK) and quantile-connectedness approaches (Bawa 2026; Mathias and Sahoo 2026) would enrich the picture. Incorporating national crypto-adoption indices and on-chain activity measures would also allow a more direct identification of the transmission channels linking crypto adoption to financial system exposure in the MENA region.

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