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RISK-ADJUSTED RETURNS AND SPILLOVER DYNAMICS AMONG EMERGING DIGITAL CURRENCIES

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ABSTRACT

This study investigates the interconnected dynamics among diverse digital currencies, specifically focusing on risk-adjusted returns, tail risks, dynamic spillovers, and portfolio implications. Unlike prior research, which typically examines individual digital currency classes separately or in limited combinations, our study integrates six distinct classes of digital currencies, namely Islamic gold-backed cryptocurrencies, green cryptocurrencies, gold-backed stablecoins, non-fungible tokens (NFTs), decentralized finance (DeFi) assets, and conventional cryptocurrencies, enabling direct comparisons of risk-return dynamics and systemic interdependencies. Using Value at Risk (VaR), Conditional Value at Risk (CVaR), quantile-based Vector Autoregression (Quantile VAR), and network connectedness analysis, we provide nuanced insights into the behavior of these assets across various market conditions (bullish, bearish, and normal states). Our results demonstrate that conventional cryptocurrencies and DeFi assets consistently deliver positive risk-adjusted returns, whereas Islamic gold-backed cryptocurrencies exhibit notably higher downside risks and negative performance. Spillover analysis reveals pronounced connectedness, particularly in extreme market states, with conventional cryptocurrencies identified as primary transmitters of market shocks and gold-backed stablecoins and Islamic gold-backed cryptocurrencies as recipients. Our findings underscore significant diversification opportunities offered by pairs of assets exhibiting low connectedness, especially in normal market conditions. Furthermore, portfolio optimization analysis highlights the superior hedging effectiveness and lower hedging costs associated with gold-backed stablecoins and conventional cryptocurrency pairs. This comprehensive investigation delivers critical implications for investors, suggesting informed strategies for asset allocation and risk management. Policymakers can also utilize our insights to design adaptive regulatory frameworks that address systemic risks arising from digital currency markets.

Keywords: Digital currency, Tail risks, Dynamic spillovers, Quantile VAR, Portfolio management, Islamic cryptocurrency, Green cryptocurrency.
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I. INTRODUCTION

The past decade has witnessed a remarkable surge in digital currencies, offering both opportunities and challenges for investors, policymakers, and researchers. Traditional cryptocurrencies, like Bitcoin and Ethereum, have captured the attention of investors, academics, and policymakers alike (Yousaf & Yarovaya, 2022a) for their decentralized nature and potential as alternative investments (Corbet et al., 2019). This has fueled a surge in trading volume, volatility, and pricing of these digital assets. Consequently, a growing body of research (Demir et al., 2018; Rizvi & Ali, 2022; Hasan et al., 2022a; Conlon & McGee, 2020) has explored the potential of cryptocurrencies as diversification and hedging tools. However, despite conflicting findings, the attractiveness of the cryptocurrency market persists, driven by substantial investments from global stakeholders. By 2021, global investments in the crypto market surpassed 30 billion USD (Hasan et al., 2022c), propelling the market capitalization to a staggering 1.19 trillion USD by July 2023[1].

However, this rapid growth of the market has been overshadowed by its inherent volatility. In addition, environmental concerns associated with traditional cryptocurrencies cast a further shadow on this already unpredictable landscape (Wang et al., 2022). These challenges have prompted the cryptocurrency community to diversify their holdings, seeking to mitigate portfolio volatility and lessen the impact of crises. In response, a new wave of digital currencies has emerged, such as Islamic gold-backed crypto and green cryptocurrencies, addressing ethical and sustainability concerns. Furthermore, gold-backed stablecoins, non-fungible tokens (NFTs), and Decentralized Finance (DeFi) assets have also entered the scene. While all are classified as digital currencies, these novel assets possess distinct features, investment purposes, and trading characteristics. While the potential decoupling of these new asset classes from existing ones and even between themselves sould offer alternative investment opportunities (hedging potential) for cryptocurrency investors (Mnif & Jarboui, 2021; Yousaf & Yarovaya, 2022a), a concern remains whether shocks experienced by one class could still ripple through the entire ecosystem, given their shared nature as digital currencies.

Green cryptocurrencies are designed to address environmental concerns by minimizing energy consumption and integrating renewable energy into the mining process. Islamic cryptocurrencies, on the other hand, adhere to Islamic principles by preventing speculative activities and ensuring asset backing, such as gold. These two emerging classes focus on ethical and sustainable finance, making them particularly relevant in today's investment landscape, where investors increasingly prioritize environmental, social, and governance (ESG) factors (Starks, 2023). Traditional Islamic assets (e.g., Islamic stocks and Sukuk) and green assets (e.g., green bonds) are usually treated as stable and resilient during crises due to their conservative nature (Hasan et al., 2022b; Yousaf et al., 2024b). Similarly, these new digital currencies, especially Islamic gold-backed and green cryptocurrencies, are ethical and sustainable assets that are perceived to offer comparatively stable returns with lower volatility, particularly during turbulent market conditions (Husain et al., 2023; Yousaf et al., 2024b). Additionally, gold-backed stablecoins,

1. Based on the data from https://coinmarketcap.com/

being asset-backed by gold, function as natural hedging instruments (Díaz et al., 2023). In contrast, NFTs and DeFi assets remain nascent and evolving, presenting alternative investment avenues with inherently high volatility (Yousaf & Yarovaya, 2022a; Karim et al., 2022). Studying these diverse digital currencies together reflects their growing importance and provides a unique opportunity to assess their portfolio diversification and hedging potential. Unveiling the complex interplay between these digital currencies, particularly regarding risk-return dynamics, interconnectedness (spillover effects), and portfolio implications, is crucial for investors, policymakers, and researchers alike.

While existing literature predominantly addresses conventional cryptocurrencies and often neglects comprehensive comparative analyses across newer digital currencies, some studies (e.g., Mnif & Jarboui, 2021; Ali et al., 2022; Rizvi & Ali, 2022; Yousaf & Yarovaya, 2022a; Wasiuzzaman et al., 2023; Ali et al., 2024; Yousaf et al., 2024b; Yousaf et al., 2024a) on these specific newer classes begin to emerge. However, studies on these emerging classes tend to focus narrowly on volatility, return connectedness, or their roles as hedging instruments vis-à-vis traditional financial assets, without adequately exploring their collective risk-return dynamics and systemic interdependencies. This limited perspective restricts investors' ability to make informed diversification decisions and inhibits policymakers from developing targeted regulatory responses to the emerging risks and dynamics in digital currency markets.

Motivated by this notable gap, our study aims to contribute in several significant ways. First, we offer a detailed comparative analysis of the risk-return dynamics, specifically examining risk-adjusted returns and tail risks across six distinct classes of digital currencies. Second, we provide an in-depth assessment of dynamic spillover effects and interconnectedness among these assets across diverse market conditions (bull, bear, and normal market states). Lastly, we evaluate practical portfolio implications, including hedge ratios, optimal portfolio weights, and hedging effectiveness, to guide investors in managing risks and optimizing returns.

To these ends, we utilize a comprehensive dataset that covers six distinct and emerging classes of digital currencies: Islamic gold-backed cryptocurrencies, green cryptocurrencies, gold-backed stablecoins, NFTs, DeFi assets, and conventional cryptocurrencies. Specifically, we select two representative digital currencies from each asset class, yielding a total of twelve assets for our empirical analysis. Our data are daily spanning from February 7, 2020, to June 1, 2023. We measure the risk-adjusted returns of these assets using three established metrics: the Sharpe ratio, Treynor ratio, and Jensen's Alpha, following Al-Yahyaee et al. (2020) and Yarovaya et al. (2021b). For assessing tail risk, we adopt a two-tiered approach by employing Value-at-Risk (VaR), capturing potential downside risk at specified confidence levels, and Conditional Value-at-Risk (CVaR), measuring expected shortfalls to address extreme losses beyond VaR thresholds (Halkos & Tsirivis, 2019; Demiralay et al., 2023). Both VaR and CVaR are estimated at various quantiles (1%, 5%, and 10%) to robustly assess potential extreme outcomes. Given structural breaks and heavy tails often observed in digital currency returns (see Section 3.1), we employ a quantile-based Vector Autoregression (Quantile VAR) method (Ando et al., 2022). Additionally, we adopt a pair-wise quantile network connectedness technique for enhanced robustness.

Our empirical findings underscore several critical insights. First, conventional cryptocurrencies and DeFi assets consistently yield superior positive risk-adjusted returns, while Islamic gold-backed cryptocurrencies exhibit significantly lower or negative returns. Moreover, we identify pronounced spillover effects during extreme market conditions, with conventional cryptocurrencies serving primarily as shock transmitters. Importantly, we demonstrate that gold-backed stablecoins and conventional cryptocurrencies possess superior hedging characteristics, making them valuable components of diversified portfolios. Our analysis explicitly grounds empirical expectations and interpretations within fundamental finance theories, including Modern Portfolio Theory (Markowitz, 1952), the Efficient Market Hypothesis (Fama, 1970), and classical portfolio hedging frameworks (Ederington, 1979; Kroner & Sultan, 1993), thereby enriching our theoretical contributions and enhancing practical implications.

The remainder of the study is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodology. Section 4 presents the empirical results and discussion. Lastly, Section 5 concludes the study with practical policy insights.

II. RELATED LITERATURE

The existing literature on digital currencies has extensively explored various Issues, which cover market efficiency (Urquhart, 2016; Nadarajah & Chu, 2017), cryptocurrency as a medium of exchange (Baur et al., 2018), hedging and safe-haven properties (Demir et al., 2018; Conlon & McGee, 2020; Hasan et al., 2022a), and herding behaviors (Yarovaya et al., 2021a). Despite extensive coverage, findings from these studies often remain inconsistent and inconclusive, reflecting the complexity and evolving nature of the cryptocurrency market.

Recent literature increasingly differentiates emerging digital currency categories from conventional cryptocurrencies based on unique characteristics, underlying assets, ethical principles, and sustainability considerations. Islamic gold-backed cryptocurrencies, for example, are distinguished by their compliance with Sharia principles, notably avoiding speculation and ensuring asset backing. Wasiuzzaman et al. (2023) and Ali et al. (2022) examine their performance during financial crises, highlighting their significant declines but affirming their effectiveness as hedging tools against traditional cryptocurrencies. Similarly, Ali et al. (2022) identify OneGram as a safe haven against Islamic equity indices, particularly during the COVID-19 pandemic. Aloui et al. (2021) further highlight distinct behavioral differences, revealing Islamic gold-backed cryptocurrencies exhibit positive correlations with gold, whereas conventional cryptocurrencies typically show weaker or negative correlations. Zhang et al. (2021) provide complementary insights by exploring the benefits of holding cryptocurrencies during periods of downside risk, documenting a positive cross-sectional correlation between downside risk and future returns.

Green cryptocurrencies, designed to mitigate environmental impact by reducing energy consumption and promoting renewable energy usage, align closely with increasing investor preference for sustainable investment options (Starks, 2023; Husain et al., 2023; Yousaf et al., 2024b). Gold-backed stablecoins similarly serve as natural hedging instruments, given their underlying asset base in gold (Díaz et al., 2023). Conversely, NFTs and DeFi assets, while innovative, remain inherently volatile and present novel investment opportunities (Yousaf & Yarovaya, 2022a; Karim et al., 2022). Yousaf & Yarovaya (2022a) find that NFTs and DeFi assets are relatively disconnected from conventional markets, providing considerable diversification potential, although their volatility and spillover risks are notably higher during market crises.

Although insightful, existing studies typically approach these emerging digital currencies narrowly, either by examining them individually or by limiting their focus to volatility, returns, or their hedging role against traditional financial assets. This fragmented perspective inadequately addresses the broader comparative risk-return dynamics, systemic interconnectedness, and portfolio implications across various digital currencies. This research gap limits the ability of investors to effectively navigate systemic risks and diversification opportunities, while simultaneously constraining policymakers' ability to develop responsive regulatory frameworks.

our study bridges this significant gap by conducting a comparative analysis across six distinct classes of emerging digital currencies. Specifically, we explore risk-adjusted returns, tail risk profiles, spillover effects, and portfolio management implications. By employing advanced econometric techniques—including VaR, CVaR, quantile-based VAR, and network connectedness analyses—we aim to provide nuanced insights into the interconnected dynamics of digital currencies, informing both investors on diversification and policymakers on managing systemic risk within this rapidly evolving financial ecosystem.

III. DATA AND METHODOLOGY

Our methodological approach is motivated by fundamental financial theories. Specifically, Modern Portfolio Theory guides our examination of risk-adjusted returns and portfolio optimization strategies, while Efficient Market Hypothesis provides context for evaluating return predictability and market interconnectedness. Moreover, established hedging theory (Ederington, 1979; Kroner & Sultan, 1993) underpins our analysis of hedge ratios and hedging effectiveness. Incorporating these theories allows us to form explicit expectations regarding asset behavior and provides robust theoretical foundations for interpreting our empirical results.

3.1. Data and Preliminary Analysis

This study analyzes the comparative performance using risk-adjusted returns, downside risk, dynamic spillover, and portfolio strategies among different types of digital currencies by utilizing the daily closing prices. We categorize digital currencies into six distinct asset classes based on their nature and the purposes they serve. They include: 1) Islamic gold-backed cryptocurrency, which is backed by gold, one of the six "Rabawi" commodities (gold, silver, wheat, barley, salt, and dates) that are permissible for trade under Shariah law (Aloui et al., 2021; Irfan et al., 2023); 2) Green cryptocurrency, which is energy efficient and incorporates renewable energy into the mining process (Husain et al., 2023); 3) Gold-backed stablecoins, which are asset-backed stablecoins pegged to gold as their underlying asset (Díaz et al., 2023); 4) Non-fungible tokens (NFTs), which are unique digital tokens representing ownership of specific digital objects such as artwork, music, videos, photos, tweets, and digital land (Dowling, 2022; Yousaf & Yarovaya, 2022c); 5) Decentralized Finance (DeFi) assets, which refer to financial services like lending, borrowing, online wallets, derivatives, and spot trading that operate in a peer-to-peer manner without central authority (Yousaf & Yarovaya, 2022c); and 6) Conventional cryptocurrency, which encompasses any form of digital or virtual currency that uses cryptography to secure transactions and operates without a central issuing or regulating authority. For each asset class, we select two assets based on their market capitalization and trading volume. The selected assets, along with their symbols and data sources, are summarized in Table 1. Our sample period spans from 07 February 2020 to 01 June 2023. The sample period is based on the availability of data for these digital currencies. The analysis of this study begins with transforming the prices of these assets into logarithmic returns using the formula: $R_t = \ln(\frac{p_t}{p_{t-1}}) \times 100$

Table 1.
Data Definitions and Sources

Asset classes	Asset names	Symbols	Data sources
Islamic Gold-backed Cryptocurrency	OneGram	OGC	https://coincodex.com/
	X8X	X8X	
Green Cryptocurrency	Cardano	ADA	
	TRON	TRX	
Gold-backed Stablecoin	PAX Gold	PAXG	
	Tether Gold	XAUT	
NFTs	Theta Network	THETA	
	Decentraland	MANA	
DeFi	Chainlink	LINK	https://coinmarketcap.com/
	Maker	MKR	
Conventional Cryptocurrency	Bitcoin	BTC	
	Ethereum	ETH	

Table 2 presents the descriptive statistics of daily returns for all variables analyzed in our study. We witness that except for OGC and X8X, all assets exhibit positive mean returns, with MANA having the highest mean returns, followed by ETH and THETA. OGC demonstrates the highest volatility, with X8X following, as indicated by their standard deviations, whereas XUAT displays the lowest volatility, followed by PAXG. The negative skewness observed in the return series of all variables, except MANA, suggests that the distribution of returns is asymmetric, with a longer or fatter tail on the left side. This implies that the returns series experiences more extreme losses than gains. Additionally, the extremely high kurtosis values across all variables highlight the presence of heavy tails or outliers, indicating leptokurtic distributions. These findings imply that the return series of the variables are likely non-normal, a hypothesis further supported by the significant Jarque-Bera test statistics, suggesting time-varying or quantile regression models over simple linear regression for more robust outcomes.

Furthermore, we employ the Augmented Dickey-Fuller (ADF) and Phillips and Perron (PP) unit root tests to ascertain the stationarity of the data series. The results from both tests confirm that our datasets are stationary. Lastly, the Ljung-Box Q(10) and Q2(10) tests indicate that our return series exhibits both autocorrelation and heteroscedasticity (ARCH effect). Consequently, employing simple linear models to estimate the interconnection between asset return series may generate spurious outcomes, warranting the use of GARCH- and quantile-based time-varying approaches (Siddique et al., 2024).

Table 2.
Descriptive Statistics, Autocorrelation, Heteroscedasticity, and Stationarity Test

Variables	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Q(10)	Q2(10)	ADF	PP
OGC	-0.880	14.667	-4.387	76.642	277300.70***	13.874***	1.161	-37.64***	-37.53***
X8X	-0.003	12.263	-0.300	28.934	33927.87***	65.352***	141.228***	-43.17***	-44.14***
ADA	0.149	5.742	-0.403	11.675	3826.48***	22.825***	51.971***	-38.16***	-38.03***
TRX	0.101	5.188	-1.212	20.836	16334.83***	40.056***	43.037***	-40.17***	-40.08***
PAXG	0.019	0.979	-0.276	10.461	2821.78***	23.652***	121.102***	-39.39***	-39.70***
XUAT	0.018	0.862	-0.492	10.871	3172.52***	9.308*	176.296***	-35.93***	-35.92***
THETA	0.158	6.835	-0.806	11.652	3905.10***	22.507***	26.007***	-38.08***	-37.95***
MANA	0.184	7.794	1.405	28.284	32629.53***	8.001	61.045***	-34.09***	-34.09***
LINK	0.054	6.390	-1.102	14.489	6900.15***	21.163***	41.496***	-38.60***	-38.60***
MKR	0.008	6.555	-1.210	40.526	71291.33***	38.163***	40.922***	-40.33***	-40.10***
BTC	0.083	3.850	-1.813	27.665	31334.96***	17.619***	12.389**	-37.59***	-37.47***
ETH	0.175	5.065	-1.528	21.051	16897.98***	25.203***	31.797***	-38.19***	-38.05***

Notes: The table reports the outcomes of descriptive statistics and unit root tests for all return series. Q(10) and Q2(10) represent the Ljung-Box test statistic for autocorrelation with 10 lags and the Ljung-Box Q2 test for heteroscedasticity (ARCH effects) with 10 lags, respectively. ADF and PP are the Augmented Dickey-Fuller and Phillips–Perron test statistics for unit roots considering both constant and trend at their levels. Standard deviation is denoted as Std. Dev. The Akaike Information Criteria (AIC) is employed for assessing optimal lag lengths. The significance levels at 1%, 5%, and 10% are marked by ***, **, and *, respectively.

Figure 1 illustrates the daily prices of all digital currencies examined in our study. The figure reveals considerable fluctuations in the prices of these assets over the sample period. Most of the assets show an upward trend in the early part of the sample, peaking around 2021. However, following this period, there is a notable decline in the prices of the majority of these assets, continuing until the end of the sample period (June 1, 2023). This pattern reflects significant volatility and a general downward trend in the latter part of the period. Our sample period encompasses several major economic crises, such as the COVID-19 pandemic from 2020 to 2021 and the ongoing Russia-Ukraine war starting in 2022, which have likely contributed to substantial volatility in the digital currency markets (Hasan et al., 2021; Boubaker et al., 2022). These crises have led to heightened uncertainty, affecting investor behavior and market stability, which in turn may have influenced the observed price dynamics.

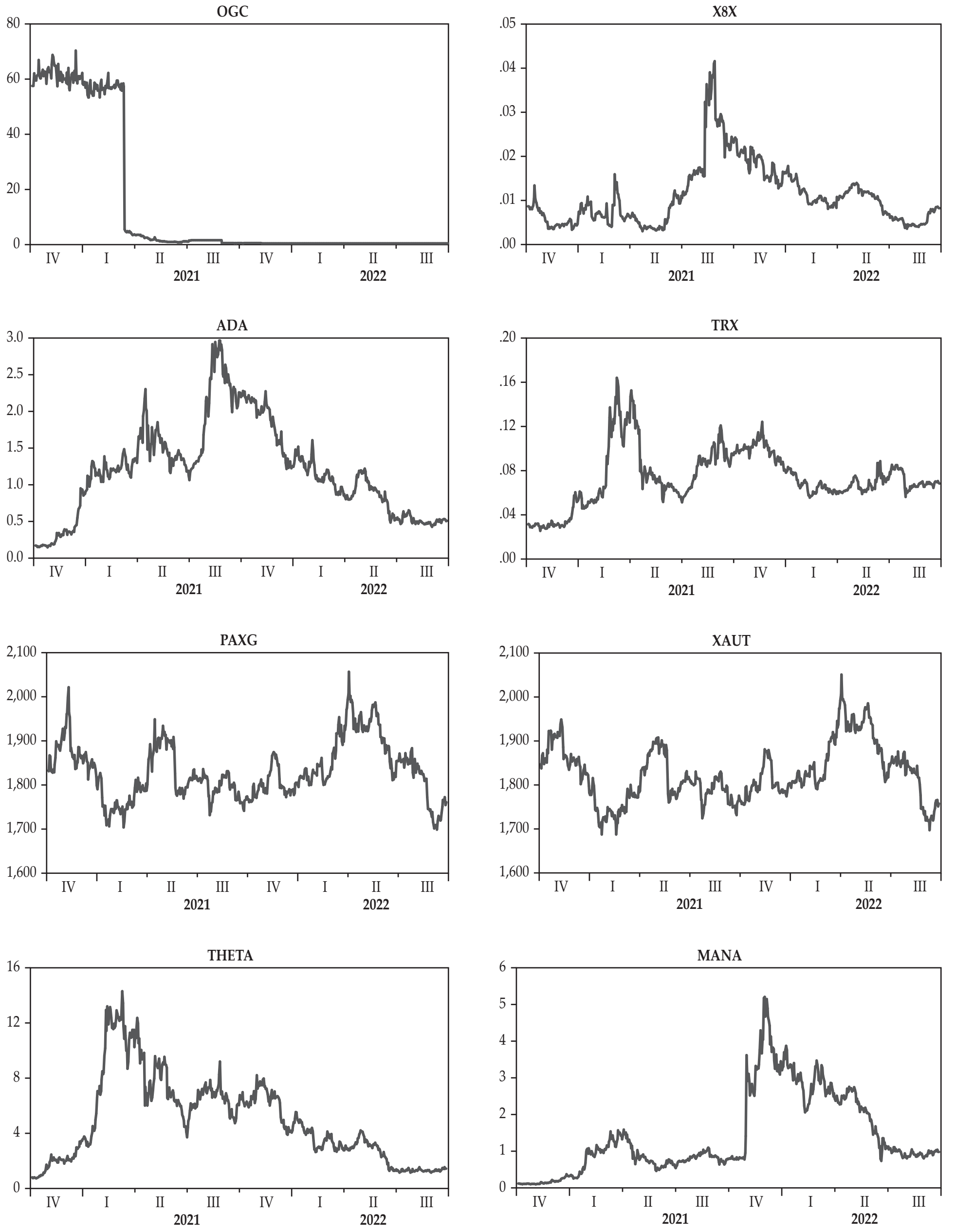


Figure 1.
Plots of Price Dynamics of Assets

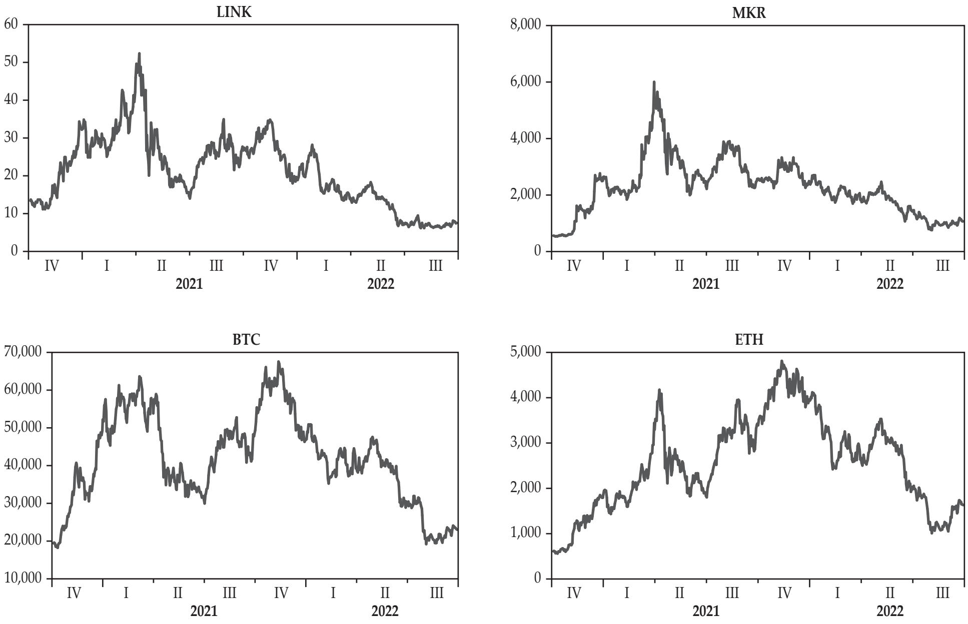


Figure 1.
Plots of Price Dynamics of Assets (Continued)

The correlation matrix among the variables is reported in Table 3. We notice that all assets, except OGC, are positively and significantly correlated to each other. Notably, OGC exhibits a negative but statistically insignificant correlation with most assets, except for PAXG and XUAT

Table 3.
Correlation Matrix

	OGC	X8X	ADA	TRX	PAXG	XAUT	THETA	MANA	LINK	MKR	BTC	ETH
OGC	1											
X8X	-0.015	1										
ADA	-0.006	0.260***	1									
TRX	-0.039	0.278***	0.647***	1								
PAXG	0.015	0.014	0.141***	0.130***	1							
XAUT	0.012	-0.008	0.082***	0.075***	0.674***	1						
THETA	-0.012	0.207***	0.596***	0.558***	0.106***	0.079***	1					
MANA	-0.023	0.239***	0.564***	0.529***	0.080***	0.043	0.561***	1				
LINK	-0.019	0.273***	0.725***	0.648***	0.109***	0.076***	0.627***	0.592***	1			
MKR	-0.032	0.256***	0.617***	0.564***	0.107***	0.016	0.523***	0.506***	0.652***	1		
BTC	-0.033	0.267***	0.700***	0.676***	0.171***	0.104***	0.642***	0.590***	0.710***	0.660***	1	
ETH	-0.022	0.300***	0.752***	0.710***	0.154***	0.103***	0.628***	0.599***	0.792***	0.746***	0.842***	1

Notes: The table presents the correlation matrix. The significance levels at 1%, 5%, and 10% are marked by ***, **, and *, respectively.

3.2. Quantile VAR Specifications

Given that our data series exhibit several issues, including non-normality, autocorrelation, and heteroscedasticity (as detailed in the data section), employing simple linear models is inappropriate. To effectively address these data challenges, we utilize the Quantile Vector Autoregression (Quantile VAR) approach. This method is particularly advantageous as it is robust to outliers and provides a nuanced understanding of connectedness across various market conditions (Ando et al., 2022). By examining multiple quantiles, we gain additional insights into tail dependencies between diverse digital currencies and can thoroughly investigate time-domain connectivity under different market scenarios. The Quantile VAR model thus provides a robust framework for analyzing the complex dependencies in our data, allowing for a more accurate and detailed understanding of market behavior.

We begin our analysis with quantile regression, following the framework by Koenker & Ng (2005) and Jena et al. (2022). Specifically, we examine the dependency of the variable γ_t on x_t at each quantile (τ) of the conditional distribution of γ_t/x_t as specified below:

$$Q_\tau\,(\gamma_t\,|x_t\,) = x_t\,\beta(\tau) \tag{1}$$

where Q_τ represents the τ^{th} conditional quantile function of γ_t where the range of every quantile between 0 and 1 is signified by τ. x_t denotes a vector of explanatory variables and $\beta(\tau)$ signifies the affiliation between x_t and the τ^{th} conditional quantile function of γ_t. The parameter vector ($\beta(\tau)$) at the τ^{th} quartile (τ) is estimated as follows:

$$\hat{\beta}_{(\tau)} = a\,rg\;\;min \textstyle\sum_{t=1}^{T}(\tau - 1_{\{y_t < x_t\,\beta(\tau)\}})|y_t < x_t\;\;\beta(\tau) \tag{2}$$

Then, the pth order of the n-variable for the Quantile VAR method is evaluated as follows:

$$y_t = c(\tau) + \textstyle\sum_{i=1}^{p} Bi(\tau)\boldsymbol{y}_{t-1} + \boldsymbol{e}_t(\tau),\;\; t = 1, \ldots, T \tag{3}$$

where, γ_t depicts the n-vector of the dependent variable, and $c(\tau)$ and $e_t(\tau)$ represent the n-vector of constants and residuals at quantile (τ), respectively. The matrix of lagged coefficients of the dependent variable at τ is denoted by $Bi(\tau)$, where i=1,…,P. Then, $\hat{\beta}_{(\tau)}$ and $\hat{c}(\tau)$ are calculated by simulating the residuals, subject to the quantile constraints, $Q_\tau\left(e_t\,(\tau)|y_{t-1}\,, \ldots y_{t-p}\,\right) = 0$. Subsequently, we represent the repercussion y for the population of the τ^{th} conditional quantile in Equation (4), allowing us to approximate an equation-by-equation analysis at each quantile τ.

$$Q_\tau\left(\gamma_t|y_{t-1}, \ldots \gamma_{t-p}\right) = c(\tau) + \textstyle\sum_{i=1}^{p} Bi(\tau)y_{t-1} \tag{4}$$

3.2.1. Measuring Connectedness at Every Quantile

Next, to compute multiple estimates of return interconnectivity at each quantile (τ), we employ a methodology introduced by Ando et al. (2022), building upon Diebold & Yilmaz's (2012) mean-based estimates. This technique has also been utilized by Su (2020) and Jena et al. (2022). Initially, Equation (3) is first adjusted as an unspecified order vector moving average (MA) process to evaluate interconnectedness across quantiles:

$$y_t = \mu(\tau) + \sum_{s=0}^{\infty} A_s(\tau)\boldsymbol{e}_{t-s}(\tau), \quad t = 1, \dots, T \tag{5}$$

where,

$$\mu(\tau) = \left(\mathrm{I}_n - B_1(\tau) - \ldots - B_p(\tau)\right)^{-1} c(\tau), \mathrm{A}_s(\tau) = \begin{cases} 0, s < 0 \colon I_n, s = 0 \\ B_1(\tau)\mathrm{A}_{s-1}(\tau) + \cdots + B_p(\tau)\mathrm{A}_{s-p}(\tau), s = 0 \end{cases} \tag{6}$$

and y_t is the summation of residuals $e_t(\tau)$.

Secondly, diverging from Su (2020), we adopt methodologies proposed by Koop et al. (1996) and Pesaran & Shin (1998), which demonstrate robustness in terms of variable ordering. For a forecast horizon H, the generalized forecast error variance decomposition (GFEVD) of a variable resulting from shocks originating from various variables is as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \Sigma_{h=0}^{H-1} (e_i' \mathrm{A}_S \, \Sigma e_j)^2}{\Sigma_{h=0}^{H-1} (e_i' \mathrm{A}_S \, \Sigma e_j)} \tag{7}$$

where $\theta_{ij}^{g}(H)$ refers to the impact of the j^{th} variable on the variance of the forecast error of the variable i^{th} at horizon H. Then, Σ is used for the vector of error variance matrix in the equation, and the j^{th} diagonal component of the Σ matrix is symbolized by σ_{jj}. e_i signifies a vector worth 1 for the i^{th} component and 0 otherwise.

Then, to standardize each component of the variance decomposition matrix, we proceed with:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\Sigma_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{8}$$

Third, we consider GFEVD, which allows us to formulate four estimations of connectivity at each quantile. Thus, we signify the total spillover index (TSI) at quantile τ using the following:

$$TSI(\tau) = \frac{\Sigma_{i=1}^{N}\Sigma_{j=1,i\neq j}^{N}\,\theta_{ji}^{\sim g}(\tau)}{\Sigma_{i=1}^{N}\Sigma_{j=1,}^{N}\,\theta_{ji}^{\sim g}(\tau)}\times 100 \tag{9}$$

We use "TO" to symbolize the total directional spillover index from index i to indices j at quantile τ as follows:

$$SI_{i\rightarrow j}(\tau) = \frac{\Sigma_{j=1,i\neq j}^{N}\theta_{ji}^{\sim g}(\tau)}{\Sigma_{j=1}^{N}\;\theta_{ji}^{\sim g}(\tau)} \times 100 = TO \tag{10}$$

On the other hand, the term "FROM" is used to depict the total directional spillover index from indices j to index i at quantile τ, as follows:

$$SI_{i\leftarrow j}(\tau) = \frac{\Sigma_{j=1,i\neq j}^{N}\theta_{ji}^{\sim g}(\tau)}{\Sigma_{j=1}^{N}\;\theta_{ji}^{\sim g}(\tau)} \times 100 = FROM \tag{11}$$

Finally, the net total directional spillover index (NSI) at quantile τ is as follows.:

$$NSI_I\;(\tau) = SI_{i\rightarrow j}(\tau) - SI_{i\leftarrow j}(\tau) = NSI \tag{12}$$

The lag length parameters recommend one lag for the empirical study depending on the AIC, and the forecast horizon is 10. To assess the time-varying spillover of different return spillover indicators, a 200-day rolling window estimation is utilized.

3.3. Hedge Ratio, Optimal Portfolio Weights, and Hedging Effectiveness

This study further estimates the hedge ratio (*HR*), optimal portfolio weights, and hedging effectiveness (*HE*) to provide enhanced hedging strategies and portfolio insights for investors and portfolio managers (Antonakakis et al., 2019). We employ the *HR* proposed by Kroner and Sultan (1993), which is based on the conditional variance and covariance of the DCC-GARCH t-Copula model. The *HR* calculates the cost of hedging a $1 long position in asset i with a β_{ijt} USD short position in asset j, encompassing various cryptocurrencies. The calculation is defined as:

$$\beta_{ijt} = \frac{h_{ijt}}{h_{jjt}} \tag{13}$$

Here, larger conditional variances translate to lower long-position hedging costs, while higher conditional covariances result in higher long-position hedging costs.

Additionally, we estimate the optimal portfolio weights, following the methodology proposed by Kroner & Ng (1998), based on the DCC-GARCH t-Copula framework. The optimal portfolio weights between pairs of digital assets are determined by:

$$W_{ijt} = \frac{h_{jjt}-h_{ijt}}{h_{iit}-2h_{ijt}+h_{jjt}}, \tag{14}$$

where W_{ijt} may exceed one or fall below zero. We set the following constraints to account for this shortcoming:

$$W_{ijt} = \begin{cases} 0, & \text{if } W_{ijt} < 0 \\ W_{ijt}, & \text{if } 0 \leq W_{ijt} \leq 1 \\ 1 & \text{if } W_{ijt} > 1 \end{cases} \tag{15}$$

Finally, we utilize Ederington's (1979) technique to evaluate hedging effectiveness and various portfolio strategies among digital assets. This can be expressed as follows:

$$HE_i = 1 - \frac{V(r_{\beta,w})}{V(r_{unhedged})}, \tag{16}$$

Here $r_{\beta,w}$ represents the hedged portfolio returns, which can be computed as:

$$\begin{cases} r_\beta = y_{it} - \beta_{ijt} y_{jt} \\ r_w = w_{ijt} y_{it} + (1 - w_{ijt}) y_{jt} \end{cases} \tag{17}$$

HE_i indicates the percent reduction in the unhedged position's variance. The variance of the unhedged position of asset *i* is denoted by $V(r_{unhedged})$. $V(r_{\beta,w})$ denotes the hedged portfolio variance either from the optimal *HR* or weight strategy. The greater risk reduction in the portfolio is associated with higher HE_i.

3.4. Value at Risk (VaR) and Conditional Value at Risk (CVaR)

To measure the tail risk, we employ both Value at Risk (VaR) and Conditional Value at Risk (CVaR), following Harris & Shen (2006), and Demiralay et al. (2023). VaR measures the potential downside risk of investments at different quantile levels over specified time intervals. We use the historical VaR simulation approach to estimate potential losses in our digital currency assets. We apply the historical VaR simulation approach in our research. The formula is:

$$VaR = V_m \frac{V_t}{V_{t-1}}, \tag{18}$$

where V_t denotes the number of variables at time t and *m* indicates the number of days from which the past returns are taken.

CvaR, also known as expected shortfall, complements VaR by quantifying the tail risk of investments beyond the VaR cut-off point. CvaR endeavors to overcome the loopholes of the VaR model. The CvaR is given by:

$$CVaR = \frac{1}{1-c}\int_{-1}^{VaR} xp(x)dx, \tag{19}$$

where $p(x)dx$ indicates the probability concentration of receiving a return with value x. c represents the cut-off *VaR* breakpoint and VaR is the pre-specified VaR level.

IV. EMPIRICAL ANALYSIS OF RESULTS

4.1. Risk-adjusted Returns Performance

We begin our analysis by evaluating the risk-adjusted return performance of assets. Table 4 exhibits the results of risk-adjusted returns for all assets under investigation, based on three widely used metrics: the Sharpe ratio, Treynor ratio, and Jensen Alpha. The findings indicate that all assets, except Islamic gold-backed cryptocurrencies, exhibit positive Sharpe ratios, suggesting that the majority of the assets provide returns that are sufficient to compensate for the risk undertaken. Regarding the Treynor ratio, which measures returns in relation to systematic risk, the majority of assets show positive Treynor ratios, indicating that their returns justify their market risk. However, OGC, TRX, PAXG, THETA, and MANA display negative Treynor ratios, signifying that their returns do not adequately compensate for their exposure to systematic risk, making them less attractive from a risk-adjusted perspective.

Consistent with the Sharpe ratio findings, Jensen's Alpha outcomes Indicate that except for Islamic gold-backed cryptocurrencies, all assets have positive Jensen's Alphas. This implies that, when compared to the expected returns based on the Capital Asset Pricing Model, most assets provide returns above their expected risk-adjusted benchmark. It is also noticed that conventional cryptocurrencies and DeFis demonstrate the most consistent positive risk-adjusted returns based on all three metrics, while Islamic gold-backed cryptocurrencies reveal the negative and lowest risk-adjusted returns. These findings align with Platanakis & Urquhart (2020), who reveal substantial positive risk-adjusted returns in traditional cryptocurrencies. Additionally, our outcomes are somewhat supported by Aloui et al. (2021), who exhibit negative mean returns for Islamic gold-backed cryptocurrencies.

The notably low risk-adjusted return profile of Islamic gold-backed cryptocurrencies is a significant finding. Table 2 and 4 reveal that gold-backed cryptocurrencies, specifically PAXG and XAUT, achieve markedly superior average and risk-adjusted returns compared to their Islamic counterparts despite both being backed by gold. The inferior risk-return profiles of OGC and X8X are primarily attributable to their relatively low market capitalizations, especially when contrasted to conventional gold-backed cryptocurrency like PAXG and XAUT. Siswantoro et al. (2020) identify substantial disagreements regarding the halal status of cryptocurrencies from Sharia perspective, contributing to Muslim investors’ reluctance to adopt Islamic gold-backed cryptocurrencies as viable investment instruments. Moreover, no Muslim-majority country has yet provided official support for cryptocurrencies, either as a medium of exchange or investment vehicles, further limiting their adoption.

Table 4.
Risk-adjusted Return Estimations

Variables	Sharpe ratio	Rank	Treynor ratio	Rank	Jenson’s Alpha	Rank
OGC	-0.0602	12	-0.5960	9	-0.8972	12
X8X	-0.0006	11	0.0420	7	-0.0058	11
ADA	0.0253	2	1.7351	3	0.1444	4
TRX	0.0187	6	-0.6368	11	0.0982	5
PAXG	0.0152	8	-0.6367	10	0.0151	8
XAUT	0.0165	7	0.8004	4	0.0141	9
THETA	0.0225	4	-0.5643	8	0.1563	3
MANA	0.0231	3	-3.0008	12	0.1805	1
LINK	0.0078	9	0.4231	5	0.0488	7
MKR	0.0007	10	0.0832	6	0.0038	10
BTC	0.0205	5	61.1623	1	0.0790	6
ETH	0.0338	1	1.7988	2	0.1702	2

Notes: The table presents the results of the Sharpe ratio, Treynor ratio, and Jensen’s alpha using the US 10-year treasury bond yield index as a proxy of the risk-free rate.

4.2. Downside Risk and Expected Shortfall Analysis

Table 5 presents the estimates of assets’ downside risk and expected shortfall using VaR and CVaR, respectively, at three quantiles (10%, 5%, and 1%). The analysis reveals that gold-backed stablecoins (XUAT and PAXG) and conventional cryptocurrencies (BTC and ETH) exhibit relatively lower downside risk across all quantiles compared to other digital currencies, as indicated by both VaR and CVaR metrics. This suggests that these assets may offer a more stable investment option with a lower potential for extreme losses, likely stemming from their established market presence and underlying asset backing (Díaz et al., 2023). Green cryptocurrencies (TRX and ADA) also show lower downside risk across most quantiles. Conversely, Islamic gold-backed cryptocurrencies (OGC and X8X), NFTs (THETA and MANA), and DeFi assets (LINK and MKR) demonstrate significantly higher downside risk across most quantiles, according to both VaR and CVaR estimates. This highlights the elevated risk associated with these assets under adverse market conditions, making them less suitable for risk-averse investors (Osman et al., 2023). It is essential to note that the magnitude of potential loss for digital asset classes increases with higher confidence levels in both VaR and CVaR estimations. This underscores the importance of considering higher confidence levels in risk assessment to account for potential worst-case scenarios more effectively.

Table 5.
VaR and CVaR estimations

Variables	VaR			CVaR		
	10%	5%	1%	10%	5%	1%
OGC	-10.822	-18.457	-38.880	-25.717	-37.517	-78.391
X8X	-8.883	-14.388	-39.650	-20.188	-29.114	-59.275
ADA	-6.068	-8.430	-13.302	-9.871	-12.661	-21.139
TRX	-4.981	-7.485	-15.023	-9.442	-12.813	-22.853
PAXG	-1.006	-1.477	-3.011	-1.782	-2.385	-3.910
XUAT	-0.865	-1.379	-2.602	-1.622	-2.155	-3.598
THETA	-7.583	-10.339	-18.086	-12.241	-15.861	-27.539
MANA	-7.473	-10.220	-17.306	-12.089	-15.685	-27.720
LINK	-6.975	-9.927	-16.888	-11.621	-15.068	-25.785
MKR	-6.397	-8.172	-14.113	-10.227	-13.332	-25.423
BTC	-3.716	-5.870	-10.785	-6.907	-9.153	-16.086
ETH	-4.973	-7.413	-14.044	-9.104	-12.080	-21.360

Notes: The table highlights the results of examined historical VaR and CVaR estimations at three quantile levels: 10%, 5%, and 1%

These findings align with Díaz et al. (2023), who reveal that gold-backed stablecoins are relatively stable and exhibit lower downside risk in portfolios. Additionally, our results are partly supported by Yousaf & Yarovaya (2022a), who document that NFTs and DeFi assets exhibit greater volatility, though they may offer higher returns.

4.3. Quantile Spillover Connectedness Analysis
4.3.1. Static Quantile Spillover Connectedness

Table 6 presents the outcomes of the static spillover connectedness (directional, pairwise, and Total Connectedness Index (TCI)) among digital currency assets under three different market conditions: bear (0.05 quantile), normal (0.5 quantile), and bullish (0.95 quantile), shown in Panels A, B, and C, respectively. The findings reveal that the TCI values, located at the bottom right corner of the table, are 95.49%, 65.27%, and 96.18% for the lower, middle, and upper quantiles, respectively. This indicates that the connectedness between digital currency assets' returns is robust, with stronger spillovers in extreme market conditions (lower and upper quantiles) compared to normal market conditions. As return shocks intensify, the spillover between digital currencies strengthens, suggesting that the degree of return spillovers is symmetric in both bull and bear markets.

When examining the transmission of shocks (indicated in the penultimate rows labeled 'TO others' in Panels A, B, and C), the analysis reveals that during bearish and normal markets, ETH and LINK play the most significant roles in transmitting shocks throughout the system. In the upper quantile, MANA and ETH transmit the highest spillover to the system. Other assets tend to spread shocks more in the extreme lower and upper quantiles compared to the normal quantile. It is also notable that conventional cryptocurrencies (BTC and ETH) dominate other classes of digital currencies in spreading spillovers across all market conditions.

Regarding spillover reception from other assets, the last column, 'FROM others' in Panels A, B, and C of Table 6, demonstrates that ETH receives the most significant spillover from the system in lower and normal market states, while ADA receives the most in the upper market. Interestingly, all assets, except OGC, receive comparable shocks from the system in the extreme markets (lower and upper quantiles). However, in the normal quantile, conventional digital currencies (BTC and ETH) receive the highest shocks from the system. Overall, the findings indicate that the magnitude of spillover, in terms of both receiving and spreading, is higher in extreme market states than in normal periods among most of the digital assets considered.

The net spillover outcomes, shown by the last 'NET' row, suggest that in the lower quantile, OGC, X8X, PAXG, XUAT, MANA, and MKR are net spillover receivers (negative values), while ADA, TRX, THETA, LINK, BTC, and ETH are net spillover spreaders (positive values). In the normal market, X8X, TRX, PAXG, XUAT, THETA, MANA, and MKR act as net spillover receivers, whereas OGC, ADA, LINK, BTC, and ETH are identified as net transmitters of spillover. In the upper quantile, OGC, X8X, TRX, PAXG, and XUAT are net absorbers, while the remaining assets (ADA, THETA, MANA, LINK, MKR, BTC, and ETH) turn out to be net spreaders. It is observed that gold-backed digital currencies (i.e., Islamic Gold-backed Cryptocurrency and Gold-backed Stablecoin) are consistent spillover receivers across all market conditions. Conversely, conventional cryptocurrencies (BTC and ETH) are consistent spillover transmitters regardless of market conditions.

BTC and ETH are the oldest and most popular cryptocurrencies, occupying the largest shares in the digital currency markets and being the most liquid. Consequently, their shocks tend to spread to other digital currency markets (Yousaf et al., 2024a). These findings are consistent with previous studies, such as Yousaf et al. (2023) and Yousaf et al. (2024a), which reveal higher connectedness between digital currencies in extreme market states compared to normal market conditions.

Given the constantly evolving macroeconomic, financial, and geopolitical crises, examining how return spillovers change over time is crucial. Therefore, the above static findings are presented dynamically in the next section.

Table 6.
Static Spillover Connectedness

Variables	OGC	X8X	ADA	TRX	PAXG	XUAT	THETA	MANA	LINK	MKR	BTC	ETH	FROM Others
Panel A: Lower return quantile (0.05)													
OGC	17.38	7.39	7.37	7.83	8.21	8.21	7.64	6.70	7.48	7.07	7.20	7.52	82.62
X8X	6.35	14.04	7.97	8.51	7.27	7.09	7.96	7.91	8.43	7.73	8.18	8.57	85.96
ADA	6.73	7.15	10.93	8.76	6.72	6.79	8.61	8.20	9.34	8.48	9.01	9.29	89.07
TRX	6.80	7.26	8.72	11.25	6.76	7.00	8.49	8.05	9.02	8.33	9.15	9.14	88.75
PAXG	7.50	6.86	7.47	7.76	13.68	11.51	7.54	7.11	7.81	7.11	7.93	7.73	86.32
XUAT	7.53	6.94	7.43	8.00	11.67	13.68	7.56	6.84	7.68	7.07	7.87	7.72	86.32
THETA	6.67	6.97	8.74	8.69	6.69	6.77	11.55	8.44	9.05	8.35	9.12	8.96	88.45
MANA	6.23	7.31	8.55	8.61	6.66	6.73	8.88	11.92	9.15	8.05	9.00	8.91	88.08
LINK	6.22	7.15	9.08	8.70	6.58	6.63	8.75	8.34	11.35	8.62	9.15	9.45	88.65
MKR	6.41	6.83	8.88	8.60	6.53	6.69	8.52	7.86	9.13	11.88	9.01	9.64	88.12
BTC	6.67	7.06	8.88	9.06	6.51	6.62	8.82	8.07	9.08	8.37	11.21	9.66	88.79
ETH	6.79	7.28	8.94	9.15	6.49	6.63	8.57	7.90	9.30	8.68	9.53	10.74	89.26
TO Others	73.89	78.19	92.03	93.68	80.08	80.66	91.35	85.41	95.49	87.86	95.17	96.58	1050.39
NET	-8.73	-7.77	2.96	4.93	-6.24	-5.66	2.91	-2.67	6.84	-0.26	6.37	7.32	TCI = 95.49
Panel B: Normal return quantile (0.5)													
OGC	93.79	0.74	0.29	0.67	0.54	0.38	0.32	0.22	0.20	0.90	1.50	0.46	6.21
X8X	1.06	56.79	5.38	4.57	0.73	0.65	4.44	4.06	5.65	4.36	5.16	7.15	43.21
ADA	1.32	2.78	25.97	8.87	0.81	0.61	8.72	7.50	12.10	8.29	10.43	12.61	74.03
TRX	1.12	2.73	9.97	31.42	0.76	0.84	8.20	6.19	9.64	6.48	10.44	12.20	68.58
PAXG	1.15	0.77	1.55	1.00	53.82	33.88	1.12	1.11	1.33	1.15	1.71	1.40	46.18
XUAT	0.87	0.64	1.17	1.14	34.73	54.13	0.85	0.83	1.16	1.18	1.72	1.57	45.87
THETA	1.36	2.58	9.70	8.24	0.64	0.55	30.97	8.20	10.72	6.93	9.93	10.18	69.03
MANA	0.62	2.78	9.33	6.59	0.60	0.50	9.61	34.89	9.95	6.77	9.12	9.25	65.11
LINK	1.17	2.99	11.56	8.61	0.75	0.55	9.27	7.75	24.63	8.94	10.16	13.63	75.37

Table 6.
Static Spillover Connectedness (Continued)

Variables	OGC	X8X	ADA	TRX	PAXG	XUAT	THETA	MANA	LINK	MKR	BTC	ETH	FROM Others
MKR	1.00	2.60	9.56	7.21	0.63	0.62	7.36	6.56	10.82	29.92	9.85	13.88	70.08
BTC	5.11	2.80	9.68	8.79	0.80	0.82	8.54	6.97	10.19	8.10	23.65	14.57	76.35
ETH	1.91	3.43	10.93	9.36	0.69	0.71	8.03	6.59	12.46	10.39	13.49	22.00	78.00
TO Others	16.68	24.84	79.11	65.05	41.67	40.11	66.47	55.98	84.22	63.49	83.50	96.89	718.02
NET	10.47	-18.38	5.08	-3.53	-4.50	-5.76	-2.55	-9.13	8.86	-6.59	7.15	18.89	TCI = 65.27
Panel C: Upper return quantile (0.95)													
OGC	14.77	7.29	7.81	7.55	8.12	7.79	7.53	8.08	7.56	7.71	7.53	8.26	85.23
X8X	6.78	11.73	8.55	8.31	7.21	7.25	7.94	8.88	7.92	8.44	8.14	8.84	88.27
ADA	6.32	7.14	10.85	7.97	6.90	6.72	8.38	10.44	8.54	8.66	8.70	9.37	89.65
TRX	6.01	7.67	8.90	10.95	7.26	7.07	8.48	8.51	8.37	8.60	8.89	9.29	89.05
PAXG	7.29	6.90	7.84	7.48	12.65	10.77	7.81	8.49	7.43	7.52	7.83	7.99	87.35
XUAT	7.22	6.99	7.49	7.56	10.55	11.89	7.67	9.61	7.54	7.59	7.72	8.16	88.11
THETA	6.31	7.10	8.79	8.14	6.98	6.84	11.08	9.26	8.67	8.51	8.91	9.41	88.92
MANA	6.60	6.89	8.43	7.37	6.63	6.81	8.84	14.79	8.02	8.23	8.25	9.14	85.21
LINK	5.98	7.12	9.22	8.30	6.51	6.64	8.76	9.17	10.83	8.93	8.77	9.76	89.17
MKR	6.32	7.38	9.17	8.12	7.05	7.04	8.27	9.45	8.35	10.90	8.51	9.44	89.10
BTC	6.53	7.25	8.53	8.35	7.04	6.85	8.96	9.61	8.55	8.29	10.36	9.69	89.64
ETH	6.41	7.18	8.75	8.36	6.76	6.66	8.79	9.54	8.87	8.28	9.17	11.24	88.76
TO Others	71.77	78.91	93.49	87.52	81.02	80.44	91.42	101.04	89.82	90.75	92.41	99.35	1057.95
NET	-13.46	-9.35	4.34	-1.53	-6.32	-7.67	2.50	15.83	0.65	1.65	2.77	10.59	**TCI =** 96.18

Notes: The table documents the pairwise directional connectedness among digital currencies for lower, normal, and upper return quantiles (0.05, 0.5, and 0.95, respectively). The total directional connectedness to and from others is represented by the "TO Others" row and the "FROM Others" column, respectively. NET and TCI refer to the net directional connectedness and total connectedness index, respectively. In lag length selection, AIC is employed

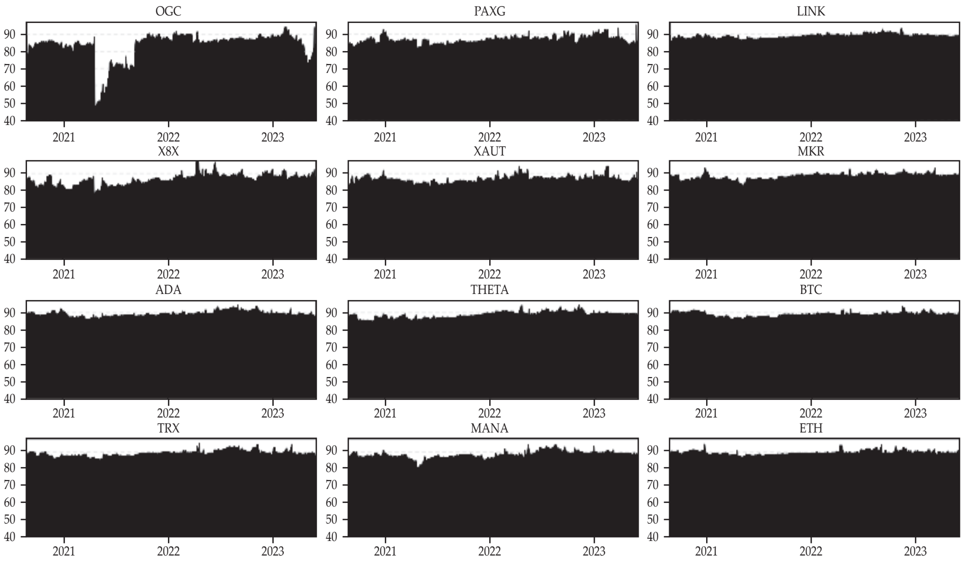
4.3.2. Dynamic Quantile Spillover Connectedness

Figure 2 illustrates the dynamic directional spillovers "from others" to digital currencies under three different market conditions, corresponding to the 'From others' column in Table 6. The figure demonstrates that most assets, with a few exceptions, receive significant and consistent spillovers from other digital currencies across all market circumstances, with more pronounced in extreme market conditions (bear and bull markets). However, the reception of spillovers for all assets varies substantially over time in the middle quantiles. This variability suggests that during normal market conditions, the interconnectedness and vulnerability of digital currencies to external shocks are more dynamic and less predictable compared to extreme market conditions. Notably, during the normal market state, Islamic gold-backed cryptocurrency (OGC and X8X) receives the lowest spillovers from others. This could be attributed to their unique structure and underlying assets, which might provide a certain level of insulation from the broader market shocks affecting other digital assets (Yousaf et al., 2024b).

The dynamic analysis also highlights that during periods of extreme market conditions, the spillover effects become more pronounced. This is evident from the consistent and significant spillovers observed in both bearish and bullish quantiles. Such behavior indicates a higher degree of interconnectedness and systemic risk among digital currencies during times of market stress or exuberance, underscoring the importance for investors to be particularly cautious during these periods.

Figure 3 illustrates the spillovers from one asset to others, corresponding to the penultimate row of Table 6. The results demonstrate that all assets transmit high levels of spillovers, approximately 100%, throughout the entire sample period across all market conditions, with more pronounced effects in extreme markets. This indicates a robust interconnectedness within the digital currency market, where shocks originating from one asset can significantly influence others. However, the transmission of spillovers varies over time for certain asset classes, such as Islamic gold-backed cryptocurrencies (OGC and X8X) and NFTs (THETA and MANA), across all quantiles. This variability suggests that while these assets generally exhibit high spillover transmission, their influence fluctuates depending on the market conditions.

Lower return quantiles (0.05)



Average return quantiles (0.5)

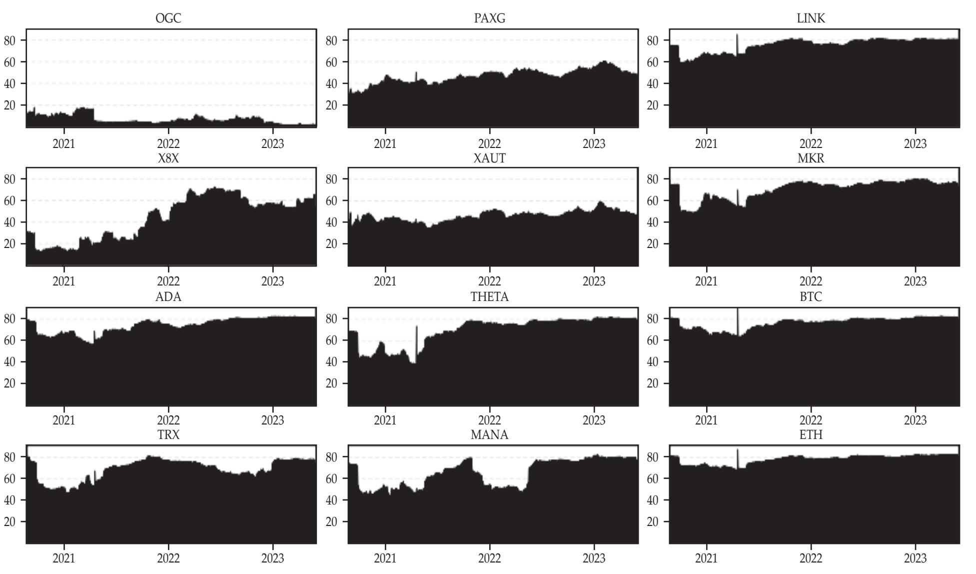


Figure 2.
Return Spillovers FROM Others for Three Return Quantiles (0.05, 0.5, and 0.95)

Higher return quantiles (0.95)

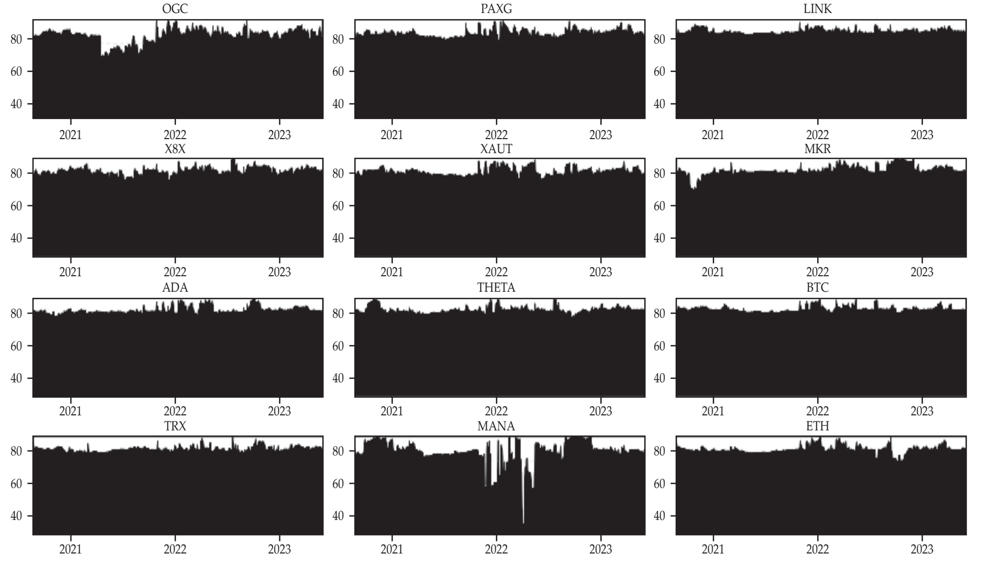


Figure 2.
Return Spillovers FROM Others for Three Return Quantiles (0.05, 0.5, and 0.95) (Continued)

Lower return quantiles (0.05)

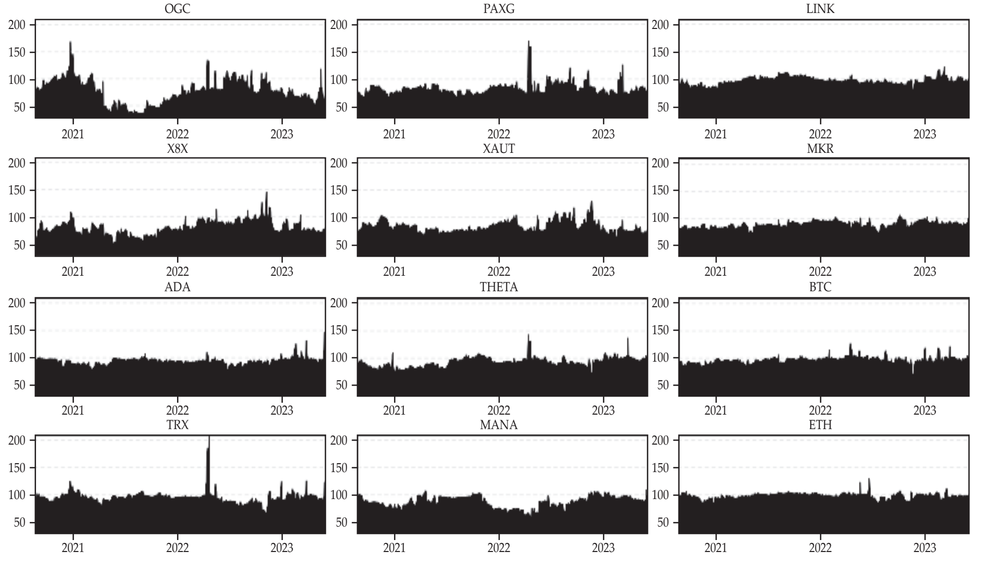
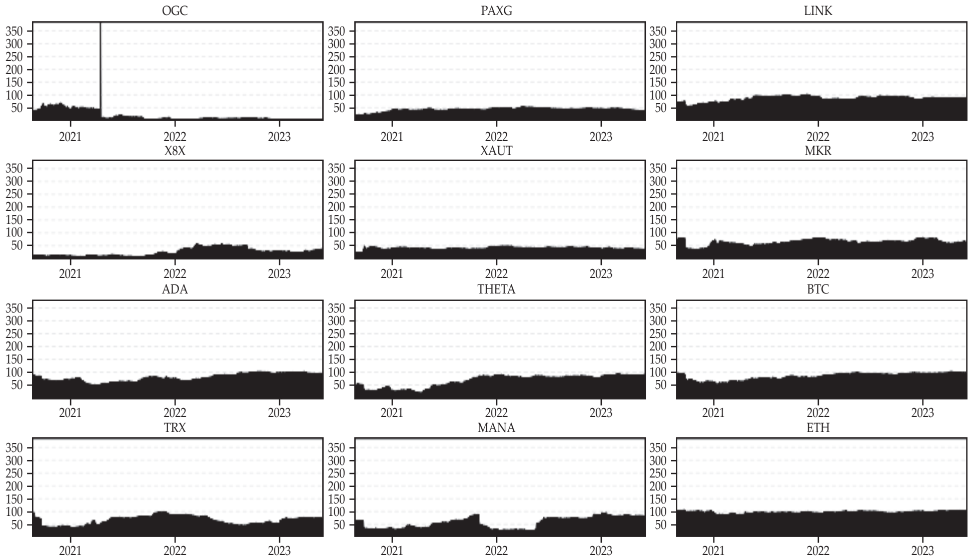


Figure 3.
Return Spillovers TO Others for Three Return Quantiles (0.05, 0.5, and 0.95).

Average return quantiles (0.5)



Higher return quantiles (0.95)

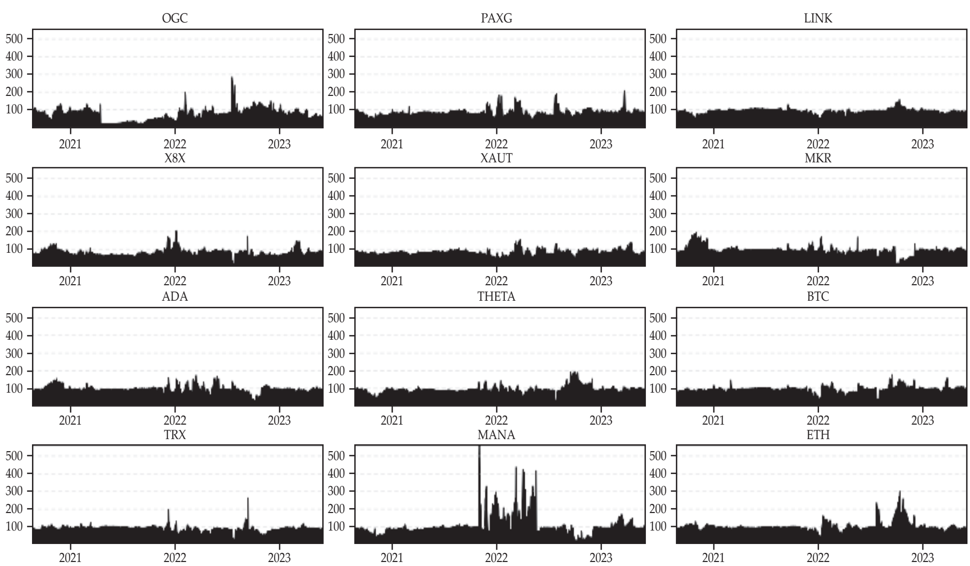


Figure 3.
Return Spillovers TO Others for Three Return Quantiles (0.05, 0.5, and 0.95).
(Continued)

The pronounced spillover effects in extreme market conditions (bearish and bullish) highlight the heightened systemic risk during these periods. It suggests that during times of market stress or exuberance, the interdependencies among digital currencies intensify, leading to a more significant transmission of shocks across the market. In normal market conditions, the dynamic spillover effects are still significant but less predictable, indicating that the interconnectedness is more stable during periods of average market activity but can change rapidly due to emerging shocks or volatility.

Lower return quantiles (0.05|0.05)

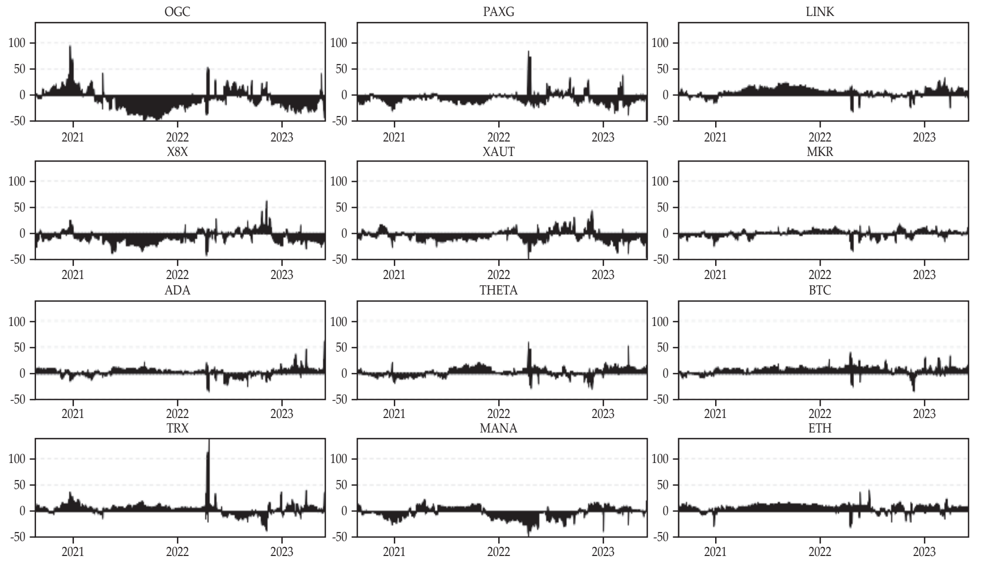
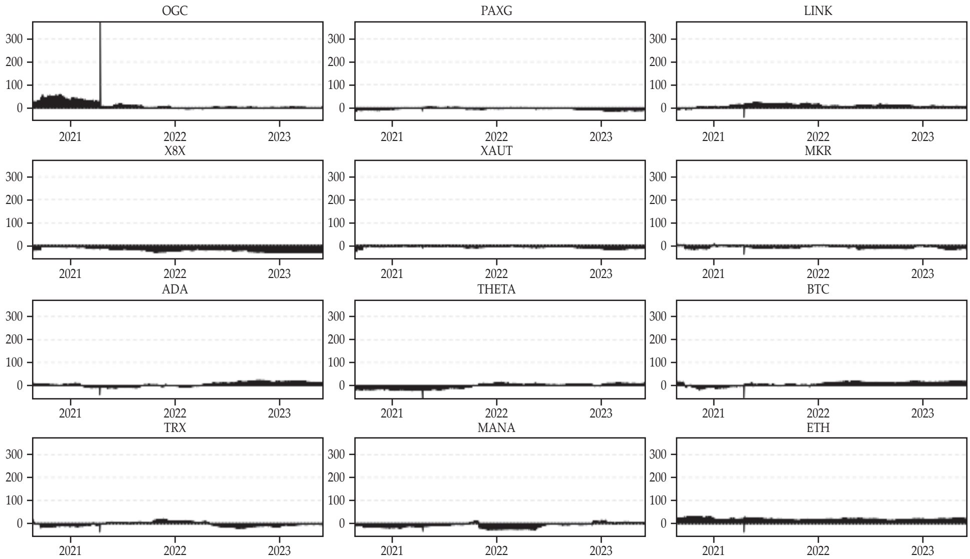


Figure 4.
Net Total Directional Spillovers for Three Return Quantiles (0.05, 0.5, and 0.95

Average return quantiles (0.5|0.5)



Higher return quantiles (0.95|0.95)

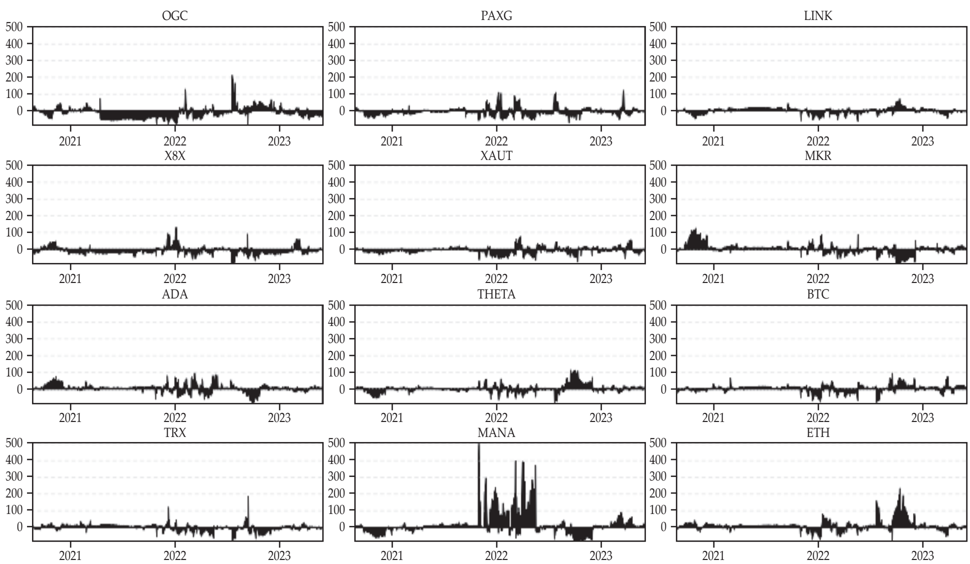


Figure 4.
Net Total Directional Spillovers for Three Return Quantiles (0.05, 0.5, and 0.95

Figure 4 presents the net directional return connectedness of digital asset classes at three quantiles. The results indicate that, consistent with earlier analyses, the net return spillovers for all digital assets are more pronounced and time-varying in extreme market conditions compared to normal markets. Specifically, Islamic gold-backed cryptocurrencies and gold-backed stablecoins are net receivers of spillover across all quantiles. This implies that these assets are more susceptible to absorbing shocks from the broader market, possibly due to their nature as stable investment options, attracting investors during times of market turbulence.

Conversely, conventional cryptocurrencies (e.g., BTC and ETH) are net spillover spreaders, indicating their influential role in transmitting shocks across the digital currency market. Their established market presence, high liquidity, and significant market capitalization likely contribute to their capacity to affect other assets substantially. However, the net spillover shocks of the remaining assets are not consistent, varying over time and quantiles. This variability highlights the dynamic nature of these assets' connectedness and their potential to either absorb or transmit shocks depending on market conditions. This underscores the importance for investors and portfolio managers to continuously monitor the market conditions and adjust their risk management strategies accordingly.

Furthermore, in the middle quantile, the findings suggest that all digital assets tend to both receive and transmit lower spillovers compared to extreme quantiles. This behavior implies that during normal market conditions, digital assets may act as potential diversifiable investments, offering lower systemic risk and potentially better portfolio diversification benefits.

Figure 5 displays the dynamic pairwise net volatility connectedness among the pairs of digital currencies under three quantiles. The findings reveal that the majority of digital currency pairs exhibit minimal to no spillover shocks across all quantiles. This suggests that digital currencies offer substantial potential for hedging and diversification, regardless of market conditions. These outcomes are somewhat corroborated by previous studies (e.g., Aloui et al., 2021; Karim et al., 2022; Yousaf & Yarovaya, 2022a, b).

However, specific exceptions are observed in the lower and middle quantiles. For instance, ETH consistently transmits spillovers to MANA, X8X, TRX, XAUT, and MKR across the entire sample period in both lower and middle quantiles, with the magnitude of shock transmission varying over time. Similarly, BTC plays a significant role in spreading shocks to XAUT, X8X, TRX, MKR, and MANA in the lower and middle quantiles, regardless of the changing degree of spillover over time. This indicates that both Bitcoin and Ethereum consistently provide hedging opportunities, as they are not significant recipients of spillover shocks from other digital currencies. These findings align with previous studies by Aloui et al. (2021) and Yousaf & Yarovaya (2022). Additionally, other digital currency pairs also exhibit minor spillover transmissions, reinforcing the hedging and diversification potential in the digital currency market.

Lower return quantiles (0.05|0.05)

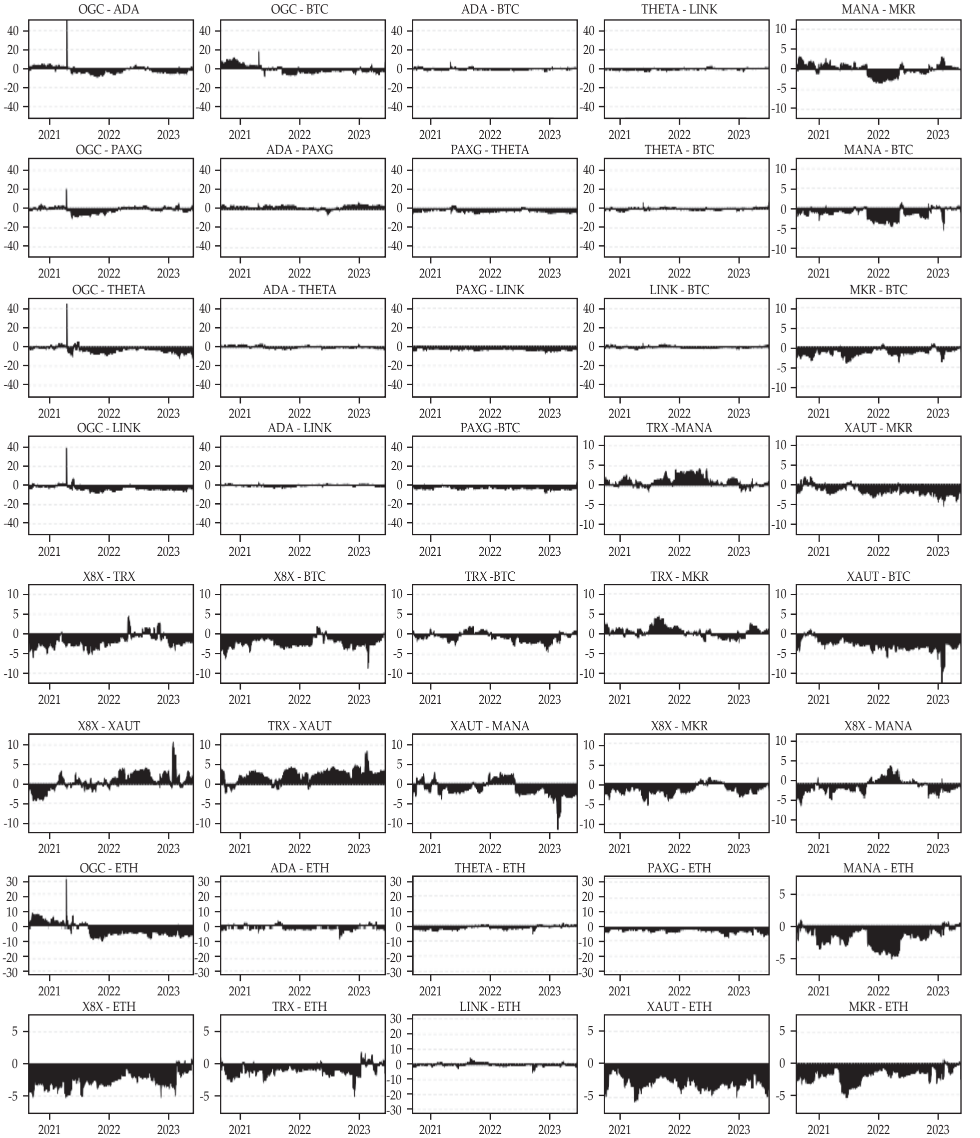


Figure 5.
Net Pairwise Directional Volatility Spillovers for Three Return Quantiles (0.05, 0.5, and 0.95)

Average return quantiles (0.5|0.5)

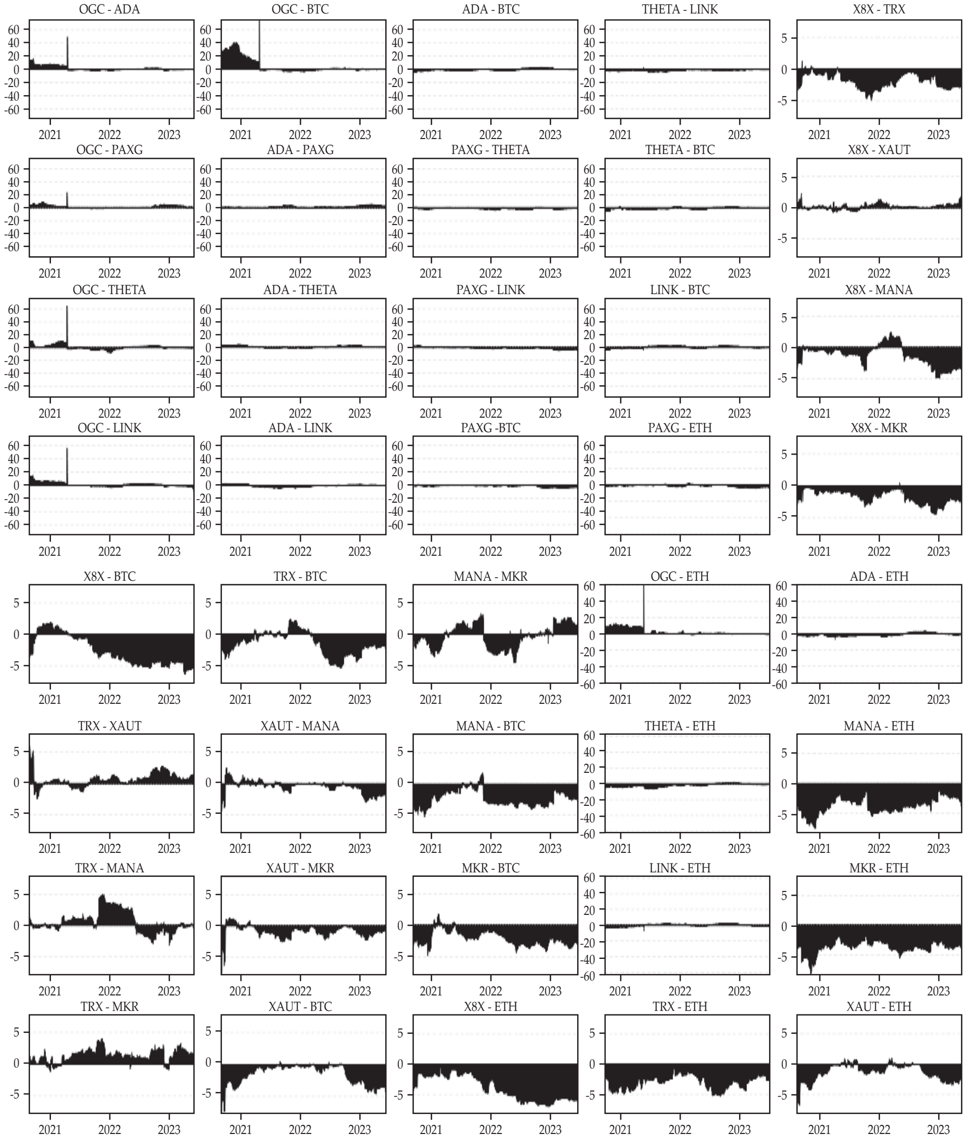


Figure 5.
Net Pairwise Directional Volatility Spillovers for Three Return Quantiles (0.05, 0.5, and 0.95) (Continued)

Higher return quantiles (0.95|0.95)

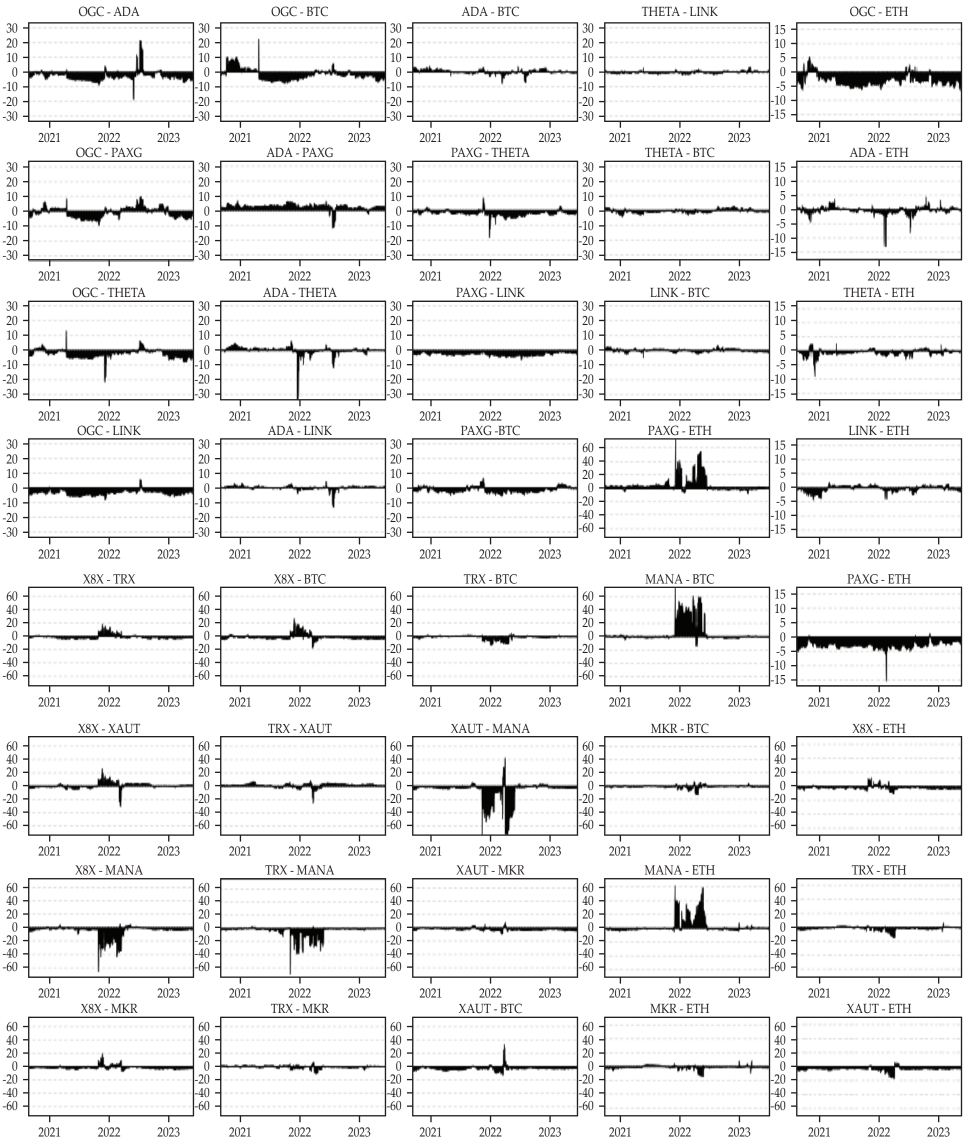


Figure 5.
Net Pairwise Directional Volatility Spillovers for Three Return Quantiles (0.05, 0.5, and 0.95) (Continued)

4.4. Pairwise Network Connectedness at Different Quantiles

This study utilizes the network connectivity technique developed by Diebold & Yilmaz (2014) in conjunction with the Quantile VAR process to gain deeper insights into the connectedness of digital currencies under varying market conditions. Figure 6 illustrates the results of the pairwise network spillover directional connectivity across three return quantiles. The Quantile VAR network connectedness map provides critical information on senders and receivers of spillovers and the degree of connectivity, which is essential for making informed decisions under different market circumstances.

The pictorial analysis indicates that the lower and upper quantiles exhibit higher connectivity compared to the normal quantile plot, which supports the findings from the Quantile VAR analysis. Specifically, in extreme markets (lower and upper quantiles), Islamic gold-backed cryptocurrencies (X8X and OGC) are the primary receivers of spillover shocks from other asset classes, followed by gold-backed stablecoins (PAXG and XAUT). In normal market conditions, X8X and MANA are the predominant shock absorbers.

In terms of spillover transmission, Bitcoin, Ethereum, and LINK are the main spreaders of shocks to other assets in the lower and normal quantiles. However, this pattern reverses in the upper quantile, where MANA becomes the leading shock transmitter, followed by Ethereum. Gold-backed stablecoins (PAXG and XAUT) neither transmit nor receive significant shocks in the normal market, making them attractive for investors seeking to diversify their portfolios with relatively lower-risk assets. This finding aligns with Díaz et al. (2023), who highlighted that stablecoins have high diversification capacities by systematically mitigating portfolio tail risk.

Lower return quantiles (0.05|0.05)

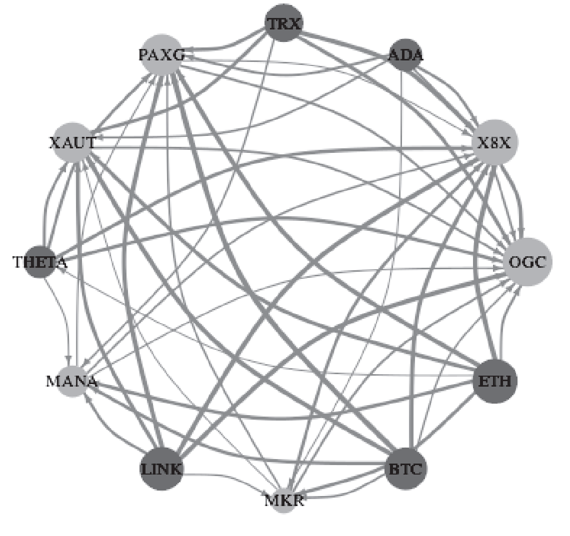
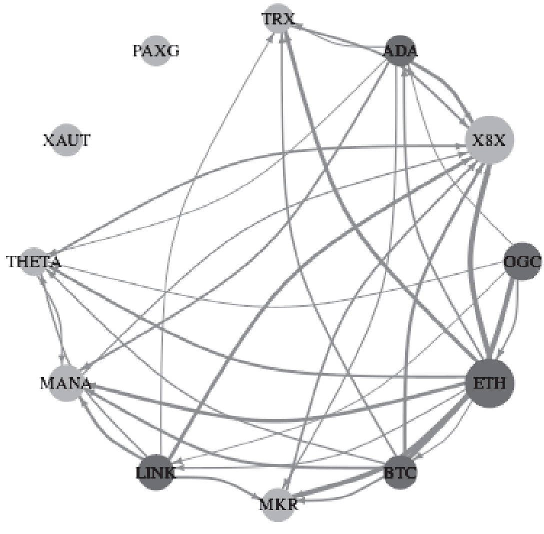


Figure 6.
Network Plots for Three Return Quantiles (0.05, 0.5, and 0.9)

Normal return quantiles (0.5|0.5)



Upper return quantiles (0.95|0.95)

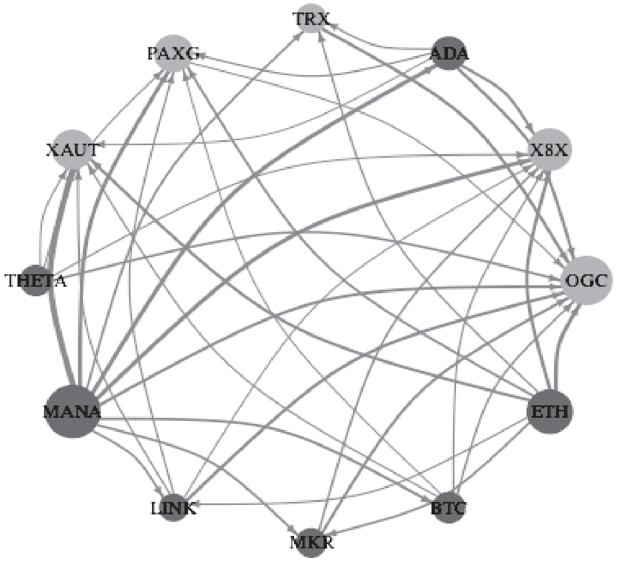


Figure 6.
Network Plots for Three Return Quantiles (0.05, 0.5, and 0.9) (Continued)

4.5. Analysis of Portfolio Implications

We further analyze hedge ratios (HR), optimal weights, and hedging effectiveness (HE) for pairs of conventional and digital currencies, as detailed in Table 7. The HR results reveal that most Bitcoin and other digital currency pairs have lower HRs, ranging from -1% to 49%. This indicates that a relatively small amount is needed in the short position to hedge a USD 1 long position in Bitcoin. Exceptions are the BTC/TRX, BTC/PAXG, and BTC/XAUT pairs, which show higher HRs. Conversely, Ethereum pairs generally require higher hedging costs, with few exceptions. Thus, investors might favor various digital currencies, especially Islamic gold-backed cryptocurrencies, for their lower HRs to mitigate Bitcoin's return variance.

Table 7.
Hedging Effectiveness with Hedge Ratios and Optimal Weights

Variables	Hedge Ratio		Optimal Weights	
	β	*HE*	*w*	*HE*
BTC/OGC	-0.01	0.00	0.53***	-0.68
BTC/X8X	0.11	0.06	0.97	0.00
BTC/ADA	0.49***	0.44	0.90	0.00
BTC/TRX	0.62***	0.43	0.58	0.07
BTC/PAXG	0.74	0.04	0.03***	0.93
BTC/XAUT	0.69	0.02	0.02***	0.95
BTC/THETA	0.38***	0.37	0.95	-0.02
BTC/MANA	0.37***	0.23	0.94	-0.02
BTC/LINK	0.45***	0.48	0.93	-0.01
BTC/MKR	0.40***	0.34	0.89	0.01
ETH/OGC	-0.06	0.00	0.46***	-0.24
ETH/X8X	0.16	0.07	0.92	0.03
ETH/ADA	0.67***	0.52	0.67	0.05
ETH/TRX	0.84***	0.46	0.36***	0.21
ETH/PAXG	0.84	0.02	0.02***	0.96
ETH/XAUT	0.90	0.02	0.01***	0.97
ETH/THETA	0.47***	0.31	0.80	0.01
ETH/MANA	0.47***	0.21	0.80	-0.01
ETH/LINK	0.63***	0.58	0.82	-0.01
ETH/MKR	0.59***	0.48	0.75	-0.01

Notes: The table presents the hedge ratio, optimal weights, and hedging effectiveness between different classes of digital currencies. The hedge ratio and optimal weights are symbolized by β and w, respectively. The hedging effectiveness is denoted by HE. ***, **, and * indicate the significance at the 1%, 5%, and 10% levels, respectively

The optimal weights findings indicate that most pairs incorporating Bitcoin and Ethereum with other digital currencies have high, though insignificant, optimal portfolio weights. This implies that a significant portion of funds should be allocated to Bitcoin and Ethereum to minimize return variance. However, pairs with gold-backed stablecoins (PAXG and XAUT) and both Bitcoin and Ethereum show the lowest and most significant optimal weights. This means that to maximize HE, ranging from 93% to 97%, over 97% of the portfolio should be invested in gold-backed stablecoins. These pairs form optimal portfolios due to their ability to significantly reduce return variance. This conclusion aligns with our earlier analysis using the Quantile-based network connectedness approach, which demonstrates that gold-backed stablecoins are less susceptible to transmitting and receiving volatility shocks from other asset classes. Consequently, these assets are robust options for hedging and diversification.

V. CONCLUSIONS AND POLICY RAMIFICATIONS

The rise of diverse digital currencies—conventional cryptocurrencies, Islamic gold-backed cryptocurrencies, green cryptocurrencies, gold-backed stablecoins, NFTs, and DeFi assets—has significantly reshaped the financial landscape. This study examines their risk dynamics, interconnectedness, and portfolio implications, addressing existing gaps through a comprehensive comparative analysis.

Our analysis, leveraging advanced econometric techniques, reveals that conventional cryptocurrencies and DeFi assets consistently deliver positive risk-adjusted returns, whereas Islamic gold-backed cryptocurrencies demonstrate negative returns and higher tail risks. These findings imply practical challenges related to market liquidity, regulatory clarity, and investor confidence for Islamic crypto-assets.

Results reveal that conventional cryptocurrencies and DeFi assets consistently provide positive risk-adjusted returns, suggesting their resilience and appeal as investment vehicles. Conversely, Islamic gold-backed cryptocurrencies exhibit significantly negative returns and heightened downside risks, indicating underlying challenges such as limited liquidity, market depth, and regulatory uncertainty.

These findings have critical implications for Islamic finance and economics. Practically, investors should exercise caution with Islamic gold-backed crypto-assets, closely monitoring developments in market infrastructure and regulatory clarity. From a policy perspective, our results highlight the urgency for establishing clear, supportive regulatory frameworks that enhance Shariah compliance and investor confidence. Theoretically, our findings challenge Islamic finance scholars to explore effective methods of operationalizing ethical principles, such as asset-backing and avoiding gharar (excessive uncertainty), within highly innovative and volatile digital markets. This opens new research avenues into the resilience and stability of ethical-based finance in fintech environments.

Our results carry valuable policy insights. Investors and portfolio managers should actively consider incorporating conventional cryptocurrencies and DeFi assets due to their consistent positive performance and relatively lower tail risks. Conversely, cautious engagement with Islamic gold-backed cryptocurrencies, NFTs, and certain DeFi assets is advisable given their higher risk profiles. Investors must also remain sensitive to market conditions, adjusting portfolio strategies dynamically to effectively manage increased risks during volatile market states.

For policymakers, the heightened interconnectedness and potential systemic risks identified call for adaptive regulatory frameworks tailored specifically for the dynamic digital currency landscape. Regulations should emphasize transparency, liquidity enhancement, and effective asset-backing criteria, especially for ethicallyoriented digital currencies. This approach would help mitigate systemic risks, foster stability, and enhance investor confidence.

Finally, while our study makes significant strides in understanding the interconnected dynamics of diverse digital currencies, it recognizes several limitations. Our dataset comprises six asset classes, each represented by two currencies; thus, future research could integrate emerging digital asset classes and additional currencies to provide more extensive insights. Employing alternative econometric techniques or machine learning models could further elucidate complex relationships between digital assets. Additionally, assessing the impact of regulatory frameworks on risk profiles and interconnectedness remains a valuable direction for future research, offering practical guidance for policymakers navigating the evolving digital currency ecosystem.

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