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Connectedness and investment strategies of volatile assets: DCC-GARCH R^2 analysis ofcryptocurrencies and emerging market sectors

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This study investigates the return propagation dynamics between cryptocurrencies and emerging market sectoral indices (EMSI), focusing on portfolio impact from Bitcoin, Ethereum, and two gold-backed cryptocurrencies (PAXG and X8X). Using data from 2019 to 2024, we apply a novel DCC-GARCH-based R^2 decomposed connectedness approach to analyse return connectedness among these high-risk assets. We also utilize innovative concepts such as minimum dynamic pairwise connectedness and minimum R^2 decomposed connectedness portfolios in our multivariate hedging portfolios. Our findings reveal that total connectedness is time-variant and influenced by economic events. Bitcoin and Ethereum are identified as net transmitters of shocks, while other assets, particularly gold-backed cryptocurrencies, serve as net shock receivers with minimal impact. Moreover, few EMSIs (financials, industrials, and materials sectors) show significant connectedness in the system. Although our suggested portfolio analysis offers improved returns, none consistently outperform the market. This research offers valuable insights for investors and policymakers regarding the interconnectedness and risk management of cryptocurrencies and EMSI.

1. Introduction

Cryptocurrencies have experienced unprecedented growth in recent years, with market capitalization surpassing $1 trillion, featuring their emergence as a significant asset class that reshapes modern financial markets and investment strategies.[1] Despite the rapid growth and potential for high returns, cryptocurrencies exhibit extreme price volatility (Kayal & Balasubramanian, 2021; Shaikh, 2020). This serves potential portfolio returns by offering diversification and high return potential (Bugan et al., 2022; Dutta et al., 2023; Guesmi et al., 2019; Jalal et al., 2021; Yousaf & Ali, 2020). Empirical papers have extensively explored how cryptocurrencies can improve overall portfolio performance in dynamic market conditions by combining them with conservative assets (Zhang et al., 2021), developed stock markets (Khalfaoui et al., 2022), and commodities markets (Gkillas et al., 2022). However, there is little research that combined them with emerging markets, especially at the sectoral level.

Investigating emerging markets is crucial, as these markets are projected to contribute 65 % of the global economic growth by 2035 and host several of the world's largest economies, which are increasingly becoming central in shaping global finance, investment flows, and sustainable development.[2] Whilst these emerging markets grow, they mirror the high-risk, high-reward end of the investment spectrum. Cryptocurrencies thus exhibit behaviour similar to emerging stock markets (Bouraoui, 2020; Hong & Zhang, 2023; Nekhili & Sultan, 2022). Both are highly volatile (Zhang et al., 2021), influenced by market sentiment (Anand et al., 2021; Gupta & Jacob, 2021; Kapar & Olmo, 2021; Parveen et al., 2020) and geopolitical events (Aysan et al., 2019; Hedström et al., 2020; Hoque & Zaidi, 2020). Further, cryptocurrencies attract investors seeking substantial returns, particularly during periods of low interest rates or economic instability (Bâra et al., 2024; Boubaker et al., 2015; Goodell et al., 2023). This similarity implies the connectedness between these two asset classes, potentially affecting portfolio benefits.

This study is motivated by the lack of attention given to emerging market sectoral indices (EMSI) as an asset class in portfolio management. While existing literature primarily focuses on the relationship between EMSIs and developed markets, the connections with other

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[1] https://www.cnbc.com/2021/12/27/12-key-moments-that-fueled-cryptos-record-growth-in-2021.html.
[2] https://www.spglobal.com/en/research-insights/special-reports/look-forward/emerging-markets-a-decisive-decade.

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similarly risky or higher-risk asset classes are largely overlooked. Research by Li and Giles (2015), Naeem et al. (2022), Belaid et al. (2023) and Altinkeski et al. (2024) has explored EMSI's links to developed markets, while Erdoğan et al., 2020, Naeem et al. (2023), Dsouza et al., 2024 and Salim et al. 2024 have examined these relationships with international assets and markets. Studies have also investigated EMSI's connectedness with various asset classes like banking (Peltonen et al., 2019), currency (Chow, 2021; Wang & Liang, 2024), ESG (Barson et al., 2024; Kilic et al., 2022), precious metals (Gençyürek & Ekinci, 2023) and oil (Mezghani & Boujelbène-Abbes, 2023). However, the dynamic relationship between EMSI and higher-risk assets, such as cryptocurrencies, remains largely unexplored, presenting a significant gap this study addresses.

Analysing the dynamic connectedness between EMSIs and cryptocurrencies could enrich the literature for several reasons. First, understanding this relationship can enhance sectoral rotation strategies within emerging markets, allowing investors to adjust portfolios based on shocks from cryptocurrencies. For example, during periods of high inflation, the banking sector of emerging markets may show an increased correlation with cryptocurrencies, potentially reducing portfolio benefits. However, investors can mitigate the shocks by shifting to defensive sectors that have no spillover with cryptocurrencies. Second, EMSI exposure to cryptocurrencies could offer valuable insights into risk management, as the high volatility of cryptocurrencies introduces additional risks or opportunities within EMSI investment. Third, the emergence of gold-backed cryptocurrencies adds a conservative element to the crypto market, offering a potential safe haven similar to traditional gold investments. This new asset class could interact with EMSI uniquely, providing investors with further diversification and risk-adjusted return opportunities.

The existing literature has extensively explored the transmission of crypto-asset shocks, particularly Bitcoin (BTC), to major financial assets, including precious metals (Mensi et al., 2019; Zhang & He, 2021), green commodities (Khalfaoui et al., 2022), equities and bonds (Zhang et al., 2021), oil futures (Gkillas et al., 2022), DeFi assets (Mensi et al., 2023; Mensi et al., 2024), commodities (Kyriazis & Corbet, 2024), as well as the US market (Khalfaoui et al., 2022) and UK market (Urom et al., 2020; Omri, 2023). However, the literature often overlooks the impact of BTC shock transmissions on emerging market indices, a gap this research aims to address. Moreover, the literature focuses only on BTC as the source of shock transmissions, neglecting the role of other major cryptocurrencies, like Ethereum (ETH). This is intriguing considering ETH's significant influence in financial markets and cryptocurrency markets (Kristjanpoller et al., 2024) and its widespread use as collateral in digital asset transactions (Ante, 2023). Additionally, gold-backed cryptocurrencies like PAX Gold (PAXG) and X8X Token (X8X) have never been empirically explored, despite their unique characteristics. These digital assets are pegged to physical gold (Hoque et al., 2024), combining the benefits of blockchain technology with the safe-haven properties of gold, representing the final gap in the current literature that we aim to address.

Building on these theoretical and empirical arguments, our study analyses the dynamic interconnectedness between EMSI and cryptocurrencies, including Bitcoin, Ethereum, and gold-backed cryptocurrencies (e.g., PAXG and X8X), using DCC-GARCH R^2 decomposed connectedness measures. We explore this topic by revealing the decomposed connectedness among cryptocurrencies and sectoral indices of emerging markets. Additionally, we conduct network analysis and examine net total directional connectedness under the R^2 decomposed regime. Finally, we assess portfolio performance based on our findings, providing valuable insights for investors and policymakers on the implications of interconnectedness in financial markets.

The contribution of this study is threefold. First, we provide new empirical evidence on the interconnectedness between two highly volatile asset classes: cryptocurrencies and EMSI. While the current literature primarily focuses on the connectedness among cryptocurrencies (Ji et al., 2019), cryptocurrencies and developed markets (Khalfaoui et al., 2022), cryptocurrencies and commodities (Gkillas et al., 2022), or among emerging markets (Yousaf et al., 2023), we enrich the literature by showing how cryptocurrencies dynamically connect with sector-level rather than market-level indices.

Second, we utilize the novel DCC-GARCH R^2 decomposed connectedness approach by Coca et al. (2024). This method allows us to examine dynamic conditional variance-covariances, correlations, R^2 goodness-of-fit measures, and decomposed R^2 contributions. It also expands the DCC-GARCH toolbox by showing how this model can generalize multiple linear regression models. A key feature is the dynamic conditional R^2 goodness-of-fit measure, which helps predict how a specific series responds to shocks in another series.

Third, we explore newly introduced two novel portfolio methodologies: the minimum bivariate R^2 portfolio and the minimum R^2 decomposed connectedness portfolio alongside other multivariate portfolios. These methodologies aim to reduce investment risk and enhance the reward-to-volatility ratio, which is crucial due to the susceptibility of clean energy markets to speculative shocks (Bohl et al., 2013). Our approach minimizes interdependencies among financial assets, providing a robust framework compared to well-known benchmark portfolio techniques. Additionally, we utilize dynamic conditional beta coefficients for constructing a multivariate hedging portfolio, assessing portfolio efficiency based on the hedging effectiveness proposed by Ederington (1979) and the Sharpe ratio introduced by Sharpe (1994).

Our findings offer at least three key insights. First, the dynamic connectedness results indicate BTC and ETH play pivotal roles in this interconnectedness. Both act as leaders and responders within the network between cryptocurrencies and EMSI. Second, while gold-backed cryptocurrencies (PAXG and X8X) have a more limited impact, three EMSIs (financials, industrials, and materials sectors) show significant connectedness. Third, a moderately high level of connectedness between the cryptocurrency market and EMSI was found, especially during extreme events like the COVID-19 pandemic, the 2021 cryptocurrency bull run, and ongoing geopolitical tensions. Those black swan events highlight the growing interdependence between digital and traditional financial markets. Moreover, PAXG, X8X, energy, information technology, and real estate sectors consistently act as net receivers of spillovers.

Our post-hoc portfolio analysis reveals four insights. Firstly, the minimum variance portfolio achieves the highest Sharpe ratio by heavily weighting PAXG and consumer staples. However, it slightly underperforms compared to market benchmarks. Secondly, the minimum correlation portfolio, designed to reduce asset correlations, allocates heavily to cryptocurrencies and various sectors. However, this portfolio faces substantial risk and a low Sharpe ratio, indicating its ineffectiveness in improving risk-adjusted returns. Thirdly, the minimum pairwise connectedness portfolio takes a more balanced approach with moderate allocations. This strategy achieves a better Sharpe ratio than the minimum correlation portfolio but still struggles to maximize returns. Lastly, advanced strategies like the minimum dynamic pairwise connectedness and minimum R^2 decomposed connectedness portfolios achieve the highest Sharpe ratio, indicating a strong risk-return balance. However, none of these portfolios outperform the market benchmark.

The remainder of the paper is outlined as follows: Section 2 reviews the literature. Section 3 introduces and describes the dataset employed in our analysis. Section 4 outlines and discusses our findings. Finally, Section 5 concludes the study, summarizing key insights and implications.

2. Methodology

We utilize the DCC-GARCH R^2 decomposed connectedness framework to investigate the connectedness between cryptocurrencies and emerging markets sectoral indices. This framework was introduced by Cocca et al. (2024) which is based on the DCC-GARCH model of Engle

(2002); R^2 decomposition of Genizi (1993) and the connectedness approach of Diebold and Yilmaz (2012; 2014). We employ this methodology because of its ability to capture the dynamic nature of financial markets, offering a comprehensive analysis of time-varying relationships through the DCC-GARCH model. The integration of dynamic conditional R^2 measures and their decomposition allow for a deeper understanding of how individual variables contribute to the overall model, offering valuable insights for informed decision-making (Genizi, 1993). Additionally, the introduction of connectedness-based portfolio strategies enhances risk management by minimizing interdependencies among assets, thereby safeguarding against systemic risk (Cocca et al., 2024). This comprehensive and sophisticated approach not only ensures theoretical rigour but also delivers practical relevance, making it exceptionally well-suited for high-stakes financial analysis and portfolio optimization in volatile market environments.

To start with, the multivariate linear regression model is estimated to be a stepping stone towards the more sophisticated DCC-GARCH model. The multivariate linear regression framework is defined as follows:

Equation 1

$$y = Xb + \epsilon$$

Where y denotes the dependent variable vector, X represents the matrix of independent variables, b is the vector of regression coefficients, and ϵ is the error term. For simplicity, we assume that all variables are mean adjusted, thereby excluding the need for an intercept in the model. The variance-covariance matrix H is central to this analysis, expressed as:

Equation 2

$$H = \begin{bmatrix} H_{yy} & H_{xy} \\ H_{yx} & H_{xx} \end{bmatrix}$$

Where H_{yy} captures the variance of the dependent variable, H_{xx} captures the variance-covariance matrix of the independent variables, and H_{xy} denotes the covariances between the dependent and independent variables. The regression coefficients are estimated using:

Equation 3

$$\widehat{b} = (X'X)^{-1}X'y = H_{xx}^{-1}H_{xy}$$

The R^2 goodness-of-fit measure, which quantifies the proportion of variance in the dependent variable explained by the independent variables, is computed as follows:

Equation 4

$$R^2 = 1 - \frac{(y - X\widehat{b})'(y - X\widehat{b})}{y'y}$$

Now, the DCC-GARCH model of Engle (2002) is employed to capture the dynamic nature of correlations and covariances among cryptocurrencies and EMSI, which are often subject to changes over time due to market conditions. The model is specified as:

Equation 5

$$z_t = D_t^{-1}\mu_t, \mu_t \sim N(0, H_t)$$

Where z_t represents the vector of returns, μ_t denotes the standardized residuals, D_t is the diagonal matrix containing conditional standard deviations, and H_t is the conditional variance-covariance matrix. The dynamic conditional correlations R_t are modelled as:

Equation 6

$$R_t = diag\,(Q_t)^{-1/2}Q_t diag\,(Q_t)^{-1/2}$$

Where Q_t evolves according to:

Equation 7

$$Q_t = (1 - a - b)Q + a\mu_{t-1}\mu_{t-1}' + bQ_{t-1}$$

In this formulation, a and b are parameters that capture the responsiveness of correlations to market shocks and their persistence over time, respectively.

Equation 8

$$H_t = D_t R_t D_t$$

The model is estimated using a two-step procedure as per Engle (2002) that ensures unbiased parameter estimates. To evaluate the explanatory power of the model over time, we employ the dynamic conditional R^2 measure. This measure, which reflects the time-varying goodness-of-fit of the model, is calculated by incorporating the dynamic components of the variance-covariance matrix H_t from the DCC-GARCH model:

Equation 9

$$R_t^2 = R_{xy,t}' R_{xx,t}^{-1} R_{xy,t}$$

Additionally, the decomposition method proposed by Genizi (1993) is applied to disaggregate the R^2 measure into contributions from each independent variable. This decomposition provides deeper insights into the role and influence of each variable in the model, allowing us to assess their impact on the overall explanatory power dynamically. The decomposition is applied as follows:

Equation 10

$$R_{xx,t} = V_t \wedge_t^2 V_t = R_{xf,t} R_{xf,t}'$$

Equation 11

$$R_{xf,t} = V_t \wedge_t V_t'$$

Equation 12

$$R_t^2 = R_{xf,t}^2 \left(R_{xf,t}^{-1} R_{xy,t}\right)^2 = R_{xf,t}^2 R_{fy,t}^2$$

Where V_t denotes the eigenvectors and $\wedge_t^2$ the diagonal eigenvalue matrix obtained by decomposing $R_{xx,t}$. The square root of the $R_{xx,t}$ is then equal to the correlations between x_t and f_t, $R_{xf,t}$. Finally, the $K \times 1$ decomposed R^2 vector, R^2 is obtained by the matrix product of $R_{xf,t}^2$ and $R_{fy,t}^2$.

Now based on the connectedness approach of Diebold and Yilmaz (2012; 2014), the traditional scaled GFEVD matrix with the R^2 decomposition matrix, so the connectedness measures are as follows:

Equation 13

$$FROM_{i,t} = \sum\nolimits_{k=1,k\neq i}^{K} R_{ik,t}^{2d} = R_{i,t}^2$$

Equation 14

$$TO_{i,t} = \sum\nolimits_{k=1,k\neq i}^{K} R_{ki,t}^{2d}$$

Equation 15

$$NET_{i,t} = TO_{i,t} - FROM_{i,t}$$

Equation 16

$$NPDC_{ij,t} = R_{ij,t}^{2d} - R_{ji,t}^{2d}$$

The average total directional connectedness to others or total directional connectedness from others is known as the total connectedness index (TCI). This means that the TCI is the same as the averaged conditional R^2 goodness-of-fit measure.

Equation 17

$$TCI_t = \frac{1}{K}\sum\nolimits_{k=1}^{K} TO_{k,t} = \frac{1}{K}\sum\nolimits_{k=1}^{K} FROM_{k,t} == \frac{1}{K}\sum\nolimits_{k=1}^{K} R_{k,t}^2$$

Since the R^2 value ranges between zero and one, the TCI also stays within this range, effectively resolving the issue of normalizing connectedness (for instance, Caloia et al., 2019; Balcilar et al., 2021; Chatziantoniou & Gabauer, 2021). The concept behind this approach is that the TCI tends to be higher when the series are strongly correlated and move in the same direction. This behaviour is particularly evident during periods of financial turmoil when the majority of financial assets experience substantial negative percentage changes.

3. Data and descriptive statistics

To analyse the connectedness between cryptocurrency and EMSI, we use the daily data. The aggregated sectoral data of EMSI is collected from DataStream. The MSCI index is chosen as a proxy for 11 emerging market sectors based on the Global industry classification standard (GICS), namely Communication services (COM), Consumer discretionary (CDC), Consumer staples (CST), Energy (ENG), Financials (FIN), Healthcare (HLT), Industrials (IND), Information technology (IT), Materials (MAT), Utilities (UTL), Real estate (RES). Furthermore, the data for cryptocurrencies are collected from the CoinMarketCap platform. Consistent with the literature (see, Yi et al., 2018; Kumar et al., 2022), we choose two major conventional cryptocurrencies such as Bitcoin (BTC) and Ethereum (ETH). Both together dominate the cryptocurrency market, accounting for around 74 % of the total market capitalization of all cryptocurrencies (Statista, 2024).[3] This dominance highlights their considerable influence and the trust they command among investors, institutions, and users worldwide.

Following, Ali et al. (2024) and Hoque et al. (2024), we also included two gold-backed cryptocurrencies, PAX Gold (PAXG) and X8X Token (X8X), to combine the stability and trust associated with physical gold with the innovative features of digital assets. Including PAXG and X8X alongside Bitcoin and Ethereum adds a layer of stability and risk management to our portfolio analysis. While Bitcoin and Ethereum offer growth potential and technological innovation, PAXG and X8X provide the security and trust of gold, a time-tested store of value (Mensi et al., 2023). This combination is particularly valuable in emerging markets, where economic conditions can be unpredictable, and there is a strong demand for assets that preserve wealth (Wasiuzzaman et al., 2023). By integrating these gold-backed cryptocurrencies, we create a balanced approach that captures the growth and innovation of digital assets while ensuring stability and protection against market volatility. Our sample period consists of September 27, 2019 to July 17, 2024, based on the data availability.

Table 1 presents the descriptive statistics of selected cryptocurrencies and EMSI. The mean returns indicate that conventional cryptocurrencies such as BTC and ETH demonstrate higher mean returns and highest standard deviations compared to other assets, which is due to greater volatility. However, PAXG, a gold-backed stablecoin, shows a more modest mean return of 0.0004 with a lower standard deviation of 0.0109, highlighting its role as a lower-risk asset within the volatile cryptocurrency market. On the other hand, most EMSI report negative or near-zero mean returns, with several sectors like COM, CDC, and CST slightly underperforming. This trend could be attributed to the inherent economic and geopolitical risks within emerging markets, which often lead to subdued returns.

However, sectors like IT and IND exhibit slightly positive mean returns (0.0006 and 0.0001, respectively), reflecting growth trends in technology and industrial production. Notably, the energy sector has a higher standard deviation (0.0143) within this group, reflecting the sector's sensitivity to commodity price volatility and geopolitical factors. The calculated skewness values are negative for all time-series except PAXG, CDC, IT, and RES, which suggests the presence of asymmetric distribution. The kurtosis estimates exceed 3 for all assets, indicating evidence of leptokurtic distribution. The Jarque-Bera test statistics reveal that all examined assets and sectors reject the null hypothesis of normality at a 1 % significance level, as indicated by the

[3] For more details see: https://www.statista.com/statistics/1269302/crypto-market-share/.

Table 1
Descriptive statistics of cryptocurrencies and emerging market sectoral indices.

	BTC	ETH	PAXG	X8X	COM	CDC	CST	ENG	FIN	HLT	IND	IT	MAT	UTL	RES
Mean	0.0017	0.0024	0.0004	−0.0014	−0.0001	−0.0001	−0.0001	−0.0001	0.0000	0.0000	0.0001	0.0006	0.0000	0.0000	−0.0006
Median	0.0005	0.0012	0.0004	0.0015	−0.0004	−0.0002	0.0003	0.0006	0.0005	0.0002	0.0005	0.0009	0.0005	0.0005	−0.0005
Maximum	0.1915	0.3537	0.0646	1.1386	0.1236	0.1583	0.0398	0.0698	0.0470	0.0596	0.0563	0.0809	0.0669	0.0495	0.0910
Minimum	−0.4647	−0.5507	−0.0777	−1.7818	−0.0754	−0.0929	−0.0745	−0.1434	−0.0739	−0.0657	−0.0750	−0.0655	−0.0971	−0.0764	−0.0769
Std. Dev.	0.0410	0.0530	0.0109	0.1325	0.0155	0.0187	0.0088	0.0143	0.0098	0.0139	0.0108	0.0141	0.0124	0.0101	0.0161
Skewness	−1.3132	−0.9775	0.0155	−1.7958	0.3850	0.3845	−1.0799	−2.2833	−1.3456	−0.1820	−0.7847	0.0302	−0.8870	−1.0530	0.2195
Kurtosis	19.2285	17.2804	8.5439	47.4297	7.9819	8.9876	11.9234	24.2180	13.7159	5.0088	9.9019	5.9395	11.6333	11.0348	7.3591
Jarque-Bera	14143.65***	10872.30***	1608.496***	103981.10***	1329.913***	1907.137***	4411.275***	24651.92***	6388.51***	218.1181***	2621.878***	452.3861***	4065.283***	3610.655***	1004.503***

Notes: This table reports the descriptive statistics of cryptocurrencies and emerging market sectoral indices. The Jarque-Bera test is test for the normality. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively.

significant p-values.

4. Results and discussion

4.1. DCC-GARCH R^2 decomposed connectedness approach

In this study, we investigate the interconnectedness between cryptocurrencies and EMSI. Following Cocca et al. (2024), we first estimate the bivariate DCC-GARCH model of Engle (2002), which allows us to capture the time-varying correlations between cryptocurrencies and EMSI. Then, the residuals from this model provide the foundation for further analysis using the R^2 decomposed connectedness approach, which enables us to quantify the degree of connectedness between cryptocurrencies and EMSI.

Table 2 displays the results for total connectedness between cryptocurrencies and EMSI. Our findings reveal that BTC and ETH play central roles in the connectedness of cryptocurrencies and EMSI. These results show that the bidirectional nature of their connectedness highlights their dual role as both leaders and responders in the financial ecosystem. Their high TO values, 75.01 for BTC and 76.32 for ETH indicate that these cryptocurrencies have substantial spillovers over the other sectors and assets. This is because BTC and ETH are the largest and most widely acknowledged cryptocurrencies, acting as benchmarks for the entire cryptocurrency market (Härdle et al., 2020). Their price movements often reflect broader market trends, which, in turn, influence investor sentiment across various asset classes (Khelifa et al., 2021).

Our results further indicate the high FROM values for BTC and ETH which are 74.64 and 74.7, respectively. These results demonstrate that these cryptocurrencies are not only influential but also highly sensitive to external changes. This sensitivity could be due to their liquidity and volatility, which make them susceptible to shifts in market dynamics and regulatory changes (Antonakakis et al., 2019). These findings are consistent with Gaies et al. (2024), who observed that Bitcoin demand rises during periods of turbulence due to inflation expectations, although its hedging ability diminishes in bearish markets. Moreover, the authors highlighted that the sensitivity of Ethereum to inflation varies, and its increased exposure to financial instability during downturns reinforces our evidence of its high exposure to external shocks. On the other hand, gold-backed cryptocurrencies like PAXG and X8X have significantly lower TO values (10.42 and 15.24, respectively), suggesting their spillovers on the EMSI are comparatively limited. These reduced spillovers can be attributed to their niche position as stablecoins, which are designed to minimize volatility and provide a safe store of value (Aloui et al., 2021). Their stability may attract risk-averse investors who prefer to use them as a hedge rather than an instrument for speculation.

Moreover, the sector-specific connectedness findings show the interconnectedness of financials, industrials, and materials within the broader financial network. Among the emerging market sectors, FIN shows a TO value of 86.93, highlighting its crucial role in the system. This suggests that the FIN sector acts as a core component of the global economy as well as financial institutions are integrated with cryptocurrencies through investments and blockchain technology adoption, increasing their sensitivity to the cryptocurrency market (Pal et al., 2021). The FROM value of 82.39 for FIN further highlights the responsiveness of the sector to changes in the system, as financial markets are typically the first to react to economic shifts and technological advancements, including those involving cryptocurrencies. Likewise, IND is another sector with higher TO and FROM values in the system. This suggests that the industrial sector is increasingly integrating digital and blockchain technologies to reshape supply chain management, and the industrial sector's influence within the network is growing (Esmaeilian et al., 2020).

The NET connectedness analysis from the TCI table reveals that BTC and ETH emerge as marginal net influencers, with NET values of 0.37

Table 2
Average DCC-GARCH R^2 decomposed connectedness.

	BTC	ETH	PAXG	X8X	COM	CDC	CST	ENG	FIN	HLT	IND	IT	MAT	UTL	RES	FROM
BTC	100	62.45	2.25	3.65	0.44	0.63	0.73	0.47	0.55	0.62	0.55	0.33	1.32	0.46	0.23	74.64
ETH	62.38	100	1.62	5.11	0.45	0.58	0.74	0.53	0.48	0.42	0.52	0.24	0.93	0.49	0.22	74.7
PAXG	2.87	1.95	100	0.29	0.4	0.41	0.9	1.03	1.33	0.53	1.17	0.55	5.5	1.06	0.41	18.41
X8X	4.01	6.16	0.25	100	0.65	0.64	1.35	0.92	1.18	0.81	1.01	0.96	1.25	0.69	0.73	20.63
COM	0.37	0.44	0.09	0.37	100	25	7.99	2.31	5.38	10.33	5.77	6.01	4.45	3.43	7.62	79.55
CDC	0.51	0.51	0.11	0.35	25.22	100	7.87	2.44	5.38	9.26	6.24	4.19	4.7	3.6	8.31	78.68
CST	0.57	0.69	0.35	0.71	7.63	7.45	100	5.74	9.47	8.93	8.89	5.6	7.4	7.39	5.47	76.28
ENG	0.43	0.57	0.55	0.68	2.56	2.65	6.13	100	10.86	1.91	6.49	2.72	11.63	10.82	3.14	61.15
FIN	0.43	0.47	0.43	0.7	5.16	5.11	9.41	10.17	100	3.69	10.69	6.71	10.6	9.62	9.2	82.39
HLT	0.77	0.57	0.24	0.53	10.28	9.05	9.34	1.83	3.9	100	6.12	6.3	4.47	4.15	5.26	62.81
IND	0.39	0.48	0.33	0.49	5.54	5.97	8.93	6.13	10.71	5.89	100	10.66	11.17	9.66	6.69	83.03
IT	0.39	0.33	0.19	0.68	6.29	4.25	5.85	2.7	7.2	6.36	11.49	100	7.15	4.09	4.09	61.05
MAT	1.19	0.87	3.34	0.8	4.27	4.53	7.42	10.92	10.67	4.28	11.17	6.79	100	7.23	4.62	78.09
UTL	0.45	0.57	0.56	0.41	3.51	3.67	7.55	10.49	9.9	4.09	10.03	3.92	7.34	100	4.87	67.36
RES	0.25	0.27	0.12	0.49	7.75	8.46	5.8	3.12	9.94	5.37	7.13	4.03	4.91	5.04	100	62.67
TO	75.01	76.32	10.42	15.24	80.15	78.4	80	58.79	86.93	62.48	87.26	59.01	82.83	67.73	60.86	981.44
Inc.Own	175.01	176.32	110.42	115.24	180.15	178.4	180	158.79	186.93	162.48	187.26	159.01	182.83	167.73	160.86	cTCI/TCI
NET	0.37	1.62	−7.99	−5.39	0.6	−0.27	3.72	−2.36	4.53	−0.32	4.23	−2.05	4.75	0.37	−1.8	70.10/65.43

Notes: This table reports the average R^2 decomposed connectedness based on DCC-GARCH model of Engle (2002) between cryptocurrencies and emerging market sectors. BTC-bitcoin, ETH-ethereum, PAXG-PAX gold, X8X-X8X token, COM-communication services, CDC-consumer discretionary, CST-consumer staples, ENG-energy, FIN-financials, HLT-healthcare, IND-industrials, IT-information technology, MAT-materials, UTL-utilities, RES-real estate.

and 1.62, respectively. Their positions highlight their dual roles as both transmitters and receivers of market spillovers, reflecting their centrality and widespread impact in the cryptocurrency market. This outcome is in-line with the findings from Mensi et al. (2019), who showed that Bitcoin often acts as a net recipient of spillovers as well as transmitting positive spillovers to other assets. Similarly, the FIN, IND and MAT sectors emerge as key net transmitters. These sectors display their capacity to drive market changes through their integration with cryptocurrencies and digital technologies. In contrast, gold-backed cryptocurrencies such as PAXG and X8X, with NET values of −7.99 and −5.39, respectively, act as significant net receivers of spillovers. As well as EMSI such as ENG, IT, and RES. These results highlight their roles as stable, less volatile assets, appealing to investors seeking stability that are consistent with Khan et al. 2023. These insights underline the complex relationship between cryptocurrencies and EMSI, offering strategic perspectives for investors and policymakers navigating this dynamic environment.

The TCI value of 65.43 represents the moderately high level of interconnectedness within the network of cryptocurrencies and EMSI. This level of connectedness indicates the growing interaction between EMSI and the cryptocurrency market, suggesting that while the spillovers are significant, there are still some independent dynamics at play within certain sectors. A similar finding has been reported by Khalfaoui et al. (2023), who found a moderate TCI between BRCIS stock indices and cryptocurrencies in the median quantile, although in our sectoral level findings, we reported a moderately TCI high index. Yet, the corrected Total Connectedness Index (cTCI) value of 70.10, which is higher than the TCI, provides an adjusted perspective that accounts for other factors and internal sector dynamics that might otherwise obscure the genuine cross-sector spillovers. Our results show that the cTCI is higher than the TCI, which implies that the actual connectedness in the network is even more pronounced than initially observed. This suggests that underlying systemic factors enhance the influence and sensitivity among sectors, emphasizing the importance of understanding these hidden dynamics for a complete picture of market interactions. This insight is crucial for investors and portfolio managers to transform portfolio strategies, as it highlights the necessity of accounting for internal sector behaviours.

4.2. Dynamic total connectedness

Fig. 1 displays the time-varying dynamic total connectedness plot between cryptocurrencies and EMSI from 2019 to 2024. The figure shows that in early 2020, there was a notable surge in connectedness, which can be attributed to the global onset of the COVID-19 pandemic. This period was marked by heightened volatility and uncertainty, driving increased correlations among financial assets as markets reacted to lockdowns and economic disruptions (Maghyereh et al., 2022). These spikes suggest that cryptocurrencies and EMSI became more interconnected due to investors seeking alternative assets amid turbulent conditions.

Furthermore, there is a considerable peak in connectedness observed in 2021 which is mainly due to a bull run in cryptocurrencies, fuelled by institutional interest and mainstream adoption. Additionally, emerging markets faced significant developments such as supply chain disruptions and inflationary pressures, influencing the integration of digital assets as hedging instruments (Cheng et al., 2023; Throughout 2022 and into 2023, the connectedness levels show several peaks, highlighting the sustained integration between cryptocurrencies and EMSI due to ongoing global challenges, such as geopolitical tensions (e.g., the Middle East crisis and Russia-Ukraine conflict) and shifting economic policies (Lau et al., 2024). As the timeline approaches 2024, connectedness slightly decreases but remains robust, highlighting the continued impact of digital currencies on EMSI. This persistent interconnectedness emphasizes the critical need for investors and policymakers to monitor these dynamic interactions, as they navigate a landscape increasingly shaped by rapid technological advancements and financial innovation.

4.3. Network analysis and net total directional connectedness

In Fig. 2, the network plot provides a visual representation of the interconnectedness and spillover dynamics between cryptocurrencies and EMSI. In this plot, blue nodes represent transmitters of spillovers, while yellow nodes signify recipients. The varying thickness of the connecting lines indicates the strength of the spillover effects, with thicker lines representing stronger influences. The plot illustrates that gold-backed cryptocurrencies such as PAXG and X8X are prominent recipients of spillovers from other assets, particularly materials and

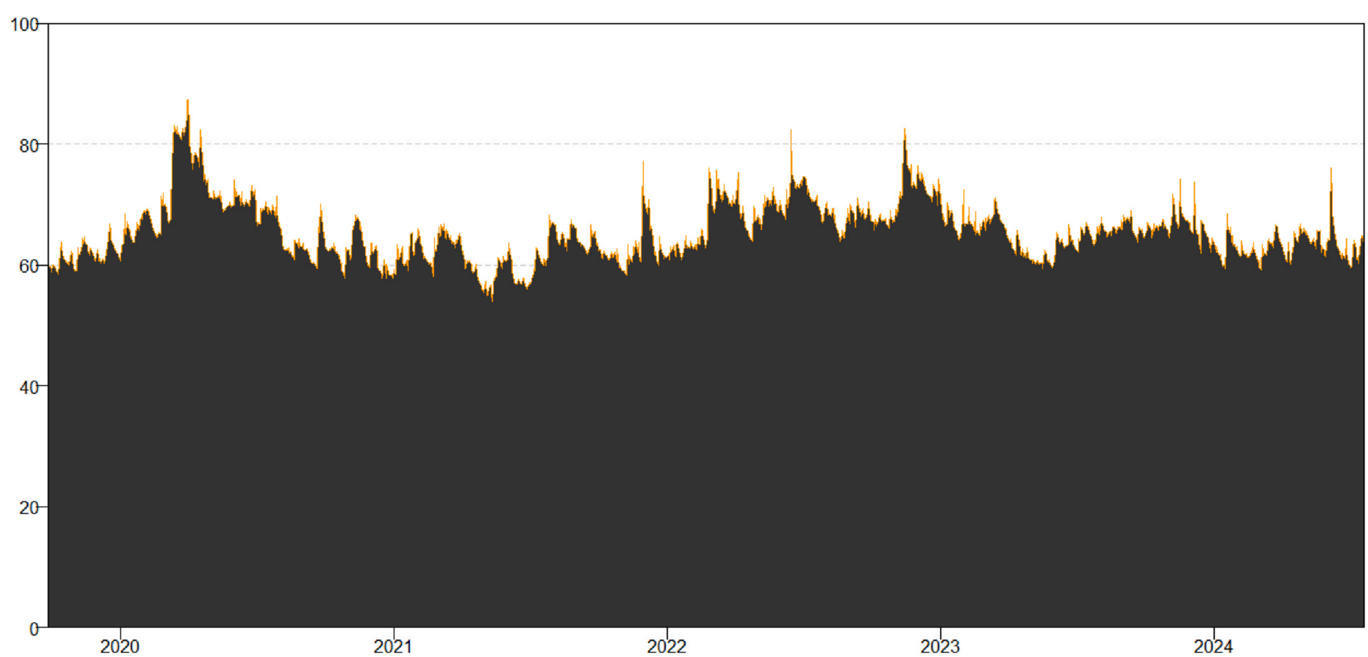

Fig. 1. Total Dynamic Connectedness Index between Cryptocurrencies and Emerging Market Sectors
Notes: This figure displays the time-varying total average DCC-GARCH R^2 decomposed connectedness index between cryptocurrencies and emerging market sectors.

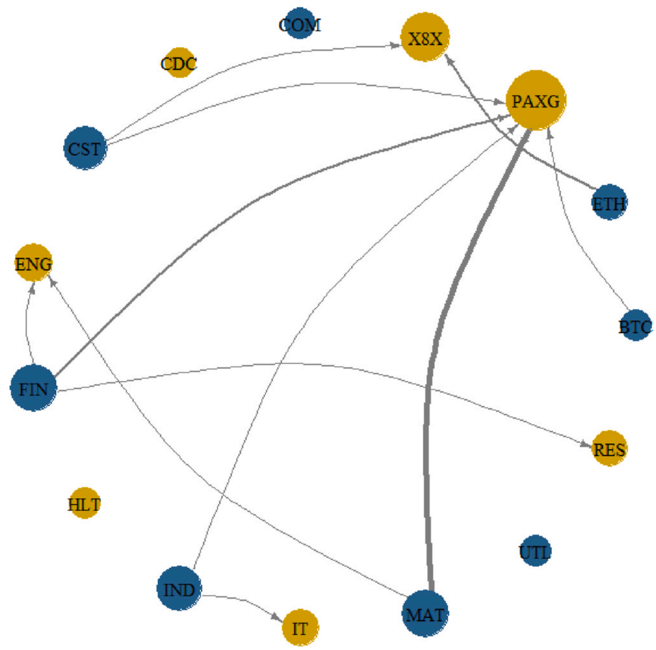

Fig. 2. Network Analysis
Notes: This figure displays the network analysis between cryptocurrencies and emerging market sectors.

financials sectors in the network. This shows that gold-backed cryptocurrencies offer a way to diversify into digital assets because investors often turn to traditional safe-haven assets like gold during turmoil. Our findings are consistent with Ali et al. (2024), who reported that gold-backed cryptocurrencies are net recipients in GCC equity markets.

In contrast, BTC, ETH, FIN, MAT, IND and CST demonstrate their roles as transmitters of spillovers to other assets in the system. The financials sector has strong connections with various nodes, illustrating its central role in driving spillovers, potentially due to its deep integration with both traditional markets and digital finance through investments and technological innovations. These results match with the findings presented in Table 2. Overall, this network plot provides valuable insights into the dynamic relationship of market forces, illustrating how EMSI and cryptocurrencies influence and react to each other.

Fig. 3 illustrates the time-varying net total directional connectedness plot for cryptocurrencies and EMSI from 2019 to 2024. Throughout this period, BTC and ETH frequently transition between being net transmitters and receivers of shocks, reflecting their volatility and central roles in the crypto market. Notably, ETH's peaks in 2021 align with its bull run and the significant technological upgrade of Ethereum 2.0 (Ahn et al., 2024), which attracted substantial investor interest. The FIN, MAT, CST and IND sectors consistently act as net transmitters. Interestingly, the ENG sector is a spillover transmitter due to a correlation with shifts in global commodity prices and the energy market, which were influenced by geopolitical tensions and the transition to renewable energy. Meanwhile, both gold-backed cryptocurrencies PAXG and X8X, largely remain a net receiver, highlighting its stability and appeal as a hedge against market volatility.

5. Multivariate portfolio analysis

In this section, we employ multivariate portfolio optimization techniques, as recommended by Cocca et al. (2024), to evaluate diversification strategies across cryptocurrencies and EMSI. These techniques enable a comprehensive analysis of risk-adjusted portfolio construction, considering different dimensions of asset interactions. The first approach, the Minimum Variance Portfolio (MVP), seeks to minimize overall portfolio risk by optimizing the variance-covariance matrix of asset returns, ensuring efficient risk allocation (Markowitz, 1952). The optimization problem is formulated as follows:

Equation 18

$$minimize\ \sigma_p^2 = w'\Sigma w \quad s.t. \quad w'1 = 1\ and\ w \geq 0$$

Where σ_p^2 is portfolio variance, w is the vector of portfolio weights and Σ denotes covariance matrix. The objective is to find the portfolio weights (w) that minimize the variance while ensuring that the sum of weights equals one, and no short selling occurs. Second, the Minimum

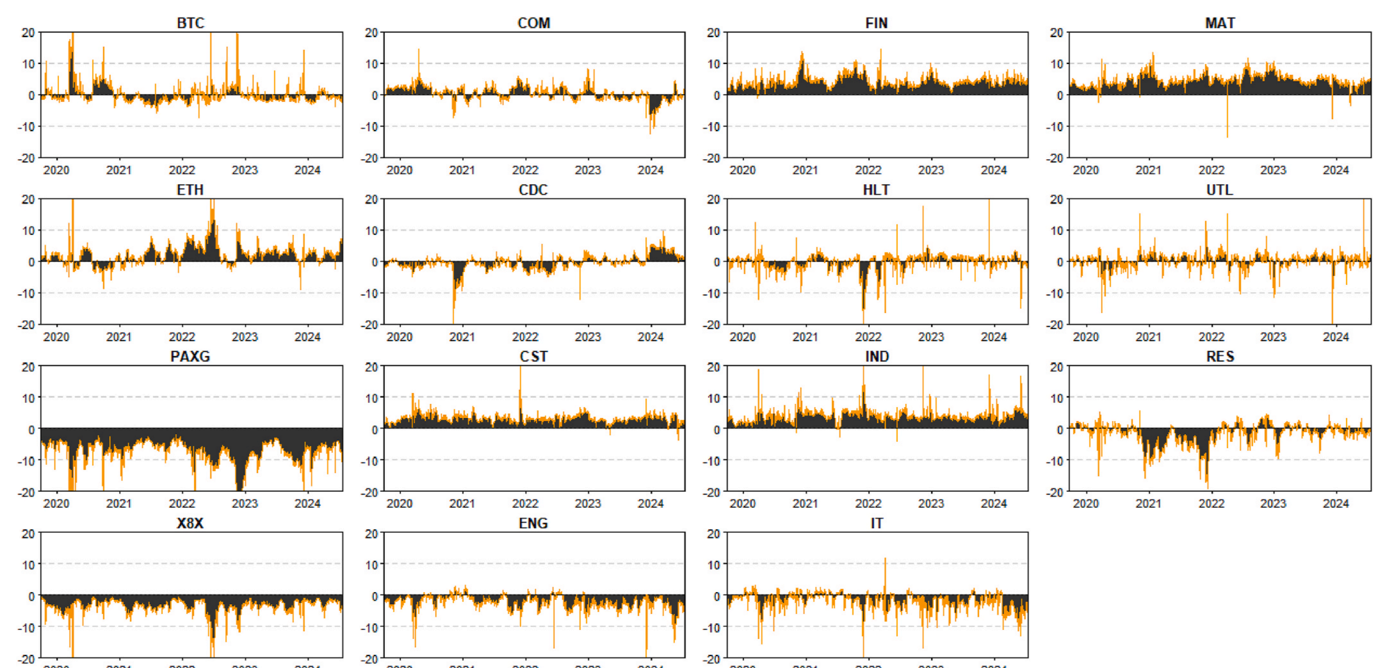

Fig. 3. Net Total Directional Connectedness
Notes: This figure displays the time-varying net total directional connectedness between cryptocurrencies and emerging market sectors.

Correlation Portfolio (MCP) minimizes the overall correlation between assets in the portfolio (Christoffersen et al., 2014). The optimization problem is expressed as:

Equation 19

$$\textit{minimize}\ \rho_p = w'Rw \quad s.t. \quad w'1 = 1 \textit{ and } w \geq 0$$

Where ρ_p is portfolio correlation and R is the correlation matrix. This method reduces the interdependencies within the portfolio by focusing on the correlations between assets rather than their variances. Third, the Minimum Correlation Portfolio (MCP) as proposed by Broadstock et al. (2022) minimizes the connectedness between cryptocurrency and emerging market sectors. The connectedness is derived from dynamic measures of risk transmission:

Equation 20

$$\textit{minimize}\ C_p = w'Cw \quad s.t. \quad w'1 = 1 \textit{ and } w \geq 0$$

Where C_p is the portfolio connectedness and C indicates connectedness matrix, which measures the transmission of shocks between assets. This portfolio aims to minimize the spillover of risks from one asset to another within the portfolio. Fourth, the Minimum Bivariate R^2 Portfolio (MBP) minimizes the bivariate R^2 values, which represent the explanatory power of one asset's returns over another (Cocca et al., 2024). The optimization is given by

Equation 21

$$\textit{minimize}\ R_p^2 = \sum_{i \neq j} w_i R_{ij}^2 w_j \quad s.t. \quad w'1 = 1 \textit{ and } w \geq 0$$

Where R_p^2 is the bivariate R^2 values of a portfolio. This method reduces the predictive power that one asset's returns have on another within the portfolio, thus lowering potential risk spillovers. Lastly, the Minimum R^2 Decomposed Connectedness Portfolio (MDP) of Cocca et al. (2024) uses a decomposed R^2 measure derived from a Dynamic Conditional Correlation (DCC-GARCH) model:

Equation 22

$$\textit{minimize}\ R_{d,p}^2 = w'R_p^2 w \quad s.t. \quad w'1 = 1 \textit{ and } w \geq 0$$

Where $R_{d,p}^2$ is the decomposed R^2 for the portfolio and R_p^2 represents the decomposed R^2 matrix. This approach provides a more detailed view of the risk transmission within the portfolio by focusing on the decomposition of R^2, which captures both contemporaneous and lagged effects between assets.

Afterwards, the performance of the above-mentioned portfolios is evaluated using two key metrics: First, the Sharpe Ratio (SR) assesses the return per unit of risk, helping to compare the effectiveness of different portfolio strategies in achieving high returns relative to risk (Sharpe, 1994). The SR is calculated as:

Equation 23

$$SR = \frac{\widehat{x}_p}{\sqrt{varx_p}}$$

Where $\widehat{x}_p$ is the average portfolio returns and $varx_p$ denotes portfolio variance. A higher SR reflects superior returns relative to portfolio risk. Assessing the SRs of different portfolios enables us to pinpoint the portfolio with the highest return while maintaining the same level of volatility. Alternatively, we incorporate the Value at Risk (VaR) and Conditional Value at Risk (CVaR) as the denominator in our analysis. Second, we calculate the Hedging Effectiveness (HE) based on Ederington (1979), this measure evaluates the extent to which a portfolio reduces risk compared to holding a single asset. The higher the HE index, the more effective the portfolio is at mitigating risk. The HE can be denoted as follows:

Equation 24

$$HE_i = 1 - \frac{var(x_p)}{var(x_i)}$$

Where $var(x_i)$ presents the variance of asset *i*. Further, to assess the significance level, we employ the HE test statistics created by Antonakakis et al. (2020).

Tables 3a and 3b presents the multivariate portfolio analysis between cryptocurrencies and EMSI. The results, based on the MVP designed to reduce overall portfolio variance, indicate a dominant weighting in PAXG and the consumer staple sector. The significant allocation to PAXG, with a mean weight of 0.173 and a relatively high standard deviation, suggests that the strategy is geared towards stability and lower volatility. PAXG's gold-backed nature offers a hedge against the inherent volatility of cryptocurrencies, justifying its larger allocation. The HE values for ETH and X8X are extremely high, indicating these assets' role in stabilizing the portfolio, although with minimal exposure. This conservative stance results in a Sharpe ratio of 0.311, highlighting its effectiveness in risk-adjusted returns but also indicating limited performance in higher-return potential.

Then the MCP focuses on minimizing asset correlations which results in increased allocations to cryptocurrencies (BTC and X8X) and EMSI such as IT, real estate and energy. This strategy aims to exploit lower correlations to enhance portfolio stability. Particularly, this significant allocation towards bitcoin comes at a higher risk, evidenced by a Sharpe ratio of 0.005, implying that while correlations are reduced, the overall risk-return profile suffers. However, the results reflect a lower allocation to EMSI, such as CST and ENG, involving a shift away from stable sectors, potentially forgoing stability for the sake of diversification. The MPP, which minimizes dynamic pairwise connectedness, balances risk through moderate allocations to cryptocurrencies and EMSI, achieving a higher Sharpe ratio of 0.088 compared to the MCP. This finding suggests that the MPP offers a more balanced approach, integrating both stability and diversification, although it still faces challenges in optimizing returns.

The result of MBP, with its emphasis on bivariate R^2 measures, allocates considerable weight to PAXG, X8X, IT and ENG assets, reflecting their perceived stability. Despite higher hedging effectiveness, the MBP's Sharpe ratio of 0.020 indicates modest returns relative to risk. On the other hand, the MDP, leveraging asymmetric connectedness measures, provides a more refined approach to managing risk, which is evident in its relatively higher Sharpe ratio of 0.112. This balanced allocation across cryptocurrencies and sectors like ENG and FIN reflects its comprehensive approach to risk, offering a comprehensive view of portfolio stability and performance. Overall, the superior Sharpe ratio of MDP relative to MCP and MBP highlights its effectiveness in balancing risk and return through advanced connectedness measures. This comparative analysis stresses the importance of selecting a portfolio strategy aligned with specific risk tolerance and investment goals, emphasizing that advanced techniques like connectedness measures can offer valuable insights for optimizing portfolio performance.

We further assess the performance of the above-discussed portfolios as compared to their market value, which is calculated as an Information ratio based on Cocca et al. (2024). Table 4 presents the comparative analysis of the five portfolio strategies which shows significant variations in performance, particularly concerning risk-adjusted returns and the Information Ratio relative to the market benchmark. The MVP emerges as the most robust option, delivering the highest return and demonstrating superior risk management with the best Sharpe ratios based on standard deviation, VaR and CVaR. This outcome shows that MVP effectively balances returns with risk, particularly in extreme market conditions. However, its Information Ratio suggests a slight underperformance compared to the market benchmark, though it remains the strongest among the portfolios.

On the contrary, the MCP performs the worst across all metrics, with extremely low returns and poor Sharpe ratios, indicating that

Table 3a
Multivariate portfolio analysis.

	Minimum Variance Portfolio (MVP)					Minimum Correlation Portfolio (MCP)					Minimum Connectedness Portfolio (MPP)				
	Mean	Std.Dev.	5 %	95 %	HE	Mean	Std.Dev.	5 %	95 %	HE	Mean	Std.Dev.	5 %	95 %	HE
BTC	0.014	0.015	0.000	0.043	0.964	0.115	0.051	0.024	0.192	0.673	0.069	0.014	0.044	0.087	0.766
ETH	0.000	0.003	0.000	0.001	0.979	0.020	0.033	0.000	0.072	0.805	0.060	0.013	0.041	0.083	0.860
PAXG	0.173	0.071	0.075	0.306	0.495	0.155	0.032	0.099	0.201	−3.623	0.119	0.005	0.111	0.128	−2.310
X8X rowhead	0.000	0.001	0.000	0.002	0.997	0.132	0.034	0.077	0.194	0.969	0.114	0.008	0.095	0.128	0.978
COM	0.038	0.053	0.000	0.147	0.749	0.033	0.043	0.000	0.123	−1.299	0.051	0.006	0.042	0.063	−0.646
CDC	0.004	0.014	0.000	0.031	0.827	0.043	0.043	0.000	0.123	−0.579	0.055	0.008	0.041	0.067	*−0.130*
CST	0.290	0.143	0.064	0.543	0.231	0.016	0.037	0.000	0.096	−6.037	0.051	0.007	0.040	0.062	−4.038
ENG	0.040	0.053	0.000	0.146	0.705	0.106	0.039	0.031	0.163	−1.698	0.075	0.006	0.066	0.086	−0.931
FIN	0.206	0.155	0.000	0.490	0.373	0.016	0.038	0.000	0.096	−4.733	0.042	0.005	0.033	0.050	−3.104
HLT	0.019	0.030	0.000	0.074	0.689	0.043	0.033	0.000	0.100	−1.849	0.069	0.007	0.056	0.080	−1.040
IND	0.115	0.118	0.000	0.343	0.482	0.016	0.038	0.000	0.096	−3.739	0.042	0.005	0.035	0.050	−2.392
IT	0.012	0.022	0.000	0.059	0.696	0.119	0.035	0.062	0.176	−1.782	0.074	0.007	0.064	0.086	−0.992
MAT	0.004	0.019	0.000	0.024	0.607	0.004	0.015	0.000	0.031	−2.592	0.042	0.006	0.033	0.051	−1.572
UTL	0.076	0.082	0.000	0.234	0.410	0.061	0.043	0.000	0.140	−4.398	0.063	0.007	0.052	0.074	−2.865
RES	0.010	0.020	0.000	0.058	0.768	0.119	0.043	0.043	0.186	−1.126	0.073	0.008	0.058	0.085	−0.522
Sharpe ratio	0.311					0.005					0.088				

Notes: This table reports the multivariate portfolio analysis of cryptocurrencies and emerging market sectoral indices. HE is the hedging effectiveness and Std.Dev. is the standard deviation. All the HE values are significant at 1 % level except the italic values are at 5 % level.

Table 3b
Multivariate portfolio analysis.

	Minimum Bivariate $\boldsymbol{R}^2$ Portfolio (MBP)					Minimum $\boldsymbol{R}^2$ Decomposed Connectedness Portfolio (MDP)				
	Mean	Std.Dev.	5 %	95 %	HE	Mean	Std.Dev.	5 %	95 %	HE
BTC	0.074	0.032	0.020	0.119	0.730	0.061	0.003	0.056	0.066	0.816
ETH	0.049	0.027	0.013	0.087	0.839	0.060	0.003	0.056	0.065	0.890
PAXG	0.131	0.029	0.077	0.165	−2.819	0.096	0.004	0.090	0.102	−1.594
X8X	0.115	0.027	0.065	0.154	0.974	0.095	0.005	0.084	0.103	0.982
COM	0.035	0.049	0.000	0.132	−0.899	0.058	0.003	0.054	0.063	−0.290
CDC	0.059	0.056	0.000	0.168	−0.304	0.059	0.004	0.053	0.066	*0.114*
CST	0.020	0.037	0.000	0.090	−4.813	0.060	0.003	0.055	0.066	−2.948
ENG	0.126	0.030	0.079	0.173	−1.229	0.070	0.003	0.065	0.076	−0.514
FIN	0.005	0.020	0.000	0.047	−3.736	0.055	0.003	0.052	0.060	−2.217
HLT	0.059	0.033	0.000	0.112	−1.353	0.069	0.004	0.062	0.075	−0.599
IND	0.008	0.028	0.000	0.059	−2.914	0.055	0.002	0.051	0.059	−1.659
IT	0.121	0.031	0.075	0.170	−1.298	0.070	0.004	0.064	0.078	−0.561
MAT	0.005	0.018	0.000	0.029	−1.968	0.057	0.003	0.054	0.062	−1.016
UTL	0.079	0.041	0.004	0.147	−3.459	0.066	0.004	0.060	0.072	−2.029
RES	0.115	0.035	0.063	0.170	−0.756	0.070	0.005	0.061	0.077	*−0.193*
Sharpe ratio	0.020					0.112				

Notes: This table reports multivariate portfolio analysis of cryptocurrencies and emerging market sectoral indices. HE is the hedging effectiveness and Std.Dev. is the standard deviation. All the HE values are significant at 1 % level except the italic values are at 5 % level.

Table 4
Portfolio performance analysis.

	MVP	MCP	MPP	MBP	MDP
Return	0.00038	0.00002	0.00028	0.00007	0.00031
Std. Dev	0.0012	0.0037	0.0031	0.0034	0.0028
Sharpe ratio (StdDev)	0.3109	0.0046	0.0879	0.0201	0.1116
Sharpe ratio (VaR)	2.8987	0.0516	0.8642	0.2104	1.0654
Sharpe ratio (CVaR)	0.9763	0.0516	0.3174	0.1056	0.3804
Information ratio	−0.6183	−0.6957	−0.6813	−0.6951	−0.6830

Notes: This table reports the performance of different portfolios. Std.Dev. is the standard deviation. MVP- minimum variance portfolio, MCP- minimum correlation portfolio, MPP- minimum connectedness portfolio, MBP- minimum bivariate R^2 portfolio, MDP- minimum R^2 decomposed connectedness portfolio.

minimizing correlation alone is not an effective strategy for enhancing risk-adjusted returns. Moreover, the MPP, MBP, and MDP portfolios offer intermediate performance, with each showing varying degrees of effectiveness in balancing risk and return. MPP and MDP show some strength in managing risk, particularly under extreme market conditions, as reflected in their higher Sharpe ratios based on VaR and CVaR. But none of these portfolios outperform the market benchmark, as indicated by their negative Information Ratios. These findings underline the challenges of constructing portfolios that not only manage risk effectively but also outperform the market in the complex landscape of emerging markets and cryptocurrencies.

6. Conclusion and implications

This study explored the connectedness dynamics between cryptocurrencies (both conventional and gold-backed) and emerging market sectoral indices (EMSI). This motivation arose from the limited literature on how cryptocurrencies can enhance a portfolio of emerging market sectoral indices. Using data from 2019 to 2024, we applied a novel DCC-GARCH-based R^2 decomposed connectedness approach to analyse return connectedness among these high-risk assets. We also utilised innovative concepts such as minimum dynamic pairwise connectedness and minimum R^2 decomposed connectedness portfolios in our multivariate hedging portfolios.

Our findings highlight that BTC and ETH play pivotal roles in this interconnectedness, acting as both leaders and responders in the system.

While gold-backed cryptocurrencies like PAXG and X8X have a more limited impact, but three EMSIs (financials, industrials, and materials sectors) show significant connectedness with digital and blockchain technologies, enhancing their influence in the broader network. Our analysis reveals a moderately high level of connectedness between cryptocurrency market and EMSI, as indicated by the total connectedness index. Moreover, gold-backed cryptocurrencies and sectors like energy, information technology and real estate act as net receivers of spillovers, highlighting their role as stable assets in times of market turbulence.

The analysis of portfolios combining cryptocurrencies with EMSI revealed several key findings. The minimum variance portfolio showed the highest Sharpe ratio, but slightly underperformed relative to market benchmarks. Moreover, the minimum correlation portfolio allocated significantly to cryptocurrencies and diverse sectors but suffered from high risk and a low Sharpe ratio. Likewise, the minimum pairwise connectedness portfolio offered a more balanced approach, and the Advanced strategies achieved the highest Sharpe ratio, but no portfolio outperformed the market benchmark.

Based on our findings, investors, portfolio managers and hedge funds should consider three key implications when managing portfolios with volatile assets like cryptocurrencies and EMSI. First, the roles of Bitcoin and Ethereum as net transmitters of shocks suggest that these assets can significantly influence the broader portfolio, particularly during periods of market turbulence. Therefore, carefully monitoring their performance and adjusting exposure based on market conditions could enhance portfolio resilience. Second, while gold-backed cryptocurrencies and certain emerging market sectors like energy and real estate consistently act as net receivers of shocks, their inclusion in a portfolio may provide stability during extreme events. These assets can serve as buffers against market volatility, offering a hedge when paired with more dynamic assets like Bitcoin and Ethereum. Finally, despite the sophisticated strategies we examined achieving strong risk-return balances, none outperformed market benchmarks, highlighting the importance of realistic expectations and the need for continuous portfolio rebalancing to adapt to shifting market dynamics.

Additionally, the identification of key sectors, such as financials and industrials, as central transmitters of market changes highlight the importance of monitoring these sectors for early signals of market shifts. For policymakers, the persistent interconnectedness between these markets shows the need for regulatory frameworks that address the unique challenges and opportunities posed by the integration of digital assets with traditional financial markets. These insights can help in constructing policies that ensure financial stability while promoting innovation in the rapidly evolving digital economy.

Future research could dig deeper into the evolving dynamics of connectedness between cryptocurrencies and EMSI, particularly as these relationships continue to be influenced by technological advancements, regulatory changes, and global economic shifts. One can investigate the role of new and emerging cryptocurrencies, as well as the potential impacts of digital central bank currencies (CBDCs), which could offer valuable insights into how these innovations might alter market interconnectedness. Additionally, future studies could explore the long-term effects of geopolitical events and environmental factors, such as the transition to renewable energy, on the interaction between cryptocurrencies and emerging markets. Expanding the analysis to include a broader range of assets and sectors, as well as incorporating machine learning techniques to predict future trends, could further enhance our understanding of these complex market interactions.

CRediT authorship contribution statement

Adnan Aslam: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Rayenda Khresna Brahmana:** Conceptualization, Formal analysis, Investigation, Resources, Supervision, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing.

Data availability statement

The data and codes are available upon request from the corresponding author.

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