Anecdote of Asymmetry: Analysis of Dependence Structure, Hedging Strategies Between Green Financial Assets and Green Crypto Assets

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Abstract
Cryptocurrency (crypto) markets have changed the investment landscape for many; however, they have started feeling the heat of the growing climate change awareness and are being prompted to shift towards green financial assets or clean/green cryptos. Climate change and sustainability have become an essential part of every discussion for businesses and investors. This study attempts to discover the connectedness between green financial assets and green cryptos. This paper builds upon a novel approach of copula analysis to shed light on the tail dependencies of the two asset classes. The findings provide interesting insights for investors to consider these two classes for portfolio diversification benefits or their hedging strategies, especially during a crisis period like COVID-19. The results indicate that the two asset classes exhibit distinct interdependencies, provide diversification and risk management opportunities, and behave differently during a crisis, and therefore present hedging and diversification opportunities to investors despite both asset classes being green.

JEL: G3, G01, G11
Keywords: Tail dependence, Copula, Green financial assets, Green crypto assets, Hedging, Portfolio

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1. INTRODUCTION

The phenomenal growth in the cryptocurrency market has led to the existence of over 8000 cryptocurrencies (Latif et.al., 2023). The growth in crypto comes at a cost, and its adverse impact on the climate is being acknowledged across the world[5] (Chamanara et. al., 2023). As climate change and environmental concerns gain momentum across the investors, the rise of green investment and green cryptos is inevitable (Patel et.al., 2024). Investing in green assets has captured significant attention from a diverse spectrum of investors. These investments typically align with projects promoting eco-friendly practices, renewable energy, and overall sustainability (Gutsche and Ziegler, 2019). Huang et al. (2022) observed that funds emphasizing green financial assets exhibit heightened quality and momentum. Impact investors, aiming to align monetary gains with societal benefits, play a pivotal role in this dynamic landscape. PwC report[6] suggests that Environmental, Social and Governance (ESG) focused institutional investments are poised to surge by 84%, reaching an estimated US$33.9 trillion by 2026. This surge underscores the increasing interest among institutional investors in incorporating green assets into their portfolios, driven by a desire to integrate ethical and environmental values into their financial goals.

Investing in green finance is not only a strategic move to moderate risk profiles compared to traditional investments but also an avenue for investors to align their financial objectives with ethical and environmental values. Firms with a strong commitment to environmental enhancement tend to outperform others in the long run (Xie et al., 2023). Furthermore, investments in green projects contribute to positive public perception, improved brand reputation, and enhanced customer loyalty (Vuong and Bui, 2023; Gao et al., 2024). The allure of green financing extends beyond financial benefits, unlocking new avenues for fundraising. As more investors and financial institutions express interest in supporting sustainable projects, companies embracing green financing options can attract a broader investor base and access funding at more favorable costs (Patel et.al., 2024).

[5] UN Study Reveals the Hidden Environmental Impacts of Bitcoin: Carbon is Not the Only Harmful By-product. (2025, May 16). United Nations University. https://unu.edu/press-release/un-study-reveals-hidden-environmental-impacts-bitcoin-carbon-not-only-harmful-product

[6] PricewaterhouseCoopers. (2022). ESG-focused institutional investment seen soaring 84% to US$33.9 trillion in 2026, making up 21.5% of assets under management: PwC report. PwC. https://www.pwc.com/gx/en/news-room/press-releases/2022/awm-revolution-2022-report.html

Internationally, regulatory bodies are increasingly endorsing green initiatives through incentives, tax breaks, grants, and favorable regulatory policies (Hermawan and Khoirunisa, 2024). These measures not only underscore the commitment to sustainability but also enhance the financial attractiveness of green financial assets. The recent issuance of standards by the International Sustainability Standards Board (ISSB)[7] further reinforces the importance of disclosing sustainability-related information, covering governance, strategy, risk management, and performance, along with industry-specific details.

While green financial assets focus explicitly on sustainability, the environmental impact of crypto assets has emerged as a concern (Wendl et. al., 2023; Chamanara et. al., 2023). Conventional energy-intensive cryptos utilizing the proof-of-work protocol have raised ecological alarms. In contrast, the energy-efficient Proof of Stake (PoS) has positioned certain crypto assets as environmentally friendly, earning them the label of green cryptos (Arora et. al., 2025).

The growing interest in green finance in the post-COVID era has led investors to consider green cryptos and green financial assets as a prominent investment alternative for their portfolio. However, there is limited literature on green cryptos and green financial assets, especially examining the interconnections between them and the possibility of hedging one with another. This paper investigates the dependency between green cryptos and green financial assets and also examines whether hedging between green financial assets and green crypto assets is a possibility. This study contributes to the existing body of literature by shedding light on the dynamics at the intersection of these two increasingly prominent investment domains.

2. RELEVANT LITERATURE

Although there are numerous studies examining the market dynamics of financial assets, very few are available on green assets. In recent times, investors highlight the need for sustainability-conscious returns while reducing systematic risk of their portfolio for positive environmental and social outcomes (Patel et.al., 2024; Mensi et al., 2022). Ren and Lucey (2022 a,b) argue that investments in green assets act as a potential diversification tool in portfolio management. The literature on hedging strategies for emerging market stock prices, exemplified by Basher and Sadorsky (2015), underscores the

[7] IFRS - Introduction to the ISSB and IFRS Sustainability Disclosure Standards. (2023). Ifrs.org. https://www.ifrs.org/sustainability/knowledge-hub/introduction-to-issb-and-ifrs-sustainability-disclosure-standards/

significance of comparing the effectiveness of various assets, including oil, gold, VIX, and bonds. This involves utilizing empirical models such as DCC, ADCC, and GO-GARCH to model volatility dynamics, conditional correlations, and hedge ratios between emerging market stock prices and diverse commodities. Cerqueti, Giacalone, and Mattera (2020) evaluate the forecasting performance of non-Gaussian GARCH models for major cryptocurrencies (Bitcoin, Litecoin, and Ethereum). They advocate for the use of skewed distributions for improved prediction performance and highlight the high volatility of cryptocurrencies and the growing competition among them, offering insights beyond previous in-sample analyses. Yadav et al. (2022) studied the interconnectedness of the green bond market with energy, cryptocurrency, and carbon markets. They indicate the existence of a risk transmission pattern, with the short run displaying lower connectedness compared to the medium and long run, emphasizing the dynamic nature of risk factors.

The rising interest in studying risk spillover effects between green bonds and other financial markets, as evidenced by Liu et al. (2021), Mensi et al. (2022), and Reboredo and Ugolini (2020), emphasizes the need to capture spillover effects of lower and higher-order moments in green financial markets. Reboredo and Ugolini (2020) focus on dynamic connectedness between green financial markets and others, assessing spillover effects in returns, volatility, skewness, and kurtosis, revealing the risk hedging potential of green financial markets. Bostanci and Yilmaz (2020) utilize network topology visualization techniques for a static spillover structure in green finance markets. Naeem, Karim, Uddin, and Juttila (2022) examine the return and volatility connectedness of emerging green assets in comparison to established US industry stocks and commodity markets. Time-varying connectedness experiences pronounced crisis jumps, indicating heightened interrelations during tumultuous periods.

Zangh, He, and Hamori (2023) observe a mild spillover effect of the Russia-Ukraine war on the green finance market but note a significant and unprecedented influence of the COVID-19 pandemic on spillovers in both lower- and higher-order moments in this market. Tiwari et al. (2023) explore the impact of fintech on green financial assets and energy markets, revealing high directionality predictability in most markets, except for lower quantile green bonds. In contrast, Wang et al. (2023) find a negative connection between green bond and clean energy markets and geopolitical risk at extreme quantiles. Ferrer, Benitez, and Bolos (2021) reveal distinct patterns of interconnection, indicating that green bonds are closely linked to Treasury and investment-grade corporate bonds, while green stocks exhibit strong ties with general stocks. Surprisingly, despite their shared climate-friendly nature, there is no significant association between green bonds and green stocks.

Huang, Duan, and Urguhart (2022) investigate time-varying market linkages between Bitcoin and green assets, noting that green assets consistently prove to be an effective hedge for Bitcoin, irrespective of the pandemic, suggesting green assets as shelters amid market uncertainties. Haq (2022) examines the time-frequency co-movement among green financial assets and cryptocurrency uncertainties, finding positive co-movements in the medium-term, suggesting the time-varying leading role of green financial assets in influencing cryptocurrency indices. Fernandes et al. (2023) investigate multifractality in green bonds, stock sector indices, and US economic sector bonds, revealing non-linear cross-correlations. Contrary to expectations, green bonds, considered exclusively for sustainable investments, exhibit inefficiencies. Asiri, Alenmer, and Bhatti (2023) explore the dynamic relationship between cryptocurrency uncertainty indices and returns and volatility across a spectrum of financial assets, highlighting interconnectedness among returns in these asset classes during the pandemic, with cryptocurrency uncertainty indices serving as influential transmitters of shocks to other financial categories.

This study attempts to uncover the dependence dynamics of green financial assets and green (clean) crypto assets, as they share subtleties from a sustainability perspective, which are unexplored in literature. If clean cryptocurrencies and green financial assets display dissimilar dynamics, this might provide opportunities to green investors for portfolio diversification. This study utilizes copula analysis to explore dependencies beyond linear correlations and attempts to capture extreme co-movements to suggest possibilities of hedging strategies for investors. The study further highlights the tail dependency of the green financial assets and green cryptos by investigating the three sub-samples covering pre-covid, during covid, and post-covid and captures the risk transmission pattern during extreme events.

3. DATA AND METHODOLOGY

Our data sample consists of the green financial assets: Green Bond Index (GBI), Dow Jones Sustainability Index (DJSI), and Global Clean Energy Index (CEI) and top three green crypto assets by market capitalization: Ethereum (ETH), Binance (BNB), and Cardano (ADA) prices from 2 January 2018 to 18 July 2023 resulting in 1438 days. The financial assets data is collected from Bloomberg, and green crypto assets data is obtained from www.coinmarketcap.com. The sample period is divided into three subsamples, the first period covers before the outbreak of the COVID -19 (2nd January 2018 to 30th December 2019), the second subperiod covers the COVID – 19 period (31st December 2019 to 23rd February 2022) and the third sub period covers post COVID – 19 (24th February 2022 to 18th July 2023) as suggested by Jlassi et al. (2023).

Table A.1 displays the descriptive statistics of the return series where the average return of BNB is higher than that of other assets. Average returns of all the assets are positive except Cardano. The Q statistics of order 12 confirm no autocorrelations in the return and squared return series. The ACRH- LM (12) test results confirm the presence of heteroscedasticity in all return series.

3.1 Methodology

To analyze the dependence structure, firstly, following Cerqueti et al (2020), we employ a GARCH-SEG model to get independent and identically distributed (i.i.d) series for non-normal distributions. Subsequently, we use the copula approach proposed by Liu et al. (2017) to analyze the dependency structure between green financial assets and green crypto assets. The copula approach precisely considers positive and negative dependence using Kendall's τ as a measure of dependency structure, ranging from asymmetric positive to negative dependence.

A bi-variate copula is a probability distribution function with uniformly distributed marginal distributions. Given two random variables {X, Y} and F representing a two-dimensional distribution function with marginal distribution function $[0,1]^2 \rightarrow [0,1]$, then the dependency of the marginal distribution of the random variables can be expressed as follows:

$$F(x, y,) = P(x< u, y<v) \quad \text{(Eq. 1)}$$

$$= C(P(x< u, y<v)) \quad \text{(Eq. 2)}$$

$$= C(F_{(}u_{)}, F(v)) \quad \text{(Eq. 3)}$$

Table A.1: Descriptive statistics of return series

Markets	Min	Max	Mean	Median	Std. Dev.	Skewness	Kurtosis	J-B	Q(12)	$Q^2(12)$	ARCH-LM (12)
Panel A: Green Financial Assets											
DJSI	-10.61	7.69	0.02	0.06	1.02	-1.19	20.05	17736.29***	157.7***	1234.7***	489.1178***
GBI	-2.41	2.27	-0.01	0.00	0.39	-0.20	8.24	1650.947***	67.967***	587.74***	189.7943***
CEI	-12.50	11.03	0.05	0.05	1.72	-0.44	10.50	3412.01***	74.847***	1042.2***	398.3311***
Panel B: Green Crypto Assets											
ETH	-55.07	34.35	0.05	0.03	5.84	-0.76	11.92	4897.953***	25.765***	45.298***	29.53145***
BNB	-54.31	52.92	0.23	0.15	6.31	-0.07	16.28	10563.33***	19.453***	120.32***	76.19332***
ADA	-50.37	32.18	-0.07	-0.08	6.68	0.02	7.46	1189.85***	24.548***	92.959***	52.65488***

Note: This Table reports descriptive statistics and stochastic properties of Green Financial assets and Green Cryptocurrencies returns. J–B is the Jarque–Bera normality test. Q(12) and $Q^2(12)$ refer to the Ljung–Box test for autocorrelation of the returns and squared returns series, respectively. The ARCH-LM (12) test checks the existence of the ARCH effect. ''***'' denotes the rejection of the null hypotheses of normality, no autocorrelation, and conditional homoscedasticity at the 1% significance level.

Where F(u) and F(v) follow uniform distribution, and F denotes the marginal probability distribution function.

Kendall's tau (τC) is a measure of tail dependency in coupling a joint distribution function with its marginals. It is a normalized expected value for continuous copulas. Kendall's tau for the r.v.s X and Y with copula C denoted as

$$\tau_c = 1 - 4 \iint_{I^2} \frac{\partial C(u,v)}{\partial u} \frac{\partial C(u,v)}{\partial v} \, du \, dv \qquad \text{(Eq. 4)}$$

Finally, we compute hedge ratios (γ_t) to minimize the conditional variances of a portfolio consisting of green financial assets and green crypto assets. The optimal hedge ratio conditional on the information portfolio set can be obtained by taking the partial derivative of the variance with respect to γ_t and setting the expression equal to zero (Baillie and Myers, 1991).

$$\gamma_t^* | I_{t-1} = \frac{cov\,(R_{ft,}R_{ct} \,|\, I_{t-1})}{var\,(R_{ct} \,|\, I_{t-1})} \qquad \text{(Eq. 5)}$$

We use the conditional volatility estimates from GARCH models to derive the hedge ratio.

4. RESULTS

We explore the price movements of green financial assets and green crypto assets (Fig. 1) to visually examine the pricing patterns, and it appears to indicate similar price dynamics between the two asset classes, indicating convergence. We further explore the return series (Fig. 2) for the two asset classes and observe slightly different patterns in the post-covid period. However, there is some price convergence among ETH, BNB & ADA. Around the COVID period, green financial assets and green crypto assets are exhibiting high volatility. The long spike in the volatility around the COVID period indicates the need for analyzing the dependency for various sub-periods. To further explore the volatility patterns, we examine the conditional covariances of both the asset classes (Fig. 3) and observe that green cryptos are relatively less volatile than the green financial assets, suggesting hedging opportunities. This necessitates a detailed investigation of the dependence-dynamics of green financial assets and green (clean) crypto assets, especially to capture extreme co-movements during the three sub-samples of pre-covid, during covid, and post-covid periods, and assess the riskiness and hedging opportunities.

Fig 1: Price Movements

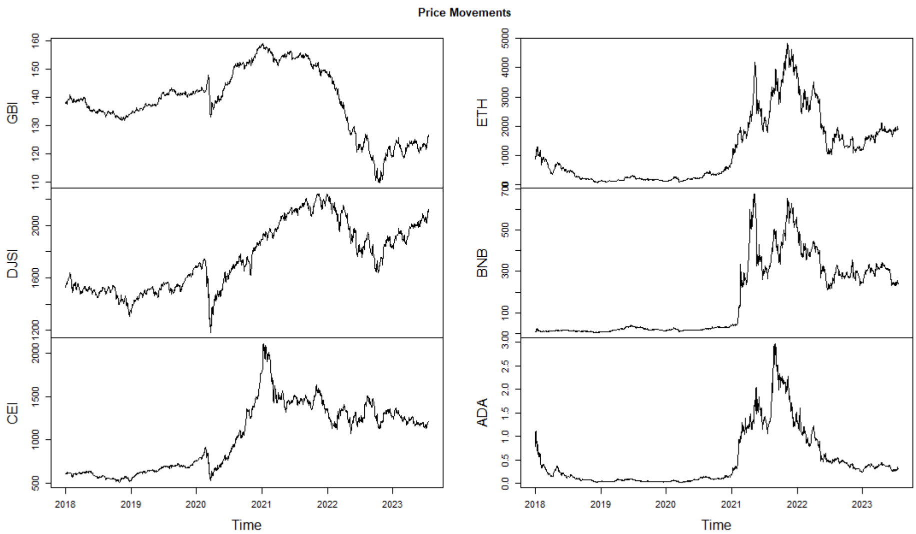


Fig. 2: Return Series

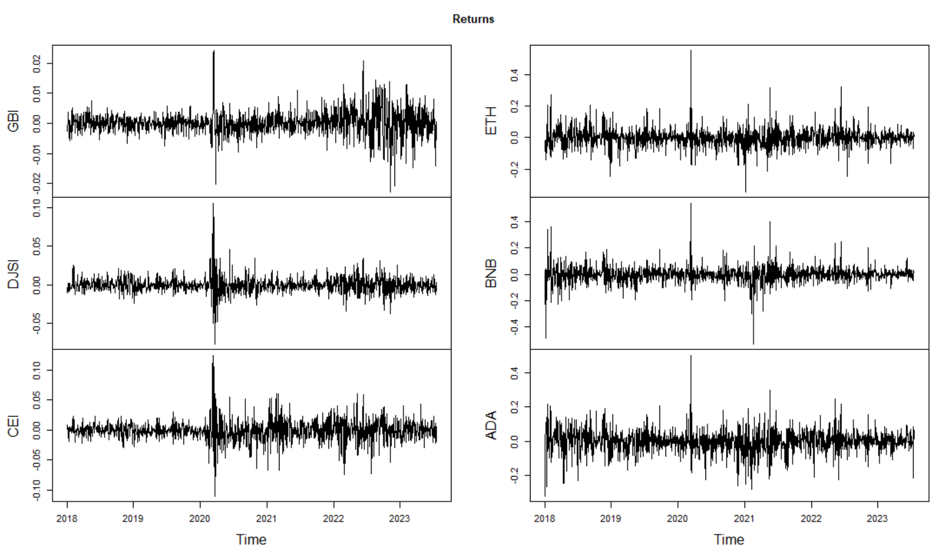
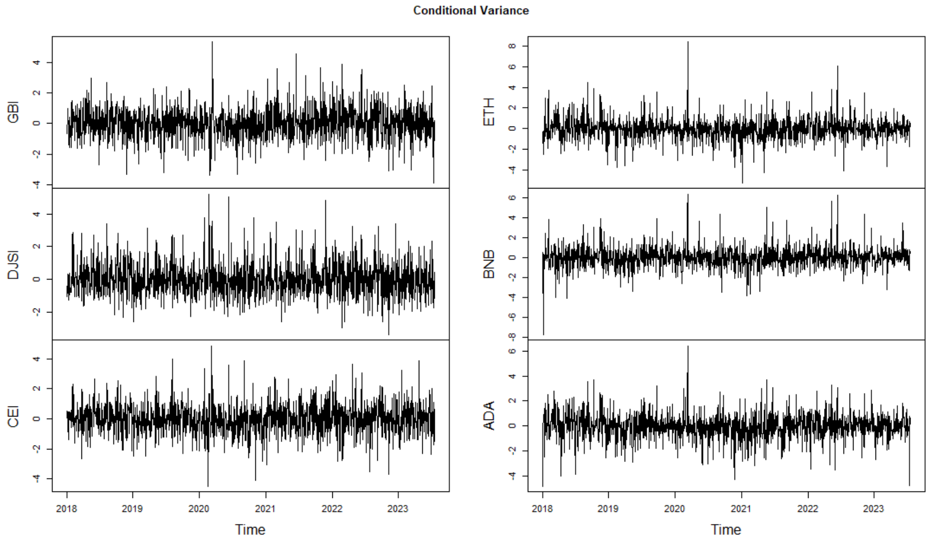


Fig. 3: Conditional Variances



We investigate the dependence structure among the different pairs of green financial assets and green crypto assets using copula analysis for the whole sample and present our findings in Table 1. The results suggest the existence of different families of copulas, such as Student t, Joe-Gumbel, Gumbel, Clayton-Gumbel, and Tawn type 1, and capture different types of dependencies. The tail dependencies suggest extreme co-movements. Within green financial assets, we observe GBI ↔ DJSI, GBI ↔ CEI, and DJSI ↔ CEI pairs are attributed to Student t copula, demonstrating moderate to significant symmetric tail dependencies between these indices. The strength and direction of the relationship among the green financial assets is observed by τC (Kendall's tau), where the values 0.18, 0.13, and 0.41 for these pairs show varying degrees of dependence, with DJSI and CEI showing the strongest correlation 0.41. The results confirm that Copulas like Joe-Gumbel and Gumbel exist among the green crypto assets (ETH ↔ BNB, ETH ↔ ADA, BNB ↔ ADA), indicating asymmetric dependence and stronger upper tail dependence. The high τC values (0.53, 0.6, 0.5) show that cryptocurrencies move together, particularly during extreme market swings. We find a weak dependency between green financial assets and green crypto assets as represented by significantly low τC values (0.08-0.15). The results show that although they do correlate, it is not as strong as it is for intra-group pairs.

Table 1: Results of Copula Analysis Comple Sample Size

Green Assets	Copula Family	Θ_1	Θ_2	Lower	Upper	τC
Within Green Financial Assets						
GBI ↔ DJSI	Student t	0.28	5.55	0.100	0.100	0.18***
GBI ↔ CEI	Student t	0.21	9.41	0.025	0.025	0.13***
DJSI ↔ CEI	Student t	0.61	6.38	0.218	0.218	0.41***
Within Green Crypto Assets						
ETH ↔ BNB	Joe-Gumbel	1.33	1.8	0	0.666	0.53***
ETH ↔ ADA	Gumbel	2.53		0	0.684	0.6***
BNB ↔ ADA	Joe-Gumbel	1.32	1.69	0	0.636	0.5***
Between Green Financial Assets and Green Crypto Assets						
GBI ↔ ETH	Clayton-Gumbel	0.09	1.04	0.001	0.049	0.08***
GBI ↔ BNB	Joe-Clayton	1.03	0.1	0.001	0.035	0.06***
GBI ↔ ADA	Clayton-Gumbel	0.07	1.04	0.000	0.049	0.07***
DJSI ↔ ETH	Gumbel	1.18		0.000	0.203	0.15***
DJSI ↔ BNB	Tawn type 1	1.29	0.33	0.000	0.147	0.11***
DJSI ↔ ADA	Gumbel	1.17		0.000	0.189	0.14***
CEI ↔ ETH	Tawn type 1	1.31	0.34	0.000	0.159	0.12***
CEI ↔ BNB	Gumbel	1.13		0.000	0.156	0.12***
CEI ↔ ADA	Gumbel	1.14		0.000	0.163	0.12***

Extant literature suggests extreme risk and returns during crisis/covid-19 periods (Liu et al. 2021; Magnanelli et al. 2022). Therefore, we investigate the dependency structure for both asset classes during the three sub-sample periods indicating pre-covid, during covid, and post-covid analysis. We use contour maps to visualize the correlation between various assets and subsequently substantiate the findings with copula analysis. From Fig. 4, Fig. 5, and Fig. 6, it is evident that for different sub-samples, the contour maps indicate tail dependency among various green financial assets and green cryptos. The Kendall tau (τC) number in Tables 2, 3, and 4 indicates the strength of the dependency for the best-fit copula model.

4.1 Pre-Covid-19 Period

The dependency structure of green financial assets and cryptocurrency assets prior to the COVID-19 pandemic is shown graphically in Figure 4 and numerically in Table 2. In Figure 4, the density of contours indicates the strength of dependency. Higher density and closeness of contours signify stronger dependence. Whereas, in Table 2, Kendall's tau (τC) shows the strength of dependencies. With a τC of 0.099, this study demonstrates that the GBI ↔ DJSI exhibits sparse contours within green financial assets, suggesting a slight joint movement and a weak yet positive dependence. While GBI ↔ CEI displays a moderate contour density with a τC of 0.083, the visual density for DJSI ↔ CEI corresponds with the numerical τC of 0.42, indicating strong co-movement. Within green crypto assets, the substantial dependency between these pairs (ETH ↔ ADA, ETH ↔ BNB, BNB ↔ ADA) is visually highlighted by the dense and elongated contour plots, which correspond to the high τC values of 0.61, 0.46, and 0.43, respectively. This suggests that, particularly under favorable extreme situations, these assets move closely together. Extremely low τC values (0.009 and 0.000038) and sparse contours demonstrate near independence between green assets and crypto assets (GBI ↔ ETH, GBI ↔ ADA) movements, highlighting no significant dependence.

Fig. 4: Pre-COVID Dependency Structure

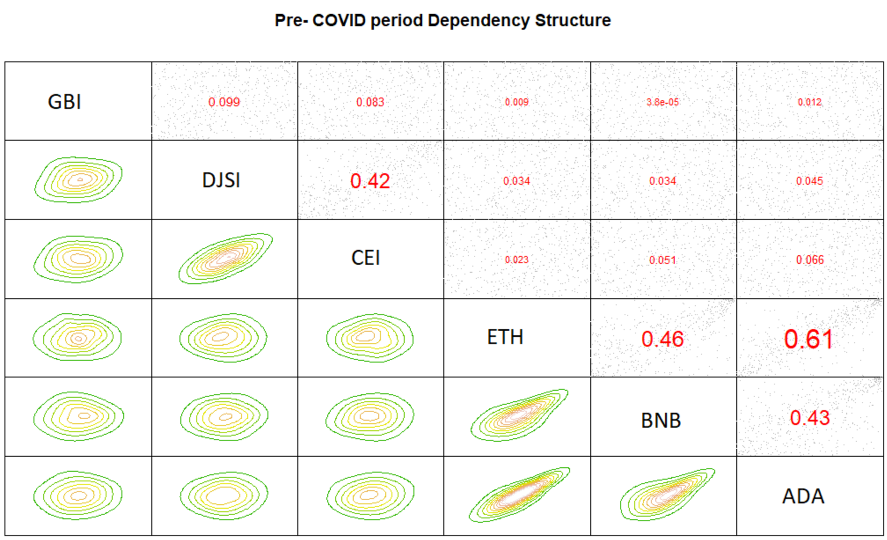


Table 2: Results of Copula Analysis Pre COVID sample (Sub Sample 1)

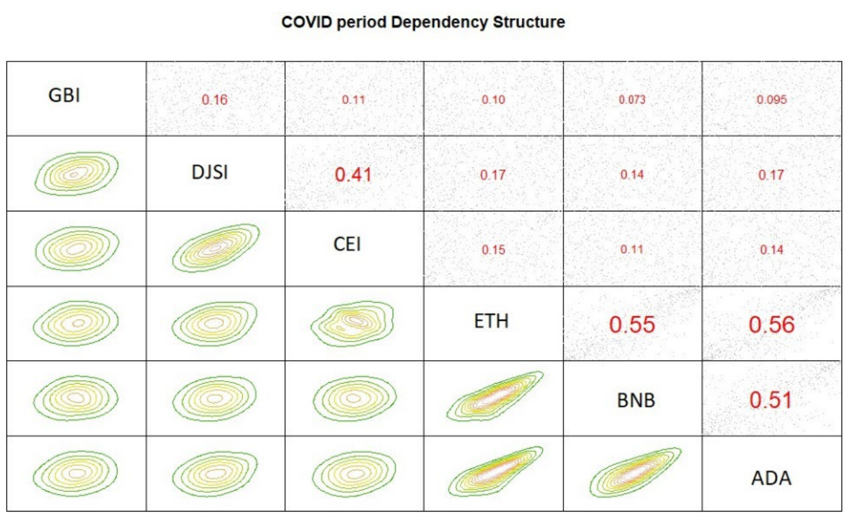
Green Assets	Copula Family	Θ_1	Θ_2	Lower	Upper	τ_C
Within Green Financial Assets						
GBI ↔ DJSI	Student t	0.16	5.34	0.074	0.074	0.10***
GBI ↔ CEI	Joe-Clayton	1.08	0.16	0.015	0.101	0.11***
DJSI ↔ CEI	Student t	0.64	4.46	0.319	0.319	0.44***
Within Green Crypto Assets						
ETH ↔ BNB	Joe-Clayton	2.33	0.17	0.018	0.654	0.45***
ETH ↔ ADA	Gumbel	2.57	0	0.690		0.61***
BNB ↔ ADA	Joe	2.21	0	0.631		0.40***
Between Green Financial Assets and Green Crypto Assets						
GBI ↔ ETH	Independence	0		0.000	0.000	0.00
GBI ↔ BNB	Tawn type 2	5.09	0.02	0.000	0.020	0.02
GBI ↔ ADA	Independence	0		0.000	0.000	0.00
DJSI ↔ ETH	Tawn type 1	1.43	0.07	0.000	0.057	0.05
DJSI ↔ BNB	Tawn type 1	1.76	0.05	0.000	0.048	0.04
DJSI ↔ ADA	Survival Clayton	0.11		0.000	0.002	0.05
CEI ↔ ETH	Tawn type 1	1.39	0.07	0.000	0.049	0.04
CEI ↔ BNB	Tawn type 1	1.53	0.08	0.000	0.065	0.05*
CEI ↔ ADA	Survival Clayton	0.12		0.000	0.004	0.06**

According to Table 2 in the pre-covid period, within Green Financial Assets, GBI ↔ DJSI is observed with a student copula, showing a moderately symmetric tail dependence with a τC of 0.10. This suggests a mild correlation in their joint movements. GBI ↔ CEI modelled with Joe-Clayton, the τC of 0.11 indicates modest asymmetric dependence with more activity in upper tail dependence, capturing extreme events better and implying potential spikes in joint performance. DJSI ↔ CEI with τC of 0.44 using Student t, exhibits substantial dependence, demonstrating robust co-movements and suggesting that these indices react similarly under different market situations. Within green crypto, all these pairs (ETH ↔ BNB, ETH ↔ ADA, BNB ↔ ADA) show the existence of strong dependences with τC values of 0.45, 0.61, and 0.40, respectively. A greater upper tail dependency is indicated by the presence of Joe-Clayton and Gumbel copulas, indicating that these cryptocurrency assets typically undergo comparable extreme positive moves during this pre-COVID era. With a τC of 0.00 indicating no dependence, Table 2 shows that GBI ↔ ETH and GBI ↔ ADA are modelled with an Independence copula, revealing fully independent movements between these green financial and green crypto assets in the pre-COVID timeframe. Tawn type 1 copulas with τC values ranging from 0.04 to 0.05 are used in pairs like DJSI ↔ ETH, DJSI ↔ BNB, CEI ↔ ETH, and CEI ↔ BNB. These copulas exhibit weak dependence, indicating little co-movement or correlation. On the other hand, the copula family of Survival Clayton is suggested by the pair DJSI ↔ ADA and CEI ↔ ADA, indicating a very weak lower tail reliance. Limited simultaneous downward movements in these pairings are suggested by the small τC values (0.05 and 0.06).

4.2 During-Covid-19 Period

Figure 5 and Table 3 show the dependency structure and result of the copula analysis during the COVID-19 period, respectively. Figure 5 highlights that with sparse contours and a τC of 0.16, the GBI ↔ DJSI within Green Financial Assets indicates modest dependency and some joint movements during the COVID period. GBI ↔ CEI depicted weaker dependence (τC of 0.11) by wider contours, suggesting less synchronization compared to DJSI ↔ CEI.

Fig. 5: COVID Dependency Structure



The strong dependency (τC of 0.41) is evident through denser contours among DJSI ↔ CEI, showing significant co-movement during stress periods. Within green crypto assets (ETH ↔ BNB, ETH ↔ ADA, BNB ↔ ADA), Figure 5 exhibits that high τC values (0.51–0.56) correspond with dense, elongated outlines, suggesting substantial co-movement, particularly under extreme circumstances. The synchronized behavior of these assets is probably caused by market stress. Sparse contours and low τC values (0.10–0.11) reveal weak dependencies in GBI with Crypto Assets, suggesting minimal response synchronization and interaction. Contours are more noticeable, according to DJSI and CEI with Crypto Assets; τC values range from 0.11 to 0.17, indicating slightly stronger but still mild dependency. This suggests synchronization is present but constrained, primarily during important/extreme events.

Table 3: Results of Copula Analysis COVID sample (Sub Sample 2)

Green Assets	Copula Family	Θ_1	Θ_2	Lower	Upper	τ_C
Within Green Financial Assets						
GBI ↔ DJSI	Student t	0.26	6.01	0.081	0.081	0.16***
GBI ↔ CEI	Tawn type 2	1.26	0.22		0.103	0.08***
DJSI ↔ CEI	Clayton-Gumbel	0.12	1.53	0.025	0.427	0.38***
Within Green Crypto Assets						
ETH ↔ BNB	Tawn type 1	2.68	0.75		0.599	0.51***
ETH ↔ ADA	Survival Clayton-Gumbel	1.46	1.28	0.283	0.691	0.55***
BNB ↔ ADA	Gumbel	2.06			0.599	0.51***
Between Green Financial Assets and Green Crypto Assets						
GBI ↔ ETH	Clayton-Gumbel	0.1	1.06	0.001	0.071	0.1***
GBI ↔ BNB	Gumbel	1.07		0.000	0.088	0.06***
GBI ↔ ADA	Gumbel	1.08		0.000	0.105	0.08***
DJSI ↔ ETH	Survival Clayton	0.4			0.174	0.17***
DJSI ↔ BNB	Gumbel	1.16			0.184	0.14***
DJSI ↔ ADA	Gumbel	1.19			0.212	0.16***
CEI ↔ ETH	Gumbel	1.18			0.203	0.15***
CEI ↔ BNB	Tawn type 2	1.28	0.31		0.138	0.11***
CEI ↔ ADA	Gumbel	1.15			0.171	0.13***

As shown in Table 2, the Student t family of copulas, which has a moderate dependence with a τC of 0.16 and a greater symmetric tail dependency than in less volatile periods, is recommended for GBI ↔ DJSI within Green Financial Assets. With a τC of 0.08 and a less asymmetric dependence, the GBI ↔ CEI advocates Tawn type 2, suggesting possible alterations in joint behavior during this time. Clayton-Gumbel is observed for DJSI↔ CEI, and its τC of 0.38 indicates a substantial asymmetric upper tail dependency. This means that these assets often undergo joint extreme fluctuations throughout the epidemic. ETH ↔ BNB (Tawn type 1), The τC of 0.51 illustrates strong dependencies, with contours indicating more synchronization in extreme scenarios. ETH ↔ ADA (Survival Clayton-Gumbel), With a τC of 0.55, this pair exhibits strong asymmetric tail dependency, implying that extreme events affect both assets similarly. BNB ↔ ADA

(Gumbel) shows robust dependence (τC of 0.51), indicating consistent positive co-movement in extreme conditions. According to Table 2, Pairs like GBI ↔ ETH, GBI ↔ BNB, and GBI ↔ ADA have low tail dependencies and weak dependencies (τC between 0.06 and 0.1), indicating that there was little interaction between these markets throughout the pandemic. However, with τC values ranging from 0.11 to 0.17, DJSI, CEI with Crypto Assets indicate somewhat stronger dependencies than GBI's. Though weak, the asymmetric dependence captured by the Gumbel and Tawn types indicates some joint behaviors in extreme scenarios.

4.3 Post-Covid-19 Period

The post-COVID era dependency and the outcome of copula analysis between green traditional assets and green crypto assets are shown in Figure 6 and Table 4, respectively. As shown in Figure 6, denser outlines between GBI ↔ DJSI suggest significant dependency among Green Financial Assets, indicating strong co-movements (τC=0.32). With a τC = 0.23, the GBI ↔ CEI shows a modest contour density and steady return co-movement. The τC of 0.44 among DJSI ↔ CEI validates extremely thick outlines that show substantial interdependence, indicating a strong correlation impacted by shared market forces. Figure 6 indicates that pairs such as (ETH ↔ BNB & ETH ↔ ADA) among the green crypto group have τC of 0.60 and 0.64, which indicate very dense and elongated contours, and confirm strong synchronized behaviour in extreme scenarios. BNB ↔ ADA (τC of 0.57) highlighted dense contours, which suggest a strong co-movement, especially during market stress. Sparse contours with τC values between 0.13 and 0.16 in GBI interactions indicate weak interdependence and restricted joint movements. However, Stronger dependencies than GBI are suggested by DJSI & CEI with Crypto- Denser contours (τC from 0.23 to 0.31), indicating greater synchronization under extreme circumstances.

Fig. 6: Post COVD Dependency Structure

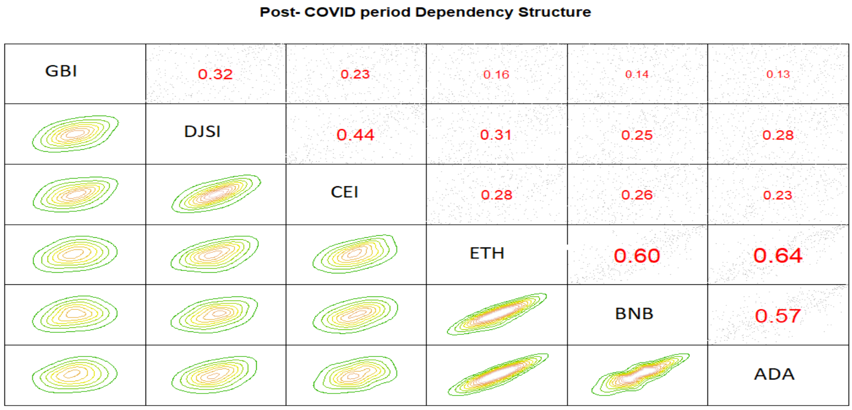


Table 4: Results of Copula Analysis Post COVID sample (Sub Sample 3)

Green Assets	Copula Family	Θ_1	Θ_2	Lower	Upper	τ_C
Within Green Financial Assets						
GBI ↔ DJSI	Joe-Clayton	1.24	0.55	0.247	0.284	0.29***
GBI ↔ CEI	Student t	0.33	4.72	0.143	0.143	0.22***
DJSI ↔ CEI	Joe-Frank	4.67	0.69	0.000	0.000	0.43***
Within Green Crypto Assets						
ETH ↔ BNB	Clayton-Gumbel	0.26	2.44	0.336	0.672	0.64***
ETH ↔ ADA	Clayton-Gumbel	0.16	2.8	0.218	0.719	0.67***
BNB ↔ ADA	Gumbel	2.58		0.000	0.691	0.61***
Between Green Financial Assets and Green Crypto Assets						
GBI ↔ ETH	Gaussian	0.26		0.000	0.000	0.16***
GBI ↔ BNB	Joe-FranK	1.71	0.82	0.000	0.000	0.15***
GBI ↔ ADA	Gaussian	0.22		0.000	0.000	0.14***
DJSI ↔ ETH	Gumbel	1.43		0.000	0.374	0.3***
DJSI ↔ BNB	Gaussian	0.39		0.000	0.000	0.25***
DJSI ↔ ADA	Gumbel	1.37		0.000	0.342	0.27***
CEI ↔ ETH	Clayton-Gumbel	0.26	1.21	0.112	0.231	0.27***
CEI ↔ BNB	Frank	2.68		0.000	0.000	0.28***
CEI ↔ ADA	Clayton-Gumbel	0.21	1.19	0.065	0.206	0.24***

Results from Table 4 in the post-COVID era within green financial assets confirm that GBI ↔ DJSI suggests Joe-Clayton as a copula family and exhibits significant asymmetric tail dependence with a τC of 0.29, indicating pronounced co-movement in extreme conditions. Moderate symmetric dependency with a τC of 0.22, suggesting a consistent correlation in returns through Student t is found among GBI ↔ CEI. Whereas, DJSI ↔ CEI reported (Joe-Frank) during analysis, resulting in significant independent tail movement (τC of 0.43), indicating robust dependencies, likely due to shared influences. However, Weak dependencies with τC ranging from 0.14 to 0.16, suggesting limited joint movements post-COVID (GBI ↔ ETH, GBI ↔ BNB).

4.4 Portfolio diversification and Hedging opportunities

Hedge ratios present opportunities for cross-hedging to minimize risk (Basher and Sadorsky, 2016). In Table 5, we present hedge ratios for green financial assets and green crypto assets across the three periods (pre-COVID, during-COVID, and post-COVID). Hedge ratios suggest how much of an asset may be hedged against another to minimize risk.

It is evident from Table 5 that hedge ratios show a significant rise (e.g. GBI ↔ DJSI from 0.49 to 0.95, GBI↔ CEI from 0.63 to 1.60) during the covid period for green financial assets suggesting higher correlation and higher risk and therefore necessitate the need for hedging. The ratios declined marginally in the post-covid period; however, they are still higher than the pre-covid period, suggesting stabilization but the risk is still persistent. It is worth noting that green crypto assets are relatively stable across all periods. It is interesting to observe that green financial assets and green crypto assets present diversification benefits owing to negative or low ratios (e.g. GBI ↔ Ethereum at -0.75) during the pre-covid period. During the COVID period, there is a sharp increase in the hedge ratios (e.g., GBI ↔ Ethereum at 3.02), suggesting requirements for greater hedging to manage risks. Post-covid period suggest relatively less risky compared to covid period, but still suggesting hedging need for managing the elevated risks.

Table 5: Hedge Ratios

Green Assets	Pre-COVID	COVID	Post COVID
Within Green Financial Assets			
Green Bond Index ↔ Dow Jones Sustainability Index	0.49	0.95	0.90
Green Bond Index ↔ Global Clean Energy Index	0.63	1.60	1.11
Dow Jones Sustainability Index ↔ Global Clean Energy Index	0.83	1.27	1.01
Within Green Crypto Assets			
Ethereum ↔ BNB	0.73	0.77	0.69

Ethereum ↔ Cardano	0.91	0.84	0.87
BNB ↔ Cardano	0.54	0.67	1.00
Between Green Financial Assets and Green Crypto Assets			
Green Bond Index ↔ Ethereum	0.75	-3.02	2.18
Green Bond Index ↔ BNB	0.28	-2.72	1.58
Green Bond Index ↔ Cardano	0.13	-2.87	2.08
Dow Jones Sustainability Index ↔ Ethereum	0.59	1.99	2.24
Dow Jones Sustainability Index ↔ BNB	0.70	1.93	1.69
Dow Jones Sustainability Index ↔ Cardano	0.64	2.01	2.32
Global Clean Energy Index ↔ Ethereum	0.31	0.95	1.21
Global Clean Energy Index ↔ BNB	0.69	0.92	0.95
Global Clean Energy Index ↔ Cardano	0.43	0.91	1.19

5. CONCLUSION AND IMPLICATIONS

This study examines the dependence of green financial assets and green crypto assets. We use daily returns of three green financial assets (GBI, DJSI, and CEI) and green crypto assets (ETH, BNB, and ADA) for three sub-sample periods covering pre-covid, during covid, and post covid to unearth the dependence-dynamics and capture extreme co-movements to suggest possibilities of hedging strategies for investors.

The pre-covid period suggests that the relationship between green financial assets and green crypto assets are relatively weak and hence indicate distinct risk patterns. However, it is evident that within each asset class stronger dependencies exist and therefore they may respond in similar fashion during extreme market conditions. It was also observed that the cross-category risks before pandemic were minimal, and it is apparent that these asset classes contribute to portfolio risk and diversification differently prior to the covid-19 period. During the COVID-19 period, the dependencies within the two asset classes intensified. However, between the asset classes, dependencies are observed to be weak, suggesting diversification benefits. But, due to increased volatility during the crisis/covid period, investors need to be cautious and need close monitoring of the assets. The post-covid dependencies were observed to be strong and suggest increased correlation within each asset class (green financial & green crypto). The results also indicate the presence of risk minimization and diversification opportunities in between the asset classes. The findings highlight the evolving landscape of inter-dependencies and, therefore, underscore the importance of close monitoring and adapting investment strategies.

The results indicate that the two asset classes exhibit distinct interdependencies, provide diversification and risk management opportunities, and behave differently during crises and therefore present hedging and diversification opportunities to investors despite both asset classes being green. The consistently observed weak dependency between the two asset classes presents asset allocation benefits for reducing risks. The crisis does have a significant impact on the dependency structure of the two asset classes and therefore post-crisis investors require extreme caution and continuous risk assessment for adjusting their investment strategies to leverage the periods of strong dependency within asset class or relatively weak dependencies across asset class, thus making market timing an essential element for their adaptability. Thus, the two asset classes present opportunities for portfolio diversification, risk management, market timing, and strategic asset allocation. The results also call for regular analysis of dependency structures to navigate the changing market dynamics effectively. Finally, this study presents conclusive evidence of the presence of hedging opportunities and guiding investors in enhancing their hedging and diversification strategies in response to changing market dynamics.

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