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Reevaluating intermarket connectedness: The impact of Monday return calculations on cryptocurrencies and traditional assets

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ABSTRACT

Cryptocurrencies trade continuously, unlike traditional assets limited to weekdays, creating challenges in calculating Monday returns. This paper investigates the impact of four benchmark closing prices—Friday, Saturday, Sunday, and a weekend average—on intermarket connectedness. Analyzing 72 cryptocurrencies (2018–2024) and their relation to the S&P500 using the TVP-VAR model, we find significant variations in economic and statistical outcomes, influencing both the magnitude and direction of spillovers. Mixed log- and non-log-based return methods yield inconsistent results for specific cryptocurrencies like THETA, GNO, GLM, and WAVES. These findings highlight the critical importance of consistent return methodologies in cryptocurrency market analysis.

1. Introduction

Early research on cryptocurrencies primarily focused on price discovery and market efficiency (Kapar and Olmo, 2019; Urquhart, 2016), aiming to understand how these assets behaved in rapidly evolving markets. However, the dramatic price surge in 2017 shifted the focus toward viewing cryptocurrencies as speculative investment assets (Corbet et al., 2019), rather than as decentralized currencies. Their decentralized nature contributed to the perception of cryptocurrencies as potential diversifiers, hedges, or safe havens during periods of market volatility (Bouri et al., 2017; Baur and Lucey, 2010). This led to numerous studies examining the co-movement of cryptocurrencies with traditional assets like equities (Naeem and Karim, 2021; Ali et al., 2022; Lu et al., 2024). Despite extensive research on cryptocurrencies' diversification potential (Bouri et al., 2017; Ali et al., 2024), a key issue remains unresolved: cryptocurrencies trade continuously while traditional assets adhere to fixed market hours. This discrepancy raises the challenge of how to align returns across asset classes with different trading hours and days, particularly when calculating Monday returns.

Monday returns have been extensively studied in the literature, even for assets with similar trading calendars, revealing variations across anomaly legs (Birru, 2018), factor premiums (Ali and Ülkü, 2019), and investor types (Ali and Ülkü, 2020). However, calculating Monday returns for cryptocurrencies poses unique challenges compared to traditional assets like equities. Unlike equities, which rely on Friday's closing price, cryptocurrencies trade continuously over the weekend, creating uncertainty about whether Friday, Saturday, Sunday, or an average weekend price should serve as the benchmark. This paper's first contribution is an empirical analysis

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to determine whether different benchmark prices for Monday returns lead to significantly different outcomes. Additionally, we explore how these calculation methods influence the diversification benefits of cryptocurrencies, shedding light on intermarket co-movements, network roles, and spillover effects—critical insights for investors, researchers, and policymakers.

Daily returns are usually based on consecutive day-end closing prices. For cryptocurrencies, Monday's return uses Sunday's close, while equities use Friday's. This creates discrepancies in investment horizons, trading periods, and rebalancing strategies. Aligning trading periods by using Friday's price makes cryptocurrencies' Monday returns three-day returns due to weekend trading, while Saturday's price similarly introduces other challenges. Ali and Ülkü (2019) addressed similar issues in the US market by averaging returns over different trading weeks. Here, we calculate Monday returns for cryptocurrencies using four benchmarks—Friday, Saturday, Sunday, and average weekend prices—and assess their diversification benefits against the S&P 500. This extends research on cryptocurrencies' hedging and diversification benefits with an all-inclusive approach.

Additionally, we address critical practical concerns regarding return estimation, specifically the use of log-based ($Ln(P_t/P_{t-1})$) versus non-log methods ($(P_t - P_{t-1})/P_{t-1}$) to calculate daily returns. This is particularly relevant when price data and return series are sourced differently. For example, many studies use return series of equity indices from sources like Kenneth French's data library, while cryptocurrency prices are sourced from platforms like Coinbase or Coinmarketcap (e.g., Ali et al., 2024; Patel et al., 2024). These platforms often calculate equity returns using the non-log method, while cryptocurrency returns are calculated using the log-based method. We aim to determine whether using different return calculation methods produces consistent results, which is essential for ensuring the robustness of findings in existing studies. Our final contribution is to highlight discrepancies in the cryptocurrency literature, particularly regarding diversification benefits, caused by differences in data sources and statistical methods used for return estimation. Section 2 describes the data and methods used in the study, Section 3 discusses the main results, Section 4 highlights and addresses additional concerns, and Section 5 concludes the paper.

2. Data and methods

2.1. Data

We explore 550 cryptocurrencies with the highest capitalization to select the sample: given that the remaining cryptocurrencies are illiquid, small, and traded for shorter periods, we ignore them. Our final sample consists of 72 cryptocurrencies actively traded between January 15, 2018, and June 15, 2024, accounting for approximately 99% of the total market capitalization and representing nearly all types (e.g., Protocol, Currency, Stablecoin, DeFi tokens, and NFTs, among others). Tickers and the full names of the selected cryptocurrencies are detailed in Table A1 in the Appendix. Data are retrieved from Yahoo Finance as it offers the lengthiest time series. The starting period is based on complete data availability for all the assets covering all major relevant events. To test differences in hedging and diversification benefits of cryptocurrencies across different estimation methods, we consider their interconnectedness with the S&P500 index. We examine the S&P500 index due to its economic importance, market capitalization, and strong presence in the finance literature. For comparison and robustness purposes, we also discuss several other equity indices from both developed and emerging equity markets: TSX (Canada), FTSE100 (UK), CAC40 (France), DAX (Germany), FTMIB (Italy), IBEX (Spain), ASX200 (Australia), NIKKEI225 (Japan), KOSPI (Korea), CSI300 (China), and BSE500 (India). However, our main results emphasize the US market.

2.2. Methods

We employ the TVP-VAR model to capture the directional connectedness from S&P500 to cryptocurrencies, from cryptocurrencies to S&P500, and net connectedness. The static and dynamic connectedness measures used in this study align with several seminal studies, including Liang et al. (2024) and Sun et al. (2023). However, different from other studies that aim to assess intermarket connectedness, we focus on understanding the differences in connectedness measures (potential diversification benefits) due to employing alternative return calculation methods. The TVP-VAR model can be specified as follows:

$$y_t = C_t z_{t-1} + \mu_t \mu_t | \rho_{t-1} \sim N(0, S_t) \tag{1}$$

$$vec(C_t) = vec(C_{t-1}) + v_t v_t | \rho_{t-1} \sim N(0, R_t) \tag{2}$$

where C_t denotes the coefficient matrix, ρ_{t-1} indicates the information set at time $t - -1$, and z_{t-1} is a $np \times 1$ vector that includes p lags of y_t, where the lag length of p is determined by the Bayesian information criterion. v_t and $\mu_t$represent the error term with $n \times 1$ and $np \times 1$ dimensional vectors. Finally, S_t and R_t are the time-varying variance-covariance matrices representing the $n \times n$ and $n^2p \times n^2p$ dimensional matrix.

The variance-covariance matrices in this condition vary via the Kalman filter estimation procedure with forgetting factors (Koop and Korobilis, 2014). Bayesian criteria initiate the Kalman filter, and the H-step ahead generalized forecast error variance decomposition (GFEVD) is used independent of the variable ordering. We first transform TVP-VAR to a vector moving average (VMA) based on the Wold theorem ($y_t = \Sigma_{i=1}^{p} C_{it} z_{t-i} + \ \mu_t = \Sigma_{j=0}^{\infty} A_{jt} \mu_{t-j}$), where A_{jt} is a $n \times n$ dimensional matrix. The GFEVD ($\varnothing_{ij,t}(H)$) can be presented as $S_{ii,t}^{-1} \sum_{t=1}^{H-1} \left(l_i' A_t S_t l_j\right)^2 \sum_{j=1}^{k} \sum_{t=1}^{H-1} \left(l_i A_t S_t A_t' l_i\right)$, where l_j corresponds to a vector with i^{th} element equaling 1 and other elements equaling zero. We normalize it following Antonakakis et al. (2020): $\widetilde{\varnothing}_{ij,t}(H) = \varnothing_{ij,t}(H) / \Sigma_{j=1}^{n} \varnothing_{ij,t}(H)$.

Table 1
Average daily returns and their differences across different benchmarks.

	Benchmark day				Difference in returns				Benchmark day				Difference in returns		
Crypto	Fri	Sat	Sun	Wknd	Fri-Sat	Fri-Sun	Fri-Wknd	Crypto	Fri	Sat	Sun	Wknd	Fri-Sat	Fri-Sun	Fri-Wknd
BTC	0.093	0.062	0.059	0.058	0.031	0.035	0.035	ZRX	-0.087	-0.183	-0.109	-0.153	0.096	0.022	0.066
ETC	-0.029	-0.082	-0.053	-0.073	0.054	0.024	0.044	HOT	-0.281	-0.159	-0.717	-0.586	**-0.122**	**0.436**	**0.305**
XRP	-0.075	-0.127	-0.067	-0.100	0.051	-0.009	0.024	ZIL	-0.117	-0.253	-0.208	-0.238	**0.137**	0.092	**0.121**
ETH	0.059	-0.010	-0.039	-0.028	0.069	0.098	0.088	ZEC	-0.198	-0.223	-0.206	-0.220	0.025	0.008	0.022
USDT	0.000	-0.003	0.000	-0.001	0.002	0.000	0.001	ANT	0.024	0.025	0.056	0.034	-0.001	-0.032	-0.010
BNB	0.205	0.159	0.157	0.154	0.046	0.048	0.050	WETH	0.059	0.013	0.022	0.012	0.046	0.037	0.047
DOGE	0.156	0.042	0.058	0.044	**0.115**	0.098	**0.112**	GAS	-0.183	-0.204	-0.232	-0.228	0.021	0.049	0.045
ADA	-0.038	-0.168	-0.147	-0.162	**0.130**	**0.109**	**0.124**	LRC	-0.105	-0.181	-0.189	-0.197	0.075	0.083	0.091
TRX	0.026	-0.057	-0.042	-0.055	0.083	0.067	0.080	TEL	-0.047	-0.017	-0.036	-0.039	-0.030	-0.011	-0.008
LINK	0.169	0.086	0.088	0.080	0.083	0.080	0.089	ICX	-0.240	-0.240	-0.217	-0.236	0.000	-0.023	-0.004
BCH	-0.104	-0.211	-0.199	-0.210	**0.107**	0.095	**0.106**	NTRN	-0.435	-0.476	0.062	-0.386	0.041	**-0.497**	-0.049
LTC	-0.066	-0.153	-0.134	-0.148	0.087	0.069	0.082	STORJ	-0.087	-0.226	-0.230	-0.238	**0.140**	**0.143**	**0.152**
XMR	-0.053	-0.110	-0.210	-0.164	0.057	**0.157**	**0.111**	RLC	-0.013	-0.094	-0.131	-0.125	0.081	**0.118**	**0.112**
XLM	-0.109	-0.184	-0.158	-0.175	0.075	0.049	0.066	WAXP	-0.205	-0.279	-0.180	-0.237	0.074	-0.025	0.032
MKR	0.037	-0.076	-0.070	-0.078	**0.113**	**0.106**	**0.115**	LSK	-0.189	-0.231	-0.189	-0.216	0.042	0.000	0.027
THETA	0.132	0.072	0.137	0.096	0.059	-0.005	0.036	IOST	-0.077	-0.132	-0.041	-0.095	0.055	-0.036	0.018
JUP	-0.360	-0.461	-0.622	-0.703	**0.100**	**0.261**	**0.342**	DGB	-0.133	-0.256	-0.186	-0.228	**0.123**	0.053	0.095
KCS	-0.016	-0.086	-0.103	-0.101	0.071	0.088	0.085	PRO	-0.036	-0.043	-0.134	-0.113	0.007	0.098	0.077
NEO	-0.162	-0.189	-0.253	-0.228	0.027	0.091	0.066	NMR	-0.035	-0.109	-0.130	-0.131	0.075	0.096	0.097
RON	-0.008	-0.004	-0.009	-0.006	-0.005	0.000	-0.002	ARK	-0.134	-0.239	-0.196	-0.227	**0.105**	0.062	0.093
GNO	-0.001	-0.013	-0.010	-0.017	0.012	0.010	0.017	XEM	-0.259	-0.352	-0.257	-0.310	0.093	-0.002	0.051
AGIX	-0.053	-0.299	-0.328	-0.326	**0.246**	**0.275**	**0.273**	OMNI	-0.237	-0.211	-0.321	-0.325	-0.026	0.085	0.089
XTZ	-0.111	-0.205	-0.187	-0.202	0.094	0.076	0.091	XNO	-0.180	-0.196	-0.160	-0.186	0.015	-0.021	0.005
MANA	0.063	-0.129	-0.079	-0.112	**0.192**	**0.142**	**0.174**	POWR	-0.099	-0.254	-0.153	-0.216	**0.155**	0.054	**0.117**
ONT	0.059	-0.010	-0.039	-0.028	0.069	0.098	0.088	CVC	-0.123	-0.222	-0.136	-0.188	0.099	0.013	0.065
BTG	-0.133	-0.161	-0.126	-0.150	0.028	-0.007	0.017	REQ	-0.099	-0.227	-0.113	-0.178	**0.129**	0.015	0.080
MEME	-0.221	-0.292	-0.058	-0.157	0.070	**-0.163**	-0.065	ERC20	0.234	0.164	0.123	-0.304	0.070	**0.111**	**0.538**
GLM	-0.051	-0.152	-0.071	-0.119	**0.101**	0.020	0.068	WAVES	-0.134	-0.185	-0.123	-0.160	0.051	-0.011	0.026
ELF	-0.069	-0.094	0.001	-0.054	0.024	-0.071	-0.015	SYS	-0.103	-0.259	-0.291	-0.285	**0.156**	**0.188**	**0.182**
DCR	-0.106	-0.170	-0.183	-0.181	0.063	0.076	0.075	SNT	-0.158	-0.276	-0.196	-0.241	**0.119**	0.038	0.084
SC	-0.140	-0.258	-0.224	-0.248	**0.119**	0.085	**0.109**	STEEM	-0.191	-0.280	-0.185	-0.238	0.090	-0.006	0.047
DASH	-0.214	-0.276	-0.257	-0.272	0.062	0.042	0.057	PHB	0.097	-0.166	-0.169	-0.197	**0.263**	**0.266**	**0.294**
TRAC	0.069	-0.012	0.104	0.035	0.081	-0.035	0.035	BNT	-0.153	-0.217	-0.251	-0.241	0.064	0.098	0.089
QTUM	-0.173	-0.245	-0.190	-0.224	0.072	0.016	0.050	MTL	-0.097	-0.186	-0.134	-0.168	0.088	0.037	0.071
BAT	-0.071	-0.134	-0.034	-0.089	0.063	-0.037	0.018	XVG	-0.190	-0.259	-0.313	-0.295	0.069	**0.123**	**0.105**
ENJ	-0.019	-0.075	0.015	-0.037	0.056	-0.034	0.018	GTC	-0.361	-0.479	-0.437	-0.469	**0.118**	0.077	**0.108**

Notes: This table presents the average daily returns and their differences due to using different benchmark days to calculate Monday returns: the return on the first trading day of the week. Fri, Sat, Sun, and Wknd indicate the calculation of Monday returns using the closing price of Friday, Saturday, Sunday, and the average of the three days (weekend), respectively. Fri−Sat, Fri−Sun, and Fri−Wknd indicate their respective differences. The data span from January 15, 2018, to June 15, 2024, consisting of 2344 daily observations for each asset under study. Differences that are higher than +0.10% or lower than −0.10% are bolded and highlighted in red color.

Table 2
Differences in Monday returns across different benchmarks.

Crypto	Fri-Sat		Fri-Sun		Fri-Wknd		Crypto	Fri-Sat		Fri-Sun		Fri-Wknd	
	Mean	t-stats	Mean	t-stats	Mean	t-stats		Mean	t-stats	Mean	t-stats	Mean	t-stats
BTC	0.156	1.19	0.175	0.94	0.176	1.25	ZRX	**0.481**	1.64	0.113	0.27	0.333	1.01
ETC	0.271	1.08	0.122	0.35	0.223	0.82	HOT	-0.612	-0.45	2.183	1.18	1.528	0.91
XRP	0.257	0.96	-0.044	-0.14	0.122	0.44	ZIL	**0.685**	1.86	0.460	1.01	**0.607**	1.66
ETH	**0.348**	1.92	**0.490**	1.80	**0.439**	2.16	ZEC	0.123	0.50	0.039	0.11	0.109	0.41
USDT	0.013	0.76	-0.001	-0.04	0.005	0.34	ANT	-0.006	-0.02	-0.161	-0.39	-0.049	-0.15
BNB	0.231	1.22	0.239	0.93	0.253	1.26	WETH	0.232	0.84	0.187	0.57	0.236	0.86
DOGE	**0.574**	1.66	0.491	1.29	**0.563**	1.65	GAS	0.106	0.28	0.248	0.50	0.227	0.56
ADA	**0.683**	2.80	**0.547**	1.70	**0.623**	2.38	LRC	0.378	1.26	0.418	0.94	0.458	1.38
TRX	**0.417**	2.05	0.338	1.08	**0.403**	1.73	TEL	-0.153	-0.44	-0.054	-0.11	-0.040	-0.11
LINK	0.415	1.34	0.402	1.05	0.444	1.40	ICX	0.003	0.01	-0.117	-0.31	-0.022	-0.08
BCH	**0.536**	1.99	0.476	1.39	**0.531**	1.87	NTRN	0.207	0.19	**-2.490**	-1.64	-0.245	-0.20
LTC	**0.435**	2.08	0.344	1.21	**0.411**	1.83	STORJ	**0.700**	1.66	0.717	1.50	**0.761**	1.77
XMR	0.285	1.47	**0.786**	2.95	**0.556**	2.71	RLC	0.408	1.25	0.592	1.21	0.564	1.50
XLM	**0.375**	1.78	0.246	0.88	0.330	1.47	WAXP	0.369	1.32	-0.127	-0.34	0.160	0.55
MKR	**0.566**	2.33	**0.533**	1.65	**0.575**	2.23	LSK	0.212	0.83	0.001	0.00	0.137	0.47
THETA	0.298	0.97	-0.025	-0.06	0.179	0.56	IOST	0.275	0.89	-0.181	-0.47	0.089	0.28
JUP	1.088	0.70	2.215	1.46	**2.430**	1.77	DGB	**0.616**	2.27	0.266	0.68	**0.479**	1.66
KCS	0.354	1.43	0.439	1.28	0.426	1.58	PRO	0.038	0.10	0.491	0.79	0.386	0.86
NEO	0.136	0.55	0.457	1.27	0.330	1.20	NMR	0.375	1.02	0.480	1.03	0.484	1.27
RON	-0.024	-0.81	0.002	0.04	-0.011	-0.36	ARK	**0.528**	1.66	0.312	0.70	0.469	1.34
GNO	0.062	0.25	0.048	0.17	0.085	0.36	XEM	**0.465**	1.69	-0.010	-0.03	0.255	0.93
AGIX	**1.203**	1.83	**1.380**	1.85	**1.367**	2.02	OMNI	-0.129	-0.19	0.425	0.49	0.445	0.67
XTZ	**0.470**	1.99	0.379	1.08	**0.454**	1.70	XNO	0.077	0.23	-0.103	-0.24	0.027	0.08
MANA	**0.960**	2.28	0.711	1.53	**0.874**	2.10	POWR	**0.776**	2.44	0.269	0.59	**0.589**	1.73
ONT	**0.348**	1.92	**0.490**	1.80	**0.439**	2.16	CVC	0.495	1.20	0.064	0.15	0.328	0.85
BTG	0.142	0.63	-0.036	-0.10	0.086	0.31	REQ	**0.645**	1.87	0.074	0.19	0.399	1.17
MEME	0.352	0.54	-0.830	-1.34	-0.325	-0.53	ERC20	0.352	0.12	0.558	0.16	2.691	1.02
GLM	**0.507**	1.65	0.099	0.24	0.341	1.01	WAVES	0.256	0.86	-0.055	-0.14	0.131	0.40
ELF	0.123	0.42	-0.355	-0.87	-0.076	-0.24	SYS	**0.781**	2.45	**0.944**	2.16	**0.913**	2.66
DCR	0.318	1.25	0.383	1.18	0.376	1.42	SNT	**0.595**	2.21	0.191	0.54	0.420	1.47
SC	**0.594**	1.82	0.424	0.97	0.544	1.52	STEEM	**0.449**	1.69	-0.030	-0.09	0.237	0.87
DASH	0.310	1.17	0.211	0.60	0.288	1.01	PHB	**1.318**	2.07	**1.335**	1.92	**1.473**	2.43
TRAC	0.405	1.10	-0.175	-0.36	0.173	0.44	BNT	0.323	1.39	0.493	1.34	**0.445**	1.64
QTUM	0.359	1.26	0.081	0.22	0.252	0.85	MTL	0.442	1.48	0.184	0.41	0.355	1.02
BAT	0.314	1.11	-0.186	-0.56	0.091	0.33	XVG	0.343	1.15	0.614	1.53	**0.528**	1.69
ENJ	0.281	1.00	-0.171	-0.48	0.090	0.31	GTC	0.592	1.20	0.384	0.66	0.543	1.08

Notes: This table presents the differences in Monday returns, the first trading day of the week, due to using different benchmark days (preceding prices) to calculate returns. Data and variables are defined in Table 1 and Table A1 in the Appendix. Differences that are statistically significant at the 10% or better (5% or 1%) levels are bolded and highlighted in red color.

Directional connectedness from S&P500 to others (TO): This measure indicates the shocks that asset i (S&P500) transmits to other assets j (cryptocurrencies in this study), defined as follows:

$$\mathrm{TO}_{i\to \mathrm{j},\mathrm{t}}(\mathrm{H}) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\varnothing}_{ji,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\varnothing}_{ji,t}(H)} \times 100 \tag{3}$$

Directional connectedness to S&P500 from others (FROM): This measure indicates the shocks that asset i (S&P500) receives from other assets j (cryptocurrencies), defined as follows:

$$\mathrm{FROM}_{j\to \mathrm{i},\mathrm{t}}(\mathrm{H}) = \frac{\sum_{j=1, i\neq j}^{N} \widetilde{\varnothing}_{ij,t}(H)}{\sum_{i,j=1}^{N} \widetilde{\varnothing}_{ij,t}(H)} \times 100 \tag{4}$$

Net total directional connectedness between S&P500 and cryptocurrencies (NET): This measure indicates the net difference between the two spillover measures defined in Eqs. (3)-(4) as follows:

$$\mathrm{NET}_{\mathrm{ij},\mathrm{t}}(\mathrm{H}) = \mathrm{TO}_{i\to \mathrm{j},\mathrm{t}}(\mathrm{H}) - \mathrm{FROM}_{j\to \mathrm{i},\mathrm{t}}(\mathrm{H}) \tag{5}$$

Table 3
Differences in interconnectedness (in percentage) due to using different benchmark days to calculate Monday returns.

Crypto	Fri-Sat			Fri-Sun			Fri-Wknd		
	TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
BTC	7.73	-17.30	-49.08	18.84	-13.78	**-55.21**	5.80	-24.05	**-61.96**
ETC	15.65	3.79	-8.39	38.10	-8.28	**-55.94**	19.05	-8.62	**-37.06**
XRP	34.16	21.74	-12.16	**55.45**	38.41	-8.11	40.59	29.35	-1.35
ETH	8.55	-13.99	-41.94	26.77	-12.96	**-62.21**	6.32	-25.10	**-64.06**
USDT	**-213.24**	**51.82**	**313.04**	**-230.88**	**-80.29**	**68.12**	**-72.06**	41.61	**153.62**
BNB	20.05	16.43	11.63	44.36	24.14	-2.66	24.81	12.71	-3.32
DOGE	**-128.77**	**-203.30**	**-505.56**	8.22	**-65.93**	**-366.67**	**-61.64**	**-147.25**	**-494.44**
ADA	-4.21	-8.47	-12.02	25.23	14.83	6.20	0.00	-5.30	-9.69
TRX	23.17	23.52	23.89	47.97	15.04	-20.80	29.67	13.35	-4.42
LINK	6.27	5.61	4.50	40.00	-2.43	**-73.50**	20.30	-4.67	**-46.50**
BCH	-29.01	-46.43	**-59.32**	-4.58	-49.03	**-81.92**	-31.30	**-60.71**	**-82.49**
LTC	-2.00	-28.00	**-54.00**	10.67	-37.67	**-86.00**	-6.67	-42.33	**-78.00**
XMR	**-149.33**	**-93.65**	**-57.02**	**-97.33**	**-105.82**	**-111.40**	**-146.67**	**-115.34**	**-94.74**
XLM	1.22	-18.10	**179.17**	32.65	-23.53	**550.00**	6.53	-31.22	**354.17**
MKR	-37.89	-43.72	-47.96	-3.11	-24.61	-40.27	-26.09	-42.93	**-55.20**
THETA	**-106.84**	**-59.72**	-1.06	**-56.41**	-21.80	21.28	**-97.44**	**-53.08**	2.13
JUP	-26.87	**-533.33**	**383.78**	1.49	**-286.67**	**235.14**	-11.94	**-560.00**	**432.43**
KCS	-20.22	-20.94	-22.22	-25.28	**-74.01**	**-161.62**	-32.02	**-55.60**	**-97.98**
NEO	8.10	-1.23	-18.10	38.57	1.23	**-66.38**	11.90	-13.80	**-60.34**
RON	-5.41	**-63.75**	**-783.33**	-45.95	**-203.75**	**-2150.00**	-20.27	**-136.25**	**-1566.67**
GNO	-27.14	-39.58	**-73.08**	14.76	-23.96	**-128.21**	-15.24	-44.44	**-123.08**
AGIX	-32.92	**-56.14**	**-110.78**	37.50	-4.09	**-101.96**	-7.08	-43.27	**-128.43**
XTZ	22.49	14.60	-12.77	48.67	23.49	**-63.83**	29.24	12.22	**-46.81**
MANA	-15.64	-46.88	**-127.66**	14.40	-31.45	**-150.00**	-13.17	**-58.16**	**-174.47**
ONT	-3.52	-19.13	-47.74	21.48	-21.87	**-101.29**	-4.58	-32.35	**-83.23**
BTG	-18.79	-28.88	**-53.73**	-3.03	-47.84	**-158.21**	-29.70	**-53.02**	**-110.45**
MEME	6.78	33.49	**68.13**	-39.83	-36.36	-31.87	-15.25	10.53	43.96
GLM	**-74.29**	**-57.45**	-43.48	-10.00	-1.51	5.53	**-59.52**	-38.44	-20.95
ELF	-25.62	-14.36	-1.67	-13.79	-28.20	-44.44	-34.48	-33.16	**-31.67**
DCR	-41.81	**-72.57**	**-121.62**	-49.15	**-72.92**	**-110.81**	**-53.67**	**-75.35**	**-109.91**
SC	-40.27	-44.09	-47.58	-3.10	-19.20	-33.87	-34.51	-45.57	**-55.65**
DASH	12.30	1.72	-17.48	37.97	-0.34	**-69.90**	17.11	-6.21	**-48.54**
TRAC	**-64.18**	**-82.89**	**-130.19**	**-105.97**	**-141.71**	**-232.08**	**-107.46**	**-132.62**	**-196.23**
QTUM	4.95	19.94	38.89	26.92	10.43	-10.42	6.59	9.20	12.50
BAT	-19.88	-16.64	-13.49	27.11	6.39	-13.78	-3.01	-11.89	-20.53
ENJ	-11.47	-2.32	10.71	41.94	29.89	12.76	7.89	9.05	10.71
ZRX	-19.14	-22.05	-25.32	18.86	-6.04	-33.97	-27.71	-35.05	-43.27
HOT	-7.54	5.51	23.29	20.60	37.10	**59.59**	-2.01	15.94	40.41
ZIL	-22.27	-24.20	-27.27	34.12	9.91	-28.79	-12.32	-20.70	-34.09
ZEC	20.11	8.88	-18.67	40.22	0.77	**-96.00**	23.37	4.25	-42.67
ANT	4.94	0.42	-8.00	21.46	-3.21	-49.20	-6.22	-18.44	-41.20
WETH	-0.47	-34.01	**-237.14**	41.04	-5.67	**-288.57**	14.15	-21.86	**-240.00**
GAS	-31.75	-29.10	-23.81	**-92.86**	**-151.32**	**-268.25**	**-75.40**	**-107.94**	**-173.02**
LRC	15.98	18.39	**52.94**	10.25	-41.76	**-788.24**	6.56	-11.49	**-270.59**
TEL	**-75.91**	**-116.77**	**-427.78**	-31.39	**-85.81**	**-500.00**	**-76.64**	**-130.32**	**-538.89**
ICX	-15.22	-14.11	-12.77	7.83	-15.31	-43.62	-10.00	-25.60	-44.68
NTRN	**-267.44**	**-352.08**	**-1080.00**	**-1053.49**	**-1412.50**	**-4500.00**	**-620.93**	**-489.58**	**640.00**
STORJ	-37.03	-28.45	-16.03	16.33	6.90	-6.75	-23.91	-30.86	-40.93
RLC	-8.88	-27.31	**-140.00**	-12.15	**-103.61**	**-662.86**	-22.43	**-88.76**	**-494.29**
WAXP	**-70.37**	3.29	43.88	3.70	36.84	**55.10**	-31.48	15.79	41.84
LSK	27.10	13.17	-11.36	-16.13	**-89.30**	**-218.18**	-6.45	-45.68	**-114.77**
IOST	**-50.63**	-37.63	-21.26	3.13	-18.47	-45.67	-40.63	-44.25	-48.82
DGB	1.86	-9.50	**-57.14**	48.61	0.50	**-201.30**	18.58	-17.50	**-168.83**
PRO	29.05	32.85	49.04	**56.98**	31.75	**-75.96**	31.98	16.61	-49.04
NMR	10.50	10.68	11.21	**60.64**	**50.33**	19.83	25.07	10.89	-31.03
ARK	-5.50	-12.89	-25.42	-8.00	-41.51	**-98.31**	-16.00	-21.38	-30.51
XEM	-18.87	-36.87	**-66.93**	36.32	28.61	15.75	-3.77	-15.34	-34.65
OMNI	42.90	34.21	44.12	35.81	**-100.00**	**54.78**	37.42	28.95	38.60
XNO	8.04	-12.91	**-55.96**	-7.14	-37.54	**-100.00**	-11.16	-46.25	**-118.35**
POWR	**-95.52**	-46.04	32.28	-27.36	-43.29	**-68.50**	**-86.57**	**-70.12**	-44.09
CVC	-22.73	-35.53	**-64.29**	-28.64	**-61.64**	**-135.71**	-37.27	**-57.23**	**-102.04**
REQ	-10.62	-28.29	**-79.49**	4.87	-13.16	**-65.38**	-16.37	-31.58	**-75.64**
ERC20	**74.79**	**87.60**	**240.00**	26.89	40.31	**200.00**	**71.43**	**82.17**	**210.00**
WAVES	-9.66	-23.80	**-71.58**	33.02	-12.50	**-166.32**	3.12	-26.20	**-125.26**
SYS	-20.48	-22.67	-29.66	27.13	17.41	-13.56	-11.44	-18.62	-41.53
SNT	-35.25	4.90	42.86	-20.86	-0.70	18.37	-39.57	-3.50	30.61
STEEM	-18.45	-1.78	47.37	-28.57	-8.89	49.12	-33.33	0.00	**98.25**

(*continued on next page*)

Table 3 (*continued*)

Crypto	Fri-Sat			Fri-Sun			Fri-Wknd		
	TO	FROM	NET	TO	FROM	NET	TO	FROM	NET
PHB	23.75	15.63	**-112.50**	15.04	-3.72	**-300.00**	7.39	-10.17	**-287.50**
BNT	-13.16	-4.51	13.33	31.64	16.49	-14.76	-0.92	-1.40	-2.38
MTL	-18.49	9.72	**68.57**	6.85	48.15	**134.29**	-12.33	31.94	**124.29**
XVG	-25.19	-18.62	-8.07	-17.05	-34.84	**-63.35**	-35.66	-38.19	-42.24
GTC	-0.85	10.45	37.37	39.41	33.43	19.19	7.63	13.43	27.27

Notes: This table presents the differences in interconnectedness between S&P500 and selected cryptocurrencies. Variables are defined in Table 1 and Table A1 in the Appendix. Differences that are larger than 50% (higher than +50% or lower than −50%) are bolded and highlighted in red color. TO, FROM, and NET are calculated using Eqs. (3), (4), and (5), respectively.

3. Results and discussion

We begin our analysis by reporting the average daily returns of the cryptocurrencies and their differences across different benchmark (preceding) days to calculate Monday returns in Table 1. As anticipated, Monday returns calculated using Friday's closing prices yield higher average returns in most cases (note that they are held for three trading days). While calculating differences in returns and spillovers, we consider Monday's returns based on Friday's closing price as the standard for consistency. The results indicate economically large differences in returns between using Friday's and other days' closing prices. In some cases, these changes are over 0.10% a day, bolded in Table 1. However, these results are based on five trading days (Monday to Friday), suggesting an underestimation of the real impact of using different benchmark days. Thus, Table 2 specifically emphasizes the Monday returns, which are directly affected by alternative benchmarks, and pinpoints discrepancies in returns exclusively due to using different benchmark days. The results exhibit economically large differences in nearly all cases, where most of these differences are statistically significant (highlighted in bold). There is no monotonic increase or decrease in the differences as we move from high- to low-capitalization cryptocurrencies, indicating that such changes are across the board (irrespective of their size). For example, the difference between using Friday and Saturday closing prices (Fri−Sat) to calculate Monday returns is 0.680 for ADA, 1.088 for JUP, 0.960 for MANA, 0.594 for SC, 0.685 for ZIL, 0.700 for STORJ, 0.776 for POWR, and 0.592 for GTC, yielding an annual difference of 35.36%, 56.58%, 49.92%, 30.89 %, 35.62%, 36.41%, 40.35%, and 30.78%, respectively. Similarly, there are economically and statistically significant differences in returns due to using other benchmark days (Fri−Sun; Fri−Wknd) irrespective of their size.

Next, we examine whether these changes are descriptive only or affect these cryptocurrencies' diversification benefits (and channels) for equity investors. Given that diversification benefits and their channels (net role in the network and the direction of spillovers) are often measured using TVP-VAR-based connectedness measures, Table 3 presents the percentage differences in interconnectedness between S&P500 and cryptocurrencies. The results are surprising: the changes in the intermarket connectedness (TO, FROM, and NET) are huge, irrespective of their directions (+/−). For example, the change in net spillover (NET) between Friday and Saturday benchmarks (Fri−Sat) is approximately +313%, −506%, +179%, +384%, −783%, −106%, −237%, −1080%, and +240% for USDT, DOGE, XLM, JUP, RON, TRAC, WETH, NTRN, and ERC20 respectively. For easy interpretation, we highlight the results where the change in interconnectedness (TO, FROM, or NET) is more than 50%. These results indicate that net transmitters of shocks in one method could be net receivers in other methods and vice versa, raising the concern of whether frequently reported existing evidence on diversification benefits is robust or misleading. More importantly, radical differences in intermarket connectedness results are most likely to affect investors' portfolio allocation decisions, subject to their trading horizon and patterns. Our findings support the concern raised by Fieberg et al. (2024) – seemingly unimportant choices momentously affect main conclusions.

Following our main objective, we only present S&P500-cryptocurrency combinations in Fig. 1 for readers' comprehensive understanding regarding intermarket spillovers while skipping intra-market spillovers among cryptocurrencies for brevity. However, we can say that substantial differences exist in risk transmission among cryptocurrencies, with results available upon request.

4. Additional concerns

Recent studies that empirically investigate the diversification benefit of cryptocurrencies utilize data for several stylized indices using different sources, including Kenneth French's data library and investing.com (e.g., Ali et al., 2022, 2024). The return data (not price) on Kenneth French's website and investing.com are calculated as the first difference between two consecutive prices scaled by the preceding price ($(P_t - P_{t-1})/P_{t-1}$); we label it Return-A. On the contrary, when price data are obtained from investing.com, Yahoo Finance, coinmarketcap.com, or any other source, returns are calculated as the first-log difference by most studies ($Ln(P_t) - Ln(P_{t-1})$), for instance (Ali et al., 2022); we label it Return-B. We conjecture that using different ways can increase the chance of under- or over-reaction in diversification benefits.

Table 4 reveals that 50 out of 72 cryptocurrencies exhibit opposite sign returns (highlighted in bold): positive using the non-log method (Return-A) and negative with the log-based method (Return-B). Among the remaining 22 cryptocurrencies, although the returns have the same sign, the differences are still economically and statistically significant. For comparison, Panel B of Table 4 examines the returns of 12 leading developed and emerging markets, showing that the difference between log and non-log returns for equities is economically negligible. This finding prompts us to investigate whether using different return estimation methods affects the diversification properties of cryptocurrencies.

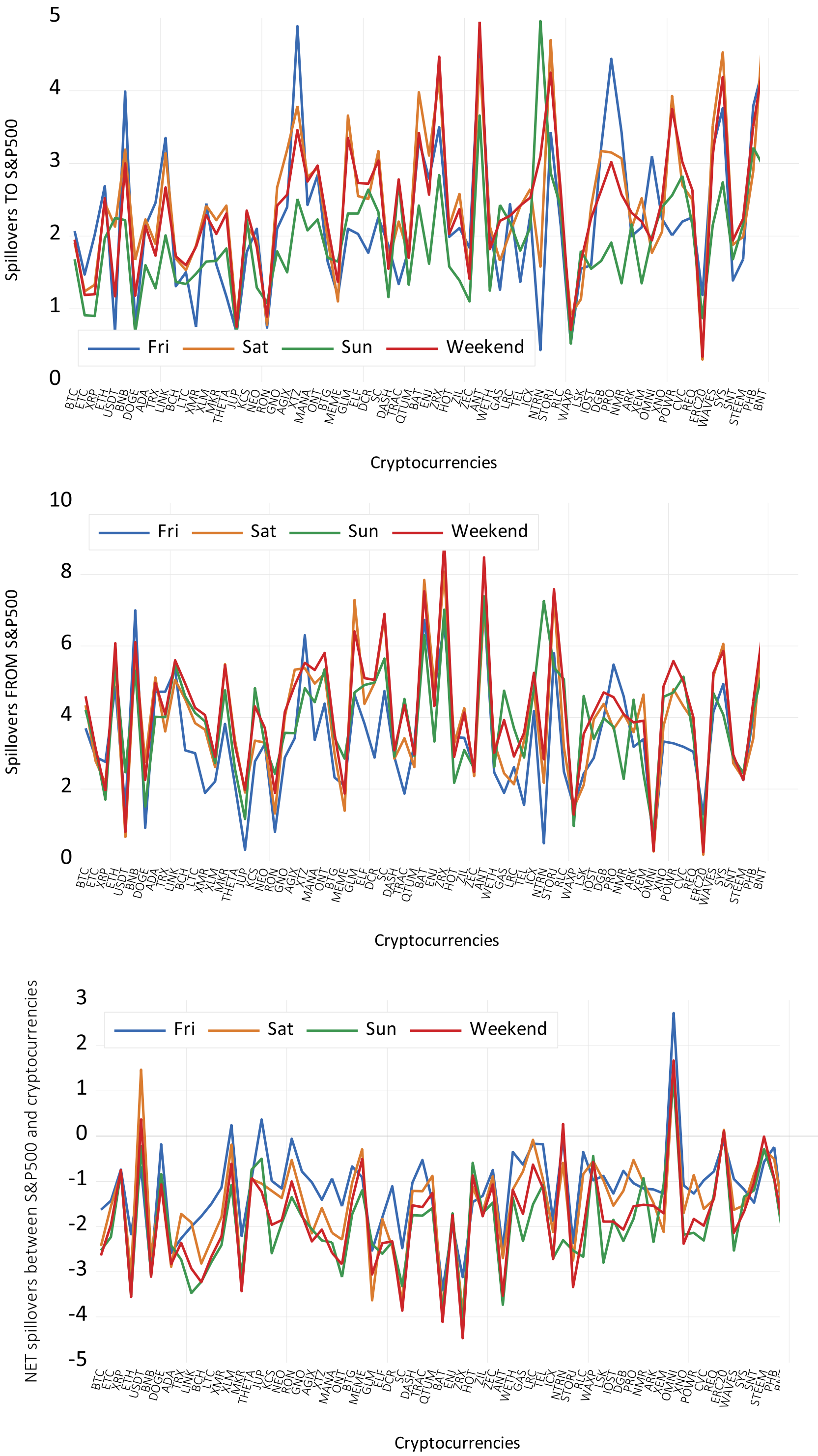

Fig. 1. Transmission of return spillovers using different benchmark days to calculate Monday returns.
Notes: This figure indicates the average (static) transmission of return spillovers between S&P500 and selected 72 cryptocurrencies. Results are based on the TVP-VAR method. Variables are defined in Table A1 in the Appendix. The data span from January 15, 2018, to June 15, 2024.

Table 5 shows the percentage differences in interconnectedness arising from using different return calculation methods. Many studies rely on pre-calculated equity returns from databases like Kenneth French's, which use non-log returns and cannot be transformed. Under this practical constraint, we analyze interconnectedness between equities and cryptocurrencies using three approaches.

Table 4
Average daily returns and their differences across the two return estimation methods.

Panel A: Cryptocurrencies

Crypto	Return-A	Return-B	Diff.	t-stats	Crypto	Return-A	Return-B	Diff.	t-stats	Crypto	Return-A	Return-B	Diff.	t-stats
BTC	0.132	0.067	0.065	13.15	ONT	0.150	0.043	0.106	14.43	RLC	**0.261**	**-0.009**	0.270	12.79
ETC	**0.142**	**-0.020**	0.162	14.70	BTG	**0.084**	**-0.095**	0.179	9.29	WAXP	**0.101**	**-0.147**	0.248	10.42
XRP	**0.099**	**-0.053**	0.152	10.58	MEME	**0.706**	**-0.158**	0.864	5.27	LSK	**0.038**	**-0.135**	0.173	15.02
ETH	0.149	0.043	0.106	14.43	GLM	**0.172**	**-0.035**	0.207	12.80	IOST	**0.211**	**-0.054**	0.265	5.24
USDT	0.000	0.000	0.001	6.23	ELF	**0.168**	**-0.051**	0.219	8.50	DGB	**0.109**	**-0.094**	0.203	15.42
BNB	0.271	0.147	0.124	10.98	DCR	**0.079**	**-0.075**	0.155	9.58	PRO	**0.431**	**-0.027**	0.457	9.72
DOGE	0.402	0.112	0.290	3.23	SC	**0.102**	**-0.100**	0.202	14.90	NMR	**0.295**	**-0.025**	0.319	6.52
ADA	**0.117**	**-0.027**	0.144	18.11	DASH	-0.008	-0.153	0.145	13.41	ARK	**0.124**	**-0.096**	0.220	14.76
TRX	0.151	0.018	0.133	14.16	TRAC	0.375	0.050	0.325	11.98	XEM	-0.024	-0.187	0.163	15.71
LINK	0.319	0.121	0.198	15.35	QTUM	**0.063**	**-0.123**	0.186	14.32	OMNI	**2.540**	**-0.167**	2.707	1.83
BCH	**0.092**	**-0.073**	0.165	12.24	BAT	**0.120**	**-0.050**	0.170	16.58	XNO	**0.111**	**-0.127**	0.238	9.54
LTC	**0.075**	**-0.046**	0.121	15.73	ENJ	**0.244**	**-0.013**	0.258	9.41	POWR	**0.162**	**-0.070**	0.232	11.48
XMR	**0.082**	**-0.038**	0.119	12.31	ZRX	**0.145**	**-0.062**	0.207	15.75	CVC	**0.193**	**-0.087**	0.280	8.26
XLM	**0.062**	**-0.078**	0.139	10.92	HOT	**5.220**	**-0.201**	5.420	1.37	REQ	**0.233**	**-0.071**	0.303	5.98
MKR	0.190	0.027	0.163	10.42	ZIL	**0.139**	**-0.082**	0.222	11.85	ERC20	8.194	0.159	8.035	1.71
THETA	0.330	0.095	0.235	15.49	ZEC	**0.007**	**-0.142**	0.149	16.85	WAVES	**0.117**	**-0.097**	0.213	13.23
JUP	**4.369**	**-0.192**	4.561	7.94	ANT	0.245	0.018	0.227	14.61	SYS	**0.190**	**-0.072**	0.262	11.86
KCS	**0.145**	**-0.011**	0.156	14.36	WETH	0.197	0.043	0.154	11.72	SNT	**0.078**	**-0.112**	0.190	10.13
NEO	**0.047**	**-0.115**	0.163	16.77	GAS	**0.111**	**-0.130**	0.241	9.34	STEEM	**0.056**	**-0.136**	0.192	12.10
RON	-0.005	-0.006	0.001	24.71	LRC	**0.178**	**-0.075**	0.253	15.05	PHB	3.566	0.068	3.498	1.20
GNO	0.149	0.001	0.148	16.26	TEL	**0.285**	**-0.033**	0.319	17.38	BNT	**0.055**	**-0.109**	0.164	13.60
AGIX	**0.444**	**-0.038**	0.482	3.10	ICX	**0.035**	**-0.171**	0.206	16.88	MTL	**0.197**	**-0.070**	0.266	5.96
XTZ	**0.101**	**-0.079**	0.180	16.00	NTRN	**3.494**	**-0.310**	3.805	7.71	XVG	**0.119**	**-0.135**	0.255	12.38
MANA	0.296	0.046	0.250	8.24	STORJ	**0.215**	**-0.061**	0.277	8.20	GTC	**0.050**	**-0.258**	0.308	7.05

Panel B: Equity indices

Equity	Return-A	Return-B	Diff.	t-stats	Equity	Return-A	Return-B	Diff.	t-stats	Equity	Return-A	Return-B	Diff.	t-stats
US	0.049	0.041	0.008	5.14	Germany	0.027	0.019	0.008	7.20	Australia	0.020	0.015	0.005	10.08
Canada	0.023	0.017	0.006	3.21	Italy	0.030	0.021	0.009	6.26	Korea	0.013	0.006	0.007	7.18
UK	0.008	0.003	0.005	6.35	Spain	0.010	0.003	0.007	6.39	China	-0.004	-0.011	0.007	14.12
France	0.026	0.019	0.007	6.57	Japan	0.039	0.031	0.007	11.13	India	0.059	0.052	0.006	5.29

Notes: This table reports the average daily returns and their differences across different estimation methods. Return-A is computed using $(C_{p,t} - C_{p,t-1})/C_{p,t-1}$, Return-B is computed using $Ln(C_{p,t}/C_{p,t-1})$, and *t*-statistics are computed using the Newey-West method to adjust for autocorrelation. "Diff" indicates the difference between the two returns calculation methods, whereas "*t*-stats" indicates the statistical significance. Returns are presented in the percentage form. Variables and data are defined in Table 1 and Table A1 in the Appendix. Average returns with opposite signs (+ / −) are presented in bold and highlighted in red color.

Table 5
Differences in interconnectedness.

Panel A: Percentage difference in spillovers

Crypto Groups	Return-A Vs Mixed			Return-A Vs Return-B		
	TO	FROM	NET	TO	FROM	NET
Group 1	8.81	3.43	0.12	7.73	3.31	0.58
Group 2	10.41	8.15	5.53	10.04	8.02	5.66
Group 3	4.08	0.44	-3.27	3.09	0.34	-2.50
Group 4	3.35	0.74	-2.00	2.28	0.66	-1.04
Group 5	8.03	1.51	-5.65	6.98	1.41	-4.83
Group 6	8.59	0.56	-9.24	7.44	0.45	-8.25

Panel B: Major changes in the net role

Return Estimation Method	**THETA**	**KCS**	GNO	GLM	ENJ	WAXP	WAVES
Return-A	T	R	T	T	T	T	R
Return-B	T	R	T	T	T	T	R
Mixed	**R**	**T**	**R**	**R**	**R**	**R**	**T**

Notes: Returns-A and Return-B are defined in Table 4, whereas the variables and data are defined in Table 1 and Table A1 in the Appendix. In the "mixed" method, S&P500 returns are estimated following the Return-A method, whereas cryptocurrency returns are estimated following the Return-B method. T indicates transmitters, whereas R indicates receivers of return spillovers in the network (group). Intermarket relationships that change their position in the network due to the change in the return estimation method are presented in bold and highlighted in red color.

First, equity returns use the non-log method, while cryptocurrency returns use the log method ("Mixed"), reflecting a common error in recent research. Second, both use the non-log method (Return-A vs. Return-A).

Third, both use the log method (Return-B vs. Return-B), based on equity index price data to ensure unbiased comparisons. Our findings show that using the same return estimation method, whether log- or non-log-based, does not alter the overall results regarding the net role of assets in the network. For clarity and brevity, we present the results in groups of 12 cryptocurrencies, with Group 1 containing the highest capitalization assets and Group 6 the lowest.[1] When comparing the results under different scenarios, we observe differences across groups when the return estimation methods vary. In Panel B, we particularly show that THETA, GNO, GLM, ENJ, and WAXP (KCS and WAVES) act as net transmitters (receivers) of shocks when returns are calculated using the same method (either A or B). However, when mixed methods are used, their roles within the network shift, with transmitters becoming receivers and vice versa (highlighted in bold).

The results suggest that if investors obtain a non-log return series for an asset, the return of other assets must be calculated using the same method to avoid misleading findings. Our results hold practical implications for investors and policymakers as market co-movements and interconnectedness that motivate the quest to optimize portfolios are essential to them.

5. Conclusion

Given the growing focus on cryptocurrencies' hedging and diversification benefits, our study identifies discrepancies in the existing literature that have not been thoroughly addressed. We demonstrate that using different benchmark days to calculate Monday returns results in significantly different outcomes, both economically and statistically. Through the TVP-VAR method, we show that these variations lead to substantial differences in risk transmission (spillovers) between the S&P500 index and the cryptocurrencies examined.

Beyond Monday returns, we emphasize the importance of consistent return estimation methods. Measuring connectedness between the assets using different methods—such as a stylized equity index with non-log returns versus a cryptocurrency with log-based returns—leads to inconsistent and misleading diversification properties. For example, we find that THETA, GNO, GLM, ENJ, and WAXP are net transmitters of return spillovers when consistent methods are used, while KCS and WAVES are net receivers. However, when different methods are applied, the net roles of these assets in the network change, highlighting the importance of methodological consistency.

Our findings extend the literature by exploring discrepancies arising from different empirical approaches in the cryptocurrency market (e.g., Fieberg et al., 2024). We recommend that future studies clearly disclose how they calculate Monday returns and how they adjust for cryptocurrency trading during weekends, as well as provide the rationale for their choices. Furthermore, when using return series from stylized indices, researchers should apply consistent return calculation methods for other assets to avoid confusing results.

For both investors and policymakers tracking intermarket connectedness and diversification benefits, understanding return patterns is crucial. Our study offers valuable insights and suggests that replicating existing empirical evidence with our recommendations will enhance the robustness of future research.

Given that our findings are confined to the US market and intermarket connectedness, future studies may extend this work by

[1] Note that using individual cryptocurrencies or groups of 12 cryptocurrencies offers identical findings regarding their connectedness with S&P500. Therefore, we report results in the form of groups for brevity.

examining other equity markets and asset classes and employing different econometric (e.g., value-at-risk or cross-quantilogram) techniques.

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CRediT authorship contribution statement

Fahad Ali: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anna Min Du:** Writing – review & editing, Writing – original draft, Validation, Investigation, Conceptualization. **Muhammad Ansar Majeed:** Writing – review & editing, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no competing interests.

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Appendix

Table A1
Tickers and full names of the selected cryptocurrencies.

Ticker	Full Name	Ticker	Full Name	Ticker	Full Name	Ticker	Full Name
BTC	Bitcoin	NEO	Neo	ZRX	Ox Protocol	NMR	Numeraire
ETH	Ethereum	RON	Ronin	HOT	Holo	ARKM	Arkham
XRP	XRP	GNO	Gnosis	ZIL	Zilliqa	XEM	NEM
ETC	Ethereum Clasic	AGIX	SingularityNET	ZEC	Zcash	OMNI	Omni Network
USDT	Tether USDt	XTZ	Tezos	ANT	Aragon	XNO	Nano
BNB	BNB	MANA	Decentraland	WETH	WETH	POWR	Powerledger
DOGE	Dogecoin	ONT	Ontology	GAS	Gas	CVC	Civic
ADA	Cardano	BTG	Bitcoin Gold	LRC	Loopring	REQ	Request
TRX	Tron	MEME	Memecoin	TEL	Telcoin	ERC20	ERC20
LINK	Chainlink	GLM	Golem	ICX	ICON	WAVES	Waves
BCH	Bitcoin Cash	ELF	aelf	NTRN	Neutron	SYS	Syscoin
LTC	Litecoin	DCR	Decred	STORJ	Storj	SNT	Status
XMR	Monero	SC	Siacoin	RLC	iExec RLC	STEEM	Steem
XLM	Stellar	DASH	Dash	WAXP	WAX	PHB	Phoenix
MKR	Maker	TRAC	OriginTrail	LSK	Lisk	BNT	Bancor
THETA	Theta Network	QTUM	Qtum	IOST	IOST	MTL	Metal Dao
JUP	Jupiter	BAT	Basic Attention Coin	DGB	DigiByte	XVG	Verge
KCS	KuCoin Token	ENJ	Enjin Coin	PRO	Propy	GTC	Gitcoin

Notes: This table presents the full names and tickers of the selected cryptocurrencies. Data are retrieved from Yahoo Finance (https://finance.yahoo.com/quote/).

Data availability

Data will be made available on request.

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