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On cryptocurrencies as an independent asset class: Long-horizon and COVID-19 pandemic era decoupling from global sentiments

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A B S T R A C T

Employing high-dimensional stochastic-volatility commonality tests on crypto-assets against a basket of global investor sentiment proxies, we report new evidence that the cryptocurrency market is decoupled from global sentiments. Our approach's novelty resides in employment of appropriate sources of risk and uncertainty and two comprehensive indices (CRIX and VCRIX) that permit treating cryptocurrencies as a united pool from 2016 to 2021. Our consolidated findings suggest nugatory association between cryptocurrencies and global risk, risk aversion, and uncertainty. Further COVID-19 resampling reinforces long-horizon results. These findings bolster the growing wave of support for recognizing crypto-assets as an independent asset class.

1. Introduction

Several authoritative literature surveys and regulatory reports claim to have a unique politico-economic-profile, own risk-reward attributes, and price independence as prerequisites for cryptocurrencies to earn the moniker of independent asset class [1–3]. Little doubt exists over the veracity of the first. We will contribute to this discourse by supplying moderate evidence for the second and strong evidence for the third, through employing a novel array of risk and uncertainty indicators. Specifically, we will show that returns and trading activities in cryptocurrencies exhibit trivial associations with risk aversion, systemic risk, economic uncertainty, equity market uncertainty, gold volatility, and implied oil volatility. We will divide our data into two distinctive periods: pre- and post-pandemic. The resultant non-integration findings prevail in all tests and subsamples. These distinctions allude to cryptocurrencies having a unique risk–reward profile and price independence. Importantly, the overall results support the diversification benefits of cryptocurrencies in general, whereas the pandemic results suggest safe-haven properties.

Advocacy for treating cryptocurrencies as an independent asset class has roots in fundamental valuation debates. The difficulty in cryptocurrencies' valuation *à la* traditional assets propels market-based price signals as an attractive valuation guide. Reports from professional trading communities suggest similar treatment by many investors. Contrary to mixed academic reports from earlier works, recent literature is coalescing on cryptocurrencies' unique price, volume, and risk features. Some have connected their price and volatility to various factors, such as social media variables, web search intensity, hash rate, and wallet-opening data [4–5]. Others have documented unique long-range dependence and herding behavior [6]. Meanwhile, many papers examine the hedging abilities of

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Table 1
Descriptive statistic.

	n	Mean	SD	Median	Trimmed	MAD	Min.	Max	Range	Skewness	Kurtosis	SE
	Panel A: Regular Sample (August 2015 to December 2019)											
AGG	1089	0.01%	0.19%	0.02%	0.02%	0.18%	-0.93%	0.78%	1.71%	-0.192	0.998	0.60%
RAI	1089	0.00%	3.63%	-0.04%	-0.05%	1.32%	-25.79%	52.16%	77.95%	3.539	60.246	11.00%
EMU	1089	-0.02%	1.46%	-0.10%	-0.07%	0.91%	-9.04%	21.77%	30.82%	3.301	49.423	4.40%
BTC	1089	0.30%	4.63%	0.26%	0.33%	2.58%	-23.87%	22.51%	46.39%	-0.07	4.255	14.00%
BTCTA	1089	0.57%	29.18%	-0.89%	0.03%	21.78%	-137.55%	128.97%	266.52%	0.275	2.306	88.40%
ETH	1089	0.35%	8.87%	-0.08%	0.15%	4.53%	-136.43%	50.97%	187.40%	-2.763	54.466	26.90%
ETHTA	1089	1.00%	43.35%	-1.63%	-0.36%	29.54%	-127.30%	192.46%	319.76%	0.481	1.822	131.40%
LTC	1089	0.21%	6.59%	-0.09%	-0.11%	3.34%	-39.50%	53.98%	93.49%	1.505	11.949	20.00%
LTCTA	1089	0.60%	40.84%	-2.25%	-1.31%	26.74%	-133.59%	311.59%	445.18%	1.029	5.518	123.80%
CORPBOND	1089	0.02%	0.24%	0.03%	0.02%	0.22%	-1.10%	0.80%	1.90%	-0.243	0.918	0.70%
CRIX	1089	0.32%	4.68%	0.36%	0.41%	2.81%	-30.90%	22.03%	52.93%	-0.462	4.981	14.20%
VCRIX	1089	-0.02%	9.82%	-0.01%	-0.02%	2.11%	-64.16%	80.84%	145.00%	0.669	16.869	29.80%
EPU	1089	0.32%	52.51%	-1.29%	-1.00%	49.06%	-183.27%	321.56%	504.83%	0.434	1.819	159.10%
DOLLAR	1089	0.00%	0.41%	0.01%	0.00%	0.35%	-2.40%	2.03%	4.43%	-0.17	2.32	1.20%
EMERGING	1089	0.03%	1.16%	0.08%	0.06%	1.00%	-6.03%	3.89%	9.92%	-0.392	1.428	3.50%
US GOVT.	1089	0.01%	0.23%	0.00%	0.01%	0.23%	-1.06%	0.92%	1.98%	-0.02	0.926	0.70%
GOLD	1089	-0.03%	5.09%	-0.41%	-0.25%	4.08%	-22.19%	28.38%	50.57%	0.505	2.549	15.40%
OIL	1089	-0.03%	4.97%	-0.28%	-0.16%	3.79%	-21.91%	46.20%	68.11%	1.241	10.092	15.00%
S&P500	1089	0.04%	0.86%	0.06%	0.08%	0.55%	-4.18%	3.83%	8.01%	-0.687	3.512	2.60%
SYSRISK	1089	-0.02%	27.30%	0.14%	0.11%	9.97%	-446.45%	529.46%	975.90%	2.239	196.948	82.70%
	Panel B: COVID-19 Sample (January 2020 to January 2021)											
AGG	255	0.02%	0.53%	0.04%	0.03%	0.18%	-0.04%	2.34%	6.43%	-3.062	29.003	0.033
RAI	255	0.08%	18.74%	-0.35%	-0.35%	4.12%	-1.35%	144.70%	279.54%	1.475	31.111	1.174
EMU	255	0.00%	14.18%	-0.19%	-0.21%	1.54%	-0.95%	180.39%	275.23%	6.762	108.561	0.888
BTC	255	0.64%	4.99%	0.48%	0.72%	2.62%	-0.46%	16.71%	63.18%	-3.155	30.886	0.312
BTCTA	255	0.70%	20.06%	0.02%	0.17%	18.36%	-0.61%	81.31%	142.69%	0.469	1.945	1.255
ETH	255	0.84%	6.77%	0.52%	0.88%	3.87%	-0.55%	32.50%	87.57%	-1.732	19.317	0.424
ETHTA	255	0.79%	22.08%	0.26%	-0.37%	17.94%	-0.56%	119.17%	174.74%	0.924	3.203	1.383
LTC	255	0.49%	6.62%	0.40%	0.63%	3.44%	-0.45%	23.66%	68.57%	-1.255	9.831	0.415
LTCTA	255	0.74%	19.50%	-0.04%	-0.28%	15.15%	-0.62%	74.02%	135.60%	0.572	1.849	1.221
CORPBOND	255	0.03%	0.90%	0.05%	0.05%	0.31%	-0.05%	6.82%	11.90%	-0.025	22.741	0.056
CRIX	255	0.75%	4.94%	0.48%	0.79%	2.61%	-0.45%	18.50%	63.16%	-2.801	27.489	0.309
VCRIX	255	0.22%	10.61%	0.00%	0.16%	2.50%	-0.75%	103.76%	179.17%	2.135	45.466	0.664
EPU	255	0.32%	41.44%	0.36%	-0.66%	29.14%	-2.69%	321.02%	589.92%	0.927	19.573	2.595
DOLLAR	255	-0.03%	0.45%	-0.02%	-0.04%	0.38%	-0.02%	1.58%	3.21%	0.464	1.932	0.028
EMERGING	255	0.07%	2.17%	0.25%	0.18%	1.41%	-0.14%	6.98%	20.54%	-1.646	9.96	0.136
US GOVT.	255	0.02%	0.40%	0.00%	0.01%	0.27%	-0.02%	2.23%	4.48%	0.215	10.268	0.025
GOLD	255	0.19%	6.88%	-0.32%	-0.08%	5.39%	-0.27%	29.77%	56.33%	0.407	2.31	0.431
OIL	255	0.08%	10.97%	-0.92%	-0.40%	5.68%	-0.62%	85.77%	148.00%	1.81	20.214	0.687
S&P500	255	0.06%	2.18%	0.24%	0.16%	1.16%	-0.13%	8.97%	21.73%	-0.866	8.514	0.136
SYSRISK	255	-0.23%	8.41%	0.14%	-0.01%	5.92%	-0.34%	29.47%	63.88%	-0.458	2.114	0.526

cryptocurrencies against downside risk in financial markets and macroeconomic malaises [7–9]. Also, some argue that traditional economic theories are inadequate for modelling cryptocurrencies' price actions [10]. Interestingly, [11] presents a roundabout argument for Bitcoin's safe-haven potential, citing its negative association with economic policy uncertainty. Studies using social media sentiments against cryptocurrency returns reinforce this conclusion. Overall, though an unsettled debate, empirical evidence somewhat favors the uniqueness proposition.

Taxonomic implications aside, the advent of the COVID-19 pandemic accelerated an already clamant debate over treating cryptocurrencies as a discrete asset class. One reason for this is the gradual erosion of investor confidence in gold as the go-to safe haven. Post-2008 research continues to underline gold's patchy performance as a portfolio insurer [12–13]. Such sentiment has amplified during the pandemic, particularly for millennials and Gen Zs, who are already digital natives and preferentially predisposed to accepting disruption. This attitude shift has serious implications for the asset management industry [14], as demographic trends show that the largest inheritance wealth transfer in history is underway. In 2019, Forbes magazine estimated that baby-boomers will pass approximately $68 trillion worth of assets to millennials by 2030. The onset of the pandemic, followed by unabashed liquidity injection by central banks, trade wars, political tensions, and uncertainty surrounding post-pandemic recovery, may make the new owners of old wealth jittery about orthodox investment instruments. If the crypto market indeed has a mind of its own, it will likely emerge as a top candidate recipient of this imminent capital inflow. Thus, identifying the (non)integrative traits of crypto assets to global trends in tranquil and turbulent times has both theoretical and practical consequences.

Several gaps exist within the discourse over cryptocurrencies' commonality with global sentiments. First, there is an inordinate focus on spillover dynamics *vis-à-vis* established stock indices and traditional asset classes [1–2, 15]. Less explored are metrics of global investor sentiment. Risk-aversion—a substantial proxy of investor apprehension, trading decisions, and capital flows—is puzzlingly underemployed. Second, even studies incorporating multiple facets of risk rely almost exclusively on VIX or some permutation of indices from the policy uncertainty family. While usage of these metrics is justified, we argue that more can be learned by expanding the gamut. Third, we draw attention to a concern raised by [16]: whether cryptocurrencies can influence the systemic risk in established financial markets. The opposite hypothesis is also interesting, given that heightened risk in systemically important institutions can trigger capital flow to the crypto sphere. These factors motivate us to employ more appropriate variables. For example, we overcome a common difficulty in cryptocurrency literature in capturing market performance by leveraging two new indices: CRIX and VCRIX. Both are newly designed capitalization-sensitive benchmark indices for returns and volatility. We also employ [17]'s daily time-varying risk-aversion and uncertainty indices. This yields a substantial advantage over the popular monthly and quarterly frequency policies' uncertainty indices. To inspect connections to systemic risk, we rely on the Cleveland Fed's systemic risk indicator. The results vindicate our variable choices by unveiling a clear distinction in cryptocurrencies' dynamics versus traditional assets.

In this paper, Section 2 outlines the chosen variables, while Section 3 details the methodology, Section 4 presents the results and analyses, and Section 5 concludes by recapitulating the salient findings and contextualizing our contributions.

2. Variable selection

The principal variables representing broad-market performance of crypto-assets in this study are CRIX and VCRIX indices. Both were designed to deal with disproportionate capitalization issues in crypto-markets and Bitcoin's dominance. CRIX, dealing with returns, is a Laspeyres-flavored multi-venue index. It is market-cap sensitive and was constructed with a dynamic divisor which ensures that any change in the index is solely because of price shifts. It also accounts for sparse trading by tweaking liquidity rules adapted from the STOXX and AEX index families. The latter is a rolling volatility index built on top of a HAR model that adapts to abrupt changes in the constituent list. Table 1 shows our dataset's descriptive statistics. It contains two subsamples: regular (pre-COVID; August 2015 to December 2019) and COVID-19 (January 2020 to January 2021). A supplementary file catalogs all variables used in this study.

3. Methodology

We measure the commonality of cryptocurrencies versus global sentiments in a stochastic volatility framework. Specifically, we adopt the approach of [18] based on Bayesian inference. This allows us to commence with a high-dimensional premise and, later, systematically induce sparsity to derive a lower-dimensioned cluster of orthogonal latent factors. We start with a vector containing log-differenced values for variables from Table 1 for n periods: $R_t = \{r_t, r_{t+1}, r_{t+2,\ldots} r_{n+t}\}$. Simultaneously, latent factors are expressed via the vector $F_t = \{f_t, f_{t+1}, f_{t+2,\ldots} f_{n+t}\}$. All latent factors stem from idiosyncratic innovations, which themselves exhibit variations. Hence, for n+L latent volatilities, $h_t = (h_t^U, h_t^V)$. Here, $h_t^U = \{h_t, h_{t+1}, h_{t+2\ldots}\}$ and $h_t^V = \{h_{+1,t\ +2,t,\ +3,t\ldots+L,\ t}\}$. Formally, we summarize as:

$$R_t = \Lambda F_t + U_t \sqrt{\{h_t^U\}\varepsilon_t} \tag{1}$$

$$F_t = V_t \sqrt{\{h_t^V\}\backslash mu_t} \tag{2}$$

Here, Λ collects the factor loadings, while $U_t\sqrt{h_t^U}$is an n^2 matrix with exponents of volatility innovations. Meanwhile, $V_t\sqrt{h_t^V}$ is an L^2 diagonal matrix of factors' individual deviations. [18] shows the log of these variables to follow a first-order autoregressive process, allowing us to express the following:

Table 2
Model parameters.

μ_i N (b_{μ}, μ); $\mu_i$$sR$ [Mean]
$\varphi_i \in (-1, 1]$; $(\varphi_i + 1/2 \sim \beta$ (a_0, b_0) [Persistence]
σ^2 β_σ * χ^2 [Volatility]

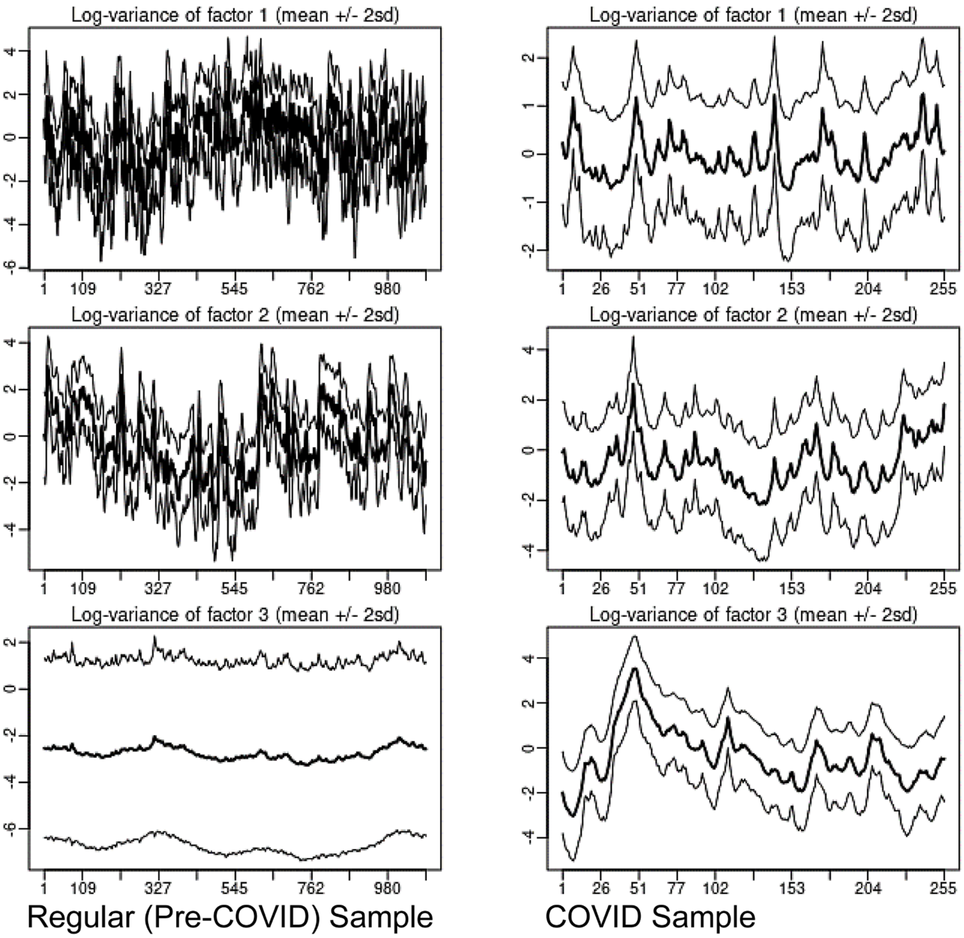

Fig. 1. Log variances of factors.

$$h_{\{it\}} = \mu_i + \phi_{i\left(h_{\{i,t-1\}} - \mu_i\right)} + \sigma_{i\eta_{\{it\}}} \tag{3}$$

In Eq. (1) and Eq. (3), the Epsilon and Eta terms correspond to innovations of the individual series and the derived factors. Both are assumed to be independent and identically distributed, allowing us to condense the above as:

$$y_t = \{\Lambda F\}_t + \in_t \tag{4}$$

$$F_t \vee h_{t;N_x\left(0, V_{t\left(h_t^V\right)}\right)} \tag{5}$$

The specification above is extensible to derivation of time-varying conditional covariances between the time series. Hence, our main concern is $\sqrt{\sigma^2(y_t|h_t)}$. We formally express the dynamic covariance as:

$$covar(y_t h_t) = \Lambda V'_{t\left(h_t^V\right)\Lambda} + U_{t\left(h_t^U\right)} \tag{6}$$

At this stage, our Bayesian inference is executed specifying the following independent priors from univariate models described above. Table 2 shows our parameters.

$$p(\mu_i, \phi_i, \sigma_i) = p(\mu_i) * p(\phi_i) * p(\sigma_i) \tag{7}$$

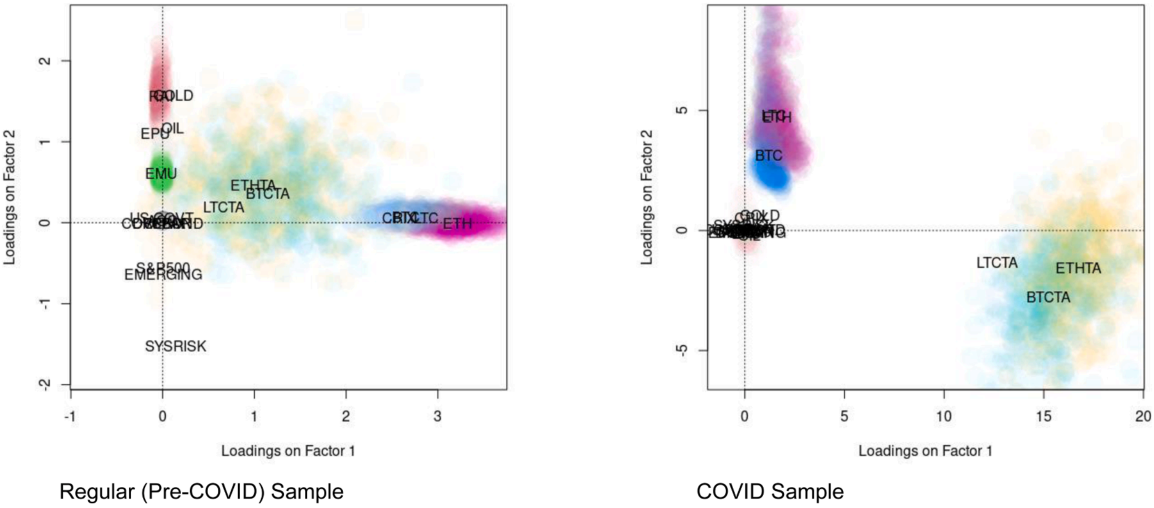

Fig. 2. Pair plots of posterior loadings for factors 1 and 2.

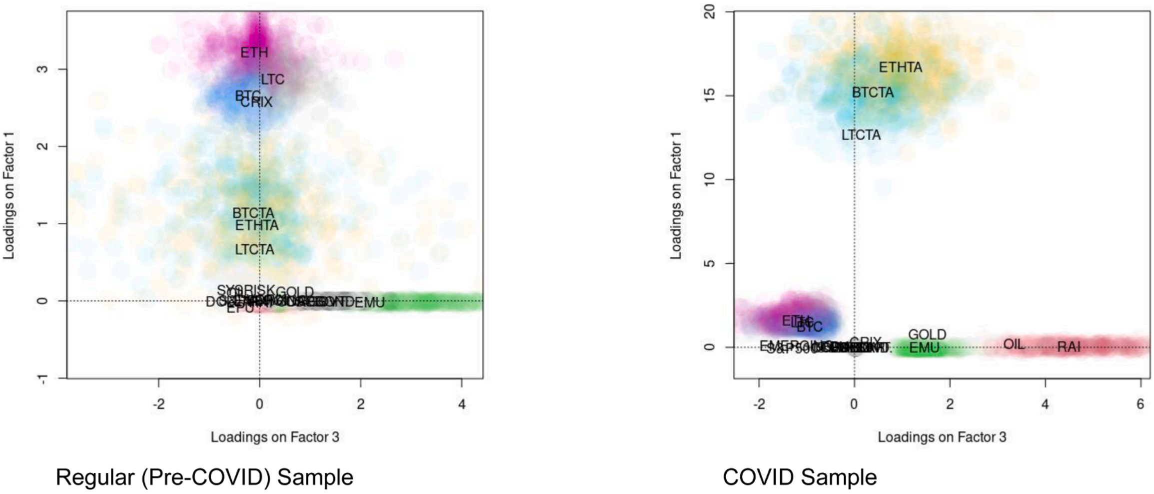

Fig. 3. Pair plots of posterior loadings for factors 1 and 3.

4. Results

Crucial to factor reduction in a high-dimensional setting is avoiding higher order models to minimize spurious or redundant factors. Heeding the recommendation of [19], we restrict factor numbers to three. Thus, we commence with posterior distributions of detected factor loadings. Better understanding of these factors comes from analysis of their log-variance (Fig. 1) and their leaders. To identify the factor leaders, we focus on Figs. 2 and 3. In the pre-COVID-19 sample, factors 1, 2, and 3 are economically identifiable as cryptocurrency prices, risk aversion, and traditional market dynamics. Clustering of the variables near the factor leaders leads to this interpretation. While factor 1 strongly indicates the cryptos' price independence from other factors, led by Ethereum, factor 2 leaders are risk Aversion and gold. This is significant and indirectly confirms gold's attractiveness as a safe haven during uncertainty. These variables are closely followed by oil, economic policy uncertainty, and global market uncertainty, all of which load null on the first factor—reaffirming the cryptos' decoupling from sentiment indicators. The third factor is more convoluted and is led by equity market uncertainty. Pertinent to this paper's scope is the fact that the crypto assets or indices load zero on this factor as well. These principal findings change somewhat post-2020. Importantly, the extent of cryptos' decoupling from global sentiments protracts in this period. For instance, unlike global uncertainties, the trading activities (volume) in cryptos emerges as an independent factor, followed by prices (factor 2). Additionally, risk aversion becomes a third and conspicuous factor driver, with loadings of gold substantially diminishing. In both samples, the relatively high loading of oil ETF volatility is prominent, which affirms a persistent role of oil price shocks. This observation is explicable both *ad hoc* and in response to suppressed global economic activity induced by the COVID-19 pandemic. Meanwhile, the log-variances of the factors suggest that, in regular times, global risk aversion is relatively stable

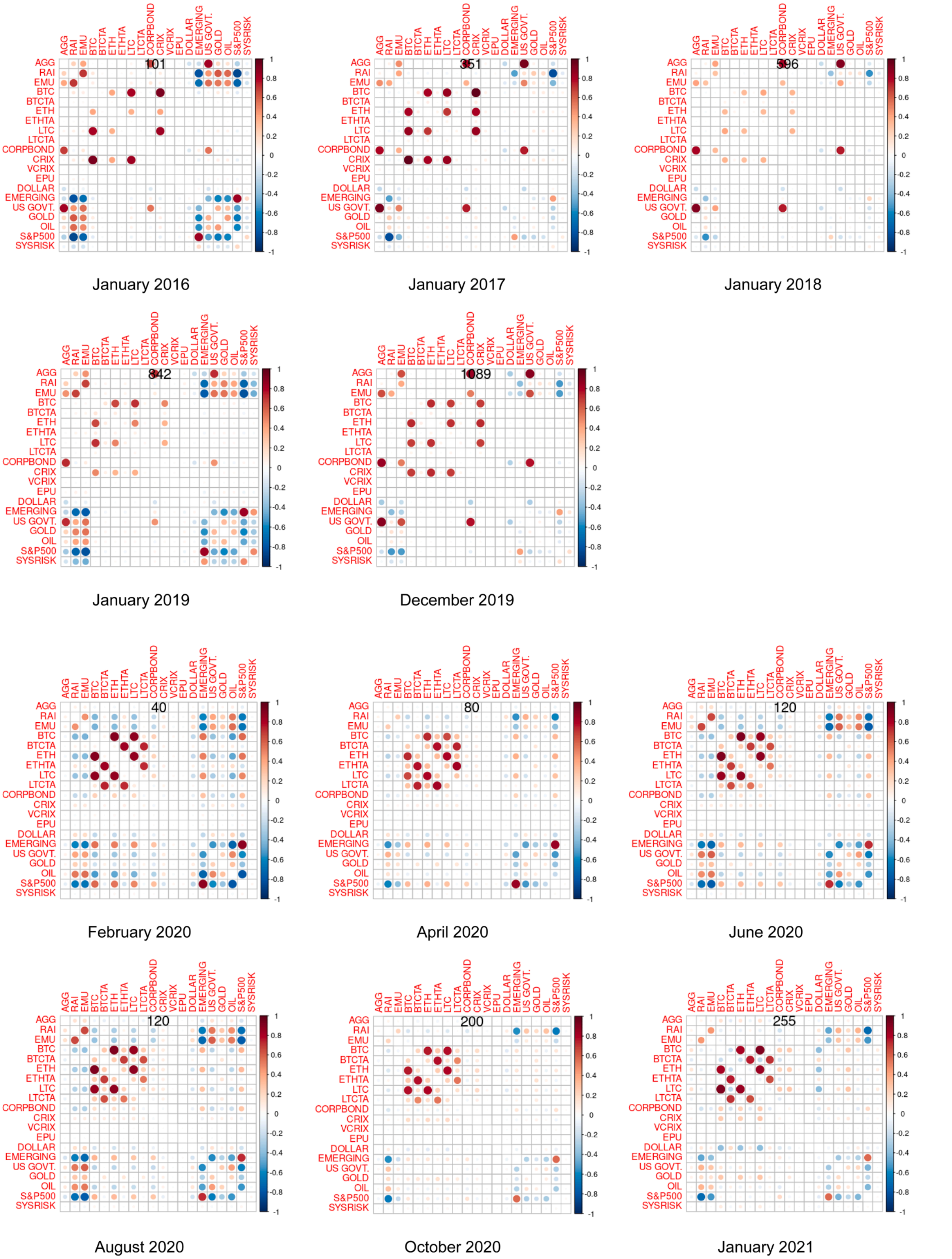

Fig. 4. Implied correlation matrices.

compared to the crypto-based factors, which exhibit locally trending features. This phenomenon is less pronounced during the COVID-19 pandemic, as all factors show choppy behavior and simultaneously peak around February 2020, coinciding with the World Health Organization's pandemic declaration.

The interpretations of the aforementioned factor loadings receive more vigorous support from the implied correlation matrices in Fig. 4. The circles in these Fig.s denote mean posterior correlations for a pair in a 100-day interval for the full sample and a 30-day interval during the pandemic. The time-varying correlations decisively demonstrate the decoupled nature of both cryptocurrencies' returns and their trading activities against market sentiments. Interestingly, even within the crypto sphere, there appears to be very little relationship between CRIX, VCRIX, and the major three coins. This implies the maturity of the crypto market, i.e., the broader market moves in the crypto sphere have become less systematic and spill over with less intensity. One interesting finding, however, pertains to the well-documented leadership of Ethereum as a price and volume leader [20]. Meanwhile, for the COVID-19 subsample, the strong positive/negative correlations among the traditional assets and sentiment variables are largely unsurprising and generally conform to economic theory. Absence of the same for the cryptocurrencies validates our earlier point about decoupling.

Our consolidated findings cohere with several important recent works. For example, [2] documents a mild association between cryptocurrencies and traditional assets, especially commodities and precious metals. Furthermore, our findings indirectly support the observation of Bianchi (and others) that intra-market investor sentiments are more prominent drivers of crypto price and volatility dynamics. The close to nil association with many risk and uncertainty indicators can be interpreted in a classical financial portfolio construction framework. For instance, our results in the implied correlation matrices comfortably qualify as being between "considerable risk reduction is possible" and "most risk can be eliminated," as per the diversification classification propounded by [21]. Risk diversification aside, Fig. 4 indicates that several crypto assets start to exhibit negative correlation with global risk aversion, uncertainty sentiments, and traditional assets (notably the U.S. dollar, U.S. treasuries, and oil). 2020 results in Fig. 4 confirm Bitcoin's role as a poor safe haven early in 2020 (only considering the S&P 500), though the phenomenon has diminished somewhat since late 2020. Nonetheless, considering a wider view of global sentiments and other asset classes, our findings broadly hint at a potentially growing role of crypto assets as safe havens [22–25].

5. Conclusion

This letter deposits to financial literature new evidence on the decoupling of cryptocurrencies from prominent indicators of global sentiments relevant to financial markets. Our results invariably point towards a dissociation of cryptocurrencies' price, volatility, and trading activities from global sentiment proxies, from 2015 to 2021. The findings are more potent when we isolate the COVID-19 pandemic period. Consequently, our findings support both the loudening call for treating cryptocurrencies as an independent asset class as well as highlighting potential safe-haven attributes and diversification benefits.

CRediT authorship contribution statement

Imtiaz Sifat: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing - original draft, Writing - review & editing, Visualization.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2021.102013.

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