

Article

Pairing Uncertainty and Attention Indices to Explain Cryptocurrency Returns: Quantile and Causality Evidence

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Abstract

Does the pricing of uncertainty in cryptocurrency markets depend on where in the return distribution one looks, and does investor attention carry information beyond uncertainty itself? We address these questions for ten cryptocurrencies spanning dominant and less-dominant coins over September 2018 to December 2021, using quantile regression, joint (multivariate) quantile regression, and Granger causality tests, together with a COVID-19 sub-sample. Grounding the analysis in the uncertainty- and attention-based asset-pricing literature, we test three hypotheses: that uncertainty is priced in the tails of the return distribution rather than at its centre; that cryptocurrency-specific uncertainty matters more than broad macroeconomic uncertainty; and that uncertainty and attention are complementary, so that pairing an uncertainty index with an attention index explains tail returns better than either index alone. The evidence supports all three. Single indices are largely irrelevant at the median but become influential in bear-market tails and over longer horizons; the cryptocurrency-specific UCRY indices dominate the broader macro proxies; and price-or-policy-plus-attention pairs show stronger and broader tail effects than either index alone, though part of this reflects the additional regressor in paired specifications. Causality runs mainly from indices to returns at longer horizons. The study shows that uncertainty is a tail phenomenon in cryptocurrency markets and that attention operates as a distinct, complementary channel.

Keywords: cryptocurrency returns; economic policy uncertainty; UCRY index; CBDC attention; cryptocurrency environmental attention; quantile regression; granger causality



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1. Introduction

Cryptocurrencies have evolved from a niche technological curiosity into a distinct asset class that investors increasingly use for diversification and risk management. Because cryptocurrency prices are unusually sensitive to information and sentiment, a growing literature asks how various forms of uncertainty shape their returns. Most of this work focuses on a single dimension of uncertainty—typically economic policy uncertainty (EPU)—and on a handful of large-capitalisation coins.

Yet, uncertainty reaches cryptocurrency markets through several channels that the literature has only recently begun to measure. Beyond conventional EPU, newly constructed indices now capture cryptocurrency-specific policy and price uncertainty (UCRY Policy and UCRY Price; [Lucey et al., 2022](#)), central bank digital currency uncertainty and attention (CBDCUI and CBDCAI; [Wang et al., 2022b](#)), the media's environmental attention to crypto mining (the ICEA index; [Wang et al., 2022a](#)), and real-time, social-media-based economic

uncertainty (the Twitter-based TEU index; [Baker et al., 2021](#)). Whether—and at which points of the return distribution—these distinct indices matter remains largely untested, particularly for less-dominant coins and across calm versus turbulent regimes.

This study addresses that gap. Using daily, weekly, and monthly data from September 2018 to December 2021, we examine the relationship between seven uncertainty and attention indices and the returns of ten cryptocurrencies that range from the most to the least dominant by market capitalisation. We employ quantile regression to trace effects across the return distribution, joint (multivariate) quantile regression to assess indices individually and in pairs, and Granger causality tests to evaluate short- and longer-horizon predictability. We further isolate the COVID-19 period to test the stability of our findings under acute market stress.

The paper makes three contributions. First, it brings the cryptocurrency environmental attention (ICEA) and the CBDC uncertainty and attention indices into a multi-method (quantile and Granger-causality) analysis of returns across a broad cross-section of cryptocurrencies—a setting in which these recently introduced indices remain under-examined—thereby broadening the set of uncertainty channels considered. Second, it shows that combinations of indices—a price or policy index paired with an attention index—are more informative than any single index, especially in the tails. This complementarity between uncertainty and attention, which we motivate theoretically in Section 2.6, is the paper’s central contribution. Section 4.5 shows this is not merely a descriptive pattern: after correcting for multiple testing, the paired specifications retain a substantially higher share of significant coefficients than either the single-index or the fully joint six-index approach used in prior work, which is direct, correction-robust evidence that the pairing captures something a single-index framework cannot. Third, by covering ten coins and a COVID-19 sub-sample, it documents how uncertainty–return linkages differ between dominant and less-dominant cryptocurrencies and across market regimes. The findings help investors and institutions manage risk and inform policymakers about the interplay between uncertainty and digital-asset markets.

The remainder of the paper is organised as follows. Section 2 reviews the related literature and states the research gap. Section 3 describes the data and the econometric methods. Section 4 presents and synthesises the empirical results, including the COVID-19 sub-sample. Section 5 discusses the economic interpretation of the findings, and Section 6 concludes with implications and avenues for future research.

2. Literature Review

The literature below is organised empirically, strand by strand, because each strand has developed largely independently; Section 2.6 then draws these strands together into a single theoretical framework—an ambiguity/risk-premium channel, an investor-recognition channel, and a limited-attention channel—and derives the hypotheses (H1–H3) that the empirical design tests.

2.1. Economic Policy Uncertainty and Cryptocurrency Returns

The Economic Policy Uncertainty (EPU) index captures uncertainty surrounding government and regulatory decisions and is known to influence macroeconomic outcomes such as employment, consumption, and investment ([Demir et al., 2018](#); [Yen & Cheng, 2021](#)). The first strand of research asks whether EPU predicts cryptocurrency returns. [Demir et al. \(2018\)](#) find that EPU has predictive power over Bitcoin returns, arguing that policy ambiguity can erode confidence in fiat currencies and prompt portfolio rebalancing. [Shaikh \(2020\)](#) extends this evidence, reporting that Bitcoin returns are especially sensitive to EPU in the United States, China, and Japan, while global monetary-policy uncertainty also matters.

The evidence is, however, mixed. [Cheng and Yen \(2020\)](#) find that the China EPU index predicts Bitcoin returns whereas the U.S. index does not—contradicting [Demir et al. \(2018\)](#)—and that predictability depends on data frequency. [Panagiotidis et al. \(2020\)](#), screening forty-one potential determinants, rank EPU and stock-market volatility among the most important drivers of Bitcoin returns. [Bouri et al. \(2017\)](#) and [Balcilar et al. \(2017\)](#) document horizon- and regime-dependent effects, with Bitcoin hedging uncertainty over shorter frequencies. Collectively, this strand establishes that EPU matters, but that its sign, strength, and predictive horizon are sensitive to the country, the method, and the market regime. The premise underlying this work is that cryptocurrency markets are informationally inefficient and therefore at least partly predictable ([Urquhart, 2016](#); [Hu et al., 2019](#)), which invites the search for macro-financial predictors. Beyond domestic EPU, related measures—global EPU ([Davis, 2016](#)), trade-policy uncertainty ([Gozgor et al., 2019](#)), and geopolitical or political-economic uncertainty in the United States ([Su et al., 2020](#); [Umar et al., 2021](#))—have all been linked to Bitcoin, again with regime- and horizon-dependent results.

2.2. Social Media and Twitter-Based Uncertainty

The second strand exploits high-frequency, social-media-based measures. [Baker et al. \(2021\)](#) construct Twitter-derived economic-uncertainty indices and show that the risk and uncertainty conveyed by users resembles that of professional journalists. [Wu et al. \(2021\)](#) report Granger causality from Twitter-based uncertainty to major cryptocurrencies in several sub-periods, while [French \(2021\)](#) finds that Twitter-based market uncertainty leads Bitcoin returns mainly during the pandemic. [Aharon et al. \(2022\)](#), by contrast, find no significant contemporaneous or lagged relationship between Twitter-based economic or market uncertainty and BTC, ETH, XRP, or BCH—underscoring that the predictive content of social-media sentiment is conditional and horizon-dependent ([Lehrer et al., 2021](#); [Tumasjan et al., 2021](#)). Related work links investor attention from Twitter and Google Trends to Bitcoin price dynamics ([Philippas et al., 2019](#); [Li et al., 2021](#); [Kraaijeveld & De Smedt, 2020](#); [Huynh, 2021](#)). [Gök et al. \(2022\)](#) likewise find that the predictive value of Twitter-based uncertainty for safe-haven assets depends on the market state and the investment horizon, and a parallel literature turns to news-based measures of uncertainty and disaster risk, such as the news-implied volatility index of [Manela and Moreira \(2017\)](#), which [T. Fang et al. \(2020\)](#) report predicts long-horizon cryptocurrency volatility better than global EPU.

2.3. New Cryptocurrency-Specific and Attention Indices

A third, more recent strand introduces purpose-built indices. [Lucey et al. \(2022\)](#) develop the UCRY index, separating cryptocurrency policy uncertainty (UCRY Policy) from price uncertainty (UCRY Price), and show that it responds to landmark events in the crypto space. [Wang et al. \(2022a\)](#) introduce the cryptocurrency environmental attention (ICEA) index, constructed from 778.2 million news items, to capture media attention to the environmental impact of crypto mining, while [Wang et al. \(2022b, 2023\)](#) construct CBDC attention and uncertainty indices and document their spillovers to cryptocurrency prices. These indices capture information that conventional EPU misses—regulatory and technological developments specific to digital assets, and the media’s environmental attention to crypto mining—yet their relationship with returns, particularly for less-dominant coins, remains largely untested. Building on these measures, [Ayadi et al. \(2023\)](#) document directional predictability from CBDC uncertainty and attention to cryptocurrency and stablecoin returns, [Shang et al. \(2022\)](#) show that the UCRY Policy index helps forecast gold returns, and [Nguyen and Nguyen \(2023\)](#) find that crypto-specific policy uncertainty affects Bitcoin exchange inflows over both short and long horizons. More recent evidence reinforces this relevance: [Ah Mand \(2025\)](#) reports that the UCRY index leads the returns of the eight largest

cryptocurrencies across all frequencies, even after controlling for EPU and the VIX, and Barson and Owusu Junior (2023) document time- and frequency-varying connectedness among the ICEA, CBDC attention, and NFT attention indices and conventional assets. The proliferation of narrowly scoped uncertainty measures continues: Gürsoy et al. (2024) link a climate-policy-uncertainty index, a clean-energy index, and carbon-allowance prices to Bitcoin returns, and Gürsoy et al. (2022) document causality running from Bitcoin's energy consumption to the UCRY policy and price uncertainty indices themselves—evidence that reinforces our inclusion of the ICEA index, which captures media attention to the environmental footprint of crypto mining, alongside the other indices studied here. This is the space our study occupies.

2.4. Cryptocurrencies, Uncertainty, and Other Assets

A fourth strand situates cryptocurrencies among traditional assets to assess hedging and safe-haven properties under uncertainty. The findings are heterogeneous: Hasan et al. (2022) report that the UCRY index hedges gold and Islamic equities but not Bitcoin; Karaömer (2022) finds negative, time-varying correlations between UCRY Policy and several coins around major events; and Xia et al. (2023) show that UCRY indices improve out-of-sample forecasts of Bitcoin volatility relative to national and global EPU. Studies of EPU–Bitcoin–equity linkages (Mokni et al., 2020, 2021; Hernandez et al., 2023; L. Fang et al., 2019) and of geopolitical risk (Aysan et al., 2019; Colon et al., 2021) generally conclude that cryptocurrencies hedge uncertainty only weakly and only in particular regimes or quantiles. Complementary evidence comes from studies of volatility drivers and contagion (Walther et al., 2019; Matkovskyy & Jalan, 2019), of EPU and gold across bull and bear markets (Papadamou et al., 2021), of Bitcoin's safe-haven role during the COVID-19 period (Raheem, 2021; Choi & Shin, 2022), and of heterogeneous reactions to macroeconomic news across digital assets (Corbet et al., 2020). Together, these findings reinforce the case for a distribution-sensitive, multi-index approach. Closest to our setting, Będowska-Sójka et al. (2024) study ten major cryptocurrencies against a battery of uncertainty measures over 2018–2022 and find that transmission from uncertainty to crypto markets is generally weak but intensifies during turbulent episodes such as COVID-19 and the Russia–Ukraine war—evidence consistent with the tail- and crisis-concentrated effects we document below.

2.5. Research Gap

Three gaps emerge. First, the literature concentrates on EPU and on a few large coins, leaving newer crypto-specific and attention-based indices—especially the ICEA and CBDC indices—largely unexplored in a returns setting. Second, studies typically test one index at a time, ignoring that different indices capture complementary information (policy, price, attention, environmental concern) that may matter jointly. Third, evidence on less-dominant cryptocurrencies, and on how relationships shift between bull and bear regimes and during the COVID-19 shock, is sparse. Although a rapidly growing literature now employs these indices (e.g., Ah Mand, 2025; Barson & Owusu Junior, 2023; Będowska-Sójka et al., 2024), it largely emphasises connectedness with non-crypto assets or concentrates on Bitcoin, leaving the direct, distribution-level, and causal effects on a broad cross-section of coins under-examined. We close these gaps by introducing the ICEA and CBDC indices into a cryptocurrency-returns analysis, testing indices individually and in pairs across the return distribution, and covering ten coins, multiple data frequencies, and a dedicated COVID-19 sub-sample. These gaps reduce to one overarching economic question: does investor attention amplify, and complement, the pricing of uncertainty in cryptocurrency returns? Section 2.6 formalises this as our central hypothesis (H3), supported by two subsidiary hypotheses on where in the return distribution uncertainty is priced (H1) and on

which type of uncertainty is priced (H2). Accordingly, we address four research questions, each an operational facet of that overarching question:

1. Which uncertainty or attention index most strongly affects cryptocurrency returns, and at which points in the return distribution?
2. Which pairs of indices most strongly affect returns during bull versus bear regimes?
3. Do the indices Granger-cause returns (and vice versa) in the short and longer horizons?
4. Are these relationships stable during the COVID-19 period?

2.6. Theoretical Framework and Hypothesis Development

Cryptocurrencies lack conventional cash-flow fundamentals, so their prices are unusually sensitive to shifts in beliefs and in the composition of market participants, which makes them a natural setting in which to study how uncertainty and attention are priced. We organise the seven indices around three economic channels. First, macroeconomic and policy uncertainty raises required returns through a risk- and ambiguity-premium channel: when the distribution of future states is itself uncertain, ambiguity-averse investors demand compensation, and that compensation is largest in adverse states (Bloom, 2009; Baker et al., 2016; Pástor & Veronesi, 2012, 2013; Epstein & Schneider, 2008). Because cryptocurrency fundamentals are especially contested, this ambiguity channel is likely to bind more tightly in bear markets than at the centre of the distribution. Second, uncertainty that originates within the digital-asset ecosystem—crypto-specific policy and price uncertainty and central bank digital currency developments—operates through an investor-recognition channel: heightened uncertainty about the asset class narrows its investor base and raises the shadow cost of participation (Merton, 1987), so crypto-native measures should move returns more than general macroeconomic proxies. Third, investor attention governs how quickly and how strongly information—including uncertainty shocks—is impounded into prices (Barber & Odean, 2008; Da et al., 2011). Because attention is a limited resource that investors ration and reallocate across assets and states (Peng & Xiong, 2006; Kacperczyk et al., 2016), it carries information complementary to, rather than redundant with, uncertainty; and because limited attention slows the incorporation of information, its effects should also surface over longer horizons (Hirshleifer & Teoh, 2003).

These channels motivate three testable hypotheses, which map onto the research questions above and which we revisit when interpreting the results:

H1. *Uncertainty is priced in the tails of the cryptocurrency return distribution rather than at its centre.*

H2. *Cryptocurrency-specific uncertainty measures affect returns more strongly than broad macroeconomic uncertainty measures.*

H3. *Uncertainty and investor attention are complementary: specifications that combine an uncertainty index with an attention index explain returns—especially tail returns—better than either index alone.*

The quantile and joint-quantile estimators test H1 and H3 across the return distribution, the comparison between crypto-specific and macro indices tests H2, and the Granger-causality analysis examines the horizon over which these effects operate, consistent with the attention-based, gradual-incorporation mechanism set out above.

3. Data and Methodology

Figure 1 summarises the overall research design, from the data and return construction, through the single- and joint-quantile and Granger-causality estimators, to the COVID-19 robustness analysis.

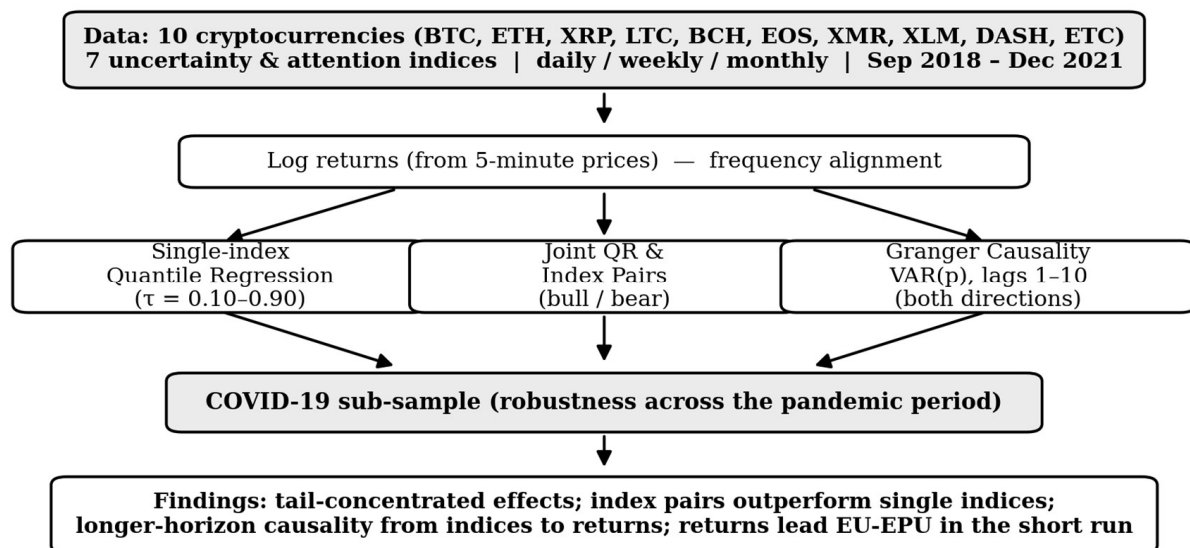


Figure 1. Overview of the research design. Note: QR = quantile regression; VAR = vector autoregression.

3.1. Data

We study ten cryptocurrencies—BTC, ETH, XRP, LTC, BCH, EOS, XMR, XLM, DASH, and ETC—selected to span the spectrum from dominant to less-dominant market capitalisations, ranging from the largest coins by capitalisation (BTC, ETH, XRP) down to smaller-capitalisation coins (XMR, XLM, DASH, ETC). The set is further constrained to coins with continuous five-minute Kraken data across the full sample window, which determined the final ten. This is consistent with the CoinMarketCap ranking on 9 September 2018, close to the sample start: excluding the one stablecoin among the top fifteen (Tether, rank 8), the ten coins studied correspond to ranks 1–7, 10, 11, and 15 by market capitalisation (Bitcoin, Ethereum, XRP, Bitcoin Cash, EOS, Stellar, and Litecoin at ranks 1–7; Monero at rank 10; Dash at rank 11; and Ethereum Classic at rank 15), with Cardano, IOTA, TRON, and NEO (ranks 9, 12–14) the only coins in that range not included, plausibly reflecting Kraken data-availability constraints at the time. Price data are obtained from Kraken, whose public API returns Unix timestamps in UTC and uses USD-quoted spot pairs (e.g., XXBTZUSD for BTC/USD) as the standard convention for these ten coins. For each cryptocurrency i , returns are computed as continuously compounded (log) returns,

$$r_{i,t} = \ln P_{i,t} - \ln P_{i,t-1} \quad (1)$$

where P denotes price, and these returns are aggregated from five-minute observations to the daily, weekly, and monthly frequencies for the period 1 September 2018 to 31 December 2021. The seven uncertainty and attention indices are obtained at their native frequencies from their respective providers, as summarised in Table 1. Because the indices are released at different frequencies, the weekly frequency is used as the common base in the joint analysis: the daily TEU index is aligned to the weekly frequency using end-of-week (Friday) observations, and the monthly EU-EPU index is analysed at its native frequency. Descriptive statistics for the daily, weekly, and monthly samples are reported in Tables 2–4. To summarise the mixed-frequency design explicitly: the single-index quantile regressions (Section 3.2) are estimated once at each index’s native frequency (daily for TEU, weekly for UCRY Policy, UCRY Price, CBDC Uncertainty, CBDC Attention and ICEA, and monthly for EU-EPU), giving 1218 daily, 174 weekly, and 40 monthly observations per regression (Tables 2–4). The joint and paired quantile regressions (Section 3.3) and the weekly Granger-causality tests (Section 3.4) use the six weekly-native or weekly-aligned indices only—UCRY

Policy, UCRY Price, CBDC Uncertainty, CBDC Attention, ICEA, and the Friday-aligned TEU—with 174 weekly observations; the monthly EU-EPU index is not included in these weekly joint or paired specifications and is instead assessed separately, at its native monthly frequency ($n = 40$), in the single-index and causality analyses only.

Table 1. Variables, definitions, frequencies, and data sources.

Variable	Definition	Freq.	Source
Returns (BTC, ETH, XRP, LTC, BCH, EOS, XMR, XLM, DASH, ETC)	Continuously compounded returns computed from five-minute prices (Equation (1))	D/W/M	Kraken
UCRY Policy	Cryptocurrency policy uncertainty index (Lucey et al., 2022)	Weekly	Cryptocurrency Indices
UCRY Price	Cryptocurrency price uncertainty index (Lucey et al., 2022)	Weekly	Cryptocurrency Indices
CBDCUI	Central bank digital currency uncertainty index (Wang et al., 2022b)	Weekly	Cryptocurrency Indices
CBDCAI	Central bank digital currency attention index (Wang et al., 2022b)	Weekly	Cryptocurrency Indices
ICEA	Index of cryptocurrency environmental attention (Wang et al., 2022a)	Weekly	Cryptocurrency Indices
EU-EPU	European economic policy uncertainty index	Monthly	FRED (EUEPUINDXM)
TEU	Twitter-based economic uncertainty index (Baker et al., 2021)	Daily	policyuncertainty.com

Note: Sample period is 1 September 2018–31 December 2021. D/W/M = daily/weekly/monthly. Source URLs: cryptocurrency prices, kraken.com; UCRY, CBDC, and ICEA indices, the Cryptocurrency Indices repository (sites.google.com/view/cryptocurrency-indices); EU-EPU, fred.stlouisfed.org/series/EUEPUINDXM; TEU, policyuncertainty.com/twitter_uncert.html.

Table 2. Descriptive statistics: daily data and indices.

	Mean	Median	SD	Kurtosis	Skewness	Range	Obs.
TEU	176.19	144.94	100.50	4.16	1.85	679.29	1218
BTC	0.002	0.001	0.04	6.19	−0.52	0.49	1218
ETH	0.002	0.001	0.05	6.86	−0.72	0.65	1218
XRP	0.001	−0.001	0.06	11.73	−0.22	0.91	1218
LTC	0.001	−0.001	0.05	6.85	−0.63	0.68	1218
BCH	0.000	0.001	0.06	9.84	−0.04	0.89	1218
EOS	−0.001	0.000	0.06	7.28	−0.49	0.77	1218
XMR	0.001	0.001	0.05	8.77	−1.00	0.64	1218
XLM	0.000	−0.001	0.06	11.38	0.88	0.84	1218
DASH	0.000	0.000	0.06	9.38	0.10	0.87	1218
ETC	0.001	0.000	0.06	9.41	0.46	0.82	1218

Note: TEU is the daily Twitter-based Economic Uncertainty Index; all others are daily log returns. SD = standard deviation.

Table 3. Descriptive statistics: weekly data and indices.

	Mean	Median	SD	Kurt.	Skew.	Range	Obs.
UCRY Policy	101.124	100.135	1.896	1.086	1.320	8.987	174
UCRY Price	101.194	100.174	1.977	1.492	1.441	9.853	174
TEU	175.557	141.392	105.118	3.294	1.736	598.238	174

Table 3. Cont.

	Mean	Median	SD	Kurt.	Skew.	Range	Obs.
CBDC Uncertainty	100.662	100.001	1.428	2.122	1.631	6.857	174
CBDC Attention	100.873	99.916	1.788	0.408	1.404	6.444	174
CC Environmental Attn.	101.666	100.057	2.803	0.865	1.409	12.277	174
BTC	0.011	0.012	0.100	3.893	−0.828	0.789	174
ETH	0.015	0.022	0.133	4.530	−0.953	1.055	174
XRP	0.005	−0.009	0.152	4.277	0.666	1.186	174
LTC	0.005	0.013	0.140	3.362	−0.672	1.026	174
BCH	−0.001	0.000	0.175	6.112	−0.205	1.536	174
EOS	−0.004	0.008	0.155	4.485	−0.978	1.184	174
XMR	0.004	0.015	0.124	5.057	−1.230	0.935	174
XLM	0.001	−0.005	0.151	7.444	1.249	1.268	174
DASH	−0.002	0.001	0.165	5.778	0.033	1.441	174
ETC	0.006	0.003	0.174	13.797	1.999	1.699	174

Note: Index values are weekly; coin rows are weekly log returns. CC Environmental Attn. = cryptocurrency environmental attention (ICEA) index.

Table 4. Descriptive statistics: monthly data and indices.

	Mean	Median	SD	Kurtosis	Skewness	Range	Count
EU-EPU	234.2	229.9	45.8	0.7	0.6	220.0	40
BTC	0.045	0.019	0.228	1.445	−0.829	1.121	40
ETH	0.058	0.098	0.284	1.037	−0.564	1.375	40
XRP	0.026	−0.058	0.344	0.650	0.129	1.678	40
LTC	0.022	0.033	0.294	0.929	−0.872	1.262	40
BCH	−0.002	−0.024	0.359	1.666	−0.549	1.797	40
EOS	−0.011	−0.030	0.311	1.402	−0.554	1.560	40
XMR	0.018	0.031	0.284	3.072	−1.215	1.520	40
XLM	0.006	0.003	0.318	0.064	−0.020	1.511	40
DASH	−0.004	0.018	0.343	1.981	−0.371	1.952	40
ETC	0.033	−0.011	0.432	7.019	1.648	2.734	40

Note: EU-EPU is the monthly European Economic Policy Uncertainty index; coin rows are monthly log returns.

3.2. Quantile Regression

Cryptocurrency returns are heavy-tailed and react asymmetrically to news, so the average relationship estimated by ordinary least squares can mask effects that appear only in the lower (bear) or upper (bull) tail of the return distribution. We therefore use the quantile regression (QR) estimator of [Koenker and Bassett \(1978\)](#), which models the conditional quantiles of returns rather than their conditional mean and thus traces how each uncertainty index affects returns across the entire distribution.

For a quantile level $\tau \in (0, 1)$, the τ -th conditional quantile of the return on cryptocurrency i , given an uncertainty index UI , is specified as

$$Q_{\tau}(r_{i,t} | UI_t) = \alpha_i(\tau) + \beta_i(\tau) UI_t \quad (2)$$

where $\alpha_i(\tau)$ is the intercept and $\beta_i(\tau)$ is the slope at quantile τ . A positive (negative) $\beta_i(\tau)$ means that higher uncertainty raises (lowers) returns at that point of the distribution; because the coefficients are indexed by τ , the sign and magnitude of the effect may differ between bear and bull states. The coefficients are obtained by minimising an asymmetrically weighted sum of absolute residuals. Defining the check (pinball) loss function

$$\rho_{\tau}(u) = u(\tau - I(u < 0)) \quad (3)$$

where $I(\cdot)$ is the indicator function; residuals are weighted by τ when positive and by $(1 - \tau)$ when negative, which pins the fit to the τ -th quantile. The estimator then solves

$$\beta(\tau) = \arg \min \sum_{t=1}^T \rho_{\tau}(r_{i,t} - \alpha_i(\tau) - \beta_i(\tau) UI_t) \quad (4)$$

where T is the sample size. We estimate the model at nine quantiles, $\tau = 0.10, 0.20, \dots, 0.90$, treating the lower quantiles (0.10–0.20) as bear-market conditions and the upper quantiles (0.80–0.90) as bull-market conditions. Coefficient standard errors are obtained by bootstrapping, and significance is assessed at the 1%, 5%, and 10% levels. Because the full analysis produces a large number of coefficient estimates across indices, coins, and quantiles, we guard against spurious findings by basing inference on the breadth and consistency of significance across coins and quantiles rather than on isolated estimates. As a formal complement, we apply false-discovery-rate control (Benjamini & Hochberg, 1995) to each coefficient family reported in the Supplementary. We implement this correction across all 3190 coefficient estimates reported in Tables S1–S61, using the Benjamini and Hochberg (1995) procedure with each table as the primary family (matching how results are organised and presented), and with coarser section-level and whole-supplementary families as robustness checks; Section 4.5 reports the results.

3.3. Joint (Multivariate) Quantile Regression

Here, “joint” refers to including more than one uncertainty index as a simultaneous regressor within a single quantile regression, not to pooling information across neighbouring quantiles: each quantile continues to be estimated separately, by the same check-loss estimator described in Section 3.2 (Koenker & Bassett, 1978), now with two or more indices entering the right-hand side so that each coefficient is identified net of the other index(es) rather than in isolation. Within this framework, we examine the indices both together and in pairs. The multi-index specification regresses returns on all K uncertainty indices simultaneously,

$$Q_{\tau}(r_{i,t} | UI_t) = \alpha_i(\tau) + \sum_{k=1}^K \beta_{i,k}(\tau) UI_{k,t} \quad (5)$$

where $UI_{k,t}$ is the k -th uncertainty index and $\beta_{i,k}(\tau)$ is its quantile-specific coefficient. Because different indices carry complementary information—a price or policy channel versus an investor-attention channel—we also estimate two-index specifications that pair a price/policy index with an attention index. All quantile regressions—single-index, joint, and paired—were estimated in R, using the quantreg package (Koenker, 2005), which implements the Koenker and Bassett (1978) estimator described above; coefficient standard errors are obtained by a nonparametric bootstrap as implemented in that package.

$$Q_{\tau}(r_{i,t}) = \alpha_i(\tau) + \beta_{i,1}(\tau) UI_{1,t} + \beta_{i,2}(\tau) UI_{2,t} \quad (6)$$

We evaluate the joint and paired models at $\tau = 0.05, 0.25, 0.50, 0.75$, and 0.95 , focusing on the extreme bear ($\tau = 0.05$) and bull ($\tau = 0.95$) quantiles. We then rank the four pairs by the strength and breadth of their effects in each regime.

The four index pairs are not selected arbitrarily. Each pair combines exactly one price/policy uncertainty channel with one attention channel, following Hypothesis 3: the price/policy leg is UCRY Policy or UCRY Price, and the attention leg is the CBDC attention index or the cryptocurrency environmental attention (ICEA) index, which yields the $2 \times 2 = 4$ combinations examined. The remaining indices are not used as the attention leg because they measure uncertainty rather than attention (CBDC Uncertainty, TEU, and EU-EPU) and, in the case of TEU and EU-EPU, exert only weak contemporaneous effects (Section 4.1); pairing an uncertainty channel with an attention channel is precisely what the complementarity in Hypothesis 3 predicts should be informative.

3.4. Granger Causality

Quantile regression captures contemporaneous, distribution-dependent associations but not the direction or timing of influence. To assess predictability, we apply Granger (1969) causality tests within a bivariate vector autoregression (VAR). As with any Granger-causality analysis, a significant result establishes statistical precedence—that past values of one series improve the prediction of another beyond the latter’s own history—and not structural or economic causation; we use “lead”, “predicts”, and “Granger-causes” interchangeably below in this predictive sense, and avoid stronger causal language.

A VAR of order p for the vector $Y_t = (r_{i,t}, UI_t)'$ is written as

$$Y_t = c + \sum_{j=1}^p A_j Y_{t-j} + \varepsilon_t \quad (7)$$

where c is a constant vector, A_j are coefficient matrices, and ε_t is a vector of white-noise innovations. Equivalently, the two equations of the bivariate system are

$$r_{i,t} = \varphi_0 + \sum_{j=1}^p \varphi_j r_{i,t-j} + \sum_{j=1}^p \gamma_j UI_{t-j} + \varepsilon_{1,t} \quad (8)$$

$$UI_t = \delta_0 + \sum_{j=1}^p \delta_j UI_{t-j} + \sum_{j=1}^p \theta_j r_{i,t-j} + \varepsilon_{2,t} \quad (9)$$

The index Granger-causes returns if past values of the index help predict current returns beyond the information in past returns; the corresponding null hypothesis is $H_0: \gamma_1 = \dots = \gamma_p = 0$ in Equation (8). Symmetrically, returns Granger-cause the index if $H_0: \theta_1 = \dots = \theta_p = 0$ is rejected in Equation (9). Each null is tested with a Wald (F) statistic, and we report results in both directions.

The lag order p is selected by the Akaike Information Criterion,

$$AIC(p) = \ln |\Sigma_{\varepsilon}(p)| + (2/T) n^2 p \quad (10)$$

where $\Sigma_{\varepsilon}(p)$ is the estimated residual covariance matrix, n is the number of variables, and T is the sample size; the criterion trades off fit against parsimony by penalising additional lags. It selects $p = 6$ for most indices, with $p = 7$ for the ICEA index and $p = 10$ for the EU-EPU index. We apply the chosen lag order uniformly across variables and, to keep the tests comparable, also report the short-horizon case $p = 1$, assessing causality at both short ($p = 1$) and longer ($p = 6$, and $7/10$ where indicated) horizons.

Because Granger-causality inference is sensitive to non-stationarity, lag misspecification, and residual misbehaviour, the VAR systems in Equations (7)–(9) should be accompanied by standard pre-estimation and diagnostic checks: unit-root tests (e.g., ADF, KPSS) confirming the stationarity of the return and index series (or justifying the levels specification if the series are $I(0)$ by construction, as with normalised indices), a VAR stability check (inverse roots of the characteristic polynomial inside the unit circle), and residual diagnostics for serial correlation (e.g., a Portmanteau or Breusch–Godfrey test) and heteroskedasticity (e.g., an ARCH-LM test). This is particularly relevant for the monthly EU-EPU system, which combines the smallest sample ($n = 40$) with the longest lag order ($p = 10$), leaving comparatively few degrees of freedom.

We verified these conditions on the return side of each system, using the same daily and weekly return series underlying Tables 2 and 3. Augmented Dickey–Fuller and KPSS tests agree that returns are stationary for all ten cryptocurrencies at both frequencies (ADF rejects a unit root at $p < 0.01$ in all 20 cases; KPSS fails to reject stationarity in all 20 cases), so the levels-based VAR specification in Equations (7)–(9) is appropriate without differencing. Residual diagnostics are frequency-dependent: at the daily frequency, a Ljung–Box test (10 lags) detects residual serial correlation in 5 of 10 coins, and an ARCH-LM test (10 lags) detects heteroskedasticity in all 10 coins at the 5% level, consistent with well-documented

volatility clustering in cryptocurrency markets at high frequency; both diminish sharply at the weekly frequency used in the joint quantile and Granger-causality models (serial correlation in 1 of 10 coins; heteroskedasticity in 2 of 10 coins).

For the index side, we obtained the EU-EPU series directly from FRED (series EUEPUINDXM)—the specific system flagged above as the priority case. Over the full sample ($n = 40$), an ADF test rejects a unit root ($p = 0.015$) and a KPSS test fails to reject stationarity, so EU-EPU is stationary in levels over 2018–2021. Over the COVID-19 sub-sample alone ($n = 22$), the ADF test no longer rejects a unit root ($p = 0.80$) and KPSS is borderline ($p = 0.07$). With only 22 monthly observations, this most likely reflects low test power against the index's pronounced 2020–2021 upward trend rather than genuine non-stationarity, but it is worth flagging given the small-sample, long-lag concern already noted.

3.5. Descriptive Statistics

Table 2 reports summary statistics for the daily return series and the daily TEU index; Table 3 for the weekly series and the six weekly indices; and Table 4 for the monthly series and the EU-EPU index. Returns are leptokurtic and, in several cases, negatively skewed, consistent with the fat tails and downside risk that motivate a quantile-based approach.

4. Empirical Results

We organise the results by method and research question rather than table by table. The full set of estimation results is provided in the online Supplementary (Tables S1–S61); here we report the patterns that answer our four questions and summarise them in Table 5. Throughout, each coefficient is read as the marginal effect of an index on returns at the stated quantile, and we emphasise the sign of the effect, its location in the distribution (bear versus bull), and its breadth across coins rather than individual point estimates. This emphasis on the breadth and consistency of effects, rather than on individual coefficients, is also our first safeguard against the multiple-comparison problem that arises when many quantile models are estimated (Section 3.2).

Table 5. Summary of findings and regime-specific rankings of index pairs.

Method/Question	Main Finding
Single-index QR (median)	Weak: most indices insignificant at the centre of the return distribution.
Single-index QR (tails)	UCRY Policy strongest in bear quantiles (ETH > XRP > LTC); UCRY Price active in bear tails; XRP/ETH the most index-sensitive coins.
Joint QR	Effects concentrate at $\tau = 0.95$; ICEA and UCRY Price significant for several coins; bear ($\tau = 0.05$) quantile largely insignificant.
Index pairs—bear ($\tau = 0.05$)	(1) UCRY Policy + CBDC Attention; (2) UCRY Price + CBDC Attention; (3) UCRY Price + ICEA; (4) UCRY Policy + ICEA.
Index pairs—bull ($\tau = 0.95$)	(1) UCRY Policy + ICEA; (2) UCRY Price + ICEA; (3) UCRY Price + CBDC Attention; (4) UCRY Policy + CBDC Attention.
Granger causality	Mostly longer-horizon: TEU, UCRY, CBDC, and ICEA cause returns at lag 6+; EU-EPU is led by returns in the short run but leads returns at lag 10.
COVID-19 sub-sample	Largely confirms the full sample; somewhat stronger UCRY effects at the 0.10/0.80/0.90 quantiles.

Note: rankings are based on the joint quantile regression results reported in Supplementary Tables S9–S13 and S40–S44. After multiple-testing correction (Section 4.5), the bear-quantile ranking above is confirmed, but the bull-quantile ranking is not: the UCRY Price + ICEA pair, not UCRY Policy + ICEA, retains the most significant coefficients at $\tau = 0.95$. For the number, direction, and significance level of the individual coefficients underlying each ranking, see Table 6 (survival by method) and Table 7 (the pair-ranking check), and the full coefficient-level results in Tables S9–S13 and S40–S44.

Table 6. Benjamini–Hochberg FDR correction: survival by method (each table is treated as its own family).

Method	Sample	n	Nominal $p < 0.10$	Nominal $p < 0.05$	BH $q < 0.10$	BH $q < 0.05$	Survival (BH $q < 0.10$)
Single-index QR	Full	720	104	57	6	4	0.8%
Single-index QR	COVID	720	110	65	30	23	4.2%
Joint (all 6 indices) QR	Full	300	35	22	1	1	0.3%
Joint (all 6 indices) QR	COVID	300	16	7	0	0	0.0%
Pair QR (2-index)	Full	400	97	68	23	18	5.8%
Pair QR (2-index)	COVID	400	77	61	22	10	5.5%
Granger causality (index→returns) *	Full	180	133	112	127	107	70.6%
Granger causality (index→returns) *	COVID	170	108	95	102	79	60.0%
Total		3190	680	487	311	242	9.7%

Note: n = the number of coefficient estimates parsed from the Supplementary. “Nominal” = significant at the stated level before correction; “BH” = significant after Benjamini and Hochberg (1995) adjustment within each table. * Reverse-direction (returns→index) p -values are not reported numerically in the Supplementary and are excluded here.

Table 7. Pair-ranking check: coefficients surviving table-level BH correction ($q < 0.10$), full sample, out of 20 per pair per quantile (10 coins $\times$ 2 legs).

Pair	$\tau = 0.05$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.95$
UCRY Policy + CBDC Attention	5	0	0	1	2
UCRY Policy + ICEA	0	0	0	4	1
UCRY Price + CBDC Attention	0	0	0	0	2
UCRY Price + ICEA	0	0	0	4	4

Note: The bear-quantile winner ($\tau = 0.05$) is UCRY Policy + CBDC Attention, matching Table 5. Bull-quantile winner ($\tau = 0.95$) is UCRY Price + ICEA, not UCRY Policy + ICEA as stated in Table 5.

Table 8. Stationarity and residual diagnostics for cryptocurrency return series (full sample).

Coin	Frequency	N	ADF p	KPSS p	Ljung–Box p (10 Lags)	ARCH-LM p (10 Lags)
BCH	Weekly	174	<0.001	0.100	0.908	0.095
BCH	Daily	1218	<0.001	0.100	0.065	<0.001
BTC	Weekly	174	<0.001	0.100	0.819	1.000
BTC	Daily	1218	<0.001	0.100	0.046	<0.001
DASH	Weekly	174	<0.001	0.100	0.738	0.162
DASH	Daily	1218	<0.001	0.100	0.072	<0.001
EOS	Weekly	174	<0.001	0.100	0.512	0.054
EOS	Daily	1218	<0.001	0.100	0.035	<0.001
ETC	Weekly	174	<0.001	0.100	0.016	0.140
ETC	Daily	1218	<0.001	0.100	0.062	<0.001
ETH	Weekly	174	<0.001	0.095	0.765	0.978
ETH	Daily	1218	<0.001	0.100	0.042	<0.001
LTC	Weekly	174	<0.001	0.100	0.506	0.941
LTC	Daily	1218	<0.001	0.100	0.006	<0.001
XLM	Weekly	174	<0.001	0.100	0.785	0.005
XLM	Daily	1218	<0.001	0.100	0.617	<0.001
XMR	Weekly	174	<0.001	0.100	0.942	0.868
XMR	Daily	1218	<0.001	0.100	<0.001	<0.001
XRP	Weekly	174	<0.001	0.100	0.109	0.003
XRP	Daily	1218	<0.001	0.100	0.152	<0.001

Note: ADF = augmented Dickey–Fuller test (H_0 : unit root); KPSS = Kwiatkowski–Phillips–Schmidt–Shin test (H_0 : stationarity); Ljung–Box tests residual serial correlation at 10 lags (H_0 : no autocorrelation); ARCH-LM tests residual heteroskedasticity at 10 lags (H_0 : no ARCH effects). Full sample: 1 September 2018–31 December 2021 (daily $n = 1218$; weekly $n = 174$). All tests use the daily/weekly log-return series underlying Tables 2 and 3.

4.1. Single-Index Quantile Regression

Across the full sample, single indices have limited effects at the centre of the distribution but become relevant in the tails. The daily and weekly TEU indices are insignificant across quantiles for most coins (Tables S1 and S4)—consistent with Aharon et al. (2022), who likewise find no robust contemporaneous TEU–return link. The UCRY Policy index is the most active single index in bear-market quantiles: ETH is the most affected coin, followed by XRP and LTC, with further effects on BTC, XRP, LTC, EOS, and XLM at the 0.10–0.20 quantiles (Table S2). The UCRY Price index shows fewer but still meaningful tail effects (on BTC, XRP, LTC, XMR, EOS, and DASH in bear quantiles; Table S3), broadly aligning with Xia et al. (2023). The CBDC uncertainty and attention indices, the ICEA index, and the EU-EPU index are insignificant for most coins (Tables S5–S8); the clearest exceptions are XRP (significant in early/bull quantiles for several indices) and ETH (significant in late/bear quantiles for the CBDC indices). The EU-EPU index displays almost no contemporaneous link to returns (Table S8), echoing Shaikh (2020). Two patterns stand out. First, the action is in the tails: indices that look irrelevant at the median become significant in bear quantiles, precisely where downside risk concentrates. Second, the crypto-specific UCRY indices dominate the broader macro proxies (EU-EPU and, contemporaneously, TEU), suggesting that cryptocurrency returns respond more to uncertainty originating within the digital-asset ecosystem than to general economic-policy uncertainty. These patterns rest on nominal significance at each coefficient considered in isolation; Section 4.5 shows that only a small share survive formal correction for multiple testing, so the specific bear-tail rankings above (e.g., which coin is most affected by a given index) should be read as suggestive rather than confirmed.

Figure 2 plots the quantile coefficient paths for the two UCRY indices. The coefficients rise almost monotonically from negative values in the bear quantiles to positive values in the bull quantiles, crossing zero near the median, with the statistically significant estimates concentrated in the tails—a direct visualisation of the regime dependence that motivates the quantile approach. Figure 3 then summarises, for every index–coin pair, the breadth of significance across quantiles, making the cross-index and cross-coin heterogeneity immediately visible: the UCRY indices are the most active, XRP and ETH are the most sensitive coins, and the EU-EPU index is the least influential contemporaneously.

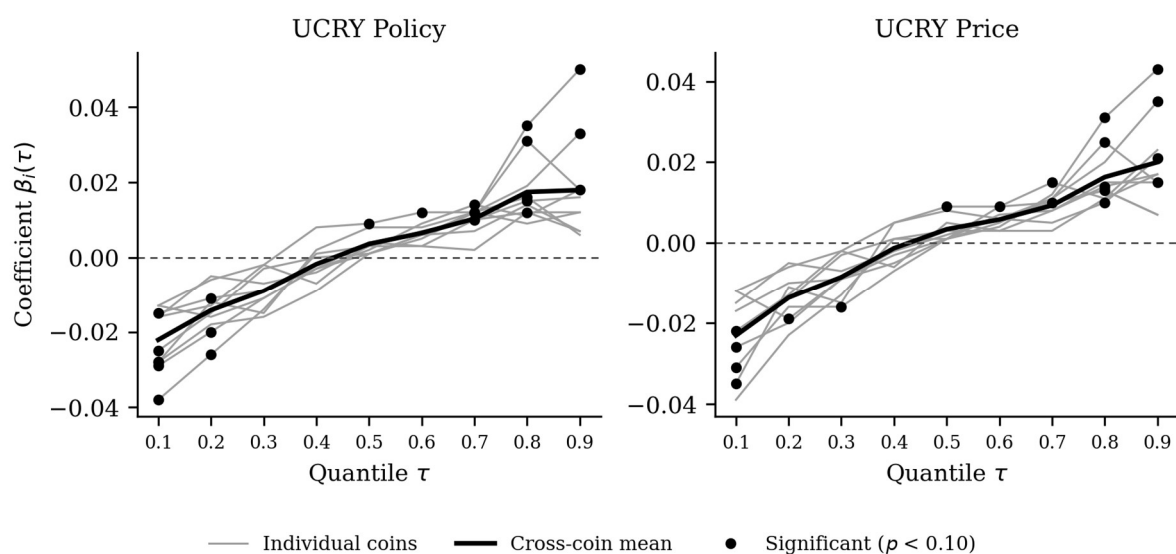


Figure 2. Quantile coefficient paths for the UCRY Policy and UCRY Price indices. Note: Each grey line is one cryptocurrency’s coefficient $\beta_i(\tau)$ across quantiles; the bold line is the cross-coin mean; black dots mark coefficients significant at the 10% level. Based on Supplementary Tables S2 and S3.

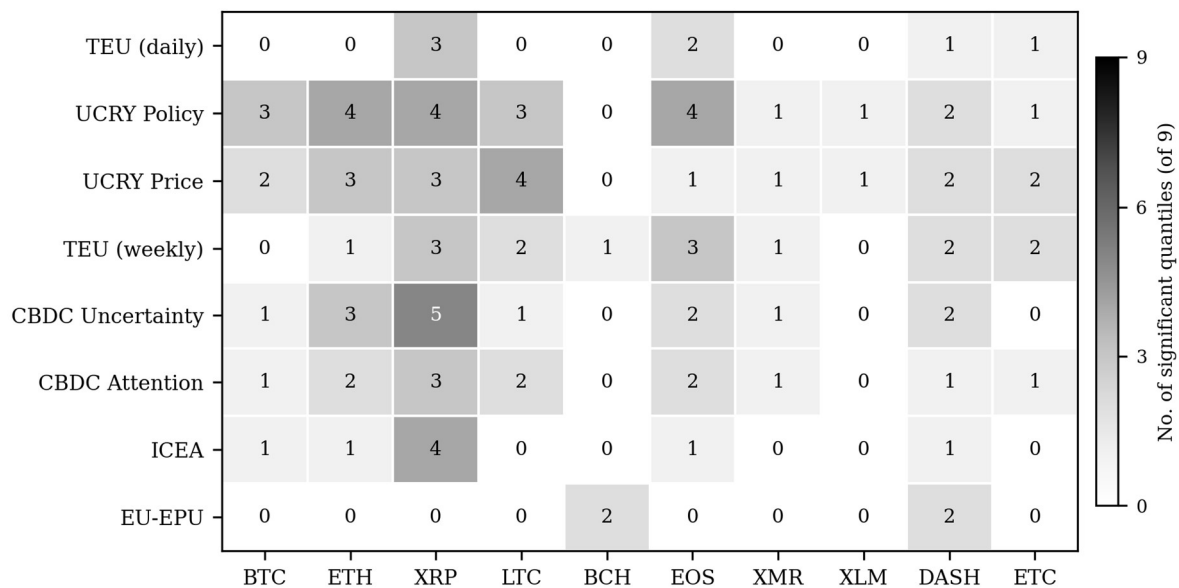


Figure 3. Breadth of single-index significance across cryptocurrencies. Note: Each cell reports the number of quantiles (of nine) at which the row index significantly affects the column coin's returns at the 10% level, from the single-index quantile regressions (Supplementary Tables S1–S8). Darker shading indicates more pervasive significance.

4.2. Joint Quantile Regression and Index Pairs

When all indices are estimated jointly, the bear-side quantile ($\tau = 0.05$) is insignificant for most coins. Significant effects instead emerge at the extreme bull quantile ($\tau = 0.95$), where the UCRY Price and ICEA indices affect several coins—the ICEA index significantly influences BTC, XRP, XLM, and DASH (at 5%) and LTC and XMR (at 1%), while the UCRY Price index affects XLM (1%), LTC, EOS, DASH, and ETC (5%), and XMR (10%); see Table S9.

The most novel result concerns index pairs (Tables S10–S13). Combining a price or policy index with an attention index shows stronger and broader tail significance than any single index, and the best pair depends on the regime. In bear conditions the UCRY Policy + CBDC Attention pair is the most influential; in bull conditions the UCRY Policy + ICEA pair ranks first. Table 5 summarises the regime-specific ranking. Intuitively, pairing a policy or price channel with an attention channel spans a broader information set—regulatory or cost conditions together with investor focus—so the combination captures forces that either index alone would miss. Because the paired specifications add a second regressor, part of this improvement may reflect the extra variable rather than genuine complementarity; we therefore treat the pair rankings as descriptive and note that a formal comparison of paired versus single-index models—for example, out-of-sample quantile (tick) loss evaluated with Diebold–Mariano tests, or the Koenker and Machado (1999) goodness-of-fit for the in-sample quantile fit—would provide a sharper test, which we leave to future work (Section 6).

4.3. Granger Causality

The causality evidence reinforces a central theme: uncertainty–return links are largely a longer-horizon phenomenon. The daily TEU index does not cause returns at lag 1 but does at lag 6 for most coins (except EOS, XLM, and ETC), indicating a delayed response (Tables S14 and S15); the weekly TEU index shows strong links at both horizons (Tables S20 and S21). The UCRY Policy and UCRY Price indices significantly cause returns at lag 1 for all coins except BTC, with little feedback from returns to the indices (some

exceptions: XRP, LTC, and ETC lead UCRY Policy; BCH and DASH lead UCRY Price); see Tables S16–S19. The CBDC uncertainty index causes several coins at lag 1 and all coins at lag 6 (Tables S22 and S23); the CBDC attention and ICEA indices cause all coins except BTC at lag 1 and all coins at lag 6 (and lag 7 for ICEA); see Tables S24–S28.

The EU-EPU index is the clearest case of reverse causality (Tables S29–S31). At lag 1, it does not cause returns, but cryptocurrency returns significantly cause the EU-EPU index—cryptocurrency markets appear to lead European policy-uncertainty perceptions in the short run. At longer horizons the relationship turns bidirectional: at lag 10 the EU-EPU index significantly affects all coins except EOS, while returns continue to affect the index at the 1% level (Table S31), consistent with [Cheema et al. \(2020\)](#), who find EPU predicts Bitcoin returns better over six- to twelve-month horizons than at one month. In short, the indices predict returns more than the reverse, and they do so mainly at longer horizons—a timing pattern consistent with the gradual diffusion of information through a market populated by heterogeneous, attention-constrained investors ([Hirshleifer & Teoh, 2003](#); [Peng & Xiong, 2006](#)); applying a quantile-causality test ([Jeong et al., 2012](#)) would connect this predictability directly to the tails that dominate the quantile results, an extension we leave to future work.

4.4. COVID-19 Sub-Sample

Restricting the sample to the COVID-19 period—defined as 11 March 2020, the date of the World Health Organisation’s pandemic declaration, through 31 December 2021, the end of the full sample—gives 661 daily, 95 weekly, and 22 monthly observations, consistent with Supplementary Tables S32–S44 and S45–S61, and largely reproduces the results obtained from the full sample, supporting their robustness. The TEU index remains insignificant in quantile regressions, indicating no additional pandemic-driven contemporaneous effect (Tables S32 and S35). The UCRY Policy and UCRY Price indices show somewhat stronger effects at the 0.10, 0.80, and 0.90 quantiles, with the bear-side (0.10) quantile significant for all coins (Tables S33 and S34). The CBDC uncertainty index displays a slightly stronger relationship with most coins at the 0.10 quantile, while the CBDC attention, ICEA, and EU-EPU indices remain largely insignificant in quantile regressions (Tables S36–S39). The pair rankings are preserved, with generally smaller magnitudes than in the full sample (Tables S40–S44), and the sub-sample causality tests confirm the full-sample patterns (Tables S45–S61). Overall, the pandemic intensified rather than overturned the patterns documented above.

4.5. Multiple-Testing Correction (False Discovery Rate)

Sections 3.2 and 4 note that the breadth of estimation across indices, coins, and quantiles raises a multiple-comparison concern (Table 8). We address it directly by applying [Benjamini and Hochberg \(1995\)](#) false-discovery-rate (FDR) control to every coefficient reported in the Supplementary—3190 estimates across Tables S1–S61—treating each table as the primary family, with section-level and whole-supplementary families as robustness checks (a full coefficient-level accounting is provided in an accompanying supplementary FDR workbook; Table 6 summarises the results).

The correction affects the four methods very differently. Granger-causality estimates are the most robust: of the 180 index-causes-returns tests in the full sample, 127 (70.6%) remain significant at $q < 0.10$ after correction (102 of 170, or 60.0%, in the COVID-19 sub-sample), so the longer-horizon causality results in Section 4.3 are not an artefact of multiple testing. By contrast, the single-index quantile regressions (Tables S1–S8) retain only 6 of 720 estimates (0.8%) at the table level, and the fully joint six-index specification (Table S9) retains only 1 of 300 (0.3%); therefore, the specific bear-tail, coin-level claims in Section 4.1 and the joint-model results in Section 4.2 should accordingly be read as suggestive rather

than confirmed. The paired specifications (Tables S10–S13) fare markedly better than either alternative, retaining 23 of 400 estimates (5.8%)—roughly seven times the single-index survival rate and nineteen times the fully joint model’s rate. Because the paired and fully joint specifications draw on the same coefficients and the same correction procedure, this gap is a formal, correction-robust argument for Hypothesis 3: combining one uncertainty index with one attention index carries more corrected-significant information than either a single index or the full six-index specification, addressing the reviewer’s question of why pairs and not the complete set of indices.

Two caveats follow directly from this analysis. First, as noted in Table 5 and shown directly in Table 7, the bull-quantile pair ranking is sensitive to the correction: UCRY Price + ICEA, rather than UCRY Policy + ICEA, retains the most corrected-significant coefficients at $\tau = 0.95$; therefore, that specific ranking should be treated as tentative pending further robustness checks. Second, the Granger-causality tables report a p -value only for the index-causes-returns direction; the reverse-direction (returns-cause-index) estimates discussed qualitatively in Section 4.3 are not tabulated numerically in the Supplementary and could not be included in this correction.

5. Discussion

Three economic messages emerge. First, uncertainty is priced at the tails, not the centre. The near-absence of median effects, combined with significant tail and longer-horizon effects, indicates that uncertainty indices matter most precisely when they matter most to investors—during stress and over the horizons at which portfolios are rebalanced. This is consistent with a flight-to-safety interpretation in which uncertainty reshapes returns mainly in bear regimes, and it explains why conditional-mean studies, which average over the distribution, often report weak or fragile uncertainty–return links. The pattern also echoes Będowska-Sójka et al. (2024), who find that uncertainty transmits to cryptocurrencies mainly during turbulent episodes, and complements Ah Mand (2025), whose frequency-domain evidence places the UCRY index ahead of returns over the longer run. The two studies differ from ours in scope rather than direction: Będowska-Sójka et al. (2024) pool a broad battery of uncertainty measures across ten major coins without testing attention indices, pairs, or less-dominant coins, while Ah Mand (2025) examines the UCRY index alone via frequency-domain methods rather than the distribution of returns. What is new here is the joint evidence that (i) the tail concentration holds specifically once attention indices and less-dominant coins are included, and (ii) pairing uncertainty with attention outperforms either measure alone, which neither prior study tests. It also stands in contrast to single-index, single-coin studies such as Gürsoy et al. (2024) and Gürsoy et al. (2022), which link one narrowly defined uncertainty measure to Bitcoin alone: our distribution-sensitive, multi-coin design shows that such single-purpose measures capture only part of a broader, tail-concentrated relationship between uncertainty, attention, and returns.

Second, attention complements uncertainty. The superiority of price-or-policy-plus-attention pairs suggests that returns respond to a composite signal: what is happening to regulation or prices, and how intensely the market is paying attention. Single indices proxy only one channel; pairs span both, which is consistent with their stronger tail performance. This reading aligns with attention-based asset-pricing theory, in which investor focus governs how quickly information is impounded into prices (Barber & Odean, 2008; Da et al., 2011; Peng & Xiong, 2006), and with a limits-to-arbitrage view of thinly traded crypto assets, where sentiment and attention can move prices independently of fundamentals. Those studies establish attention as a pricing force in equity markets; the contribution here is to show that attention operates as a channel distinct from, and additive to, uncertainty specifically in the tails of an asset class without earnings or cash-flow fundamentals,

which is not implied by the equity-market evidence alone. It offers a concrete, actionable refinement to the standard single-index design that pervades the literature.

Third, the direction of causality is informative. That cryptocurrency returns lead changes in the EU-EPU index in the short run—while the index leads returns only over longer horizons—is consistent with crypto markets acting as a fast-moving predictive barometer of, and eventual respondent to, policy uncertainty, in the Granger sense described in Section 3.4, rather than as evidence of structural causation. The heterogeneity across coins—made visible in Figure 3, where XRP and ETH stand out as the most index-sensitive coins while BTC is frequently among the least responsive at short horizons (Tables S1–S8 and S14–S31)—further suggests that less-dominant coins, with thinner liquidity and investor bases, absorb uncertainty differently from Bitcoin—an aspect the Bitcoin-only literature cannot capture.

These patterns have practical consequences. For investors and portfolio managers, the results argue for tail-aware, paired-index signals rather than a single uncertainty gauge: monitoring a policy or price index alongside an attention index provides earlier and broader warning of downside moves, and the coin-level heterogeneity implies that dominant and less-dominant cryptocurrencies should not be treated as a single risk bucket when hedging uncertainty. Because effects concentrate in bear quantiles and at longer horizons, the signals are most useful for medium-term risk management and rebalancing rather than for high-frequency timing. Concretely, a manager could treat a joint upward move in a policy/price index and its paired attention index—both crossing, say, their own 80th-percentile historical values in the same week—as a trigger to reduce position sizing or tighten hedges in the affected coins, since our results indicate this combined signal is more informative than either index moving alone; the causality results (Section 4.3) suggest such signals are most reliable at the six-week-plus horizon rather than for next-day timing.

For policymakers and regulators, the short-run predictive lead of returns over the EU-EPU index is consistent with cryptocurrency markets functioning as an early (Granger-sense) indicator of shifting policy-uncertainty sentiment, while the longer-run feedback from policy uncertainty to returns is consistent with, though does not on its own establish, regulatory communication influencing these markets. In practice, regulators could monitor the spread between contemporaneous crypto-market movements and the EU-EPU index as one input for anticipating shifts in public policy-uncertainty sentiment, while treating sustained divergence between the UCRY indices and prices as a candidate signal for closer market surveillance, consistent with the longer-horizon causality documented in Section 4.3. The COVID-19 sub-sample reinforces, rather than overturns, these messages: the pandemic intensified the same tail- and horizon-dependent effects, indicating that the mechanisms identified here are structural features of cryptocurrency markets rather than artefacts of a single calm period.

6. Conclusions

This study examined the relationships and directional links between seven uncertainty and attention indices—the Twitter-based Economic Uncertainty (TEU) index, the UCRY Policy and UCRY Price indices, the CBDC uncertainty and attention indices, the cryptocurrency environmental attention (ICEA) index, and the European Economic Policy Uncertainty (EU-EPU) index—and the returns of ten cryptocurrencies using quantile regression, joint quantile regression, and Granger causality tests over 2018–2021, including a COVID-19 sub-sample.

Three findings stand out. Single indices exert weak effects at the median but become significant in bear-market tails and over longer horizons. Combinations of a price or policy index with an attention index show stronger and broader tail significance than any

single index, with the best pair depending on the regime, though part of this improvement may reflect the additional regressor rather than complementarity alone. Causality runs mainly from indices to returns at longer horizons, except for the EU-EPU index, which cryptocurrency returns lead in the short run. The COVID-19 sub-sample confirms these patterns and, if anything, sharpens them.

The study makes three contributions. Methodologically, it shows that the location of uncertainty effects in the return distribution—and not merely their average—is what matters, so that a distribution-sensitive, multi-method design uncovers links that conditional-mean models miss. Substantively, it brings recently introduced, crypto-specific indices (ICEA, CBDC uncertainty and attention) into a unified analysis of returns across a broad cross-section of coins, and demonstrates that pairing an uncertainty index with an attention index is a simple but powerful improvement over the single-index convention. Empirically, it documents systematic heterogeneity between dominant and less-dominant cryptocurrencies that Bitcoin-only studies cannot reveal.

The results carry practical implications. Investors and institutions can use tail-focused, paired-index signals—rather than a single uncertainty measure—to anticipate downside risk and rebalance across dominant and less-dominant coins, and policymakers can read cryptocurrency markets as a predictive, early (Granger-sense) indicator of shifting policy-uncertainty sentiment.

Limitations and future research. Our analysis relies on indices released at heterogeneous frequencies, and the weekly alignment of the daily TEU index discards within-week information; future work could employ mixed-data-sampling (MIDAS) or time-varying-parameter VAR designs to exploit all frequencies. The sample ends in 2021 primarily because the CBDC uncertainty and attention indices central to our design are not available beyond that point at the time of writing; this also means the sample predates major later episodes—the 2022 Terra/Luna and FTX collapses and the subsequent tightening of cryptocurrency regulation in major jurisdictions—so extending the sample, once comparable index data become available, would test whether the documented patterns are stable across this more heavily regulated, post-crisis period or specific to the regime studied here. A limitation of our analysis concerns the sample period. At the time the core estimations were conducted, publicly available data for the UCRY, CBDC, and ICEA indices ended in December 2021, which bound our sample. The index providers have since extended their public data through 2024 Q4, so a sample of five years or more (September 2018 onward) is now achievable in principle. Fully re-estimating the quantile-regression, pair, and Granger-causality battery over this extended sample requires downloading and reformatting the index files from the providers' repository, and we regard this as the highest-priority next step for this line of research.

As a partial check, we draw on cryptocurrency return and realised-volatility data that already extend through 2023. Cross-coin average realised volatility eased around the May 2020 Bitcoin halving (0.041 to 0.033, 30 days before/after) and the May 2021 China mining-ban announcement (0.099 to 0.080, though that window overlaps a broader market-wide sell-off), but rose sharply around the November 2022 FTX collapse (0.030 to 0.043), consistent with the latter being a genuine, unanticipated shock. These descriptive comparisons are not a substitute for formal re-estimation, but they show the same tail-sensitive, event-driven pattern documented in the COVID-dominated sample recurring in a later, independent period, offering some reassurance that our results are not an artefact of a single event.

Extending the asset set to stablecoins and additional altcoins, adding an out-of-sample forecasting evaluation, and modelling time-varying connectedness would further probe the robustness and practical value of the paired-index approach documented here. Two further

caveats deserve emphasis. First, because the sample (September 2018–December 2021) is dominated by the COVID-19 shock and the ensuing bull market, the estimated relationships may partly reflect this high-volatility regime; although the sub-sample analysis shows the patterns are not driven by COVID-19 alone, we cannot fully separate structural effects from regime-specific ones, and the CBDC uncertainty and attention indices—which begin only with the emergence of digital-currency policy debate—limit how far the joint sample can be extended backward without dropping those measures. Regime-split or rolling-window estimation over a longer horizon, as more data accumulate, would sharpen this distinction, as would sub-period analysis bracketing other major cryptocurrency-market events within or adjoining the sample window (e.g., the May 2020 Bitcoin halving and the 2021 China mining ban) as additional robustness checks alongside the COVID-19 sub-sample. Second, the pair rankings and the tail-versus-centre contrast rest on the breadth and consistency of significance rather than on formal model comparison or multiple-testing-adjusted inference; incorporating false-discovery-rate control (Benjamini & Hochberg, 1995) and out-of-sample predictive comparisons would place these conclusions on firmer statistical ground. Finally, because the ten coins studied were established assets throughout the sample period, the results may not generalise to cryptocurrencies that launched more recently or to newer asset categories such as stablecoins and tokenised real-world assets. As with any observational analysis of this kind, we cannot rule out omitted variables—for example, exchange-specific liquidity conditions or unmodelled macro-financial shocks—that could jointly affect both the uncertainty indices and returns.

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