International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(3), 24-32.

ESG-Proxy Shocks and Cryptocurrency Returns: Reduced-Form Evidence for Green-Tilted versus Conventional Crypto Baskets

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Received: 07 January 2026 **Accepted:** 08 April 2026 **DOI:** https://doi.org/10.32479/ijeep.23478

ABSTRACT

This study examines whether an aligned ESG proxy is associated differently with the returns of green-tilted and conventional cryptocurrency baskets. We combine an annual France-based ESG score from Refinitiv Datastream with daily cryptocurrency prices spanning December 12, 2021-September 27, 2023. Daily log returns are aggregated into two equally weighted baskets - a green-tilted basket (GC: ADA, XTZ, THETA, ETH) and a conventional basket (CC: BTC, LTC, ETC) - and then averaged within month, yielding monthly average daily basket returns and 22 monthly observations. Because the ESG proxy is annual, it is mapped to daily frequency using a stepwise (forward-fill) transformation and then averaged to monthly frequency; the empirical exercise is therefore interpreted in reduced-form descriptive terms. We estimate a time-varying parameter VAR and compute generalized impulse responses (GIRFs) and generalized forecast-error variance decompositions (GFEVDs), complemented by connectedness and minimum-variance hedge metrics. A one-standard-deviation shock to ΔESG generates an immediate negative return response for both baskets ($h = 0$: -0.003385 for GC and -0.002674 for CC), followed by rapid reversion toward zero. GFEVD results indicate that ΔESG shocks account for 24.0% of GC's forecast-error variance at $H = 10$, compared with 13.794% for CC. Connectedness at $H = 10$ highlights strong within-crypto spillovers, with CC's variance largely explained by GC innovations (69.187%). Pillar decompositions imply smaller Social effects and comparatively larger short-run responses to governance innovations. Hedge ratios are close to one and cross-hedging reduces variance by 78%, indicating limited diversification between the two baskets. Overall, the aligned ESG proxy is more tightly linked to GC than to CC, although the evidence remains descriptive given the annual proxy and short sample.

Keywords: Environmental, Social, and Governance Proxy, Cryptocurrencies, Green-Tilted Crypto, Time-Varying Parameter VAR, Generalized Impulse Response, Generalized Variance Decomposition, Connectedness; Hedge Ratio
JEL Classifications: G1, G23, Q5, O3

1. INTRODUCTION

Environmental, social, and governance (ESG) information has become central to asset-pricing and disclosure debates, as investors increasingly incorporate sustainability signals into allocation decisions (Amel-Zadeh and Serafeim, 2018; Friede et al., 2015). ESG-related policies and disclosure practices may affect perceived risk and financing conditions (El Ghoul et al., 2011; Fairfax, 2022; Pollman, 2022). At the same time, the rapid diffusion of cryptocurrencies has intensified concerns about energy use, climate externalities, and broader societal impacts (Howson and de Vries, 2022; Stoll et al., 2022; Wendl et al., 2023; Zhang et al., 2023).

Against this backdrop, a natural question is whether sustainability-related information is associated differently across segments of the cryptocurrency market. Two empirical frictions motivate a cautious design. First, widely used ESG measures are typically low-frequency and partly jurisdiction-specific, whereas cryptocurrency prices are high-frequency and prone to regime shifts. Second, within the crypto universe, "green" labeling is often tied to technological features (e.g., consensus mechanisms) rather than issuer-level reporting, implying that ESG proxies may capture broad information and narrative shifts as much as structural determinants of digital-asset fundamentals.

We address this question by contrasting two equally weighted cryptocurrency return baskets: A green-tilted basket (GC: ADA, XTZ, THETA, ETH) and a conventional basket (CC: BTC, LTC, ETC). Sustainability information is proxied by an annual France-based ESG score from Refinitiv Datastream, aligned to the return data via a stepwise mapping and converted to monthly changes (ΔESG). We estimate a time-varying parameter VAR (TVP-VAR) and summarize dynamic transmission through generalized impulse responses (GIRFs), generalized forecast-error variance decompositions (GFEVDs), connectedness measures, and minimum-variance hedging metrics. Given the proxy construction and the short sample, the exercise is interpreted in reduced-form descriptive terms.

GC constituents are selected to reflect comparatively lower-energy or transition-oriented consensus designs (primarily proof-of-stake or other lower-energy mechanisms). In particular, Ethereum is included because its transition to proof-of-stake ("The Merge," executed on September 15, 2022) is associated with an estimated ~99.95% reduction in network energy consumption (Ethereum.org, 2026). Because ETH was not proof-of-stake over the full sample, GC should be read as a green-tilted basket rather than as a strict taxonomy of assets that are uniformly green throughout the period.

The paper makes three contributions. First, it constructs transparent green-tilted and conventional crypto baskets and documents their time-varying interactions in a compact system. Second, it aligns a low-frequency, country-level ESG proxy with monthly averages of daily crypto-basket returns and evaluates the resulting co-movements using generalized identification, impulse responses, and variance decompositions. Third, it decomposes the ESG proxy into Social and Governance pillars and discusses spillover and hedging implications within a reduced-form design.

Given the annual construction of the ESG proxy and the short monthly sample, the analysis is interpreted throughout as reduced-form evidence on time-varying associations rather than as a structural causal model.

The remainder of the paper is organized as follows. Section 2 reviews related work and develops the hypotheses. Section 3 presents the data, variable construction, and empirical design. Section 4 reports the baseline, pillar, and hedging results. Section 5 concludes.

2. RELATED LITERATURE AND HYPOTHESES DEVELOPMENT

A growing body of work studies how ESG information is produced, disclosed, and incorporated into prices. Survey evidence suggests that investors rely on ESG signals for decision-making (Amel-Zadeh and Serafeim, 2018), and meta-analytic evidence documents systematic links between ESG performance and financial outcomes (Friede et al., 2015). Mechanisms emphasized in related research include risk and financing channels (El Ghoul et al., 2011), disclosure quality and textual characteristics (Li et al., 2023), governance and organizational frameworks (Huang, 2022), and the role of board structures in shaping ESG disclosure (Nuhu and Alam, 2024). Broader perspectives also highlight investor attention, reputation, and information frictions (Coval and Moskowitz, 2001; Meng et al., 2023; Spence, 1973).

The disclosure environment is evolving, with debates over voluntary versus mandatory ESG reporting and the meaning of ESG concepts in practice (Fairfax, 2022; Pollman, 2022). Complementary work links stakeholder relationships and operational controversies to sustainability outcomes (Srivastava et al., 2024; Tamayo-Torres et al., 2019), while systematic reviews synthesize evidence across ESG-finance linkages (Saini et al., 2023). Recent studies also connect ESG to digitalization and technological change, including technology-enabled ESG disclosure and digital transformation (Asif et al., 2023; Wang and Esperança, 2023), and policy instruments that may alter ESG outcomes through financing constraints (Liu et al., 2023).

Within sustainable finance and FinTech, research explores green finance mechanisms and digital channels that may influence environmental quality and investment dynamics (Cen and Yin, 2024; Hossain et al., 2024; Işık et al., 2024; Jiao et al., 2024; Kwong et al., 2023; Qin et al., 2023; Yang et al., 2024). Connectedness and spillover tools are increasingly used in this context (Polat et al., 2024; Wang et al., 2024).

Cryptocurrencies raise distinct sustainability questions due to energy consumption, consensus mechanisms, and associated social externalities (Howson and de Vries, 2022; Stoll et al., 2022; Wendl et al., 2023; Zhang et al., 2023). Related empirical work studies crypto interactions with climate- and eco-friendly assets and adjacent technology sectors (Abakah et al., 2023), examines links between Bitcoin and clean-energy or emissions-related markets using time-varying methods (Dogan et al., 2022), analyzes the roles of stable versus nonstable cryptocurrencies in Bitcoin market dynamics (Brik et al., 2022), and contrasts green cryptocurrencies with sustainable investments using nonlinear and multifractal tools (Vogl and Kojić, 2024). The hedging and portfolio dimension is also active, including evidence on hedging performance under cryptocurrency uncertainty (Zhong et al., 2023).

Building on this literature, we formulate three hypotheses. Because the empirical design relies on a low-frequency ESG proxy aligned to monthly returns, these hypotheses are interpreted as directional predictions within a reduced-form setting rather than as structural causal claims.

Hypothesis 1 (H_1). A positive one-standard-deviation shock to ΔESG has a larger absolute impact on GC returns than on CC returns.

Hypothesis 2 (H_2). The return response of CC to ΔESG shocks is weaker and less persistent than the response of GC.

Hypothesis 3 (H_3). Within the pillar specifications, Governance innovations generate larger short-run return responses than Social innovations.

H_1 and H_2 are evaluated using GIRFs that trace the sign, impact magnitude, and persistence of return responses to ΔESG innovations across horizons, whereas H_3 is assessed using pillar specifications that replace ΔESG with Social (ΔS) and Governance (ΔG) innovations.

3. DATA AND EMPIRICAL DESIGN

This section presents the data and empirical design used in the analysis. It first describes the sample period, the construction of the green-tilted and conventional cryptocurrency baskets, and the France-based ESG proxy, together with the corresponding descriptive statistics, correlations, and stationarity diagnostics. It then outlines the econometric framework used to assess dynamic responses, spillovers, connectedness, and hedging properties.

3.1. Sample and Variable Construction

We construct monthly return series for two cryptocurrency baskets (GC and CC) and an ESG proxy. Daily cryptocurrency prices are collected for the constituents of each basket over December 12, 2021-September 27, 2023. Daily log returns are computed for each constituent, aggregated into equally weighted daily basket returns, and then averaged within month to obtain monthly averages of daily basket returns. We use this monthly average-daily-return measure throughout. The estimation sample therefore spans December 2021-September 2023 at a monthly frequency (n = 22).

The ESG proxy is an annual Refinitiv Datastream ESG score for France (0-100). Because the ESG metric is annual, it is mapped to daily frequency through a stepwise (forward-fill) procedure - each annual observation is carried across all days within the corresponding year - and then aggregated to monthly frequency using the within-month mean. In the current sample, the annual ESG values underlying the monthly series are 79.027 (December 2021), 77.012 (2022), and 75.033 (2023). Consequently, within-year month-to-month changes in the mapped ESG series are mechanically close to zero, and non-zero ΔESG realizations primarily occur at year transitions. The model therefore summarizes how basket returns co-move with these discrete shifts in the measured proxy rather than with rich month-to-month ESG news. To address non-stationarity of the ESG level, the baseline model uses the first difference, ΔESG.

Table 1 summarizes variable definitions and constructions. Tables 2-4 report descriptive statistics, correlations, and stationarity diagnostics.

The return and ESG constructions are defined as follows.

$$r_{i,d} = ln(P_{i,d}) - ln(P_{i,d-1}) \tag{1}$$

Where P is the daily price of cryptocurrency i on day d and r is the corresponding daily log return; i indexes the cryptocurrency and d indexes the day.

$$r_{k,d} = (\frac{1}{n_k}) \sum_{i \in k} r_{i,d}, K \in \{GC, CC\} \tag{2}$$

Where r is the daily return of basket k (k = GC or CC); the average is taken over constituents i in basket k, with the number of constituents denoted by n subscript k.

$$r_{k,t} = mean_{d \in month\ t}(r_{k,d}) \tag{3}$$

Where r is the monthly average daily return of basket k computed as the within-month mean of daily basket returns; t indexes months.

$$ESG_d = ESG_{year}(d) \text{ and } ESG_t = mean_{d \in month\ t}(ESG_d) \tag{4}$$

Where the annual France ESG score for the year containing day d is assigned to each day within that year (stepwise forward-fill) and monthly ESG is the within-month mean of the resulting daily series.

$$\Delta ESG_t = ESG_t - ESG_{t-1} \tag{5}$$

Where ΔESG is the month-to-month change in the ESG proxy.

3.2. Econometric Framework

Let y(t) collect the monthly variables GC, CC, and ΔESG at time t. We estimate a time-varying parameter VAR of order p:

$$y_t = c_t + A_{1,t} y_{t-1} + ... + A_{p,t} y_{t-p} + u_t \tag{6}$$

Where c is a time-varying intercept; the A matrices are time-varying autoregressive coefficients for lags 1,…,p; and u is a reduced-form innovation with time-varying covariance matrix Σ.

To quantify dynamic transmission, we compute generalized impulse response functions (GIRFs) and generalized forecast-error variance decompositions (GFEVDs), which are invariant to variable ordering (Pesaran and Shin, 1998). The GIRF traces the response of each return series to a one-standard-deviation innovation in the ESG proxy (ΔESG) and, in pillar specifications, to innovations in ΔS and ΔG. We report impulse responses with 90% uncertainty bands over horizons measured in months.

$$GIRF_{i \leftarrow j}(h) = E(y_{i,t+h} \mid \varepsilon_{j,t} = \delta, I_{t-1}) - E(y_{i,t+h} \mid I_{t-1}) \tag{7}$$

Where y(i,t) is variable i at time t; ε(j,t) is the innovation to variable j at time t; δ is set to one standard deviation of ε(j,t); and I(t-1) denotes the information set at time t-1.

The GFEVD allocates each variable's H-step-ahead forecast-error variance to shocks in each variable, producing shares that sum to 100% by row. Based on the GFEVD matrix, we compute connectedness measures using the sum of off-diagonal variance shares (Diebold and Yilmaz, 2012; 2014):

$$FROM_i(H) = \sum_{j \neq i} GFEVD_{i \leftarrow j}(H) \tag{8}$$

Where FROM(i,H) measures the share of variable i's H-step-ahead forecast-error variance explained by shocks from other variables.

$$TO_i(\text{iH}) = \sum_{j \neq i} GFEVD_{j \leftarrow i}(H) \tag{9}$$

Where TO(i,H) measures the contribution of shocks in i to the forecast-error variance of other variables.

$$NET_i(H) = TO_i(H) - FROM_i(H) \tag{10}$$

Table 1: Variable definitions and constructions

Variable	Type	Description	Construction/measurement	Relevance
Green-tilted crypto basket (GC)	Endogenous	Equally weighted return of a stylized green-tilted basket: ADA, XTZ, THETA, ETH. Classification reflects comparatively lower-energy designs and ETH's post-Merge proof-of-stake status.	Compute daily log returns for each constituent; form the equal-weighted daily basket return; aggregate to monthly frequency as the within-month mean of daily basket returns.	Captures the performance of the green-tilted basket relative to CC under a stylized lower-energy/transition classification.
Conventional crypto basket (CC)	Endogenous	Equally weighted basket return of conventional cryptocurrencies: BTC, LTC, ETC.	Compute daily log returns for each constituent; form the equal-weighted daily basket return; aggregate to monthly frequency as the within-month mean of daily basket returns.	Captures price dynamics of conventional cryptocurrencies and provides a benchmark for differential ESG sensitivity.
ESG score (France-based proxy)	Exogenous/endogenous in VAR	Annual Refinitiv Datastream ESG score for France (0-100).	Map the annual score to a daily stepwise series via forward-fill within year; compute the monthly mean; use monthly changes (ΔESG) in the baseline VAR. Within-sample changes occur mainly at year transitions.	Proxy for the country-level sustainability information environment rather than a crypto-specific ESG measure.

GC and CC are monthly averages of equally weighted daily basket log returns. ESG is an annual score mapped to daily by forward-fill and averaged within month; ΔESG denotes the month-to-month change in the proxy

Table 2: Descriptive statistics (monthly frequency)

Variable	N	Mean	Standard deviation	Min	Median	Max
ESG score (level)	22	76.294	1.154	75.033	77.012	79.027
Green-tilted basket return (GC)	22	−0.001410	0.006448	−0.010466	−0.001787	0.011935
Conventional basket return (CC)	22	−0.000353	0.006700	−0.011861	−0.000410	0.015244

N is the number of monthly observations. ESG is in level (0-100). GC and CC are monthly averages of daily basket log returns

Table 3: Pairwise correlations

Variable	ESG	GC	CC
ESG	1.000	−0.255	−0.162
GC	−0.255	1.000	0.883***
CC	−0.162	0.883***	1.000

***Denotes significance at the 1% level

Table 4: Stationarity diagnostics (ADF and KPSS)

Variable	ADF statistics	ADF P-value	KPSS statistics	KPSS P-value	Conclusion
GC	−3.315	0.014	0.221	≥0.10	Stationary
CC	−3.536	0.007	0.061	≥0.10	Stationary
ESG (level)	−0.753	0.833	0.682	0.015	Non-stationary
ΔESG	−3.084	0.028	0.092	≥0.10	Stationary

ADF is the Augmented Dickey-Fuller test (null: Unit root). KPSS is the Kwiatkowski-Phillips-Schmidt-Shin test (null: Stationarity)

Where NET(i,H) is the net spillover measure; NET(i,H) > 0 indicates that i is a net transmitter.

$$TCI(H)=(\frac{1}{N})\sum_{i=1}^{N} FROM_i(H) \tag{11}$$

Where TCI(H) is the total connectedness index and N is the number of variables in the system.

Finally, we report minimum-variance hedge ratios and hedging effectiveness based on unconditional second moments of basket returns:

$$\beta_{x|y}=\frac{Cov(r_x,r_y)}{Var(r_y)} \tag{12}$$

Where β is the hedge ratio for hedging asset x using asset y, and Cov(·) and Var(·) denote covariance and variance computed from the monthly basket series defined in Section 3.

$$HE=1-\frac{Var(r_x-\beta_{x|y}\, r_y)}{Var(r_x)} \tag{13}$$

Where HE is hedging effectiveness; larger values indicate greater variance reduction relative to an unhedged position.

The TVP-VAR is interpreted in reduced-form terms. Because GIRFs and GFEVDs rely on generalized identification and because ΔESG is obtained from an annual proxy aligned to monthly frequency, the resulting responses should be read as associations with innovations in the measured proxy rather than as structural sustainability shocks.

4. EMPIRICAL RESULTS

This section reports the main empirical findings. It begins with the baseline evidence on the response of the two cryptocurrency baskets to innovations in the ESG proxy, then turns to the Social and Governance pillar specifications, and finally discusses the hedging results. Taken together, these results provide evidence on the short-run pricing, spillover, and portfolio implications associated with ESG-related information in cryptocurrency markets.

4.1. Baseline Results

Table 5 reports GIRFs of GC and CC to a one-standard-deviation shock in ΔESG. The contemporaneous response (h = 0) is negative for both baskets, with a larger impact for GC (−0.003385) than for CC (−0.002674). Responses revert rapidly toward zero at longer horizons, consistent with short-lived pricing of ESG-proxy innovations in the monthly basket series.

Figure 1 visualizes these GIRFs with 90% uncertainty bands. The two return series exhibit similar mean-reversion patterns, while the magnitude of the initial decline is larger for GC, which is consistent with H_1. The limited persistence beyond the first months is consistent with H_2.

Table 6 summarizes the generalized forecast-error variance decomposition for the baseline system over horizons H = 1, 5, and 10 months. At H = 10, ΔESG shocks explain 24.000% of GC forecast-error variance and 13.794% of CC variance. In contrast, CC variance is primarily driven by shocks to GC (69.187% at H = 10), highlighting strong cross-basket spillovers.

Figure 2 plots the GFEVD share attributable to ΔESG shocks. The GC line lies persistently above the CC line across horizons, indicating a stronger ESG-related variance component for the green-tilted basket.

Table 7 reports connectedness measures based on the H = 10 GFEVD matrix. The total connectedness index is 36.13%, indicating meaningful spillovers in the three-variable system. GC and ΔESG are net transmitters (NET: 46.037 and 36.385, respectively), while CC is a pronounced net receiver (NET: −82.422).

Figure 3 presents the connectedness (GFEVD) matrix at H = 10 as a heatmap. The large off-diagonal entry from GC to CC (69.187) reinforces that conventional-crypto variation is strongly driven by green-crypto innovations. At the same horizon, the ΔESG contribution to GC (24.000) is materially larger than the ΔESG contribution to CC (13.794), aligning with the differential ESG sensitivity documented above.

4.2. Pillar Results

To assess which dimensions of ESG matter most for crypto returns, we estimate pillar specifications that replace ΔESG with shocks to the Social pillar (ΔS) and the Governance pillar (ΔG). Appendix Tables A1-4 report the corresponding GIRFs and GFEVD matrices.

4.2.1. Social pillar

Figure 4 shows GIRFs to a one-standard-deviation ΔS shock. The contemporaneous effects are negative and smaller in magnitude than in the baseline ΔESG case (Appendix Table A1). Figure 5 reports the GFEVD share attributable to ΔS shocks; at H = 10, ΔS accounts for 10.000% of GC variance and 15.000% of CC variance (Appendix Table A2).

Figure 1: GIRF to a 1 s.d. ΔESG shock (baseline). Generalized impulse responses of GC and CC monthly basket series to a one-standard-deviation shock in ΔESG. Shaded areas represent 90% uncertainty bands. Horizon is measured in months

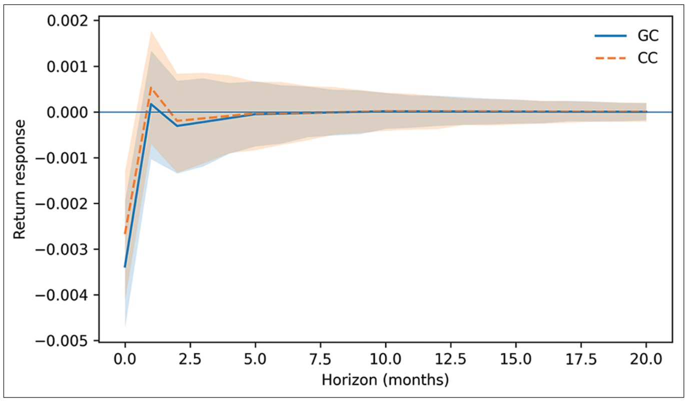


Figure 2: GFEVD: Share of forecast error variance due to ΔESG shocks (baseline). Generalized FEVD share (percent) attributable to ΔESG shocks for GC and CC, plotted over horizons H = 1,…,10 months

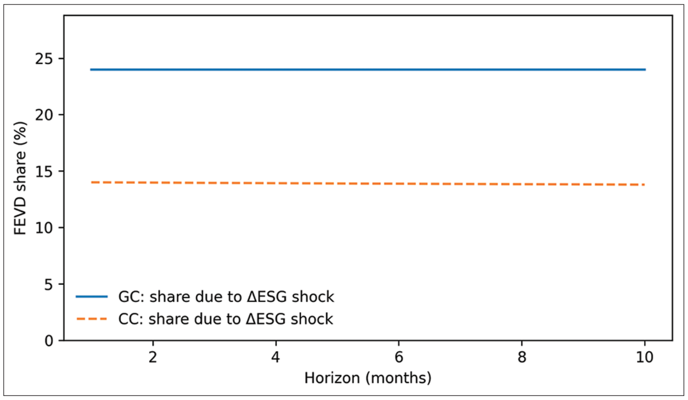


Table 5: Generalized impulse responses to a ΔESG shock (1 s.d.)

h	GC IRF	GC 90% CI (L)	GC 90% CI (U)	CC IRF	CC 90% CI (L)	CC 90% CI (U)
0	−0.003385	−0.004767	−0.002085	−0.002674	−0.004151	−0.001166
1	0.000168	−0.000918	0.001252	0.000527	−0.000591	0.001699
2	−0.000310	−0.001200	0.000560	−0.000198	−0.001086	0.000754
5	−0.000051	−0.000522	0.000421	−0.000034	−0.000557	0.000528
10	0.000012	−0.000223	0.000233	0.000009	−0.000221	0.000248

GIRFs are computed from the TVP-VAR. Confidence bands are 90%. Horizon h is measured in months

Table 6: Generalized FEVD for the baseline model (%, variables: GC, CC, ΔESG)

Variable	H=1 (GC)	H=1 (CC)	H=1 (ΔESG)	H=5 (GC)	H=5 (CC)	H=5 (ΔESG)	H=10 (GC)	H=10 (CC)	H=10 (ΔESG)
GC	76.000	0.000	24.000	76.000	0.000	24.000	76.000	0.000	24.000
CC	68.500	17.500	14.000	68.900	17.200	13.900	69.187	17.019	13.794
ΔESG	0.500	0.300	99.200	0.700	0.400	98.900	0.850	0.559	98.591

Rows sum to 100 at each horizon H. Entries report the percent share of variable i's H-step-ahead forecast-error variance attributable to shocks in variable j

Figure 3: Connectedness (GFEVD matrix, H = 10). Heatmap of the H = 10 generalized FEVD matrix for variables GC, CC, and ΔESG. Cell values are FEVD shares (percent)

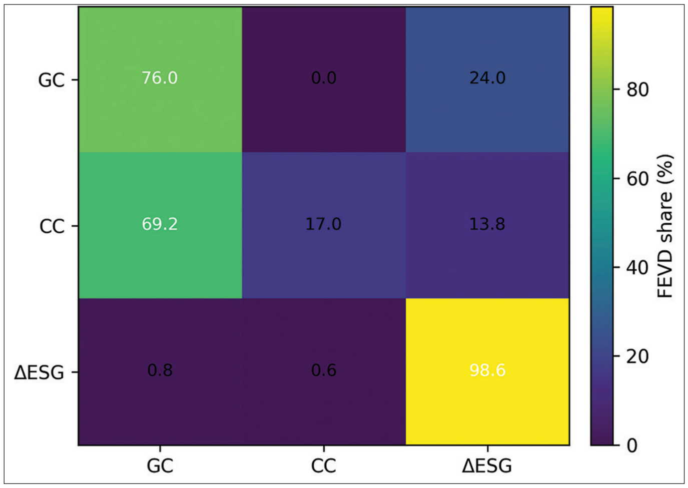


Figure 4: GIRF to a 1 s.d. ΔS (Social) shock. Generalized impulse responses of GC and CC monthly basket series to a one-standard-deviation shock in ΔS. Shaded areas represent 90% uncertainty bands. Horizon is measured in months

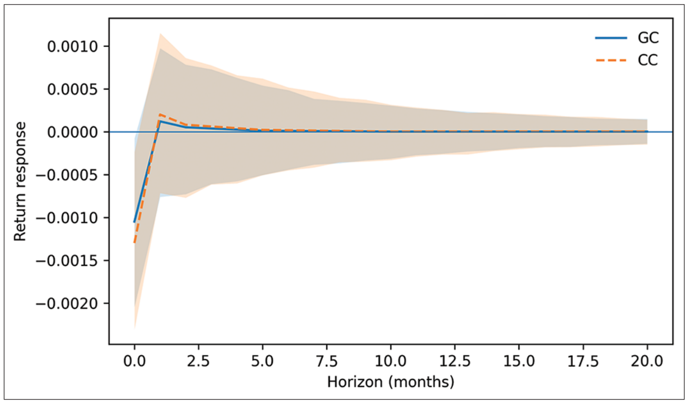
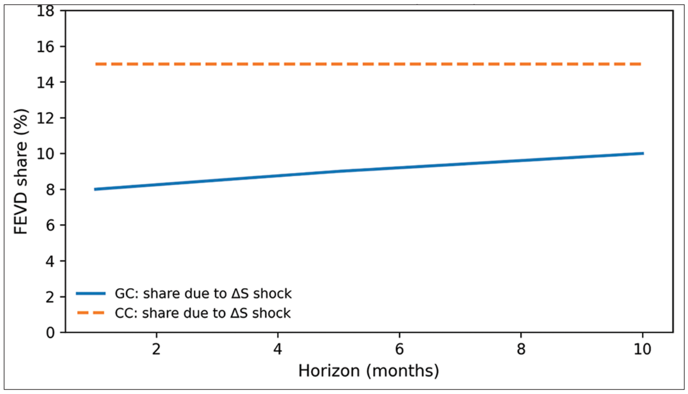


Figure 5: GFEVD: share due to ΔS (Social) shocks. Generalized FEVD share (percent) attributable to ΔS shocks for GC and CC, plotted over horizons H = 1,…,10 months



4.2.2. Governance pillar

Figure 6 displays GIRFs to a one-standard-deviation ΔG shock. In contrast to the baseline and Social cases, the short-run responses are positive for both baskets, with larger magnitudes for GC (Appendix Table A3). Figure 7 plots the GFEVD share due to ΔG shocks. At H = 10, ΔG shocks account for 18.000% of GC variance and 12.000% of CC variance (Appendix Table A4). Together, these results are consistent with H_3 and indicate that governance-related sustainability information is associated with comparatively larger short-run pricing effects in GC.

Figure 6: GIRF to a 1 s.d. ΔG (Governance) shock. Generalized impulse responses of GC and CC monthly basket series to a one-standard-deviation shock in ΔG. Shaded areas represent 90% uncertainty bands. Horizon is measured in months

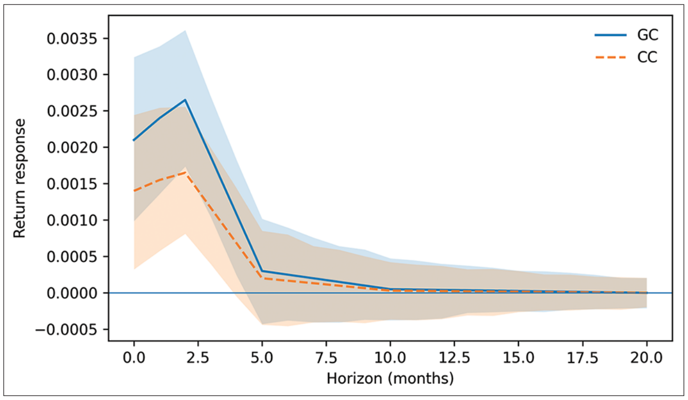


Figure 7: GFEVD: share due to ΔG (Governance) shocks. Generalized FEVD share (percent) attributable to ΔG shocks for GC and CC, plotted over horizons H = 1,…,10 months

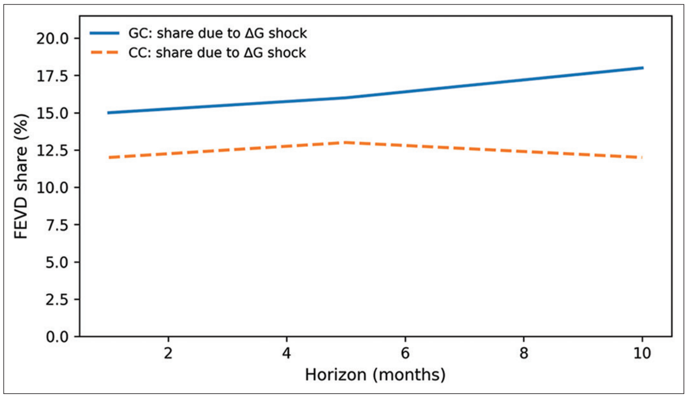


Table 7: Connectedness measures based on the baseline GFEVD (H=10)

Variable	GC	CC	ΔESG	FROM/TCI
GC	76.000	0.000	24.000	24.000
CC	69.187	17.019	13.794	82.981
ΔESG	0.850	0.559	98.591	1.409
TO	70.037	0.559	37.794	36.13
NET	46.037	−82.422	36.385	

FROM is the sum of off-diagonal row shares; TO is the sum of off-diagonal column shares; NET=TO - FROM. TCI is the total connectedness index

4.3. Hedging Results

Table 8 reports minimum-variance hedge ratios and hedging effectiveness for cross-hedging between the two baskets. The hedge ratios are close to one (0.9175 for hedging CC with GC; 0.8501 for hedging GC with CC), reflecting the high correlation between GC and CC (Table 3). Hedging effectiveness equals

Table 8: Minimum-variance hedge ratios and hedging effectiveness

Strategy	Hedge ratio (β)	Hedging effectiveness (HE)
Hedge CC with GC	0.9175	0.7800
Hedge GC with CC	0.8501	0.7800

Hedge ratios are computed as Cov (r (x), r (y))/Var (r (y)). Hedging effectiveness is computed as 1-Var (r (x)-β r (y))/Var (r (x)), using the monthly basket series defined in Section 3

0.7800 for both strategies, implying a 78% reduction in return variance relative to an unhedged position.

From a portfolio perspective, the strong co-movement limits diversification benefits within this GC-versus-CC segmentation, which is consistent with the dominance of cross-basket spillovers in the connectedness analysis. These findings connect to recent work on hedging and portfolio strategies under sustainability and cryptocurrency uncertainty (Zhong et al., 2023).

5. CONCLUSION

This paper examines whether sustainability-related information is reflected differently across segments of the cryptocurrency market by relating monthly averages of daily basket returns for a green-tilted basket (GC) and a conventional basket (CC) to innovations in an aligned France-based ESG proxy within a TVP-VAR framework.

The baseline results show that a one-standard-deviation innovation in ΔESG is associated with an immediate negative return response in both baskets, followed by rapid mean reversion. GFEVDs and connectedness measures further indicate that ΔESG explains a larger share of GC forecast-error variance than of CC variance, while spillovers - especially from GC to CC - remain central to conventional-crypto dynamics.

The pillar analysis points to heterogeneity across ESG dimensions. Social innovations are associated with comparatively smaller short-run effects, whereas Governance innovations are linked to positive short-run responses and non-negligible variance shares for GC. The hedging results likewise show strong co-movement between the two baskets: Cross-hedging reduces variance substantially, but diversification benefits within this segmentation remain limited.

For investors and regulators, these results suggest that the aligned ESG proxy is more tightly linked to the green-tilted basket than to the conventional basket, while also underscoring the importance of within-crypto spillovers for portfolio management and interpretation. At the same time, country-level ESG scores are not tailored to crypto-specific externalities and, in this sample, the aligned monthly series changes mainly at year boundaries.

Accordingly, shocks to the measured proxy may capture changes in the information environment and investor narratives rather than structural shifts in crypto fundamentals. This caution is consistent with ongoing debates about the meaning, verification, and comparability of ESG information and disclosure regimes.

The evidence should therefore be interpreted in light of several limitations: The monthly sample is short (n = 22), the ESG proxy is annual and aligned to daily and monthly frequency through a stepwise mapping, and non-zero ΔESG realizations arise mainly at year transitions. In addition, GC is a stylized green-tilted basket rather than a strict taxonomy, particularly because ETH's proof-of-stake regime begins only in September 2022. The return measure is the within-month average of daily basket log returns, so the reported evidence is conditional on that aggregation choice, the alignment rule, and the basket composition.

Future research could extend the sample as additional ESG observations become available, test alternative alignment rules and sustainability proxies, examine constituent sensitivity within the two baskets, and incorporate broader macro-financial controls to clarify the mechanisms behind the observed co-movements.

6. DISCLOSURE OF INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

7. AUTHORS' CONTRIBUTIONS

A. F: Conceptualization, methodology, formal analysis, investigation, writing original draft, review and editing, visualization, supervision

8. FUNDING

This research received no external funding.

9. AVAILABILITY OF DATA AND MATERIALS

The datasets used during the current study are available from the corresponding author on reasonable request.

REFERENCES

Abakah, E. J. A., Tiwari, A. K., Ghosh, S., & Doğan, B. (2023). Dynamic effect of Bitcoin, fintech and artificial intelligence stocks on eco-friendly assets, Islamic stocks and conventional financial markets: Another look using quantile-based approaches. Technological Forecasting and Social Change, 192, 122566.

Amel-Zadeh, A., & Serafeim, G. (2018). Why and how investors use ESG information: Evidence from a global survey. Financial Analysts Journal, 74(3), 87-103.

Asif, M., Searcy, C., & Castka, P. (2023). ESG and Industry 5.0: The role of technologies in enhancing ESG disclosure. Technological Forecasting and Social Change, 195, 122806.

Brik, H., El Ouakdi, J., & Ftiti, Z. (2022). Roles of stable versus nonstable cryptocurrencies in Bitcoin market dynamics. Research in International Business and Finance, 62, 101720.

Cen, Y., & Yin, J. (2024). Navigating climate challenges: Focusing on the effectiveness of natural resource rents, fintech, green finance, environmental quality, and digitalisation. Resources Policy, 95, 105102.

Coval, J. D., & Moskowitz, T. J. (2001). The geography of investment: Informed trading and asset prices. Journal of Political Economy, 109(4), 811-841.

Dogan, E., Majeed, M. T., & Luni, T. (2022). Are clean energy and carbon emission allowances caused by bitcoin? A novel time-varying method. Journal of Cleaner Production, 347, 131089.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28(1), 57-66.

Diebold, F. X., & Yilmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics, 182(1), 119-134.

El Ghoul, S., Guedhami, O., Kwok, C. C. Y., & Mishra, D. R. (2011). Does corporate social responsibility affect the cost of capital? Journal of Banking & Finance, 35(9), 2388-2406.

Ethereum.org. (2026, February 16). The Merge. https://ethereum.org/roadmap/merge

Fairfax, L. M. (2022). Dynamic disclosure: An exposé on the mythical divide between voluntary and mandatory ESG disclosure. Tex. L. Rev., 101, 273.

Friede, G., Busch, T., & Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. Journal of Sustainable Finance & Investment, 5(4), 210-233.

Hossain, M. R., Rao, A., Sharma, G. D., Dev, D., & Kharbanda, A. (2024). Empowering energy transition: Green innovation, digital finance, and the path to sustainable prosperity through green finance initiatives. Energy Economics, 136, 107736.

Howson, P., & de Vries, A. (2022). Preying on the poor? Opportunities and challenges for tackling the social and environmental threats of cryptocurrencies for vulnerable and low-income communities. Energy Research & Social Science, 84, 102394.

Huang, D. Z. X. (2022). An integrated theory of the firm approach to environmental, social and governance performance. Accounting & Finance, 62, 1567-1598.

Işık, C., Ongan, S., Islam, H., Balsalobre-Lorente, D., & Sharif, A. (2024). ECON-ESG factors on energy efficiency: Fostering sustainable development in ECON-growth-paradox countries. Gondwana Research, 135, 103-115.

Jiao, L., Zhou, D., & Xu, R. (2024). Resource dynamics and economic expansion: Unveiling the asymmetric effects of natural resources and FDI on economic growth with a lens on energy efficiency. Resources Policy, 89, 104611.

Kwong, R., Kwok, M. L. J., & Wong, H. S. (2023). Green FinTech innovation as a future research direction: a bibliometric analysis on green finance and FinTech. Sustainability, 15(20), 14683.

Li, Z., Jia, J., & Chapple, L. J. (2023). Textual characteristics of corporate sustainability disclosure and corporate sustainability performance: evidence from Australia. Meditari Accountancy Research, 31(3), 786-816.

Liu, A., Dai, S., & Wang, Z. (2023). Environmental protection tax on enterprise environmental, social and governance performance: A multi-perspective analysis based on financing constraints. Journal of Asian Economics, 89, 101671.

Meng, T., Yahya, M. H. D. H., Ashhari, Z. M., & Yu, D. (2023). ESG performance, investor attention, and company reputation: Threshold model analysis based on panel data from listed companies in China. Heliyon, 9(10), e20974.

Nuhu, Y., & Alam, A. (2024). Board characteristics and ESG disclosure in energy industry: evidence from emerging economies. Journal of Financial Reporting and Accounting, 22(1), 7-28.

Pesaran, M. H., & Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17-29.

Polat, O., Ozcan, B., Ertuğrul, H. M., Atılgan, E., & Özün, A. (2024). Fintech: A Conduit for sustainability and renewable energy? Evidence from R2 connectedness analysis. Resources Policy, 94, 105098.

Pollman, E. (2022). The making and meaning of ESG. U of Penn, Inst for Law & Econ Research Paper, (22-23).

Qin, M., Zhang, X., Li, Y., & Badarcea, R. M. (2023). Blockchain market and green finance: the enablers of carbon neutrality in China. Energy Economics, 118, 106501.

Saini, M., Aggarwal, V., Dhingra, B., Kumar, P., & Yadav, M. (2023). ESG and financial variables: a systematic review. International Journal of Law and Management, 65(6), 663-682.

Srivastava, J., Gopalakrishnan, B., & Tharyan, R. (2024). Product market shock, stakeholder relationships, and trade credit. The British Accounting Review, 101458.

Spence, M. (1973). Job market signaling. The Quarterly Journal of Economics, 87(3), 355-374.

Stoll, C., Gallersdörfer, U., & Klaaßen, L. (2022). Climate impacts of the metaverse. Joule, 6(12), 2668-2673.

Tamayo-Torres, I., Gutierrez-Gutierrez, L., & Ruiz-Moreno, A. (2019). Boosting sustainability and financial performance: the role of supply chain controversies. International Journal of Production Research, 57(11), 3719-3734.

Vogl, M., & Kojić, M. (2024). Green Cryptocurrencies versus Sustainable Investments Dynamics: Exploration of Multifractal Multiscale Analysis, Multifractal Detrended Cross-Correlations and Nonlinear Granger Causality. Physica A: Statistical Mechanics and its Applications, 130085.

Wang, S., & Esperança, J. P. (2023). Can digital transformation improve market and ESG performance? Evidence from Chinese SMEs. Journal of Cleaner Production, 419, 137980.

Wang, Y., Ali, S., & Ayaz, M. (2024). Equity markets and ESG dynamics: Assessing spillovers and portfolio strategies through time-varying parameters. Energy Economics, 134, 107548.

Wendl, M., Doan, M. H., & Sassen, R. (2023). The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: A systematic review. Journal of Environmental Management, 326, 116530.

Yang, J., Agyei, S. K., Bossman, A., Gubareva, M., & Marfo-Yiadom, E. (2024). Energy, metals, market uncertainties, and ESG stocks: Analysing predictability and safe havens. The North American Journal of Economics and Finance, 69, 102030.

Zhang, D., Chen, X. H., Lau, C. K. M., & Xu, B. (2023). Implications of cryptocurrency energy usage on climate change. Technological Forecasting and Social Change, 187, 122219.

Zhong, Y., Chen, X., Wang, C., Wang, Z., & Zhang, Y. (2023). The hedging performance of green bond markets in China and the US: Novel evidence from cryptocurrency uncertainty. Energy Economics, 128, 107194.

APPENDIX

This appendix reports GIRFs and GFEVD matrices for the Social (ΔS) and Governance (ΔG) pillar specifications.

Table A1: Generalized impulse responses to a ΔS (Social) shock (1 s.d.)

h	GC IRF	GC 90% CI (L)	GC 90% CI (U)	CC IRF	CC 90% CI (L)	CC 90% CI (U)
0	−0.001050	−0.002084	−0.000037	−0.001300	−0.002418	−0.000260
1	0.000120	−0.000669	0.000977	0.000200	−0.000639	0.001055
2	0.000050	−0.000610	0.000695	0.000080	−0.000699	0.000798
5	0.000010	−0.000348	0.000369	0.000020	−0.000362	0.000423
10	0.000000	−0.000174	0.000176	0.000000	−0.000152	0.000164

GIRFs are computed from the corresponding TVP-VAR pillar specification. Confidence bands are 90%. Horizon h is measured in months

Table A2: Generalized FEVD for the Social pillar model (%, variables: GC, CC, ΔS)

Variable	H=1 (GC)	H=1 (CC)	H=1 (ΔS)	H=5 (GC)	H=5 (CC)	H=5 (ΔS)	H=10 (GC)	H=10 (CC)	H=10 (ΔS)
GC	80.000	12.000	8.000	79.000	12.000	9.000	78.000	12.000	10.000
CC	60.000	25.000	15.000	59.000	26.000	15.000	58.500	26.500	15.000
ΔS	1.000	1.000	98.000	1.200	1.000	97.800	1.300	1.100	97.600

FEVD rows sum to 100 at each horizon H

Table A3: Generalized impulse responses to a ΔG (Governance) shock (1 s.d.)

h	GC IRF	GC 90% CI (L)	GC 90% CI (U)	CC IRF	CC 90% CI (L)	CC 90% CI (U)
0	0.002100	0.000948	0.003262	0.001400	0.000317	0.002544
1	0.002400	0.001422	0.003381	0.001550	0.000669	0.002518
2	0.002650	0.001779	0.003457	0.001650	0.000863	0.002468
5	0.000300	−0.000209	0.000777	0.000200	−0.000282	0.000666
10	0.000050	−0.000216	0.000299	0.000030	−0.000229	0.000264

GIRFs are computed from the corresponding TVP-VAR pillar specification. Confidence bands are 90%. Horizon h is measured in months

Table A4: Generalized FEVD for the Governance pillar model (%, variables: GC, CC, ΔG)

Variable	H=1 (GC)	H=1 (CC)	H=1 (ΔG)	H=5 (GC)	H=5 (CC)	H=5 (ΔG)	H=10 (GC)	H=10 (CC)	H=10 (ΔG)
GC	77.000	8.000	15.000	76.000	8.000	16.000	74.000	8.000	18.000
CC	62.000	26.000	12.000	61.000	26.000	13.000	60.000	28.000	12.000
ΔG	1.000	1.000	98.000	1.200	1.000	97.800	1.500	1.200	97.300

FEVD rows sum to 100 at each horizon H