Ahmad Al-Harbi, PhD

Assistant Professor
Alasala Colleges, Dammam, Saudi Arabia
College of Business Administration
E-mail: ahmad.alharbi@alasala.edu.sa
Orcid: https://orcid.org/0000-0003-1593-7835

GREEN DREAMS OR SPECULATIVE SCHEMES? EMPIRICAL EVIDENCE OF ASSET BUBBLES IN CLEAN ENERGY ETFS (2013–2024)

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Abstract

This paper examines explosive price behaviour in twenty green and ESG exchange-traded funds (ETFs) and seven conventional benchmarks using daily data from 2013 to 2024. We apply the Phillips, Shi and Yu (2015) SADF and GSADF tests, date-stamp episodes using backward SADF, and use Benjamini–Hochberg and Bonferroni corrections. Eight of nine clean energy ETFs reject the unit root null, seven after controlling the false discovery rate. All nine show explosive signals between September 2020 and May 2021, peaking in January 2021. Broad ESG equity funds show no comparable behaviour, while green bond signals coincide with episodes in the conventional bond market. Present value calibration suggests that discount rate declines explain only part of the appreciation. Evidence from QQQ and XLE further supports a speculative interpretation specific to clean energy. These findings reveal substantial differences in speculative exposure across green financial instruments, with implications for investors, fund sponsors and regulators.

Keywords: green finance, asset bubbles, SADF and GSADF tests, clean energy ETFs, ESG investing, explosive behaviour

1. INTRODUCTION

The integration of Environmental, Social, and Governance (ESG) criteria into portfolio management represents a structural transformation of global capital

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markets. Driven by international climate treaties and surging investor allocations, capital managed under sustainable mandates expanded from a niche segment into a multi-trillion-dollar industry by the early 2020s. Global benchmarking estimated USD 35.3 trillion under sustainable mandates across major developed markets at the start of 2020 (GSIA, 2021), with industry projections anticipating sustainable assets to surpass USD 50 trillion by 2025 (Bloomberg Intelligence, 2021). This massive reallocation of capital has fundamentally altered equilibrium asset pricing and expected returns (Pástor, Stambaugh, & Taylor, 2021; Bolton & Kacperczyk, 2021). A substantial share of these inflows entered exchange traded funds (ETFs), which provide retail and institutional investors liquid, low-cost exposure to renewable technologies, green debt, and screened equities.

However, the price trajectories of these instruments have been remarkably turbulent. Around the COVID-19 pandemic, pure-play clean energy funds underwent parabolic appreciation followed by a prolonged, severe collapse. The Invesco WilderHill Clean Energy ETF (PBW) appreciated by over 200% in 2020 before losing more than four-fifths of its peak value over the subsequent four years; the iShares Global Clean Energy ETF (ICLN) followed an identical boom-bust cycle. These violent swings prompted active debate over whether parts of green finance experienced a speculative bubble. The competing view holds that the volatility reflects the ordinary risks of financing early-stage technologies amplified by shifting macroeconomic conditions, and that statistical evidence of an asset bubble is lacking. Distinguishing speculative detachment from rational repricing is vital: if asset prices detached from fundamentals, capital was misallocated during the boom, raising the cost of equity during the subsequent crash; if prices reflected rational discount-rate repricing, regulatory or investor interventions would themselves constitute distortions.

This paper formally tests for explosive price behaviour in a comprehensive universe of twenty United States listed green and ESG ETFs between January 2013 and December 2024, evaluated against seven conventional benchmarks spanning broad equity (SPY), long-duration growth (QQQ), small caps (IWM), fossil energy (XLE), gold (GLD), and fixed income (BND, LQD). We employ the supremum ADF (SADF) and generalized supremum ADF (GSADF) recursive right-tailed unit root testing framework developed by Phillips, Shi, and Yu (2015; PSY), date-stamp explosive episodes via backward SADF (BSADF) sequences, and control the false discovery rate across the green universe. Although listed in the United States, several clean energy funds hold globally diversified portfolios; hence, the results reflect the globally invested clean energy sector as priced in the deepest, most retail-accessible ETF market.

The paper makes three primary contributions. First, it demonstrates that green finance is highly heterogeneous: the statistical signature of the 2020–2021 episode is confined strictly to pure-play clean energy and adjacent thematic equities, whereas broad ESG equities show no explosive tendencies and green bond signals simply mirror the broader fixed-income market. Second, it directly addresses leading non-bubble explanations: a present value calibration reveals that

plausible discount-rate reductions account for only a fraction of the observed price appreciation, while the absence of explosiveness in an equally duration-sensitive growth benchmark (QQQ) further weakens a purely fundamental interpretation. Third, by testing twenty green funds jointly under false discovery rate control and matched-window checks (Appendix A, Table A1), it mitigates data-snooping and sample-heterogeneity biases. In doing so, the paper connects directly to recent empirical investigations into the economics of the clean energy transition (Gelo & Družić, 2025) and behavioural crisis decision-making (Suljić Nikolaj, Olgić Draženović, & Nisbet, 2025). The remainder of the paper reviews the literature (Section 2), outlines data and econometric methods (Section 3), presents empirical results (Section 4), discusses economic mechanisms and policy implications (Section 5), and concludes (Section 6).

2. LITERATURE REVIEW

2.1. Financial bubbles and detection methodologies

Theoretical asset pricing allows bubbles to emerge even under rational expectations. Blanchard and Watson (1982) demonstrated that a self-fulfilling bubble component can satisfy standard asset pricing recursions, while Diba and Grossman (1988) showed that such components grow explosively. However, Evans (1991) proved that standard unit root tests suffer severe power collapse when applied to periodically collapsing bubbles, as collapse regimes cause explosive series to mimic stationary or random-walk processes. Behavioural finance complements this perspective by emphasizing feedback trading, narrative contagion, and credit conditions as key drivers detaching prices from fundamentals (Shiller, 2000; Aliber, Kindleberger, & McCauley, 2015), with sharp sector-level run-ups predicting heightened crash probabilities (Greenwood, Shleifer, & You, 2019).

To overcome Evans' critique, Phillips, Wu, and Yu (2011) and Phillips, Shi, and Yu (2015) developed recursive right-tailed ADF tests. The SADF test computes ADF t-statistics over forward-expanding windows anchored at the sample origin, restoring power against a single bubble episode. The GSADF test generalizes this by allowing both start and end points to vary, providing consistency against multiple periodically collapsing episodes. Dating of bubble origin and termination is performed via the backward SADF (BSADF) sequence. Homm and Breitung (2012) confirmed the superior power and structural robustness of supremum-type recursive tests. The PSY framework has been validated across housing (Pavlidis et al., 2016), cryptocurrencies (Cheung, Roca, & Su, 2015; Corbet, Lucey, & Yarovaya, 2018), and commodities (Gutierrez, 2013; Etienne, Irwin, & Garcia, 2014), establishing that recursive tests detect periods of extreme market stress as well as euphoria, necessitating careful inspection of price direction.

2.2. Green assets, investor sentiment and the pricing of climate exposure

Recent literature has established that climate risk is an active component of the stochastic discount factor (Bolton & Kacperczyk, 2021). Theoretically, green assets should earn lower expected returns in equilibrium because investors derive non-pecuniary utility from holding sustainable assets (Pástor, Stambaugh, & Taylor, 2021). However, unanticipated positive shifts in green preferences generate strong realized returns during transition phases (Pástor, Stambaugh, & Taylor, 2022). In fixed income, corporate green bonds command a modest negative premium ('greenium') and reflect contractual cash flows dominated by yield curves and credit spreads (Zerbib, 2019; Flammer, 2021; Baker et al., 2022), providing a theoretical prior that green debt should not exhibit equity-like speculative dynamics.

For clean energy equities, earlier boom-bust cycles have exhibited speculative bubble dynamics: Bohl, Kaufmann, and Stephan (2013) documented a 'hero to zero' performance reversal in German renewable stocks in the mid-2000s, closely mirroring the 2020–2024 trajectory. Furthermore, alternative energy equities interact dynamically with technology and crude oil markets (Henriques & Sadorsky, 2008; Sadorsky, 2012; Kumar, Managi, & Matsuda, 2012; Bondia, Ghosh, & Kanjilal, 2016; Dutta, 2017). Bouzguenda and Jarboui (2025) find that clean energy ETFs act as net shock transmitters during market stress. Additionally, ETF market microstructure amplifies volatility via arbitrage demand shocks (Ben-David, Franzoni, & Moussawi, 2018), which retail attention and herding can dramatically escalate (Da, Engelberg, & Gao, 2011; Barber et al., 2022).

2.3. Alternative explanations and the research gap

Any bubble claim must confront the rational repricing alternative under the Campbell and Shiller (1988) present value framework, wherein prices surge when discount rates fall or expected cash flows rise. Because clean energy firms are long-duration growth assets with cash flows concentrated far in the future, their valuations are acutely sensitive to discount-rate declines (Lettau & Wachter, 2007). In 2020, United States Treasury yields declined by approximately 100 basis points while federal climate policy expectations surged. While prior studies typically examined individual clean energy indices in isolation, our empirical design addresses this research gap by testing a comprehensive, multi-segment green universe alongside duration and energy benchmarks, adjusting for multiple testing, and calibrating fundamental present value effects.

3. DATA AND METHODOLOGY

3.1. Data

The dataset comprises daily adjusted closing prices (adjusted for splits and dividends) from Yahoo Finance for twenty-seven ETFs from 2 January 2013 to 30 December 2024 (Table 1). The green universe spans nine pure-play clean energy funds (ICLN, PBW, QCLN, TAN, FAN, PBD, CNRG, SMOG, ACES), three thematic equity funds (LIT, DRIV, KARS), two dedicated green bond funds (GRNB, BGRN), one ESG bond fund (EAGG), and five broad ESG equity funds (ESGU, ESGV, SUSL, DSI, USSG). Seven benchmarks provide identification controls: SPY, QQQ, IWM, XLE, GLD, BND, and LQD. Nine green funds cover the full twelve-year span (3,019 trading days), while newer funds begin between 2016 and 2019.

Table 1 Testing universe, categories and sample coverage

Ticker	Fund Name	Category	N	Start Date
ICLN	iShares Global Clean Energy	Clean energy equity	3,019	2013-01-02
PBW	Invesco WilderHill Clean Energy	Clean energy equity	3,019	2013-01-02
QCLN	First Trust NASDAQ Clean Edge Green Energy	Clean energy equity	3,019	2013-01-02
TAN	Invesco Solar	Clean energy equity	3,019	2013-01-02
FAN	First Trust Global Wind Energy	Clean energy equity	3,019	2013-01-02
PBD	Invesco Global Clean Energy	Clean energy equity	3,019	2013-01-02
CNRG	SPDR S&P Kensho Clean Power	Clean energy equity	1,556	2018-10-23
SMOG	VanEck Low Carbon Energy	Clean energy equity	3,019	2013-01-02
ACES	ALPS Clean Energy	Clean energy equity	1,636	2018-06-29
LIT	Global X Lithium & Battery Tech	Green thematic equity	3,019	2013-01-02
DRIV	Global X Autonomous & Electric Vehicles	Green thematic equity	1,688	2018-04-17
KARS	KraneShares Electric Vehicles & Future Mobility	Green thematic equity	1,744	2018-01-25
GRNB	VanEck Green Bond	Green bond	1,968	2017-03-07
BGRN	iShares USD Green Bond	Green bond	1,532	2018-11-27
EAGG	iShares ESG Aware US Aggregate Bond	ESG bond	1,556	2018-10-23
ESGU	iShares ESG Aware MSCI USA	Broad ESG equity	2,029	2016-12-06
ESGV	Vanguard ESG US Stock	Broad ESG equity	1,579	2018-09-20
SUSL	iShares ESG MSCI USA Leaders	Broad ESG equity	1,420	2019-05-10
DSI	iShares MSCI KLD 400 Social	Broad ESG equity	3,019	2013-01-02
USSG	Xtrackers MSCI USA ESG Leaders Equity	Broad ESG equity	1,464	2019-03-08
SPY	SPDR S&P 500 (broad equity)	Benchmark	3,019	2013-01-02
QQQ	Invesco QQQ, Nasdaq-100 (growth equity)	Benchmark	3,019	2013-01-02
IWM	iShares Russell 2000 (small-cap equity)	Benchmark	3,019	2013-01-02
XLE	Energy Select Sector SPDR (fossil energy)	Benchmark	3,019	2013-01-02
GLD	SPDR Gold Shares (commodity)	Benchmark	3,019	2013-01-02
BND	Vanguard Total Bond Market (aggregate bond)	Benchmark	3,019	2013-01-02
LQD	iShares iBoxx USD Investment Grade Corporate Bond	Benchmark	3,019	2013-01-02

Note: N is the number of daily price observations to 30 December 2024. All funds trade on US exchanges.

Source: Yahoo Finance, author's classification.

Data availability and replication. All prices are daily adjusted closing prices from Yahoo Finance, retrieved on 14 September 2026 through the yfinance Python

interface and adjusted for splits and dividend distributions; unadjusted prices are not used at any stage. No observation was manually corrected, interpolated or imputed, and no missing value was filled: each series enters the analysis exactly as downloaded, over its full history from inception to 30 December 2024, and analyses that need matched series use pairwise common trading days only. The replication package is available from the corresponding author upon reasonable request. The full Data Availability Statement appears at the end of the article, before the References.

3.2. Descriptive statistics and unit root pretesting

We compute annualized returns, volatility, Sharpe ratios (constant 2% risk-free rate; robustness across 0%, 5%, and time-varying T-bill rates evaluated in Appendix A, Table A2), skewness, excess kurtosis, maximum drawdowns, historical Value at Risk (95% and 99%), and Jarque–Bera tests. Right-tailed explosive tests presume the series are I(1) under the null. We verify integration using Augmented Dickey–Fuller (ADF) tests (AIC lag selection) and KPSS tests (Newey–West automatic bandwidth) on log levels and first differences (Table 2). Every series is decisively I(1) in log levels and I(0) in first differences.

Table 2 Unit root pretests, full universe

Ticker	ADF Level	ADF 1st Diff.	KPSS Level	KPSS 1st Diff.	Result
ICLN	-1.791	-9.947***	6.402***	0.210	I(1)
PBW	-1.365	-10.740***	3.491***	0.232	I(1)
QCLN	-1.622	-11.320***	7.096***	0.185	I(1)
TAN	-1.759	-10.800***	4.684***	0.227	I(1)
FAN	-2.257	-20.381***	7.688***	0.228	I(1)
PBD	-1.775	-10.488***	5.391***	0.271	I(1)
CNRG	-2.073	-9.587***	2.719***	0.389	I(1)
SMOG	-1.816	-19.778***	7.255***	0.152	I(1)
ACES	-1.421	-9.679***	1.539***	0.436	I(1)
LIT	-1.065	-17.893***	6.693***	0.144	I(1)
DRIV	-1.398	-12.999***	4.272***	0.098	I(1)
KARS	-1.320	-13.547***	2.037***	0.212	I(1)
GRNB	-2.021	-46.541***	0.827***	0.212	I(1)
BGRN	-1.724	-9.304***	1.638***	0.343	I(1)
EAGG	-1.793	-28.918***	1.529***	0.341	I(1)
ESGU	-0.690	-13.763***	6.552***	0.036	I(1)
ESGV	-0.718	-12.178***	4.956***	0.061	I(1)
SUSL	-1.027	-11.426***	4.461***	0.052	I(1)
DSI	-0.501	-15.222***	8.991***	0.028	I(1)
USSG	-0.922	-11.482***	4.697***	0.051	I(1)
SPY	-0.358	-11.711***	9.025***	0.026	I(1)
QQQ	-0.465	-12.137***	9.039***	0.032	I(1)
IWM	-1.645	-11.081***	8.188***	0.037	I(1)
XLE	-1.303	-10.775***	2.420***	0.098	I(1)
GLD	-0.072	-31.156***	6.938***	0.468	I(1)
BND	-1.452	-10.925***	6.156***	0.133	I(1)
LQD	-1.434	-12.144***	6.771***	0.077	I(1)

Note: ADF null is a unit root; KPSS null is stationarity. *** $p < 0.01$. All series are I(1) in levels and I(0) in differences.

Source: author's calculations.

3.3. Explosive-root testing: SADF, GSADF and date-stamping

For a log price series yt, the recursive ADF regression estimated over window [r1, r2] is:

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2}\, y_{t-1} + \Sigma_{i=1}^{k} \gamma_i\, \Delta y_{t-i} + \varepsilon_t, \quad (1)$$

testing H0: $\beta = 0$ against H1: $\beta > 0$. The SADF statistic is the supremum of ADF statistics over forward-expanding windows anchored at $r1 = 0$; the GSADF statistic allows both endpoints to vary across $0 \le r1 \le r2 - r0$ and $r0 \le r2 \le 1$. The BSADF sequence evaluated at each point provides date-stamping, with an explosive episode declared when BSADF exceeds its simulated 95% critical value for at least $\lceil \ln N \rceil$ consecutive trading days (PSY). The minimum window follows the PSY rule $r0 = 0.01 + 1.8/\sqrt{N}$ (129 days for N = 3,019). Critical values are generated via 10,000 Monte Carlo replications of the driftless random walk null at each sample length (empirical p-value = $(r + 1)/(S + 1)$); simulation details are documented in Appendix B. Multiple testing across the twenty green funds is controlled using Benjamini–Hochberg (FDR $q = 0.05$) and Bonferroni ($\alpha = 0.05/20 = 0.0025$) corrections.

4. EMPIRICAL RESULTS

4.1. Descriptive statistics and tail risk

Table 3 reports descriptive statistics for the core funds representing each market segment, incorporating rolling 252-day volatility metrics. Clean energy funds carry equity risk of an entirely different order: annualized volatility reaches 26.21% for ICLN and 35.38% for PBW (with rolling peaks of 47.38% and 59.24%), against 16.76% for SPY. Their maximum drawdowns of 64.26% and 85.71% dwarf the 33.72% broad-market decline over the twelve-year period. Full-sample annualized returns were modest (5.57% for ICLN, 1.85% for PBW) because the post-2021 collapse absorbed nearly all gains from the 2020 boom. Daily Value at Risk for PBW reaches 3.64% (95%) and 5.77% (99%), roughly 2.3 and 1.9 times that of SPY. Conversely, the green bond fund BGRN behaves like its conventional counterpart BND across all dimensions, with volatility near 5.3% and drawdowns concentrated in the 2022 tightening, while the broad ESG fund ESGU closely tracks SPY.

Table 3 Descriptive statistics and volatility regimes, core funds

Statistic	BGRN	ICLN	PBW	ESGU	SPY	GLD	BND
Sample start	2018-11-28	2013-01-03	2013-01-03	2016-12-07	2013-01-03	2013-01-03	2013-01-03
N (observations)	1,531	3,018	3,018	2,028	3,018	3,018	3,018
Mean daily return (%)	0.0061	0.0221	0.0074	0.0546	0.0532	0.0129	0.0059
Std. dev. daily return (%)	0.3328	1.6513	2.2289	1.1856	1.0555	0.9441	0.3239
Annualized volatility (%)	5.28	26.21	35.38	18.82	16.76	14.99	5.14
Rolling vol. min (%)	3.09	12.78	16.54	5.88	6.73	9.25	2.53
Rolling vol. max (%)	8.25	47.38	59.24	34.94	33.90	22.40	9.53
Rolling vol. mean (%)	5.32	25.16	33.38	18.27	15.85	14.26	4.68
Annualized return (%)	1.54	5.57	1.85	13.76	13.41	3.24	1.48
Sharpe ratio*	-0.087	0.136	-0.004	0.625	0.681	0.083	-0.100
Skewness	0.0029	-0.3795	-0.2110	-0.8034	-0.8152	-0.5055	-1.1814
Excess kurtosis	4.5453	6.6015	3.6438	16.1396	14.3525	5.6289	42.3520
Minimum daily return (%)	-1.7189	-13.7093	-15.6373	-12.7863	-11.5887	-9.1905	-5.5920
Maximum daily return (%)	2.7363	10.7998	13.5028	9.2523	8.6731	4.7874	4.1334
Maximum drawdown (%)	-19.16	-64.26	-85.71	-33.87	-33.72	-38.60	-18.58
VaR 95% (%)	-0.5638	-2.6103	-3.6376	-1.7666	-1.6024	-1.5004	-0.4688
VaR 99% (%)	-0.8856	-4.2272	-5.7691	-3.3845	-3.0560	-2.5303	-0.8630
Jarque–Bera statistic	1,307.08	5,531.04	1,684.68	22,112.68	26,144.74	4,096.74	225,491.10
JB p-value	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001	< 0.001

Note: N is daily log returns. VaR = historical Value at Risk. Annualized figures assume 252 trading days. *Sharpe ratios use a constant 2% risk-free rate; robustness across alternative rates is reported in Appendix A, Table A2.

Source: author's calculations.

4.2. Annual returns and boom-bust asymmetry

Table 4 presents calendar-year returns, illustrating the boom-bust asymmetry directly. In 2020, clean energy funds surged by 141.83% (ICLN) and 204.75% (PBW), while SPY gained 18.33%. However, from 2021 through 2024, clean energy suffered four consecutive years of negative returns, erasing the decade's gains, whereas SPY and ESGU recovered fully from the 2022 drawdown within twelve months.

Table 4 Annual returns (%), core funds

Year	BGRN	ICLN	PBW	ESGU	SPY	GLD	BND
2014	–	-4.80	-15.41	–	13.46	-2.19	5.82
2015	–	3.81	-8.78	–	1.23	-10.67	0.56
2016	–	-16.89	-20.35	–	12.00	8.03	2.52
2017	–	21.47	39.91	21.07	21.71	12.81	4.00
2018	–	-9.03	-13.49	-4.24	-4.57	-1.94	0.12
2019	9.70	44.36	62.58	31.72	31.22	17.86	8.83
2020	6.86	141.83	204.75	22.54	18.33	24.81	7.72
2021	-2.80	-24.18	-30.09	26.89	28.73	-4.15	-1.86
2022	-13.06	-5.43	-44.55	-20.27	-18.18	-0.77	-13.11
2023	6.50	-20.40	-20.03	25.79	26.18	12.69	5.65
2024	2.90	-25.39	-29.08	24.83	25.34	25.87	1.55

Note: Calendar-year total returns. Dashes denote pre-inception years.

Source: author's calculations from Yahoo Finance data.

4.3. SADF and GSADF tests with multiple testing corrections

Table 5 reports the headline bubble detection results. Explosive behaviour is overwhelmingly concentrated in pure-play clean energy. Eight of the nine clean energy funds reject the unit root null under the GSADF test at unadjusted $p < 0.05$ (most $p < 0.001$), with the ninth (FAN, wind energy) marginal at $p = 0.086$. Seven survive false discovery rate control (BH 5%), and six survive the stringent Bonferroni threshold ($\alpha = 0.0025$). Broad ESG equities show zero evidence of explosiveness (all unadjusted $p > 0.055$). Green and ESG bond funds (GRNB, BGRN, EAGG) reject under BH, but so do conventional benchmarks BND and LQD; as shown below, their episodes coincide exactly with macro interest rate shifts rather than green dynamics. Benchmarks SPY, QQQ, and GLD show no full-sample explosiveness, while XLE and IWM reject solely due to brief crash episodes.

Table 5 SADF and GSADF test results

Ticker	SADF	p (SADF)	GSADF	p (GSADF)	95% CV SADF	95% CV GSADF	BH 5%	Bonf. 5%
ICLN	3.017	0.0005	3.906	0.0002	1.596	2.495	Yes	Yes
PBW	3.200	0.0002	3.719	0.0003	1.596	2.495	Yes	Yes
QCLN	2.434	0.0032	3.597	0.0006	1.596	2.495	Yes	Yes
TAN	1.085	0.1821	3.358	0.0019	1.596	2.495	Yes	Yes
FAN	0.521	0.4692	2.321	0.0855	1.596	2.495	No	No
PBD	2.975	0.0006	3.918	0.0002	1.596	2.495	Yes	Yes
CNRG	2.073	0.0113	2.475	0.0380	1.576	2.395	No	No
SMOG	1.777	0.0298	3.153	0.0045	1.596	2.495	Yes	No
ACES	2.274	0.0063	3.375	0.0016	1.589	2.419	Yes	Yes
LIT	1.761	0.0315	2.899	0.0112	1.596	2.495	Yes	No
DRIV	1.354	0.0876	2.140	0.1095	1.561	2.391	No	No
KARS	1.278	0.1091	1.647	0.3935	1.576	2.424	No	No
GRNB	0.027	0.7077	3.063	0.0053	1.594	2.427	Yes	No
BGRN	1.440	0.0710	2.719	0.0180	1.562	2.394	Yes	No
EAGG	0.938	0.2170	2.854	0.0088	1.576	2.395	Yes	No
ESGU	1.053	0.1803	2.410	0.0551	1.594	2.447	No	No
ESGV	-0.053	0.7392	1.518	0.4805	1.582	2.405	No	No
SUSL	0.405	0.4842	1.735	0.2956	1.555	2.396	No	No
DSI	-0.114	0.7939	2.228	0.1143	1.596	2.495	No	No
USSG	-0.239	0.8133	1.455	0.5183	1.538	2.385	No	No
SPY	-0.254	0.8480	2.214	0.1191	1.596	2.495	n.a.	n.a.
QQQ	0.256	0.6111	1.122	0.8874	1.596	2.495	n.a.	n.a.
IWM	-0.628	0.9427	3.538	0.0007	1.596	2.495	n.a.	n.a.
XLE	3.208	0.0002	6.429	0.0001	1.596	2.495	n.a.	n.a.
GLD	0.323	0.5750	2.023	0.2077	1.596	2.495	n.a.	n.a.
BND	1.831	0.0264	2.970	0.0086	1.596	2.495	n.a.	n.a.
LQD	1.376	0.0933	3.551	0.0007	1.596	2.495	n.a.	n.a.

Note: 10,000 Monte Carlo replications of null random walk. BH 5% and Bonf. 5% evaluate GSADF p-values across green funds; benchmarks (n.a.) are excluded from the correction family.

Source: author's calculations.

4.4. Date-stamping: anatomy of the 2020–2021 clean energy episode

Table 6 lists all dated explosive episodes lasting at least 30 trading days for green funds and 20 days for benchmarks. The 2020–2021 clean energy episode is exceptional across three dimensions. It is extraordinarily prolonged: running 122 days for

ICLN, 153 for PBW, 154 for QCLN, 149 for TAN, 124 for SMOG, and 127 for PBD (compared to a median of 20 days across other sample episodes). It is remarkably synchronized: all nine clean energy funds were explosive simultaneously in January 2021, peaking within days of each other (seven peaking on 7 or 12 January 2021). And it is strictly directional: prices escalated by 25% to 56% within the explosive windows. Onsets occurred between September and December 2020, accelerated following the US election, and terminated between February and May 2021 as valuations broke down. Figure 1 plots the BSADF sequences for ICLN, PBW, TAN, and XLE.

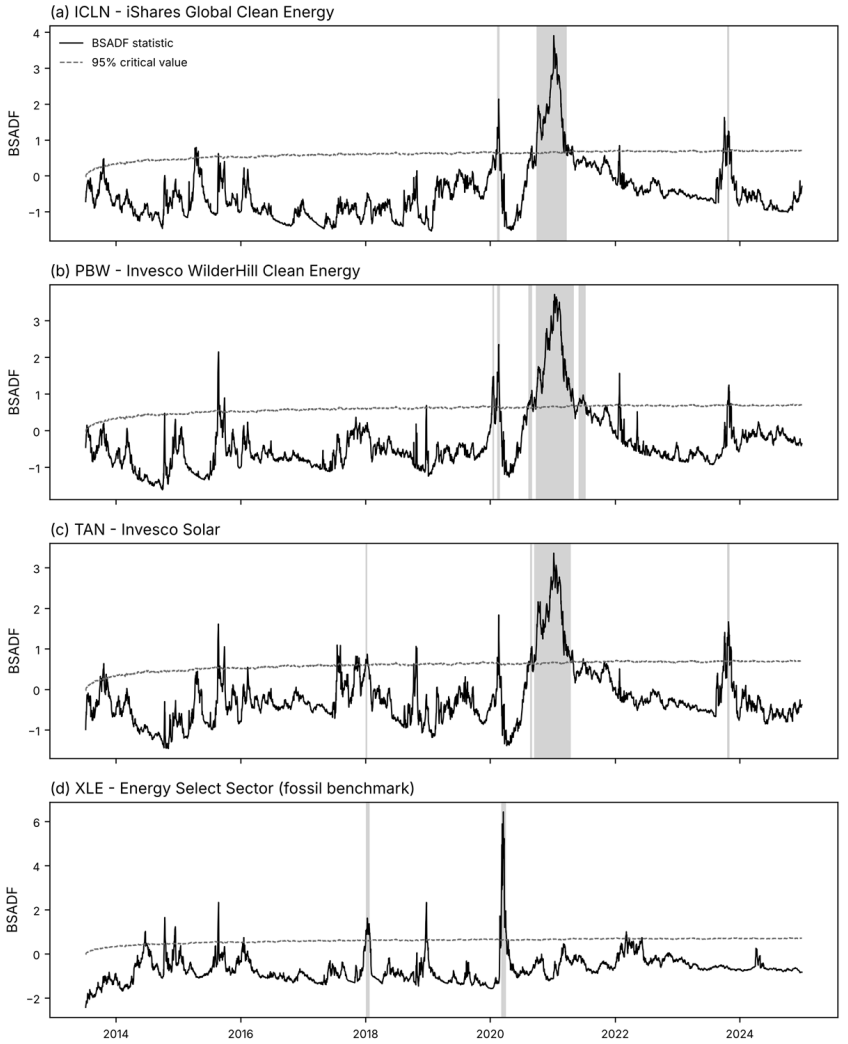
Table 6 Principal date-stamped explosive episodes

Ticker	Category	Start	End	Days	Peak Date	Peak BSADF
BND	Benchmark	2019-05-06	2020-03-11	215	2019-08-15	2.97
BND	Benchmark	2020-06-26	2020-08-13	34	2020-08-04	0.92
BND	Benchmark	2022-04-05	2022-05-26	37	2022-04-19	2.55
BND	Benchmark	2022-05-31	2022-06-30	22	2022-06-14	2.69
BND	Benchmark	2022-09-08	2022-11-14	48	2022-10-20	2.17
LQD	Benchmark	2016-06-28	2016-07-29	23	2016-07-08	1.52
LQD	Benchmark	2019-03-20	2019-05-01	30	2019-03-28	1.67
LQD	Benchmark	2019-05-21	2020-03-10	203	2019-08-27	2.93
LQD	Benchmark	2022-04-08	2022-05-23	31	2022-04-19	1.88
LQD	Benchmark	2022-09-22	2022-11-09	35	2022-09-27	1.58
GLD	Benchmark	2019-08-07	2019-09-05	21	2019-09-04	1.28
GLD	Benchmark	2020-07-21	2020-09-18	43	2020-08-06	2.02
SPY	Benchmark	2018-01-03	2018-02-01	21	2018-01-26	2.21
XLE	Benchmark	2020-03-05	2020-04-03	22	2020-03-18	6.43
ACES	Clean energy	2020-01-07	2020-02-26	35	2020-02-19	3.38
ACES	Clean energy	2020-11-11	2021-03-02	75	2021-01-12	2.29
CNRG	Clean energy	2020-12-15	2021-02-24	48	2021-01-22	2.12
FAN	Clean energy	2013-09-26	2013-11-06	30	2013-10-22	1.03
FAN	Clean energy	2020-12-15	2021-02-22	46	2021-01-07	2.32
ICLN	Clean energy	2020-09-28	2021-03-23	122	2021-01-07	3.91
PBD	Clean energy	2020-10-29	2021-05-03	127	2021-01-07	3.92
PBW	Clean energy	2020-09-25	2021-05-05	153	2021-01-12	3.72
PBW	Clean energy	2021-06-01	2021-07-13	30	2021-06-28	0.97
QCLN	Clean energy	2020-09-28	2021-05-07	154	2021-01-12	3.60
QCLN	Clean energy	2021-05-20	2021-08-16	61	2021-06-28	1.13
QCLN	Clean energy	2021-10-13	2021-12-10	42	2021-11-08	1.25
SMOG	Clean energy	2020-11-03	2021-05-03	124	2021-01-08	3.15
TAN	Clean energy	2020-09-14	2021-04-16	149	2021-01-07	3.36
EAGG	ESG bond	2022-04-05	2022-05-25	36	2022-05-06	2.39
EAGG	ESG bond	2022-09-06	2022-11-15	51	2022-10-20	2.24
BGRN	Green bond	2022-03-07	2022-07-21	95	2022-05-02	2.72
BGRN	Green bond	2022-08-29	2022-11-09	52	2022-10-20	1.99
GRNB	Green bond	2022-03-02	2022-07-27	102	2022-06-14	3.06
GRNB	Green bond	2022-08-26	2022-11-21	61	2022-10-20	2.29
DRIV	Green thematic	2021-01-05	2021-03-03	40	2021-01-12	1.50
KARS	Green thematic	2020-12-30	2021-03-02	42	2021-01-12	1.40
LIT	Green thematic	2017-08-31	2017-12-04	66	2017-09-19	2.90
LIT	Green thematic	2020-12-15	2021-02-24	48	2021-01-07	1.99
LIT	Green thematic	2021-06-23	2022-01-04	136	2021-11-08	1.52

Note: Minimum duration ceil(ln N) days. Green fund episodes < 30 days and benchmark episodes < 20 days omitted for readability. Complete list of 87 episodes in replication archive.

Source: author's calculations.

Figure 1 BSADF date-stamping for ICLN, PBW, TAN and XLE



Note: Solid line = BSADF statistic; dashed line = 95% Monte Carlo critical value sequence; shaded bands = dated explosive episodes.

Source: author's calculations.

4.5. Benchmark explosiveness, energy confounding, and dependence structure

A primary identification concern is whether clean energy explosiveness was inherited from broader energy market volatility. Testing the fossil energy benchmark XLE reveals this concern is unfounded: XLE generates a massive GSADF statistic (6.43), but date-stamping confirms its signal is driven entirely by a 22-day collapse in March–April 2020 during the pandemic oil price shock. XLE exhibits zero explosive behaviour during the September 2020–May 2021 clean energy boom. Furthermore, energy-factor-purged tests (Appendix C, Table C2) show that removing contemporaneous XLE returns leaves the clean energy bubble statistics intact. Similarly, green bond episodes (GRNB, BGRN, EAGG) in 2019 and 2022 coincide to the day with conventional benchmarks BND and LQD, reflecting duration rallies and Federal Reserve rate tightening rather than green-specific dynamics.

Table 7 reports the lower-triangle Pearson correlation matrix. Broad ESG equity is almost identical to the market (ESGU–SPY r = 0.977), indicating ESG screening functioned essentially as large-cap beta. Clean energy funds correlate strongly with each other (ICLN–PBW r = 0.824) but only moderately with SPY (r ≈ 0.67), retaining large idiosyncratic exposure. Green bonds track aggregate fixed income (BGRN–BND r = 0.811) and correlate weakly with equities (r = 0.17).

Table 7 Pearson correlation matrix of daily log returns, core funds

Asset	BGRN	ICLN	PBW	ESGU	SPY	GLD	BND
BGRN	1.000						
ICLN	0.243***	1.000					
PBW	0.203***	0.824***	1.000				
ESGU	0.173***	0.662***	0.672***	1.000			
SPY	0.166***	0.665***	0.672***	0.977***	1.000		
GLD	0.356***	0.124***	0.095***	0.101***	0.042*	1.000	
BND	0.811***	0.175***	0.120***	0.157***	0.095***	0.343***	1.000

Note: *** $p < 0.001$, * $p < 0.05$. Overlapping pairwise samples.

Source: author's calculations.

Table 8 presents weekly Granger-type lead-lag tests. While no predictive relationships exist at lag 1, clean energy returns at lag 4 carry modest predictive content for subsequent SPY returns ($p = 0.029$ for ICLN, $p = 0.037$ for PBW), reflecting shared macroeconomic risk-appetite transmission rather than structural causality (extended lag checks and VAR impulse responses in Appendix C, Table C4, confirm this association is economically negligible).

Table 8 Granger-type lead-lag tests, weekly returns

Direction	Lag1 F	Lag1 p	Lag4 F	Lag4 p	Decision
SPY → BGRN	0.097	0.7553	2.101	0.0806	No association
BGRN → SPY	3.543	0.0607	1.295	0.2718	No association
SPY → ICLN	1.112	0.2920	1.437	0.2201	No association
ICLN → SPY	2.430	0.1195	2.726	0.0286	Lead-lag association*
SPY → PBW	2.158	0.1424	1.314	0.2634	No association
PBW → SPY	1.555	0.2129	2.568	0.0372	Lead-lag association*
SPY → ESGU	0.850	0.3571	0.528	0.7154	No association
ESGU → SPY	0.158	0.6914	0.223	0.9257	No association

Note: * $p < 0.05$. Tests indicate predictive content only; structural causality is unidentified under common macro shocks.

Source: author's calculations.

5. DISCUSSION

5.1. Economic mechanisms and present value calibration

The synchronized 2020–2021 clean energy episode conforms closely to theoretical bubble models: prices surged alongside expanding retail participation, zero-commission trading, and heightened policy optimism, peaked simultaneously, and subsequently experienced protracted collapse. To rigorously test the rational discount-rate alternative, Table 9 evaluates price appreciation justified by a permanent discount-rate reduction in a constant-growth present value model across initial spreads ($r - g$) of 2% to 4% and rate cuts of 50 to 150 basis points. Under conventional parameters (3%–4% spread), even an aggressive 150 bp decline justifies 60% to 100% appreciation – well short of the 142% to 205% observed in ICLN and PBW. Matching observed returns requires knife-edge assumptions (spreads near 2%), under which valuation becomes unbounded. Furthermore, the Nasdaq-100 (QQQ), an equally duration-sensitive growth benchmark, showed no explosive behaviour (GSADF $p = 0.887$). Thus, while fundamental repricing occurred, a substantial speculative overlay drove the clean energy peak.

Table 9 Price appreciation justified by a permanent discount-rate decline

Initial spread ($r - g$)	$\Delta r = -50$ bp	$\Delta r = -100$ bp	$\Delta r = -150$ bp
4 p.p.	+14%	+33%	+60%
3 p.p.	+20%	+50%	+100%
2 p.p.	+33%	+100%	+300%

Note: Entries show percentage price increase in a constant-growth model. Calendar-2020 returns were +141.8% (ICLN) and +204.8% (PBW).

Source: author's calculations.

5.2. Implications for investors and policymakers

For investors, the findings highlight that 'green investing' comprises distinct asset classes. Pure-play clean energy equities exhibit venture-like tail risk (volatility > 35%, drawdowns > 80%) and belong strictly in satellite allocations, offering poor downside diversification. Conversely, green bonds provide fixed-income stability without speculative equity risk. For policymakers, the boom-bust cycle represents a double-edged sword: while the boom reduced firms' cost of equity, the subsequent crash raised transition financing costs. Regulatory frameworks must counter misleading product labelling. Initiatives such as the SEC's 2023 Names Rule amendments and ESMA's 2024 guidelines on ESG fund names provide essential differentiation, ensuring retail investors do not mistake speculative thematic equities for defensive sustainable investments (Suljić Nikolaj et al., 2025; Srdelić & Barišić, 2025).

6. CONCLUSION

This paper investigated whether green and ESG ETF price dynamics contained statistical evidence of asset bubbles between 2013 and 2024. Applying the PSY recursive right-tailed framework to twenty green funds and seven benchmarks, we find that speculative bubbles were real, large, and confined almost exclusively to pure-play clean energy equities. Eight of nine clean energy funds rejected the unit root null under GSADF tests, date-stamping a synchronized episode peaking in January 2021 before severe collapse. Broad ESG equity displayed no bubble behaviour, while green bond signals inherited broader bond market yield dynamics. A present value calibration confirms that discount-rate shifts cannot fully explain observed appreciation, confirming a speculative overlay.

Several limitations qualify these conclusions. First, the sample necessarily includes only surviving funds, which may bias class-level average performance upward while leaving fund-level episode identification intact. Second, recursive tests cannot fully separate irrational manias from rational one-time preference shifts (Pástor et al., 2021). Third, flow data were unavailable to identify structural price-flow feedback. Future research should integrate fund-level flow dynamics, examine European and Asian green ETF markets, and incorporate delisted instruments.

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APPENDIX A

MATCHED-WINDOW TESTS AND SHARPE RATIO SENSITIVITY

Table A1 reports SADF and GSADF tests over the common window from 10 May 2019 to 30 December 2024 (N = 1,420), holding the testing period constant across all twenty-seven funds. Table A2 reports Sharpe ratios under 0%, 2%, 5%, and time-varying three-month Treasury bill rates.

Table A1 SADF and GSADF tests on the matched window (2019–2024, N = 1,420)

Ticker	SADF	p (SADF)	BH 5%	GSADF	p (GSADF)	BH 5%
ICLN	2.255	0.0064	Yes	2.289	0.0681	No
PBW	1.999	0.0129	No	2.352	0.0568	No
QCLN	1.816	0.0225	No	1.853	0.2234	No
TAN	1.738	0.0287	No	2.395	0.0503	No
FAN	1.347	0.0831	No	2.955	0.0076	No
PBD	2.397	0.0037	Yes	2.678	0.0200	No
CNRG	1.938	0.0154	No	2.597	0.0259	No
SMOG	1.833	0.0213	No	1.833	0.2355	No
ACES	2.534	0.0020	Yes	3.375	0.0013	Yes
LIT	1.735	0.0293	No	2.067	0.1281	No
DRIV	1.117	0.1441	No	2.143	0.1045	No
KARS	1.009	0.1798	No	1.706	0.3152	No
GRNB	1.121	0.1436	No	3.063	0.0050	Yes
BGRN	1.220	0.1129	No	2.719	0.0171	No
EAGG	0.792	0.2737	No	2.854	0.0110	No
ESGU	0.020	0.6967	No	1.668	0.3446	No
ESGV	-0.001	0.7076	No	1.636	0.3684	No
SUSL	0.405	0.4842	No	1.735	0.2956	No
DSI	0.036	0.6898	No	1.536	0.4477	No
USSG	0.064	0.6759	No	1.486	0.4873	No
SPY	0.237	0.5810	n.a.	1.752	0.2844	n.a.
QQQ	0.537	0.4075	n.a.	0.900	0.9068	n.a.
IWM	2.557	0.0019	n.a.	4.818	0.0001	n.a.
XLE	5.693	0.0001	n.a.	5.715	0.0001	n.a.
GLD	0.280	0.5557	n.a.	2.276	0.0707	n.a.
BND	0.153	0.6309	n.a.	2.842	0.0114	n.a.
LQD	0.869	0.2386	n.a.	3.984	0.0002	n.a.

Note: 10,000 Monte Carlo replications at N = 1,420 (95% CV: SADF 1.555, GSADF 2.396).
Source: author's calculations.

Table A2 Sharpe ratio sensitivity to risk-free rate assumptions, core funds

Asset	rf = 0%	rf = 2%	rf = 5%	Time-varying rf
BGRN	0.291	-0.087	-0.655	-0.166
ICLN	0.213	0.136	0.022	0.156
PBW	0.052	-0.004	-0.089	0.010
ESGU	0.731	0.625	0.465	0.616
SPY	0.801	0.681	0.502	0.712
GLD	0.216	0.083	-0.117	0.117
BND	0.289	-0.100	-0.684	0.000

Note: Full-sample statistics. Time-varying rate uses 3-month Treasury bill (mean 1.49%).
Source: author's calculations.

APPENDIX B

MONTE CARLO DOCUMENTATION

Critical values and empirical p-values are obtained from 10,000 Monte Carlo replications of the driftless random walk null with standard normal innovations, simulated separately at each distinct sample length appearing in Table 1 with minimum window $r0 = 0.01 + 1.8/\sqrt{N}$ and lag order $k = 0$. BSADF critical value sequences are pointwise 95% quantiles of simulated sequences from the same draws. The pseudo-random number generator seed is fixed at 20250101. Across five independent seeds with 1,000 replications each at N = 3,019, 95% critical values range from 1.558 to 1.655 (SADF) and 2.463 to 2.496 (GSADF), with Monte Carlo standard errors of 0.012 and 0.004 at 10,000 replications—well below the margin of every reported rejection.

APPENDIX C

ROBUSTNESS: SPECIFICATION SENSITIVITY, ENERGY-FACTOR PURGING, AND LOWER FREQUENCY

Table C1 evaluates GSADF sensitivity across lag orders $k \in \{0, 1, 4\}$ and minimum windows $r0 \in \{PSY, 0.05, 0.10\}$ for clean energy funds. With $k = 0$, every fund except FAN rejects across all windows. With $k = 1$, all nine funds reject. With $k = 4$, seven funds reject. Table C2 reports tests on energy-factor-purged prices (cumulated residuals from regressions on XLE returns); all nine clean energy funds remain GSADF-significant ($p \leq 0.0094$). Table C3 reports month-end sampling (144 months), where eight of nine funds remain significant at the 5% level. Table C4 reports extended Granger tests (lags 1–8) and bivariate VAR impulse responses.

Table C1 Specification sensitivity of GSADF statistic, clean energy funds

Ticker	PSY,k=0	PSY,k=1	PSY,k=4	0.05,k=0	0.05,k=1	0.05,k=4	0.10,k=0	0.10,k=1	0.10,k=4
ICLN	3.906*	4.278*	3.591*	3.906*	4.278*	3.591*	3.906*	4.278*	3.591*
PBW	3.719*	3.772*	3.151*	3.719*	3.772*	3.151*	3.719*	3.772*	3.151*
QCLN	3.597*	3.700*	3.201*	3.597*	3.700*	3.201*	3.597*	3.700*	3.201*
TAN	3.358*	3.377*	2.812*	3.358*	3.377*	2.812*	3.358*	3.377*	2.812*
FAN	2.321	2.811*	2.095	2.321	2.811*	2.056	2.321*	2.811*	2.056
PBD	3.918*	4.658*	3.521*	3.918*	4.658*	3.521*	3.918*	4.658*	3.521*
CNRG	2.475*	2.508*	2.637	2.597*	2.596*	3.233*	2.353*	2.508*	2.637
SMOG	3.153*	3.317*	2.783*	3.153*	3.317*	2.783*	3.153*	3.317*	2.783*
ACES	3.375*	3.738*	4.141*	3.375*	3.738*	4.141*	2.851*	3.279*	4.141*
CV, N = 3,019	2.495	2.620	2.676	2.438	2.620	2.676	2.198	2.620	2.676
CV, N = 1,556	2.395	2.487	2.772	2.438	2.487	2.772	2.179	2.487	2.772
CV, N = 1,636	2.419	2.451	2.757	2.440	2.451	2.757	2.188	2.451	2.757

Note: * denotes significance at the 5% level against lag-specific simulated critical values.

Source: author's calculations.

Table C2 SADF and GSADF tests on energy-factor-purged log prices, clean energy funds

Ticker	SADF	p (SADF)	GSADF	p (GSADF)	95% CV SADF	95% CV GSADF
ICLN	4.600	0.0001	5.244	0.0001	1.605	2.463
PBW	5.258	0.0001	5.555	0.0001	1.605	2.463
QCLN	3.894	0.0002	4.621	0.0001	1.605	2.463
TAN	1.981	0.0149	4.787	0.0001	1.605	2.463
FAN	1.006	0.2119	2.964	0.0094	1.605	2.463
PBD	4.939	0.0001	5.478	0.0001	1.605	2.463
CNRG	2.462	0.0033	3.062	0.0048	1.570	2.415
SMOG	3.321	0.0002	4.454	0.0001	1.605	2.463
ACES	3.182	0.0001	4.207	0.0002	1.574	2.407

Note: Tests applied to cumulated residuals of daily returns regressed on XLE returns.

Source: author's calculations.

Table C3 SADF and GSADF tests on month-end log prices, clean energy funds

Ticker	SADF	p (SADF)	GSADF	p (GSADF)	95% CV SADF	95% CV GSADF	Months
ICLN	2.046	0.0078	3.190	0.0022	1.329	2.045	144
PBW	2.856	0.0006	3.319	0.0017	1.329	2.045	144
QCLN	2.269	0.0032	3.505	0.0010	1.329	2.045	144
TAN	0.638	0.2137	2.645	0.0094	1.329	2.045	144
FAN	-0.282	0.6465	1.606	0.1416	1.329	2.045	144
PBD	2.298	0.0031	3.369	0.0016	1.329	2.045	144
CNRG	1.862	0.0113	2.133	0.0362	1.279	1.987	75
SMOG	1.486	0.0330	2.774	0.0065	1.329	2.045	144
ACES	2.057	0.0058	2.057	0.0439	1.271	2.003	79

Note: Monthly sampling (last trading day).

Source: author's calculations.

Table C4 Extended lead-lag Granger tests and vector autoregression analysis

Panel A. Granger-type F-test p-values, weekly log returns, lags 1 to 8

Direction	L1	L2	L3	L4	L5	L6	L7	L8
SPY → BGRN	0.755	0.791	0.064	0.081	0.114	0.045	0.061	0.104
BGRN → SPY	0.061	0.169	0.265	0.272	0.389	0.192	0.084	0.124
SPY → ICLN	0.292	0.519	0.141	0.220	0.320	0.353	0.234	0.242
ICLN → SPY	0.120	0.290	0.216	0.029	0.053	0.080	0.103	0.156
SPY → PBW	0.142	0.134	0.194	0.263	0.299	0.374	0.223	0.275
PBW → SPY	0.213	0.313	0.023	0.037	0.098	0.147	0.200	0.281
SPY → ESGU	0.357	0.352	0.578	0.715	0.831	0.890	0.934	0.829
ESGU → SPY	0.691	0.690	0.898	0.926	0.960	0.980	0.991	0.955

Panel B. Orthogonalized impulse responses (%), bivariate weekly VAR (SPY ordered first)

Response	Impact (h=0)	h = 1 (s.e.)	h = 2	h = 4	Cum. h=1–8
Clean energy ← SPY shock	2.786	-0.142 (0.156)	0.014	0.000	-0.129
SPY ← clean energy shock	0 (by construction)	0.111 (0.089)	-0.010	0.000	0.103

Note: VAR(1) in weekly returns of clean energy portfolio and SPY (626 weeks).

Source: author's calculations.

Dr. sc. Ahmad Al-Harbi

Docent
Alasala Colleges, Dammam, Saudijska Arabija
Fakultet poslovne administracije
E-mail: ahmad.alharbi@alasala.edu.sa
Orcid: https://orcid.org/0000-0003-1593-7835

ZELENI SNOVI ILI ŠPEKULATIVNE SHEME? EMPIRIJSKI DOKAZI O BALONIMA IMOVINE U ETF-OVIMA ČISTE ENERGIJE (2013.–2024.)

Sažetak

Rast ulaganja temeljenih na okolišnim, društvenim i upravljačkim kriterijima (ESG) potaknuo je raspravu o mogućem špekulativnom balonu u zelenim financijama. Rad istražuje eksplozivno ponašanje cijena dvadeset zelenih i ESG ETF-ova te sedam konvencionalnih referentnih fondova na dnevnim podacima od siječnja 2013. do prosinca 2024. Primjenjuju se SADF i GSADF testovi, postupak BSADF te Benjamini–Hochbergova i Bonferronijeva korekcija. Rezultati otkrivaju izražene razlike među segmentima zelenih financija. Osam od devet ETF-ova čiste energije pokazuje statistički značajnu eksplozivnost, sedam i nakon korekcije, uz zajedničku epizodu od rujna 2020. do svibnja 2021. Široki ESG dionički fondovi ne pokazuju usporedivu dinamiku, dok signali zelenih obveznica uglavnom odražavaju kretanja konvencionalnog obvezničkog tržišta. Analiza diskontnih stopa te usporedba s QQQ i XLE oslabljuju isključivo fundamentalno tumačenje. Unatoč metodološkim ograničenjima, nalazi upućuju na različitu izloženost špekulativnoj dinamici unutar zelenih financija, što je važno ulagateljima, sponzorima fondova i regulatorima.

Ključne riječi: zelene financije, baloni imovine, SADF i GSADF testovi, ETF-ovi čiste energije, ESG ulaganja, eksplozivno ponašanje.

JEL klasifikacija: G12, G14, Q42, Q56.