Do investors in clean energy ETFs herd?

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This study offers novel and valuable insights into herding behaviour in US clean energy ETFs between 2016 and 2023. The baseline herding tests by Christie and Huang (1995) and Chang et al. (2000) revealed significant herding behaviour in this market. This evidence was supported by asymmetric and time-varying herding tests. That is, investors herd both in bear and bullish markets, and periodically. In addition, we found that climate risks (both physical and transition) reduced the probability of herding in US clean energy ETFs, indicating that an increase in climate-related risk encouraged efficient or climate-hedging behaviour by investors. Therefore, the results suggest that climate-related uncertainty did not drive herding behaviour in this market. The results suggest that investors are appropriately identifying opportunities that mitigate climate risk, thereby reducing the probability of herding-driven system risk.

Keywords: Herding Behaviour, Climate Change, Energy
JEL Codes: G14, Q54, P18

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1 Introduction and literature review

Climate sustainability is a major concern for financial markets and investors. The growing interest in climate sustainability is primarily driven by the increasing materialisation of climate risks, and the actions of governments, institutions and organizations towards a sustainable future (Giglio et al., 2021). To ensure returns, investors increasingly seek to hedge against climate risks by investing in green financial products. Although the evidence is mixed, indications that returns from green financial products are comparable to traditional financial (see amongst others, D'Ecclesia et al., 2024; Nguyen et al., 2025; Pástor et al., 2022; and Naqvi et al., 2022).

In this new climate sustainability paradigm, investors face many pressures that not only bear on returns but also the stability of financial markets. For example, resulting regulations aimed at reducing emissions can surprisingly reduce the profitability of fossil-fuel-based companies, or the possible mispricing of assets from ignoring climate risks can lead to significant losses (Nguyen et al., 2025). In addition to these climate risks, a general change in investor attitudes can drive the inclusion of green assets in their portfolio can lead to systemic risk.[1]

Specifically, climate change presents risks to investor portfolios through two primary sources - physical and transition risks. Physical risks or direct impact refer to extreme climate events such as floods and droughts, which impact business operations and infrastructure; and transition risks are the policy, technological, and other costs that societies bear to achieve low carbon economies (Nguyen et al., 2025; and Giglio et al., 2021, amongst others). Investors, therefore, recognise these risks and seek to mitigate them, as they seek return-enhancing green financial products.

Exchange-traded funds (ETFs) are a key feature of green financial products. ETFs are a type of security that involves a collection of securities that often tracks an underlying index. However, they can invest in various industry sectors or strategies. In addition, environment, social, and governance (ESG) ETFs serve as a market discovery tool for investors to identify and invest in environmentally friendly companies (Brière and Ramelli, 2023). Among the ESG

[1]These pressures notwithstanding the possible contribution that financial markets can play in mitigating and reducing the negative effects of climate change (Giglio et al., 2021)

ETFs, the Clean Energy (CE) ETFs have been the best-performing ones in 2022, followed by the Cybersecurity and Artificial Intelligence (AI) ETFs (D'Ecclesia et al., 2024). The clean energy transition represents one of the largest multi-decade secular growth opportunities. After the inclusion of Green energy financing in the list of United Nations Sustainability Goals (SDGs) as SDG 7, the role, importance, and visibility of green financial products have escalated enormously (Naqvi et al., 2022). That is, the growth of green assets under management is likely to continue. Lastly, the limited availability of data on ESG complying investment tools (Avramov et al., 2022; Nguyen et al., 2025) justifies the use of green (CE) ETFs as best candidates of green assets.

However, given how recent the inclusion of climate sustainability in investment decisions is, it is not clear what the actual impact will be in the long run. In this study specifically, we ask whether the rapid adoption of CE ETFs could be driven by market fads, or is a fundamental change in investor behaviour. Investors, for example, can believe that peers have information about climate risks that they do not, investors may herd to avoid losses compared to peers, or investors may be encouraged to herd by the desire to align to climate-related social values (Ciciretti et al., 2021; Gavrilakis and Floros, 2023; Loang, 2023). Therefore, market volatility and crisis, financial performance, and investor sentiment can drive herding in ESG markets.

It is well established that herding literature is vast with contradictory results depending mainly on the market, the employed methodology and the period under consideration (Spyrou, 2013). Herding behavior can be either spurious in cases when investors make similar decisions as a result of processing the same information set and intentional herding when investors imitate the actions of others (see inter alia, Bikhchandani and Sharma, 2000; Galariotis et al., 2015). Empirical studies on herding usually fall into two categories: namely those that employ holdings data aiming at measuring institutional investor herding (Lakonishok et al., 1992), and studies that use market returns data and investigate herding towards the market consensus (Chang et al., 2000; Galariotis et al., 2015). Our paper falls within the latter category and tests for herding towards the market consensus for clean energy US ETFs.

Herding behaviour in ESG markets is not without precedent. Amongst others, Loang (2023) found that compliance with SDG goals can introduce bias in investor sentiment, which leads to herding behaviour. Using a Twitter (or X) uncertainty index, Koutmos (2024) found evidence of herding in US-based ESG index fund investors. Przychodzen et al. (2016) found herding behaviour amongst fund managers who incorporated ESG strategies in their portfolios. Lastly, Rubbaniy et al. (2021) highlight evidence of herding in the MSCI US ESG Leader Index during extreme periods (bear and bull periods).

However, to the best of our knowledge, no studies exist that focus on herding behaviour in CE ESGs. This study, therefore, aims to extend the broader literature on herding behaviour in commodity and energy markets. Several studies in this area were conducted. For example, **?** conducted a commodity sectoral study and found herding behaviour in grains but not in other sectors. Similarly, Gilbert (2010) showed herding behaviour amongst speculators in non-ferrous commodities. Others did not find evidence of herding in similar markets. Babalos et al. (2015) found significant anti-herding behaviour in metal commodities futures after the global financial crisis. Pierdzioch et al. (2010) showed that forecasters in oil and metals markets deviated from the crowd, indicating a rational response to market information. Steen and Gjolberg (2013) also found no herding behaviour in international commodity markets. Overall, the literature in this area is mixed, which indicates scope for further study.

In addition, our study extends the results of Dragomirescu-Gaina et al. (2021) who examined herding behavior of investors in the US energy sector and herding sensitivity to various proxies of policy uncertainty and financial risk. They employed the energy equities included in the S&P 500 and concluded that herding among investors in the US energy market sector is sensitive to green volatility shocks

Therefore, this study investigates herding behaviour in alternative energy ETFs in the US between 2016 and 2024. We then demonstrate how climate-related uncertainty can drive herding behaviour in these markets. Methodologically, we follow the standard herding tests by Christie and Huang (1995) and Chang et al. (2000). The traditional approach was supplemented by quantile regressions (Koenker and Bassett, 1978) in order to capture the time-varying aspects of herding. Lastly, we extend recent approaches by Bua et al. (2024) and others, which seek to establish a link between climate uncertainty and herding behaviour.

The next section describes the data and methodology, followed by the results and conclusions.

2 Data and methodology

2.1 Data

The sample consists of alternative energy equity ETFs (green ETFs) that are traded in the US markets (see Table A1 in the Appendix).[2] The number of available alternative energy ETFs in our sample varied from 10 in the beginning of analysis to 30 at the most. The period of analysis runs from May 1st of 2016 through 19th June of 2024. The starting date was selected on the basis of the UN Climate Change Conference (COP) Paris agreement. Daily logarithmic returns were computed from the closing prices of ETFs for a total of 2122 observations.

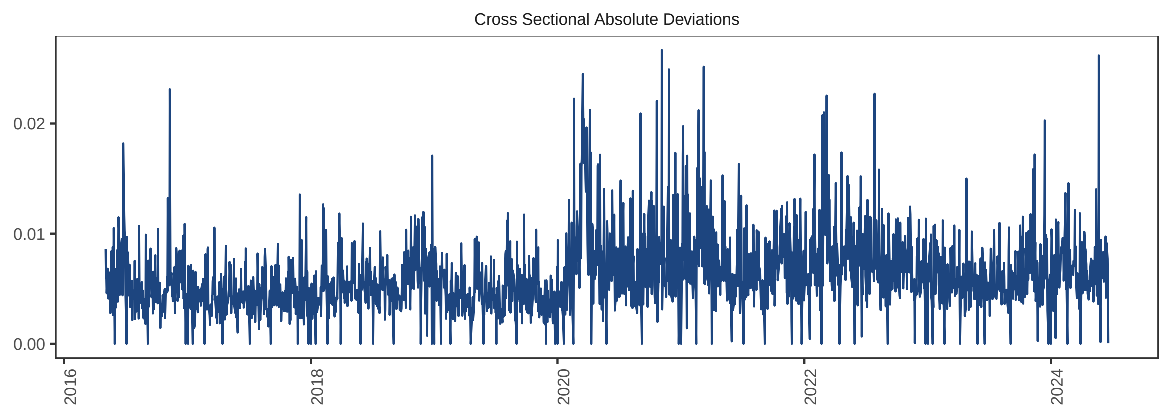

Figure 1: Cross Sectional Absolute Deviation (CSAD) for US Alternative Energy ETFs

The development of the CSAD measure over time for the clean energy ETFs is presented in Figure 1. In general, the CSAD measure remains within certain bounds. However, we observe several cases when the CSAD measure deviates significantly from the market consensus: around the announcement of the Paris agreement (2016-2017), the covid-19 pandemic crisis (2020–2021), the war outbreak in Ukraine (2022) among others. Table 1 presents the descriptive statistics of the data.

[2]The data were sourced from https://datastream.org/en-ca/

Table 1: Descriptive statistics of the data

	Mean	St.dev	Skewness	Kurtosis
CSAD	0.0062	0.0034	1.5598	7.9355
Absolute CSAD	0.0094	0.0107	3.3175	23.8725

2.2 Methodology

Following the relevant literature (Christie and Huang, 1995; and Chang et al., 2000), we compute dispersion of the i^{th} ETF from the market return. This is known as the Cross Sectional Absolute Deviation ($CSAD_t$) measure. Empirically the $CSAD_t$ is defined in the following manner:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}|, \tag{1}$$

where $R_{i,t}$ is the return and $R_{m,t}$ is the cross sectional average of returns for the sample of ETFs available for each day. The return dispersion measures the directional similarity of ETF returns to the market return. This return similarity forms the basis for the herding behaviour tests. Following Galariotis et al. (2015) we estimate Equation 2:

$$CSAD_t = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 R^2_{m,t} + \epsilon_t, \tag{2}$$

where γ_0 is the intercept, γ_1 is the coefficient of the linear term, γ_2 is the coefficient of the quadratic term or the herding behaviour term, and ϵ_t is the error term. The coefficient $\gamma_2 < 0$ when herding is present, and $\gamma_2 > 0$ when anti-herding is present. To ensure the robustness of the estimate, we estimate $CSAD_t$ with Newey-West standard errors (See Newey and West, 1987).

Based on the above and in order to provide additional insight on the herding phenomenon we examine whether herding presents an asymmetric response on days when the market is up vis-à-vis days when the market is down. To this end, we augment Equation 2 as follows:

$$CSAD_t = \gamma_0 + \gamma_1(1-D)R_{m,t} + \gamma_2 DR_{m,t} + \gamma_3(1-D)R^2_{m,t} + \gamma_4 DR^2_{m,t} + \epsilon_t, \tag{3}$$

where D is a dummy variable that takes the value of 1 when the market return is negative and 0 otherwise. Therefore, our exploration of asymmetric behaviour of herding phenomenon is carried through the inspection of the statistical significance and the sign of the two estimated coefficients γ_3 versus γ_4 (up versus down markets).

3 Results

3.1 Herding behaviour

Rational asset pricing models (for example, Black, 1972) predict a linear relationship between return dispersion and market returns under normal conditions, a relationship that is no longer valid in the presence of herding. Herding behaviour leads to an increasing or decreasing cross sectional dispersion with respect to market returns. In other words, herding is captured by a non-linear term in the standard pricing equation indicating a decreasing or an increasing returns' dispersion.

Stated differently, as Chang et al. (2000) argue, in the case of herding the coefficient on the non-linear term (γ_2) will be negative and statistically significant. Table 2 presents the results of herding for the full sample employing the non-linear Equation 2. The estimated coefficient on market return is positive and highly significant as expected. The estimated coefficient on the non-linear term is negative (-1.2773) and statistically significant with a t-statistic of -9.71 suggesting that herd behaviour is present and robust in the US alternative energy ETFs.

Table 2: Estimation results of herding in the U.S. equity alternative energy ETFs

γ_0	γ_1	γ_2
0.0038**	0.2883***	-1.2773***
(47.09)	(33.333)	(-9.71)

Note: *,**,*** denotes significance at 10%,5% and 1% respectively.

There is ample evidence in the relevant literature that herding behaviour in various asset markets (see Pochea et al., 2017) exhibits asymmetry and time-varying characteristics. To this end, we proceed to estimate Equation 2 using the quantile regression (QR) proposed by

Koenker and Bassett (1978). Table 3 presents the results of estimating Equation 2 across various quantiles of the returns dispersion. Our focus is on the herding coefficient γ_2, as a significant negative value of γ_2 is indicative of herding. Such a finding is observed at two quantiles namely 25% and 50% with a value of -1.1056 and -1.165 which are highly significant. It is worth mentioning that the sign of the herding coefficient remains negative for almost all quantiles while the significance changes from significant to insignificant while we move from low and middle to upper quantiles (75% and 90%).

Table 3: Estimation results of herding across various quantiles

Quantile	γ_0	γ_1	γ_2
$\tau = 10\%$	0.0016***	0.2536***	-1.3736
$\tau = 25\%$	0.0026***	0.2461***	-1.1056***
$\tau = 50\%$	0.0037***	0.2648***	-1.165***
$\tau = 75\%$	0.0048***	0.3011***	-1.1473***
$\tau = 90\%$	0.0064***	0.2999***	0.2314

Note: This table presents the estimation results of herding of US Alternative energy equity ETFs according to Equation 2 in various quantiles 10, 25, 50, 75 and 90% of the returns distribution. *,**,*** denotes significance at 10%,5% and 1% respectively.

3.2 Herding behaviour during extreme market periods

It is widely accepted that asset returns are characterized by asymmetry, that is, return dispersion tend to behave differently in rising and falling markets (see Geert and Guojun, 2000; Zhou and Anderson, 2013; Longin and Solnik, 2001). It should be noted, that examining the relationship between returns dispersion and market-wide returns across various quantiles of the returns distribution allows us to make more robust inference regarding the true behaviour of the phenomenon. Table 4 reports the estimation results of herding in the up and down markets based on Equation 3. In general, we find that herding is more likely to occur in down markets than in up markets, which is indicative of the asymmetry of herding behaviour.

Table 4: Estimation results of herding in up and down markets

Quantile	γ_0	γ_1	γ_2	γ_3	γ_4
$\tau = 10\%$	0.0016***	0.2532***	-1.3669***	-0.2522***	-1.1522
$\tau = 25\%$	0.0026***	0.2475***	-1.2383**	-0.2477***	-1.1171***
$\tau = 50\%$	0.0038***	0.2247***	0.3838	-0.2634***	-1.3144***
$\tau = 75\%$	0.0050***	0.2500***	1.3135	-0.2785***	-0.9721***
$\tau = 90\%$	0.0065***	0.2788***	1.0169	-0.2942***	-1.2003***

Note: This table presents the estimation results of herding of US Alternative energy equity ETFs according to Equation (3). *,**,***denotes significance at 10%,5% and 1% respectively.

Herding is present at all quantiles when markets are rising with an estimated coefficient γ_3 of -1.3669 and -1.2383 and highly significant respectively. However, when markets are declining, investors seem to neglect their own information set and imitate the actions of others resulting in a highly significant coefficient of herding (γ_4) across four out of five quantiles. Furthermore, we find that in high quantiles (75% and 90%) and when markets are rising the coefficient of interest (γ_3) turns positive but insignificant.

3.3 Time-varying herding behaviour

There is ample evidence that herding might vary in response to market conditions (see Babalos et al., 2015; Klein, 2013; Stavroyiannis and Babalos, 2019). In order to gain further insight on the time varying nature of herding we conducted a rolling window analysis. The size of the rolling window is related to the time-scales of the system (response times), and the aim of the research (Babalos et al., 2015). There is no golden rule for the right size of the rolling window, there is a trade-off between having a long enough window to estimate the metrics, and short enough to have a sufficient number of windows in order to be able to derive a trend. In light of the above discussion we set off to conduct a rolling window analysis of 50 observations. Figure 2 plots the time evolution of the value of the estimated significance of the herding coefficient (γ_2) using the rolling window analysis.

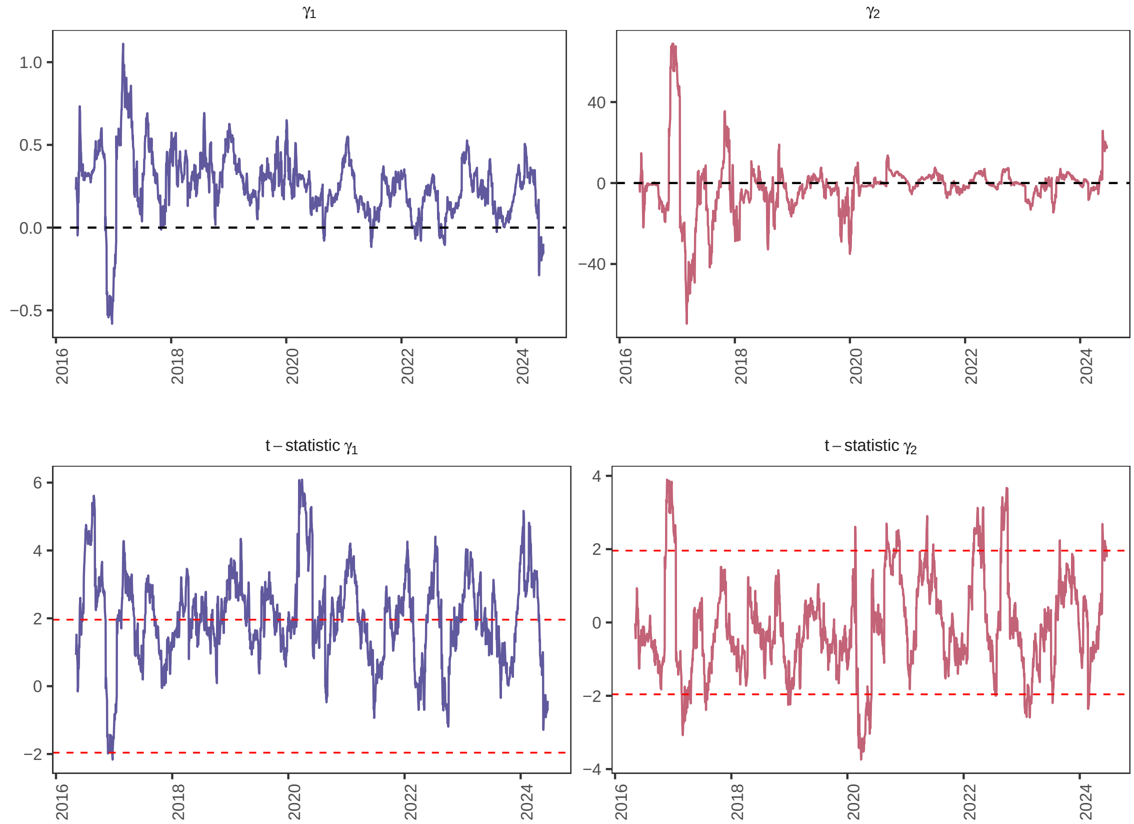

Figure 2: Rolling window herding estimates. Note: The red perforated lines indicates the 95% confidence interval.

We observe several periods of herding behaviour as reflected in the troughs in Figure 2. The most prominent cases of herding occur between March and May of 2020 followed by several instances of herding in the period that extends from March through April of 2017 and the period of February-March of 2023. On the other side, we derive significant moments of anti-herding behaviour in the clean energy ETFs by observing the spikes in Figure 2. Cross sectional dispersion appears to increase with respect to market-wide returns which is a sign of anti-herding behaviour on behalf of investors around December of 2016 and later during September of 2022.

3.4 Climate-related uncertainty and herding behaviour

The behaviour of participants in energy markets is closely related to the developments in the field of climate risks, carbon emissions and environmentally friendly policies. In particular, following the implementation of the Paris agreement in November 2016, climate policy uncertainty has become in the epicenter of interest across carbon and energy markets. There are a few studies that attempt to quantify the effects of uncertainty related to climate on the economy and financial markets (see inter alia, Gabriel and Pinho, 2024; Bolton and Kacperczyk, 2021; Krueger et al., 2020). To this end, Bua et al. (2024) developed two climate risk related indexes namely transition and physical risk using a text-based approach in order to study the effect of these risks in financial markets. It is expected that investors would prefer to hold assets that perform well in the face of increasing climate change risks, even if this entails accepting lower returns for such climate-hedging assets. Therefore, in the context of our study and following previous studies that study the determinants of herding behaviour (see Bouri et al., 2019; Demirer et al., 2018), we attempt to study the effect of climate-related uncertainty on the formation of herding behavior in the clean energy market.

We use a probit model to relate herding to the two climate risk indexes developed by Bua et al. (2024) in the following manner:

$$Pr(D^{herd} = 1 | \lambda_0 + \lambda_1 TRI + \lambda_2 PRI) = \lambda_0 + \lambda_1 TRI + \lambda_2 PRI, \tag{4}$$

where D^{herd} takes a value of 1 during periods of statistically significant herding (i.e., for days when the rolling t-statistic on $\gamma_2 < -1.96$ in Figure 2) and zero otherwise. TRI is the transitional risk index and PRI is the physical risk index.

The results from the Probit model are reported in Table 5, where only the physical risk index significantly decreases the probability of herding.[3] In other words, climate risks is good news for clean energy stocks or firms resulting in anti-herding behaviour. This implies that in the presence of higher physical risk with respect to the climate, clean energy ETFs become a more attractive investment option for investors that allocate their money to the various alternative

[3]It should be noted that due to availability issues the probit analysis ends in December of 2023.

energy investment products. As a result, the cross-sectional dispersion of clean energy ETFs tends to increase. Our results are in line with those of rrelevant studies such as Gabriel & Pinho (2024) who claimed that in the event of climate policy shocks, clean energy assets could serve the role of hedging instruments.

Table 5: Estimation results of the probit model

Variable	Coefficient
λ_0	-1.506***
λ_1	-4.607***
λ_2	-1.318
Log Likelihood	-484.7
Observations with Dependent Variable (Dep) = 0	1816
Observations with Dependent Variable (Dep) = 1	134

Notes: **,*** denotes statistically significant at 5% and 1%

Furthermore, we develop two additional models to study the effect of climate risks on herding behaviour. We split the sample into two groups based on the median value of the TRI and PRI. We then estimate the following two models:

$$Pr(D^{herd} = 1|\lambda_0 + \lambda_1 D^{TRI}_{high} TRI + \lambda_2 D^{PRI}_{high} PRI) = \lambda_0 + \lambda_1 D^{TRI}_{high} TRI + \lambda_2 D^{PRI}_{high} PRI, and \quad (5)$$

$$Pr(D^{herd} = 1|\lambda_0 + \lambda_1 D^{TRI}_{low} TRI + \lambda_2 D^{PRI}_{low} PRI) = \lambda_0 + \lambda_1 D^{TRI}_{low} TRI + \lambda_2 D^{PRI}_{low} PRI, \quad (6)$$

where D^{herd} is the same as in Equation 4. D^{TRI}_{high} and D^{PRI}_{high} are dummy variables that take a value of 1 if the value of the TRI and PRI are above the median and zero otherwise. Similarly, D^{TRI}_{low} and D^{PRI}_{low} are dummy variables that take a value of 1 if the value of the TRI and PRI are below the median and zero otherwise.

Table 6: Estimation results of the probit model with high and low climate risk indexes (above or below median)

	High	Low
λ_1	-6.736*	-6.118
λ_2	-1.798	-2.581

Notes: *, denotes statistically significant at 10%

We use these high PRI and high TRI in one probit regression and low TRI and low PRI in another. Results are presented in Table 6. We observe higher uncertainty that stems from physical or transition risk causes anti-herding which is in line with the logic we discussed earlier.

4 Conclusion

This study offers novel and valuable insights into herding behaviour in clean energy ETFs. We used various herding behaviour tests to achieve this. First, the baseline herding tests revealed significant evidence of herding behaviour. Second, the asymmetric herding tests showed that herding behaviour was present in both bear and bull markets. Lastly, the results of the time-varying tests point to significant periodic herding. However, the results further indicate that herding in US clean energy ETFs was not mainly related to climate-related risks or uncertainty. The probit analysis showed that climate-related uncertainty reduced the probability of herding or led to investor anti-herding behaviour. We differ to the literature on the factors that drive herding in these ETFs (for example, Loang, 2023; Koutmos, 2024; Przychodzen et al., 2016). Our results, similar to Bua et al. (2024), indicate that investors did not herd on climate-related uncertainty, and sought returns whilst hedging against climate-related risk. This is a positive for the financial stability of these growing alternative investment indices.

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A Appendix

A.1 ETFs used in the study

Table A1: List of green ETFs used in the study

ETF
ALPS CLEAN ENERGY ETF
BLUE HORIZON BNE ETF
SPDR S&P KENSHO CLEAN POWER ETF
GLOBAL X CLEANTECH ETF
PROSHARES S&P KENSHO CLEANTECH ETF
INVESCO MSCI SUSTAINABLE FUTURE ETF
FIRST TRUST GLOBAL WIND ENERGY ETF
FIDELITY CLEAN ENERGY ETF
GLDS.BLOOMBERG CN. EN. EQ.ETF
FST.NQ.CN.EDGE SMRT.GRID INFRA IDX ETF
DEFIANCE NEXT GEN H2 ETF
DIREXION HYDROGEN ETF
GLOBAL X HYDROGEN ETF
ISHARES GLOBAL CLEAN EN. ETF
BLACKR.WLD.EXUS CRBN TSTN.READINESS
NUB.CBN.TSTN.& INFRA
TCW TRANSFORM SYSTEMS ETF
VANECK URANIUM AND NUCLEAR ENERGY
NUVEEN GLOBAL NET ZERO TRANSITION ETF
SPDR MSCI USA CIM. PA. ALIGNED ETF
INVESCO GLOBAL CLEAN ENERGY ETF
FST.NQ.CN.EDGE GREY.ETF
GLOBAL X SOLAR ETF
GLOBAL X RENEWABLE ENERGY PRODUCERS
TRUESHARES EAG.GLB. RENWEN.ETF
VANECK LOW CARBON ENERGY ETF
SMARTETFS SUST.EN. II ETF
INVESCO SOLAR ETF
VIRTUS DUFF & PHELPS CLEAN ENERGY ETF
GLOBAL X WIND ENERGY ETF

Note: Details on these funds can be found on Yahoo Finance.