Do investors in clean energy ETFs herd?

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1 Introduction

Climate sustainability has become a major concern for financial markets and investors. This growing interest is primary driven by the increasing materialisation of climate risks, and the actions of governments, institutions and organizations towards a sustainable future (Giglio et al., 2021). In order to ensure returns investors increasingly seek to herd 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 other, D'Ecclesia et al., 2024; Nguyen et al., 2025; Pástor et al., 2022; and Naqvi et al., 2022). Therefore, the growth of green assets-under-management is likely to continue.

A key feature of the green financial products is the exchange traded funds (ETFs). ETFs are a type of security that involves a collection of securities—such as stocks—that often tracks an underlying index, although they can invest in any number of industry sectors or use various strategies. In addition, environment, social, and governance (ESG) ETFs serve as a market discovery tool for investors to identify and invest in companies that are environmentally friendly (Brière and Ramelli, 2023). Thus, ESG ETFs exhibit environment friendly characteristics.

Among the ESG 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; all have escalated enormously (Naqvi et al., 2022).

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).[1] The number of available alternative energy ETFs

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

in our sample varied from 10 in the beginning of analysis to 30 at the most. The period of analysis runs from May 1^{st} of 2016 through 19^{th} 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.

2.2 Methodology

Following the relevant literature (Christie and Huang, 1995; and Chang et al., 2000), we compute dispersion of the *ith* 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. The CSAD measure for US Alternative Energy ETFs is presented in Figure A1. Following Galariotis et al. (2015) we estimate Equation 2:

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

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:

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

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 1 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 1: 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) and Table 2 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 2: 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 3 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 3: 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 low 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 Herding behaviour over-time

There is ample evidence that herding might be time dependent (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 1 plots the time evolution of the value of the estimated significance of the herding coefficient (γ_2) using the rolling window analysis.

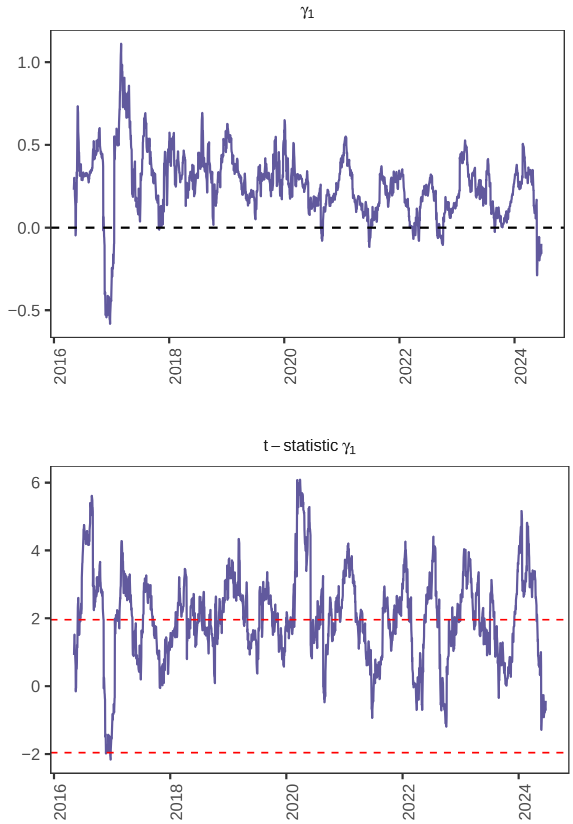

Figure 1: Rolling window herding estimates. Note: The red perforated lines indicates the 95% confidence interval.

We observe several periods of herding behaviour as reflected in the troughs in Figure 1. 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 1. 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. 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....). 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 1) 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 4, where only the physical risk index significantly decreases the probability of herding.[2] 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 energy investment products. As a result, the cross sectional dispersion of clean energy ETFs tends to increase.

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

Table 4: 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:

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

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

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 5: 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 Table 5. 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 on herding behavior in clean energy ETFs.

Results of baseline and rolling window analysis points to significant herding for the whole period and in various instances.

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A Appendix

A.1 Cross-sectional average deviations

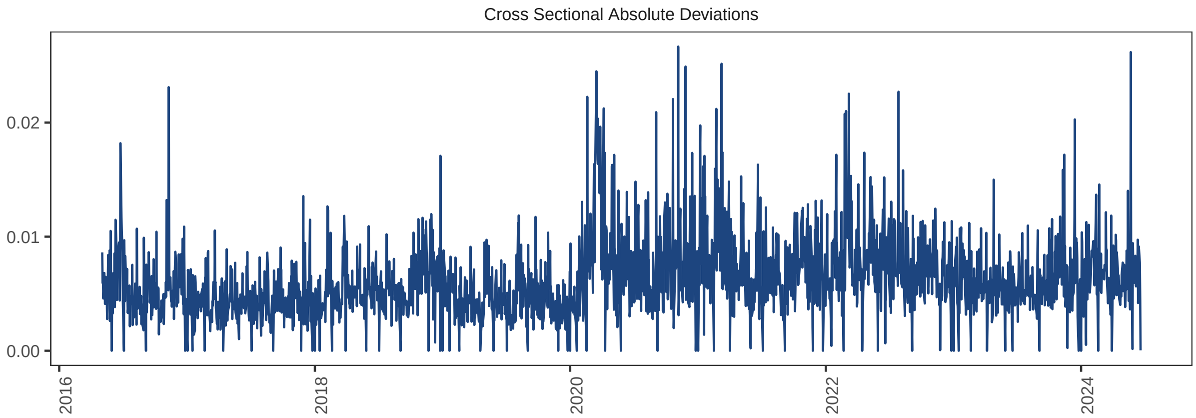

Figure A1: Cross Sectional Absolute Deviation (CSAD) for US Alternative Energy ETFs

A.2 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

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 this funds can be found on Yahoo Finance.