Do investors in clean energy ETFs herd?

Vassilios Babalos[*] Xolani Sibande[†] Riza Demirer[‡] Rangan Gupta[§]

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[*]Department of Accounting and Finance, University of Peloponnese, Kalamata, Greece; Email: v.babalos@uop.gr.

[†]Corresponding Author. Department of Economics, University of Pretoria, Pretoria, South Africa; Email: xolaniss@gmail.com. Economic Research Department, South African Reserve Bank, Pretoria, South Africa.

[‡]Department of Economics and Finance, Southern Illinois University Edwardsville, Edwardsville, IL 62026-1102, USA; Email: rdemire@siue.edu

[§]Department of Economics, University of Pretoria, Pretoria, South Africa; Email: rangan.gupta@up.ac.za.

1 Introduction

Argument: Investment interest on green ETFs has been explosive mainly by climate risks faced by the global economy and the actions of policy makers, goverments and organizations towards a sustainable future.

Derived from D'Ecclesia et al. (2024): 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. The clean energy transition represents one of the largest multi-decade secular growth opportunities.

From Naqvi et al. (2022): 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 enormousl

2 Literature review

3 Data and methodology

3.1 Data

The sample consists of alternative energy equity ETFs (green ETFs) that are traded in the US markets. 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 COP Paris agreement. Daily logarithmic returns were computed from the closing prices of ETFs for a total of 2122 observations.

Table 1: List of used alternative energy equity ETFs

ETF	Source
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	

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

3.2 Methodology

Following the relevant literature we calculate the Cross Sectional Absolute Deviation (CSAD) measure for each day in the following manner. We compute the difference of the ith ETF and market return where market return is proxied by the cross sectional average of returns for sample of our ETFs available for each day using equation (1):

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

The behavior of the CSAD measure for US Alternative Energy ETFs is presented in Figue 1.

At a later stage we estimate a non-linear regression as in Galariotis et al. (2015).

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

The testing procedure of herding relies on the above Equation (2). Rational asset pricing models 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 behavior 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.

4 Results

4.1 General herding behaviour

Stated differently, as Chang et al. (2000) argue, in the case of herding the coefficient on the non-linear term (2) will be negative and statistically significant. Table 2 presens 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 behavior 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)

There is ample evidence in the relevant literature that herding behavior 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 3 presents the results of estimating Equation (2) across various quantiles of the returns dispersion. Our focus is on the herding coefficient 2, as a significant negative value of 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 insifnificant 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

4.2 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). 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 Eq. 2 as follows:

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

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 behavior of herding phenomenon is carried through the inspection of the statistical significance and the sign of the two estimated coefficients 3 vs 4 (up vs down markets). 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 behavior of the phenomenon.

Table 4 reports the estimation results of herding in the up and down markets based on Eq. 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 behavior.

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***

Herding is present at low quantiles when markets are rising with an estimated coefficient 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 (4) across four out of five quantiles. Furthermore, we find that in high quantiles (75% & 90%) and when markets are rising the coefficient of interest (3) turns positive but insignificant.

4.3 Rolling window analysis

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 timescales 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 (2) using the rolling window analysis.

We observe several periods of herding behavior 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 behavior 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 behavior on behalf of investors around December of 2016 and later during September of 2022.

4.4 Probit analysis

The behavior of participants in energy markets is closely related to the developments in the field of climate risks, carbon emmissions and environmentally friendly policies. There are a few studies that attempt to quantify the effects of unceretainty 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 behavior (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. Given this, we define a dummy variable, which takes a value of 1 during periods of statistically significant herding (i.e., for days when the rolling t-statistic on $2 < -1.96$) and zero otherwise, and then, we use a Probit model to relate this dummy to the two climate risk indexes developed by Bua et al. (2024). It should be noted that due to availability issues the probit analysis ends in December of 2023. The results from the Probit model are reported in Table 2, where only the physical risk index significantly decreases the probability of herding. In other words, climate risks is good news for clean energy stocks or firms resulting in anti herding behavior.

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.

Table 5: Estimation results of the probit model

Variable	Coefficient
Transition Risk	-4.607***
Physical Risk	-1.318
Constant	-1.506***
LogL	-484.7
Observations with Dependent Variable (Dep) = 0	1816
Observations with Dependent Variable (Dep) = 1	134

Furthermore, suppose we get the median values of these two series. then we define values above median as high and below median as low.

We define a dummy =1 if values>median and 0 otherwise and in this way we will have PRI values that are bigger than median and 0 otherwise. We also define a dummy which is lower than median, i.e., 1 and 0 otherwise, then we use these high PRI and high TRI in one probit regression and low TRI and low PRI in another. Results are presented in the following table.

We observe higher uncertainty that stems from physical or transition risk causes antiherding which is in line with the logic we discussed earlier.

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

	High	Low
Physical Risk	-6.736*	-6.118
Transition Risk	-1.798	-2.581

5 Conclusion

This study offers novel and valuable insights on herding behavior in clean energy ETFs.

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