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Feedback trading in socially responsible ETFs: Does geopolitical risk matter?

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Abstract: Socially responsible ETFs have grown in popularity as investors seek socially conscious investments. This study examines feedback trading in U.S.-listed socially responsible ETFs from 2019 to 2023 using asymmetrical GARCH models. The results indicate that investors exhibit positive feedback (momentum) trading, and this behavior intensifies when geopolitical risk (GPR) decreases. This study is the first to link feedback trading in socially responsible ETFs to GPR, highlighting how behavioral factors and risk perceptions influence market dynamics. The findings have important implications for ETF investors and regulators, offering insights into investment behavior and the interaction between risk and trading patterns.

Keywords: exchange traded funds; geopolitical risk; feedback trading; socially responsible investment

1. Introduction

In recent years, Exchange-Traded Funds (ETFs) have gained popularity among both retail and institutional investors due to the wide range of benefits they offer. By definition, an ETF is a pooled investment fund that seeks to replicate the return profile of a specific benchmark or index (Converse et al., 2023). Given that ETFs trade on securities exchanges, their advantages include high liquidity, low expenses, trading flexibility, and diversification capabilities relative to their closest rival, mutual funds, which do not trade on exchanges (Liebi, 2020). The first U.S.-Listed ETF was launched in 1993, and although initial growth was sluggish, assets under management (AUM) grew at an average annual rate of 132% between 1995 and 2001 (Deville, 2008). By the end of 2023, the U.S. ETF market had accumulated more than $8 trillion in AUM (ETFGI, 2024). This growth may be attributed to the demand for low-cost, passive instruments and represents the indispensable role of these funds (Joshi & Dash, 2024).

Financial market participants have also exhibited a trend toward socially responsible investments as investors become more socially and environmentally conscious (Hornuf & Yüksel, 2024). A recent report by Bloomberg Intelligence projects that global assets under management in the ESG sector will grow from $30 trillion in 2022 to $40 trillion by 2030, despite regulatory and economic uncertainties (Diab & Mahtani, 2024). This trend has increased demand for social funds, including socially responsible ETFs. According to Rodríguez and Romero (2019), socially responsible ETFs track benchmarks whose underlying constituents consider both financial returns and social well-being. These ETFs could follow three styles: impact investing, which constitutes assets with positive social and environmental benefits; ESG investing, which considers ratings in asset allocation; and socially responsible investing, which avoids assets with negative social and environmental impacts based on ethical guidelines (Kanuri, 2020). Existing research suggests that socially responsible funds outperform conventional funds (Lee et al., 2021; Dumitrescu et al., 2023; ElBannan, 2024) and exhibit lower investment risk (Saci et al., 2022). However, trading in

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socially responsible investments may be influenced by investors' behavior and preferences (Blomqvist & Stradi, 2024), with feedback trading being among the most common strategies used by investors in both developed and emerging markets (Mukherjee & Chatterjee, 2024).

By definition, feedback trading is a trading strategy that is based on the belief that price trends will either continue or reverse (Charteris & Rupande, 2017). In particular, positive feedback trading, also referred to as momentum trading, is used by investors who believe that price trends will continue and, therefore, buy (sell) when prices are rising (declining) (Charteris & Musadziruma, 2017). Negative feedback trading, also known as contrarian investing, occurs when investors expect price trends to reverse and therefore buy (sell) when prices decline (rise). Therefore, feedback trading, an investment strategy that relies on past prices, contradicts the weak form of the Efficient Market Hypothesis (EMH), which asserts that profits cannot be made from historical prices (Charteris & Musadziruma, 2017). Notably, existing research suggests that feedback trading is used by different investor groups (retail and institutional), under different market conditions (rising and falling), and for various asset classes (including stocks, bonds, derivatives, property, cryptocurrencies, and exchange-traded funds) (Koutmos, 2014; Karaa et al., 2021). The existence of feedback trading in these markets induces serial correlation in returns and exacerbates volatility (Economou et al., 2023). As a result, the predictability of returns is enhanced, driving prices further from fundamental values and subsequently leading to market inefficiencies (Karaa et al., 2021). In the case of ETFs, such fragilities may be transmitted to their underlying constituents through arbitrage mechanisms. Furthermore, the resulting volatility may hamper these funds' hedging and price-discovery capabilities. Given the destabilising effects of feedback trading, it is important to understand its sources.

Existing literature suggests that feedback trading is driven by social trends, speculative actions, informational asymmetries, technical analysis, style investing, risk aversion, and investor sentiment (Economou et al., 2023). In particular, the level of feedback trading increases during periods of optimism or rising market sentiment, primarily due to investor sentiment-driven trading (Chau et al., 2011; Hu et al., 2015). On the contrary, Chau et al. (2016) report that sentiment-driven trading is more frequent during periods of declining sentiment or bear markets. An additional factor that may influence the prevalence of feedback trading in socially responsible ETFs is the composition of their investor base. Prior evidence suggests that ESG-oriented ETFs attract higher retail participation than conventional ETFs (Fiordelisi et al., 2023). This investor composition may amplify sentiment-driven and momentum-based trading behaviour. Notably, research suggests that fluctuations in geopolitical risk (GPR) may influence sentiment-driven trading, as increases in GPR dampen investor sentiment, whereas declines in GPR promote it (He, 2023). Therefore, it is plausible to expect that GPR may influence the level of feedback trading through its impact on investor sentiment. However, the effect of GPR on feedback trading remains unstudied.

The motivation for this study arises from the growing popularity of socially responsible investments amid rising geopolitical tensions. Demand for environmentally and socially conscious investments continues to increase despite market disruptions such as the COVID-19 pandemic, bank failures, and fintech innovations, with AUM expected to expand rapidly in the coming years (Dmuchowski et al., 2023). Geopolitical risks, including the U.S.–China trade war, the Russia–Ukraine conflict, and other global tensions, have intensified (S&P Global, 2024), underscoring the need to understand how these risks influence trading behavior in socially responsible ETFs. Against this background, the study aims to investigate whether socially responsible ETF investors engage in feedback trading. Further, the study investigates whether GPR influences the level of feedback trading. To achieve these objectives, U.S.-listed socially responsible ETFs are evaluated for the period 2019–2023 using the Sentana and Wadhwani (1992) framework with asymmetric GARCH models. Collectively, the results suggest that socially responsible ETF investors exhibit positive feedback (momentum) trading on average, and that this momentum is intensified as GPR decreases.

This study contributes to existing literature in several ways. First, despite the growing interest in socially responsible investments, literature on socially responsible ETFs remains limited to performance analyses (Lobato et al., 2021; Rompotis, 2022; Dai et al., 2023). In this regard, the current study extends the existing literature by providing insight into the trading behavior of socially responsible ETF investors. Second, the presence of feedback trading in ETFs has been explored for three of the largest U.S-listed ETFs (Chau et al., 2011), energy ETFs (Chang & Ke, 2014), emerging market ETFs (Charteris et al., 2014), country ETFs (Kallinterakis et al., 2020), and Saffron ETFs (Shaerattar & Banajan, 2023), while the presence of feedback trading in socially responsible ETFs is yet to be assessed. Given the destabilising effects of feedback trading, an investigation into feedback trading in socially responsible ETFs is vital to identify potential mispricing. This knowledge is fundamental for investors who use these funds for hedging and risk management. Furthermore, this knowledge is important for other countries and ETF providers that are considering the introduction of socially responsible ETFs. Finally, the novel contribution of this study is its linkage of GPR to feedback trading, which has not been explored previously. Although studies have linked investor sentiment to feedback trading (Chau et al., 2011; Hu et al., 2015; Dai & Yang, 2018), the association between GPR and the level of feedback trading remains uninvestigated. Given that GPR shocks can lead to investor pessimism or optimism (He, 2023), this study is important to understand the effects of GPR on investors' trading behaviours. Overall, the results of this investigation provide a deeper understanding of how feedback trading arises.

This paper is outlined as follows: Section 2 discusses the data and methodology, whilst Section 3 presents the results. Section 4 concludes the study.

2. Data and Methodology

2.1. Data

This study surveys ten of the largest socially responsible ETFs trading in the United States, ranked by assets under management (AUM). Table 1 lists these 10 funds, based on data from etf.com (2024), as of the end of August 2024. This study uses a daily frequency because feedback trading tends to be more prevalent in the short term (Chau et al., 2011). Accordingly, daily closing prices for the funds are extracted from EquityRT, and daily returns are computed as the natural logarithm of the ratio of the current price to the previous price. Daily global GPR ratings are obtained from Caldara and Iacoviello (2022), available at https://www.matteoiacoviello.com/gpr.htm. The GPR index, constructed by Caldara and Iacoviello (2022), measures the proportion of articles in leading U.S., U.K., and Canadian newspapers that mention unpleasant geopolitical events and threats, relative to the total number of published articles. As such, an increase in the index value is associated with rising global geopolitical risk and uncertainty. Global rather than country-specific GPR ratings are used because global GPR shocks have a greater impact on volatility than localised GPR shocks (Bouras et al., 2019). The five-year sample period, from January 2019 to December 2023, captures both upward and downward market movements.

2.2. Empirical Feedback Trading Model

The analysis of feedback trading in socially responsible ETFs is explored using the Sentana and Wadhwani (1992) model. The model assumes the existence of two investor groups: rational investors who trade on fundamental information, and feedback traders who respond to historical price changes rather than fundamental information. On the one hand, rational investors seek to maximize their expected mean-variance utility, thereby resulting in the following demand for securities in the period. t (S_t):

$$S_t = \frac{[E_{t-1}(R_t) - \alpha_0]}{\theta(\sigma_t^2)} \tag{1}$$

In Equation (1), $E_{t-1}(R_t)$ is the return expected in the period? $t-1$, α_0 is the risk-free rate of return, θ is the risk aversion coefficient, and σ_t^2 is the conditional variance in period t.

Table 1. Sample of ETFs

No.	Ticker	Fund Name	Issuer	AUM	Benchmark Index	Inception Date
1	SMH	VanEck Semiconductor ETF	VanEck	$23.35B	MVIS US Listed Semiconductor 25 Index	20-Dec-2011
2	EFG	iShares MSCI EAFE Growth ETF	Blackrock	$15.81B	MSCI EAFE Growth Index	01-Aug-2005
3	ESGD	iShares ESG Aware MSCI EAFE ETF	Blackrock	$8.58B	MSCI EAFE Extended ESG Focus Index	28-Jun-2016
4	IQLT	iShares MSCI Intl Quality Factor ETF	Blackrock	$8.37B	MSCI World ex USA Sector Neutral Quality Index	13-Jan-2015
5	EZU	iShares MSCI Eurozone ETF	Blackrock	$7.88B	MSCI EMU Index	25-Jul-2000
6	BBEU	JPMorgan BetaBuilders Europe ETF	JPMorgan Chase	$7.14B	Morningstar® Developed Europe Target Market Exposure Index	15-Feb-2018
7	SUSA	iShares MSCI USA ESG Select ETF	Blackrock	$3.65B	MSCI USA Extended ESG Select Index	24-Jan-2005
8	FEZ	SPDR Euro STOXX 50 ETF	State Street Global Advisors	$3.64B	EURO STOXX 50 Index	15-Oct-2002
9	EWU	iShares MSCI United Kingdom ETF	Blackrock	$3.20B	MSCI United Kingdom Index	12-Mar-1996
10	IHDG	WisdomTree International Hedged Quality Dividend Growth Fund	WisdomTree	$2.80B	WisdomTree International Hedged Quality Dividend Growth Index	05-Jul-2014

Notes: Table 1 presents the ETFs included in this study, along with their stock exchange tickers, issuers, assets under management (AUM), benchmark indices, and inception dates. While not all of these funds explicitly follow a sustainable, impact, or ESG investment mandate, they have strong ESG ratings and are therefore appealing to socially conscious investors. As a result, etf.com classifies them as ESG ETFs.

On the other hand, feedback traders make trading choices based on historical price changes, such that their demand for securities is given as follows:

$$F_t = \gamma R_{t-1} \tag{2}$$

In Equation (2), R_{t-1} Is the return generated in the period? $t-1$ and γ is the feedback trading coefficient. In particular, a positive γ coefficient is indicative of positive traders who buy (sell) after a price increase (decrease), and a negative coefficient γThe coefficient indicates negative feedback: traders who buy (sell) after a price decrease (increase) (Chau et al., 2011).

At equilibrium, all securities must be held such that. $S_t + F_t = 1$, Therefore, combining Equations (1) and (2) results in the following equilibrium model:

$$E_{t-1}(R_t) - \alpha_0 = \theta(\sigma_t^2) - \gamma\theta(\sigma_t^2)R_{t-1} \tag{3}$$

Assuming rational expectations exist such that $R_t = E_{t-1}(R_t) + e_t$ where e_t is an i.i.d error term, Equation (3) can be rewritten as:

$$R_t = \alpha_0 + \theta(\sigma_t^2) - \gamma\theta(\sigma_t^2)R_{t-1} + e_t \tag{4}$$

Equation (4) suggests that the degree of autocorrelation depends on the predominant type of feedback traders and on the conditional variance. Notably, as volatility increases, traders demand more securities, and autocorrelation intensifies (Karaa et al., 2021).

Sentana and Wadhwani (1992) translate Equation (4) above into the following empirical model:

$$R_t = \alpha_0 + \theta(\sigma_t^2) + (\vartheta_0 + \vartheta_1\sigma_t^2)R_{t-1} + e_t \tag{5}$$

In Equation (5), ϑ_0 is included to account for alternative sources of autocorrelation while $\vartheta_1 = -\gamma\theta$ and, therefore, a positive (negative) ϑ_1 coefficient that is statistically significant is synonymous with the presence of negative (positive) feedback traders.

Following Karaa et al. (2021), the conditional variance, σ_t^2, is captured using the asymmetric GJR-GARCH framework introduced by Glosten, Jagannathan, and Runkle (1993) to account for the leverage effect in return volatility as follows:

$$\sigma_t^2 = m + \beta_1\sigma_{t-1}^2 + \beta_2 e_{t-1}^2 + \delta I_{t-1}e_{t-1}^2 \tag{6}$$

In Equation (6), m is a constant term while I_{t-1} is a dummy variable that takes the value of 1 in the presence of bad news, that is, if $e_{t-1} < 0$, and 0 otherwise. Therefore, δ represents an asymmetry coefficient which suggests that bad news (or adverse shocks) have a greater impact on future volatility than positive shocks of the same magnitude when the coefficient is positive and significant. In the current study, the presence and type of feedback traders are examined by adopting Equation (5) as the conditional mean equation and Equation (6) as the conditional variance equation in the GJR-GARCH framework. The errors are modelled using the Generalized Error Distribution (GED).

To investigate the effect of GPR on the degree of feedback trading in socially responsible ETFs, the conditional mean equation for the GJR-GARCH framework is adapted from Chau et al. (2011) as follows:

$$R_t = \alpha_0 D_t^{GPR} + \alpha_1(1 - D_t^{GPR}) + \theta_0(\sigma_t^2) + \theta_1(1 - D_t^{GPR})(\sigma_t^2) + D_t^{GPR}\big(\vartheta_{0,0} + \vartheta_{1,0}\sigma_t^2\big)R_{t-1} + (1 - D_t^{GPR})\big(\vartheta_{0,1} + \vartheta_{1,1}\sigma_t^2\big)R_{t-1} + e_t \tag{7}$$

where is D_t^{GPR} is a dummy variable that takes the value of 1 on days when GPR increases and 0 otherwise.

Notably, the sample period encompasses major global shocks, including COVID-19 and the Russia–Ukraine conflict. However, the use of asymmetric GARCH models and alternative volatility specifications in the robustness analysis mitigates the influence of extreme observations. Moreover, these events are intrinsically reflected in the geopolitical risk index.

3. Results and Analysis

3.1. Preliminary Analysis

Table 2 presents descriptive statistics for the funds' returns and the raw GPR index, based on 1258 daily observations. On average, the socially responsible ETFs exhibit positive daily returns ranging from 0.024% (EWU) to 0.112% (SMH). However, whilst the EWU fund exhibits the lowest average return, it has the highest daily profit of 10.93%. In contrast, the SMH fund exhibits the most significant daily loss of 15.56%, despite having the highest daily average return. Accordingly, SMH exhibits the highest standard deviation (2.21%), indicating that better performance is associated with higher risk. Nevertheless, the negative skewness of the funds' return distributions suggests that the funds generate returns greater than their average returns –confirming that socially responsible ETFs tend to realise profits on average. The global GPR has an average score of 117.683, which is influenced by extreme geopolitical events, as evidenced by the inflated maximum score of 540.827. These geopolitical events included, but are not limited to, Russia's invasion of Ukraine, Hamas' attack on Israel, U.S-China trade wars, and the COVID-19 pandemic.

Table 3 presents the results of the Phillips-Perron unit root test, which is employed to assess the stationarity of the series used in this study. Overall, the test rejects the null hypothesis of a unit root in the series at the 1% significance level and concludes that the series is stationary at its levels. This includes the series of fund returns and the dummy variable (*D*) in Equation (7).

The presence of ARCH effects or heteroskedasticity in the returns is examined using the ARCH test, and the results are presented in Table 4. For all return series, the null hypothesis of homoskedasticity is rejected at the 1% significance level, thereby confirming heteroskedasticity in the funds' returns. As such, ordinary least squares (OLS) regression may yield biased results. Therefore, GARCH-type models are more appropriate for modelling the funds' returns. This is confirmed by the post-estimation ARCH test results in Table 5, which fail to reject the null hypothesis of homoskedasticity in the funds' returns, indicating that the returns are not heteroskedastic when GARCH models are employed. The results of the GARCH models are presented in the subsequent sections.

Table 2. Summary of Descriptive Statistics

Series	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
BBEU	0.00041	0.0984	-0.1242	0.0135	-1.1316	17.9005
EFG	0.00033	0.0723	-0.1103	0.0126	-0.8659	14.7449
ESGD	0.00032	0.0843	-0.1170	0.0125	-1.1568	17.7056
EWU	0.00024	0.1093	-0.1277	0.0139	-1.1707	18.2936
EZU	0.00035	0.0834	-0.1355	0.0149	-1.2038	16.2731
FEZ	0.00040	0.0899	-0.1331	0.0153	-1.0342	14.7250
IHDG	0.00050	0.0743	-0.1141	0.0112	-1.2766	20.8077
IQLT	0.00039	0.0768	-0.1064	0.0123	-1.0117	15.7045
SMH	0.00112	0.0982	-0.1556	0.0221	-0.3116	6.7507
SUSA	0.00058	0.0998	-0.1092	0.0135	-0.4651	13.7521
GPR	117.6827	540.8274	9.4916	62.0341	2.1767	11.4096

Notes: Table 2 shows the descriptive statistics for each fund's returns and the GPR index. Std. Dev. denotes the standard deviation.

Table 3. Phillips-Perron Unit Root Test Results

Series	Adj. t-stat.	Prob.
BBEU	-38.5576	0.0000
EFG	-39.6577	0.0000
ESGD	-39.5153	0.0000
EWU	-39.2734	0.0000
EZU	-37.9723	0.0000
FEZ	-37.9691	0.0000
IHDG	-42.4164	0.0001
IQLT	-39.4070	0.0000
SMH	-41.3599	0.0000
SUSA	-40.9966	0.0000
D	-53.7564	0.0001

Notes: Table 3 reports the adjusted test statistics (Adj. t-stat) from the Phillips-Perron unit root test, along with the corresponding p-values (Prob.) *D* denotes the dummy variable capturing an increase in GPR.

3.2. Baseline Analysis

The presence of feedback trading in the socially responsible ETFs is observed using GJR-GARCH models with Equation (5) as the conditional mean and Equation (6) as the conditional variance, and the results are presented in Table 6. In terms of the conditional variance estimates, the results reveal that volatility in socially responsible ETFs is highly persistent as β_1 is positive and significant in all funds—additionally, the positive and significant. δ parameters suggest that the conditional variance is an asymmetric function of previous squared residuals, that is, adverse residual shocks have a greater impact on future volatility than positive residual shocks of equal magnitude. Further, the volatility of the EWU, FEZ, and SUSA funds responds significantly to past news, as evidenced by the significant. β_2 coefficients.

Table 4. Preliminary ARCH Test Results

Fund	F-stat.	Prob.	Obs*R-squared	Prob.
BBEU	75.9739	0.0000	410.8317	0.0000
EFG	67.6590	0.0000	379.5316	0.0000
ESGD	65.5679	0.0000	371.2883	0.0000
EWU	81.0727	0.0000	428.9348	0.0000
EZU	66.5238	0.0000	375.0756	0.0000
FEZ	60.6879	0.0000	351.4300	0.0000
IHDG	85.8523	0.0000	445.2087	0.0000
IQLT	78.4424	0.0000	419.6949	0.0000
SMH	37.5691	0.0000	243.6727	0.0000
SUSA	84.5401	0.0000	440.8054	0.0000

Notes: Table 4 presents the results of the ARCH test, which was used to detect heteroskedasticity in the funds' returns prior to applying GARCH models. F-stat denotes the F statistic, Prob. represents the p-values, and ObsR-squared* is the product of the number of observations and the R-squared.

Table 5. Post-estimation ARCH Test Results

Series	F-stat.	Prob.	Obs*R-squared	Prob.
BBEU	0.5475	0.8211	4.3960	0.8197
EFG	0.2339	0.9846	1.8823	0.9844
ESGD	0.5854	0.7906	4.6995	0.7892
EWU	0.8491	0.5594	6.8048	0.5578
EZU	0.3667	0.9382	2.9479	0.9376
FEZ	0.4932	0.8617	3.9617	0.8606
IHDG	0.3118	0.9618	2.5074	0.9614
IQLT	0.4948	0.8606	3.9744	0.8594
SMH	0.2170	0.9880	1.7459	0.9878
SUSA	0.3068	0.9637	2.4673	0.9632

Notes: Table 5 presents the results of the ARCH test conducted after applying the GARCH models to confirm their reliability. F-stat denotes the F statistic, Prob. represents the p-values, and ObsR-squared* is the product of the number of observations and the R-squared.

Table 6. GJR-GARCH Results for Unconditional Feedback Trading

Fund	$\boldsymbol{\alpha_0}$	$\boldsymbol{\theta}$	$\boldsymbol{\vartheta_0}$	$\boldsymbol{\vartheta_1}$	$\boldsymbol{m}$	$\boldsymbol{\beta_1}$	$\boldsymbol{\beta_2}$	$\boldsymbol{\delta}$
BBEU	0.0006	1.7738	-0.0223	-69.901	0.0000*	0.8858*	0.0192	0.1371*
EFG	0.0007**	-0.5113	-0.0171	-149.18***	0.0000*	0.9156*	0.0064	0.1228*
ESGD	0.0004	1.4021	-0.0261	-106.58	0.0000**	0.9119*	0.0080	0.1240*
EWU	0.0003	2.3843	-0.0491	-44.784	0.0000*	0.8504*	0.0372***	0.1430*
EZU	0.0005	1.4639	-0.0018	-56.621	0.0000**	0.8890*	0.0206	0.1402*
FEZ	0.0005	1.7728	-0.0123	-52.500	0.0000*	0.8705*	0.0347***	0.1489*
IHDG	0.0007	0.5950	-0.0234	-121.55***	0.0000*	0.8405*	-0.0022	0.2204*
IQLT	0.0005	0.6742	-0.0199	-107.49	0.0000*	0.8893*	0.0161	0.1482*
SMH	0.0012	0.3461	-0.0085	-105.20**	0.0000*	0.8792*	0.0270	0.1158*
SUSA	0.0009*	-0.1430	0.0114	-108.32***	0.0000*	0.8134*	0.0528**	0.2149*

Notes: Table 6 presents the results of the GJR-GARCH models estimated for each fund to identify feedback trading, without incorporating GPR. The GJR-GARCH models are estimated using Equation 5 for the conditional mean and Equation 6 for the conditional variance. Refer to Section 2.2 for a full description of each coefficient. *, **, *** denote statistical significance at a 1%, 5%, and 10% level of significance, respectively.

In terms of feedback trading, the parameter of interest is ϑ_1. ϑ_1 is statistically insignificant in six funds (BBEU, ESGD, EWU, EZU, FEZ, and IQLT), suggesting that feedback trading is absent in these ETFs. On the contrary, ϑ_1 is negative and statistically significant in the remaining four ETFs, suggesting the presence of positive-feedback traders. However, ϑ_1 is statistically significant at the 5% level for the SMH ETF and at the 10% level for the EFG, IHDG, and SUSA ETFs, indicating weak evidence of feedback trading in these socially responsible ETFs. While statistically significant, the magnitude of the feedback coefficient suggests economically modest but non-negligible effects, indicating behavioural inefficiencies rather than guaranteed arbitrage opportunities. Such trend-chasing behaviours could lead to inefficiencies in these funds (Charteris & Musadziruma, 2017), which may spill over to their underlying constituents. Similar evidence of momentum trading in U.S-listed ETFs was reported by Chau et al. (2011).

The effect of GPR on feedback trading is explored using GJR-GARCH models with Equation (7) as the conditional mean and Equation (6) as the conditional variance, and the results are presented in Table 7. The unreported conditional variance estimates are similar to those in Table 6, confirming persistence and asymmetry in volatility. The average return (or constant) is generally higher, and in some cases significant, when GPR decreases (α_1) compared to GPR increases (α_0). On the contrary, the coefficient on the conditional variance is greater in magnitude and mostly significant when GPR increases (θ_0) relative to GPR decreases (θ_1). Turning to feedback trading, the relationship between autocorrelation and volatility is negative when GPR decreases ($\vartheta_{1,1}$) but only significant in seven funds (BBEU, EFG, ESGD, EWU, IHDG, SMH, and SUSA). This finding is consistent with the presence of momentum trading in these funds when GPR decreases. When GPR decreases, investors become more optimistic (He, 2023). Therefore, this finding of momentum trading when GPR decreases aligns with studies reporting momentum trading during high-sentiment periods, including Chau et al. (2011), Hu et al. (2015), and Karaa et al. (2021). On the contrary, there is no evidence of feedback trading in the socially responsible ETFs when GPR increases ($\vartheta_{1,0}$). Figure 1 visually confirms that feedback trading intensifies during periods of declining geopolitical risk, consistent with the regression results in Table 7.

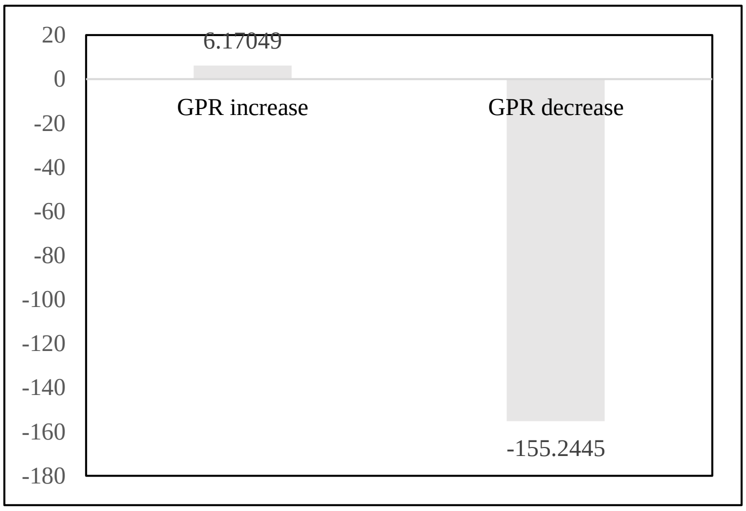
Together, the results in Tables 6 and 7 suggest that the market for socially responsible ETFs exhibits higher levels of momentum trading and its associated irrationality and inefficiency as GPR decreases, driven by increased optimism and participation by noise traders. This is evidenced by the increase in the magnitude of the significant relationships ($\boldsymbol{\vartheta_{1,1}}$ relative to $\boldsymbol{\vartheta_1}$) and the increase in the number of significant relationships (four in Table 6 relative to seven in Table 7).

Table 7. GJR-GARCH Results for Feedback Trading Conditional on GPR

Fund	$\boldsymbol{\alpha_0}$	$\boldsymbol{\alpha_1}$	$\boldsymbol{\theta_0}$	$\boldsymbol{\theta_1}$	$\boldsymbol{\vartheta_{0,0}}$	$\boldsymbol{\vartheta_{1,0}}$	$\boldsymbol{\vartheta_{0,1}}$	$\boldsymbol{\vartheta_{1,1}}$
BBEU	0.0000	0.0009***	8.5583**	-2.7620	-0.0763	29.347	0.0257	-149.63***
EFG	0.0005	0.0005	6.5201***	-2.5448	-0.0448	-26.197	0.0027	-223.47***
ESGD	-0.0000	0.0007	9.1471**	-3.1563	-0.0840***	20.777	0.0219	-176.14***
EWU	-0.0002	0.0006	9.6189*	-2.7455	-0.1189*	59.262	0.0140	-129.19***
EZU	0.0000	0.0009***	7.1253**	-2.8504	-0.0509	28.582	0.0370	-120.59
FEZ	0.0000	0.0009***	6.9230**	-2.3980	-0.0489	27.606	0.0194	-103.79
IHDG	0.0005	0.0007***	7.2346	-0.9066	-0.0280	-16.769	-0.0162	-183.26***
IQLT	-0.0002	0.0006	7.4819**	-4.9790	0.0155	-3.4791	-0.0067	-134.465
SMH	-0.0009	0.0020	6.1939**	-1.4370	-0.0101	-26.122	-0.0002	-175.14*
SUSA	0.0007	0.0009***	4.6250	-1.5552	0.0378	-31.302	-0.0089	-156.77***

Notes: Table 7 presents the results of the GJR-GARCH models estimated for each fund to identify feedback trading, after accounting for GPR. The GJR-GARCH models are estimated using Equation 7 as the conditional mean equation with Equation 6 as the conditional variance equation. Refer to Section 2.2 for a full description of each coefficient. *, **, *** denote statistical significance at a 1%, 5%, and 10% level of significance, respectively.

Figure 1. Average feedback coefficient among sampled ETFs



Notes: Figure 1 shows the average feedback trading coefficient when GPR increases and decreases.

3.3. Robustness Analysis

To confirm the robustness of the results presented in Table 7, three additional models are estimated for each fund, and the results are presented in Table 8. The first model, denoted (S), is estimated using the Student-t distribution for standardized residuals, replacing the GED distribution. The second model, denoted (E), employs an E-GARCH model rather than a GJR-GARCH model. The third model, denoted (M), uses the 7-day moving average of the GPR index to compute the dummy variable, rather than the current value of the GPR index. Overall, the results in Table 8 concur with the main conclusions from Table 7 –GPR decreases foster momentum trading – since $\vartheta_{1,1}$ is negative and significant in most cases. Interestingly, there is also evidence of momentum trading when GPR decreases in the three ETFs, a pattern previously absent. In part, the script theta sub 1,1 is negative and significant for EZU and FEZ in the E-GARCH models and for IQLT in all three models. Collectively, the results in Tables 7 and 8 confirm that changes in GPR have significant effects on the levels and directions of feedback trading in socially responsible ETFs.

4. Conclusions

The popularity of socially responsible ETFs has soared in recent years due to increased demand for socially conscious investments. However, participation in these markets may be driven by behavioural dynamics and trend-chasing, which are intensified by risk exposure. Given the recent rise in geopolitical uncertainty, this study aimed to assess the presence of feedback trading in socially responsible ETFs and whether GPR influences the level of feedback trading. To achieve this objective, ten U.S-listed ETFs were assessed using the Sentana and Wadhwani (1992) framework within a GJR-GARCH model. The findings of this study revealed that socially responsible ETFs tend to display positive feedback (momentum) trading, notably when GPR decreases.

These findings have important implications for various stakeholders. The presence of momentum trading when GPR decreases suggests that traders could exploit the trend-chasing behaviour of socially responsible ETF investors by entering positions during periods of GPR increases and unloading them during periods of GPR decreases, when feedback traders are likely to be on the buy side, and prices are expected to be high. The existence of feedback trading in these markets could lead to inefficiencies and fragilities in broader ETF markets, which could be transmitted to the funds’ constituents. Therefore, it is important for regulators to regularly communicate the risks associated with investing in these funds and to identify strategies to mitigate the destabilising effects of feedback trading. From a risk-management perspective, periods of declining geopolitical risk may warrant tighter monitoring of momentum-driven mispricing in ESG ETFs. Risk managers could adjust hedge ratios or rebalance exposures earlier in low-risk environments where trend-chasing behaviour intensifies. For researchers, there are various avenues for future studies. This study is limited to ten U.S.-listed socially responsible ETFs, which constrains the generalisability of the findings to other regions and ETF structures. Future research could extend the analysis to international ESG ETFs to assess cross-market consistency. Furthermore, given the widespread evidence of feedback trading in stock markets, future research could examine the effects of GPR shocks on feedback trading to determine whether the results of this study apply to other financial markets. Additionally, this study is limited to feedback traders; however, evidence suggests that various behavioural dynamics influence ETF trading, such as overconfidence, overreaction, and herding. In this regard, future studies can explore the effect of GPR on alternative behavioural dynamics.

Table 8. Robustness Results

Fund	α_0	α_1	θ_0	θ_1	$\vartheta_{0,0}$	$\vartheta_{1,0}$	$\vartheta_{0,1}$	$\vartheta_{1,1}$
BBEU (S)	-0.0001	0.0010***	8.8628**	-2.8227	-0.0627	36.218	0.0169	-132.56
BBEU (E)	0.0000	0.0007	6.0606*	-4.6423*	0.0042	-7.807	0.0132	-94.72*
BBEU (M)	0.0002	0.0007	4.4677	0.5696	0.0190	-32.119	-0.051	-116.65
EFG (S)	0.0004	0.0007	6.5216	-3.2676	-0.0420	-11.530	-0.0038	-210.35***
EFG (E)	0.0004	0.0005	6.8768**	-2.1562	-0.0540	-14.616	-0.0043	-221.29**
EFG (M)	0.0007	0.0005	1.2439	0.1939	0.0428	-116.59	-0.0520	-206.61***
ESGD (S)	-0.0002	0.0008	9.3451**	-3.3431	-0.0817	23.764	0.0123	-165.27
ESGD (E)	-0.0000	0.0006	8.7232*	-3.0066	-0.1003**	19.231	0.0217	-175.16**
ESGD (M)	0.0003	0.0004	4.0681	1.2730	-0.0093	-49.746	-0.0337	-183.83***
EWU (S)	-0.0004	0.0007	9.9470*	-3.1216	-0.0995*	58.297	-0.0034	-105.56
EWU (E)	-0.0002	0.0006	8.9869*	-2.0141	-0.1188*	46.472	0.0032	-131.79**
EWU (M)	0.0003	0.0002	4.7240	2.3231	-0.0241	-12.411	-0.0621	-108.93
EZU (S)	-0.0002	0.0010***	7.3166**	-3.0476	-0.0465	28.861	0.0299	-118.98
EZU (E)	-0.0000	0.0008***	6.8528**	-2.5114	-0.0617	27.111	0.0284	-114.96***
EZU (M)	0.0003	0.0007	3.6878	0.4461	0.0156	-20.698	-0.0153	-120.22
FEZ (S)	-0.0001	0.00104***	7.4167**	-3.0685	-0.0410	28.193	0.0150	-101.45
FEZ (E)	0.0000	0.0008***	6.8358**	-2.1974	-0.0550	25.783	0.0089	-99.812***
FEZ (M)	0.0003	0.0007	4.0807	0.4597	0.0097	-23.526	-0.0231	-103.84
IHDG (S)	0.0004	0.0009**	7.5742	-3.3234	-0.0228	-22.912	-0.0165	-171.39***
IHDG (E)	0.0003	0.0006	8.7519***	0.2295	-0.0315	-2.5618	-0.0226	-176.04**
IHDG (M)	0.0003	0.0010**	4.3964	1.0251	0.0596	-69.82	-0.0986**	-150.88
IQLT (S)	0.0000	0.0008	9.1663**	-3.9301	-0.0382	34.406	0.0003	-177.65***
IQLT (E)	0.0000	0.0006	9.3895*	-2.8320	-0.0583	33.542	-0.0008	-191.14**
IQLT (M)	0.0005	0.0004	2.8544	1.8033	0.0244	-60.145	-0.0508	-188.34***
SMH (S)	-0.0008	0.0023***	6.0865**	-2.1067	-0.0183	-20.600	0.0021	-173.98*
SMH (E)	-0.0012	0.0020**	6.8846*	-1.6067	-0.0029	-25.050	0.0002	-165.14*
SMH (M)	-0.0006	0.0020	2.4288	1.4240	0.0258	-57.505	-0.0156	-194.90*
SUSA (S)	0.0007	0.0009**	5.6558	-1.5556	0.0349	-14.722	0.0075	-156.99***
SUSA (E)	0.0002	0.0009	4.7780*	-4.0183*	0.0296	-27.588	-0.0116	-139.88*
SUSA (M)	0.0003	0.0013*	1.3717	0.3559	0.0709	-68.936	-0.0434	-158.94***

Notes: Table 8 presents the results of the robustness checks conducted. Here, (S) denotes the model estimated using the Student-t distribution, (E) employs the E-GARCH specification, and (M) uses the 7-day moving average of the GPR index to construct the dummy variable. *, **, *** denote statistical significance at a 1%, 5%, and 10% level of significance, respectively.

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