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Twitter Economic Uncertainty and Herding Behavior in ESG Markets

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Abstract: Attention to environmental, social, and governance (ESG) investing has grown in recent years. Even after the SARS-CoV-2 (COVID-19) global pandemic, there has been a rise in financial instruments that are structured according to certain prescribed "sustainable finance" objectives. From a risk management perspective, and as we continue to see a rise in inflows into such instruments, it is important to appreciate that ESG markets will have a growing influence on our financial system and its development. In light of this, and using a sample of some of the most common and popular US-based ESG index funds, this study explores the extent to which herding behaviors are present in such markets. From a regulatory point of view, such behaviors are important to identify, given that they can lead to excess price volatility, bubbles, and other such market-destabilizing phenomena. In addition, this study builds a framework for exploring whether Twitter-based economic uncertainty, which is arguably a forward-looking indicator of investors' expectations, can exacerbate herding behaviors in ESG markets. Overall, this study shows the following: (i) herding behaviors are present in ESG markets; (ii) rises in Twitter economic uncertainty can potentially exacerbate such herding; (iii) although ESG funds, like traditional asset classes, generally show a negative risk–return tradeoff, this can be driven by changes in Twitter economic uncertainty.

Keywords: economic policy uncertainty; ESG investing; herding; sustainable finance; Twitter

JEL Classification: C32; G12; G17; G40

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1. Introduction

Shareholder wealth maximization (SWM) serves as the conventional principle in modern-day corporate finance, portfolio and investment management, and asset allocation decision making. At its core, SWM maintains that the immediate and fundamental objective of a firm is to maximize shareholders' return on their equity capital (Bainbridge 1993; Cheffins 2020; Denis 2019; Friedman 1970; Inkpen and Sundaram 2022; Windsor 2010). Insofar as the firm is operating within the law, it is expected that such a corporate objective will result in the most socially and economically efficient allocation of scarce capital resources (Friedman 1962; Windsor 2010). Since the seminal work of Friedman (1962, 1970), the SWM framework has been extended to numerous fields within the social sciences and has been given various other terms within the literature (e.g., shareholder primacy, the shareholder model, profit maximization, and stock value maximization) (Jones and Felps 2013). Despite the various applications and designations of SWM, their implications and deductions are largely analogous.

The divergent view that has emerged more recently is that firms' operations potentially affect broader segments of society; therefore, it is inadequate to only consider shareholders (Jones and Felps 2013). This view is often referred to as the stakeholder theory argument

(Freeman et al. 2021; Phillips et al. 2003). Like SWM, stakeholder theory has also been explored across disciplines (Barney and Harrison 2020; Bozos et al. 2022; Donaldson 1999; King et al. 2017; Parmar et al. 2010; Waheed and Zhang 2022). While few can argue that firm management should at least consider the societal impact of their operations and decisions, the evidence thus far is mixed at best in terms of whether stakeholder theory is a better alternative to, or provides a clearer roadmap for firm management than, the SWM view (Orts and Strudler 2009). This debate is likely to persist vigorously in the near- and long-term future and will likely take center stage in regulatory and legislative deliberations, at international investor forums, within public discourse, and, naturally, during political debates (Olsen 2017).

In recent decades, there has been, and continues to be, increasing attention on stakeholder theory and its integration into financial markets. From an investment management view, it has led to the creation and rising popularity of so-called environmental, social, and governance (ESG) investing, or ESG funds. These financial instruments are one of the latest innovations that seek to invest in, or form index funds using, criteria based on ESG considerations (Cornell 2020). Much of the motivation for these funds stems from the United Nations' Principles for Responsible Investment (PRI), which outlines key ESG initiatives and strategic goals.[1] Among its other objectives, PRI fosters a network of signatories, consisting of asset managers, investment companies, as well as publicly traded companies from a range of industries, which have committed to incorporating ESG factors into their investment and operational decision making.[2]

These principles, along with interests in ESG issues, have spurred the creation of ESG funds that are available for retail and institutional investors alike. According to some estimates, global ESG assets are predicted to surpass USD 40 trillion in assets under management (AUM) by the year 2030 (Bloomberg 2024). This is a staggering amount and a testament to the growing influence which ESG markets will have on our financial system and its development. This is especially the case given the growing demand by investors for new financial products that can potentially serve as hedges against market risk. For example, at the onset of the SARS-CoV-2 (COVID-19) global pandemic, Morningstar even referred to ESG as an "equity vaccine" against pandemic-induced fear and pessimism (Willis 2020).

Following the COVID-19 pandemic, there is a budding strand of literature that examines whether ESG markets are unique asset classes that can provide investors with new diversification opportunities. The evidence thus far is mixed, with some finding that ESG can provide diversification benefits under certain conditions and in certain markets (Cerqueti et al. 2021; Lee et al. 2021; Pástor et al. 2021), while others find that they do not (Cerqueti et al. 2021; Demers et al. 2021). Nevertheless, others show there may be such strong sustainability preferences among certain investors that they are actually willing to sacrifice absolute returns in order to engage in ESG investing (Eccles et al. 2017; Kräussl et al. 2024). Finally, others question whether mutual fund managers who become signatories to PRI truly put ESG issues at the forefront of their investment strategic goals (Kim and Yoon 2023).

Motivated by the findings of these aforementioned studies, the momentum in ESG-related policies that are presently being discussed on a global scale, as well as a growth in investors' attention toward ESG-centered funds, this study explores whether herding behaviors are evident in ESG markets. This study specifically tests for feedback trading, which is a form of herding in financial markets. In the words of Nofsinger and Sias (1999), "...although a recent growing body of literature is devoted to investor herding and feedback trading, extant studies take divergent paths..." (p. 2263). This present study looks at a specific class of herding behaviors known as "feedback trading". As Nofsinger and Sias (1999) indicate, "... Most herding models suggest that investors follow some common signal...feedback trading, a special case of herding, results when lag returns, or variables correlated with lag returns...act as the common signal..." (p. 2263).

Thus, "herding behaviors", or "feedback trading" in the literature on asset pricing and risk management, are concerned with, among other dynamics, identifying the relationship between investors' current buying and selling behaviors in relation to the underlying asset's lagged returns (Guo and Ou-Yang 2015; Koutmos 2012; Nofsinger and Sias 1999). Herding activity among investors is important to identify, since it can lead to sharp rises in market volatility, asset price bubbles, and other such market-destabilizing phenomena. During normal market conditions, herding behaviors and their nature is important to quantify, given that they can exert short- and medium-term pressure on asset prices.

In addition, this study builds a framework to explore whether Twitter-based economic uncertainty drives, or exacerbates, herding behaviors. For this purpose, it builds a model that integrates Baker et al.'s (2021) Twitter-based economic uncertainty (TEU) index and explores the extent of herding behaviors during times when TEU rises and falls, respectively. The TEU index is unique, in that it captures the (forward-looking) sentiment of investors. To construct this index, Baker et al. (2021) use the Twitter API to extract all available English tweets containing a keyword that is related to uncertainty. Specifically, the following four keywords are considered, respectively: "uncertain", "uncertainties", and "uncertainty". This index can provide an informationally useful indicator for sentiment, given that social media has become ubiquitous not only in our everyday lives but in financial markets and investing as well (Sul et al. 2017). According to some present-day estimates, almost a quarter of US adults purport that they use Twitter.[3] It is well-documented in the literature on behavioral financial economics that sentiment stemming from social media can influence investors' trading behaviors, even after controlling for sentiment stemming from mainstream news outlets (Duz Tan and Tas 2021).

Herding behavior (e.g., trading solely on the basis of past asset prices) is a popular strategy among investors around the world and can be implemented across asset classes, such as equities, currencies, bonds, derivatives, real estate, and index funds (Karaa et al. 2021). The presence of such trading is not particularly confined to retail investors but can also manifest itself in institutional investors' trading patterns (Economou et al. 2023). Sophisticated traders, such as hedge funds, may engage in herding, or feedback trading, despite possessing information about an underlying asset's fundamentals. As discussed in, among others, Schauten et al. (2015), such traders may have rational considerations for engaging in feedback trading or may have a tendency to only herd in certain markets or in certain assets. Finally, and as shown in Koutmos (2014), the presence of noise traders, who look at the behaviors of past asset prices and not fundamental values, can exacerbate herding behaviors and obscure arbitrageurs' abilities to distinguish noise from fundamental information. Institutional investors, like retail investors, are also affected by noise, or sentiment, especially given the ease at which it can proliferate on social media (Duz Tan and Tas 2021).

Given the growing interest in ESG investing, as well as the plethora of various sustainability-type indicators that are now publicly available for market participants (see Li et al. 2024 and references therein), it is important to see whether feedback-type trading behaviors are present and statistically discernible in such markets. From the perspective of market participants, ESG markets may present novel investments, or hedging opportunities (Andersson et al. 2022). In light of the aforementioned, this study makes the following novel contributions. Firstly, it shows that herding behaviors are indeed present in ESG markets. Specifically, the evidence herein shows that such herding investors engage in "positive-feedback" trading strategies, whereby they buy shares in ESG funds when prices rise and sell when prices decline. This type of "bandwagon" behavior is also well-documented in traditional equity markets and has received much attention following the crash of 1987, the burst of the 2000 tech bubble, the 2008–2009 financial crisis, and the recent 2020 stock market crash due to the COVID-19 pandemic. Secondly, this study shows how TEU can potentially exacerbate herding behaviors in ESG markets. This is an important finding, as it shows that ESG markets, like traditional asset markets, are not entirely immune from fluctuations in investor sentiment. Finally, the evidence herein shows that ESG funds generally show a negative risk–return tradeoff. This is again something that we observe in traditional asset markets and is often referred to as the "volatility feedback effect" (Campbell and Hentschel 1992). Finally, and as a contribution to the finance literature that explores the risk–return relation of asset classes (see Barroso and Maio 2024 and references therein), this study shows that the risk–return tradeoff in ESG markets can be driven by changes in TEU.

The remainder of this study is structured as follows. Section 2 discusses the sample data that were used and some of their statistical properties. Section 3 builds the analytical framework for detecting herding behaviors and seeing whether TEU plays a role in the model estimates. Section 4 discusses the findings. Finally, Section 5 concludes and discusses avenues for future research.

2. Sample Data

This section discusses the ESG funds that were sampled in order to ascertain the extent to which there are herding behaviors in such markets. Section 2.1 lists the sampled funds and the data ranges used in this study. Section 2.2 provides descriptions of the statistical properties of their returns along with unconditional risk–return metrics.

2.1. ESG Funds

Over the last two decades, several high-profile investment management companies have launched ESG-centered mutual funds. These index funds comprise, among other criteria and factors, companies that either report, and maintain some type of ESG rating, or are invested in companies whose purported objectives align with the aforementioned PRI principles.[4] While there is no clear and widely accepted guideline or set of criteria as to *what* constitutes an ESG investment, several fund managers are using a variety of techniques in order to form index funds which are sold to retail and institutional investors (Przychodzen et al. 2016).

In addition, and given the proliferation of new funds that have emerged during, and after, the COVID-19 pandemic, there are stark differences in the sizes of available funds in terms of their assets under management (AUM). Given that this study is concerned with identifying herding behaviors in the time-series behaviors of fund prices, large index funds which are representative of ESG markets and which represent key ESG indexes that are watched by investors were chosen. This sampling approach is thus comparable to that of, among others, Giese et al. (2019) and Jain et al. (2019). In these studies, large ESG index funds were sampled, given that they are representative of the whole ESG market. From a practical investment point of view, ESG-motivated retail and institutional investors buy and sell such funds for both short- and long-term portfolio-allocation decisions (Owadally et al. 2021).

Table 1 lists the sampled ESG index funds that are explored in this study. In this table, the ticker, index fund name, sample range, number of observations, current net expense ratios, and AUMs, respectively, are shown for each fund. For each fund, daily market prices, or net asset values (NAVs), were collected. It is important to note that the sample ranges are uneven, given that the inception dates for each of the funds are naturally dissimilar. These funds are some of the largest in the entire ESG market, which feature prominently in the financial press and attract some of the largest inflows of capital. Data for these funds were obtained through a variety of sources, such as Morningstar, Fidelity, Vanguard, BlackRock (iShares), Invesco, and the ETF Database (etfdb.com). Accessed on 1 April 2024.

Table 1. Sampled ESG index funds.

Ticker	Index Fund	Sample Range	No. of Obs.	Expense Ratio (Net)	AUM (in USD)
1. ESGU	iShares ESG Aware MSCI USA	12/06/2016–04/21/2023	N = 1664	0.15%	12,550,000,000
2. ESGV	Vanguard ESG US Stock ETF	09/21/2018–04/21/2023	N = 1196	0.09%	8,450,000,000
3. ESGD	iShares ESG Aware MSCI EAFE	08/25/2016–04/21/2023	N = 1737	0.20%	7,900,000,000
4. DFSIX	DFA US Sustainability Core 1	06/01/2011–04/21/2023	N = 3103	0.17%	6,750,000,000
5. FITLX	Fidelity US Sustainability Index	05/09/2017–04/21/2023	N = 1554	0.11%	4,100,000,000
6. VSGX	Vanguard ESG International Stock	09/20/2018–04/21/2023	N = 1197	0.12%	3,800,000,000
7. ICLN	iShares Global Clean Energy	06/01/2011–04/21/2023	N = 3103	0.41%	2,100,000,000
8. EFAX	SPDR MSCI EAFE Fossil Fuel Reserves Free	11/03/2016–04/21/2023	N = 1687	0.20%	267,500,000
9. XVV	iShares ESG Screened S&P500	09/25/2020–04/21/2023	N = 671	0.08%	252,000,000
10. SDG	iShares MSCI Global Sustainable Development Goals	04/22/2016–04/21/2023	N = 1826	0.49%	248,000,000
11. ALPS	ALPS Clean Energy	06/29/2018–04/21/2023	N = 1259	0.55%	202,000,000
12. ETHO	Amplify Etho Climate Leadership US	11/19/2015–04/21/2023	N = 1937	0.45%	177,000,000
13. ESG	FlexShares STOXX US ESG Select	07/14/2016–04/21/2023	N = 1767	0.32%	USD 175,000,000
14. ERTH	Invesco MSCI Sustainable Future	06/01/2011–04/21/2023	N = 3103	0.62%	170,000,000
15. XJR	iShares ESG Screened S&P Small-Cap	09/25/2020–04/21/2023	N = 671	0.12%	73,500,000
16. CTEC	Global X CleanTech	10/29/2020–04/21/2023	N = 647	0.50%	41,000,000

Notes: This table lists the sampled ESG funds that are used in this study. Funds' tickers are provided in the first column. The second column identifies the name of the fund. The third and fourth columns provide the sample range and the number of observations, respectively. Sample ranges differ depending on the funds' inception dates. The fifth and sixth columns show the funds' most recent annual expense ratio and assets under management (AUM), respectively.

In all, 16 funds were selected for this study, which have a combined current AUM of over USD 47 billion. The largest of these funds, iShares ESG Aware (ESGU), has a current AUM of USD 12.55 billion. Of the sampled funds, seven have AUMs in the billions, while the remaining nine are in the millions. It is also important to note that while some of the funds are more broadly ESG-centered (such as ESGU and ESGV), others focus more on certain aspects of ESG, such as the climate (e.g., EFAX, ALPS, and CTEC). The expense ratios for the funds range from 0.08% to 0.62%. To put this range in context, the current and average annual expense ratio among all mutual funds is approximately 0.36%.[5]

Figure 1 shows time-series plots of their respective price behaviors. All these sampled funds (with the exception of XVV, XJR, and CTEC) have price data prior to the COVID-19 pandemic, given their inception dates. As can be seen from Figure 1, these funds experience a severe decline in their prices around the time when the World Health Organization (WHO) announced the official name for the novel coronavirus outbreak ("COVID-19") on 11 February 2020.

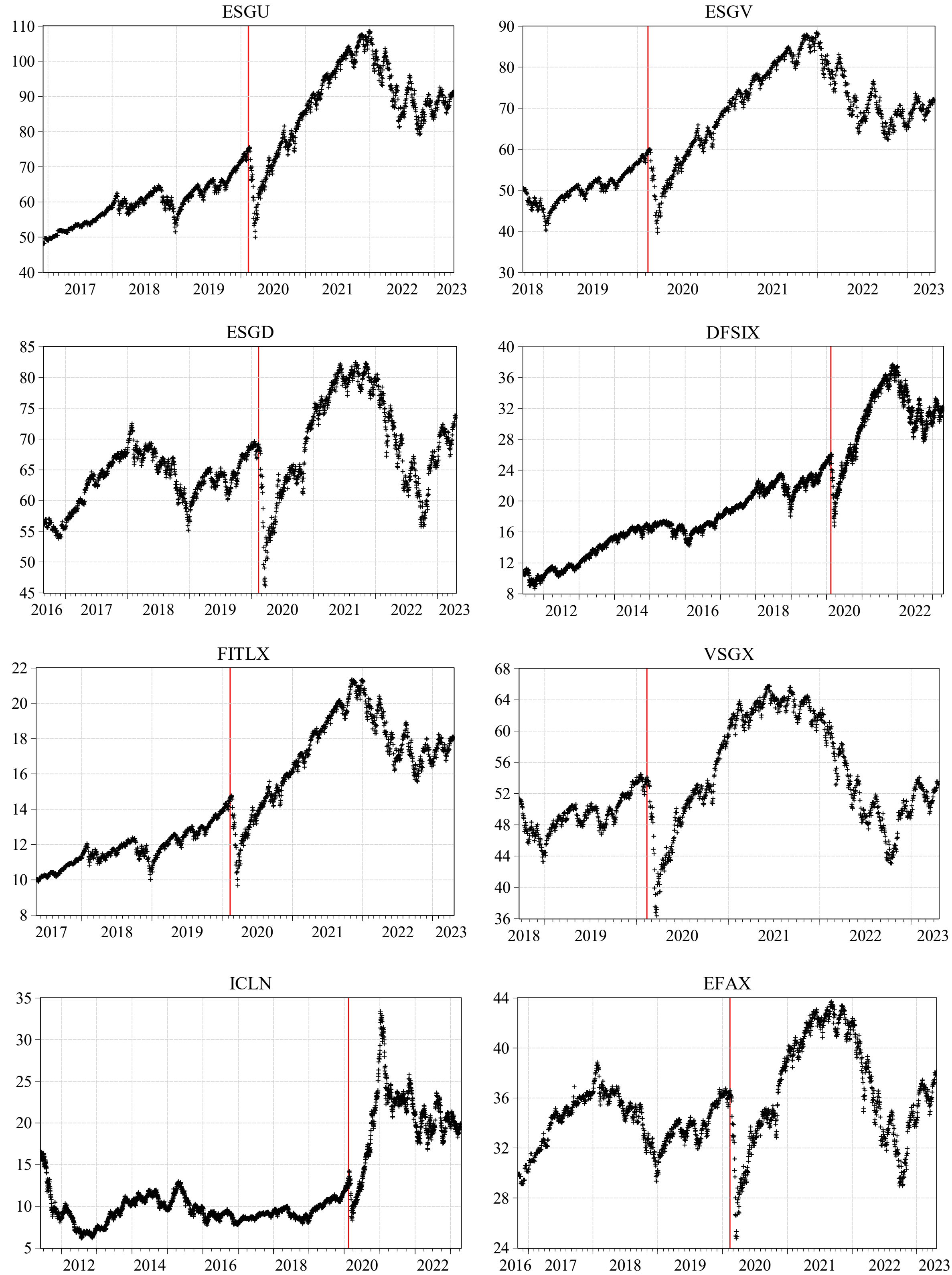

Figure 1. *Cont.*

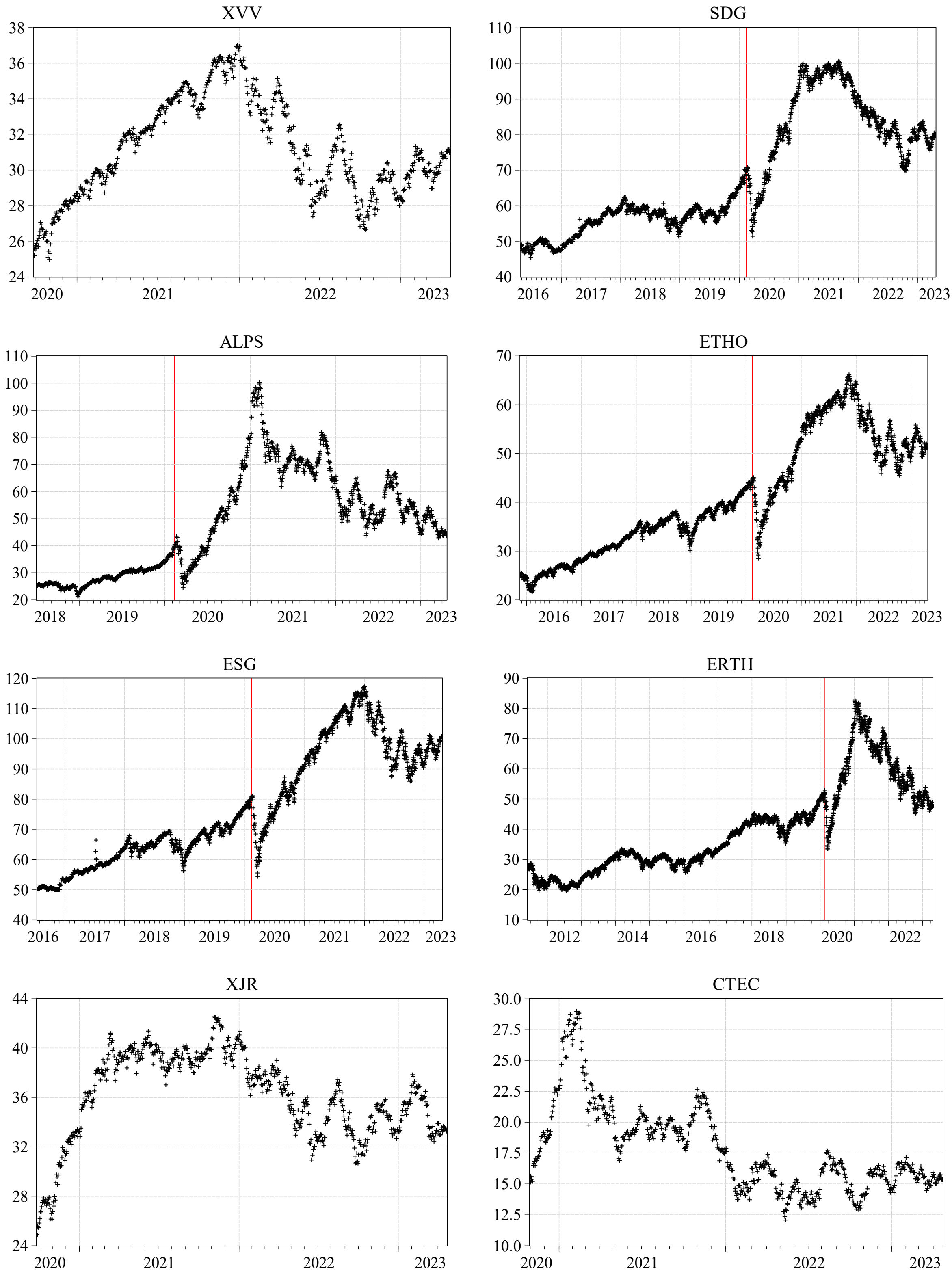

Figure 1. Time-series plots of sampled ESG fund prices. Notes: This figure shows time-series plots of the prices of the sampled ESG funds. The vertical red line denotes when the World Health Organization (WHO) announced the official name for "COVID-19" on 11 February 2020 (see https://www.cdc.gov/museum/timeline/covid19.html) Accessed on 1 April 2024.

2.2. Summary Statistics

Table 2 shows summary statistics of the unconditional moments (mean, standard deviation, skewness, and kurtosis, respectively) of each of the ESG funds' returns, computed as logarithmic first differences of their respective price series, P: $100 * \ln(P_t/P_{t-1})$. In addition, the unconditional Sharpe ratio for each funds' return series, R, is also estimated as $\left(R_t - r_f\right)/\sigma$, whereby r_f denotes the risk-free rate.[6] The denominator for the Sharpe ratio is the unconditional standard deviation of the respective funds' returns, σ. Using the mean and standard deviations of the funds' returns, we can estimate their respective value at risk (VaR) as follows: $\text{VaR} = W\left(\mu\Delta t - n\sigma\sqrt{\Delta t}\right)$, whereby μ is the mean return, W reflects the value invested within the underlying fund, n denotes the number of standard deviations depending on the confidence level, σ is the standard deviation, and Δt reflects the time window (Signer and Favre 2002).

Table 2. Unconditional moments and risk–return characteristics.

Index Fund	Mean	Std. Dev.	Skew.	Kurt.	VaR	Modified VaR	Sharpe	Modified Sharpe
1. ESGU	0.0380	1.2477	−0.7981	18.8017	−2.4075	−4.3753	0.0305	0.0087
2. ESGV	0.0296	1.4397	−0.6483	12.6601	−2.7922	−4.3986	0.0206	0.0067
3. ESGD	0.0154	1.1206	−1.2234	20.2247	−2.1810	−4.1429	0.0137	0.0037
4. DFSIX	0.0339	1.1420	−0.7523	14.0813	−2.2044	−3.6221	0.0297	0.0094
5. FITLX	0.0378	1.2864	−0.7808	17.8574	−2.4835	−4.4235	0.0294	0.0085
6. VSGX	0.0031	1.2332	−1.2743	17.9452	−2.4140	−4.3867	0.0025	0.0007
7. ICLN	0.0048	1.7023	−0.4381	9.1892	−3.3317	−4.7123	0.0028	0.0010
8. EFAX	0.0144	1.1198	−1.2123	19.2033	−2.1804	−4.0609	0.0129	0.0035
9. XVV	0.0308	1.1882	−0.2332	4.6086	−2.2981	−2.7962	0.0259	0.0110
10. SDG	0.0275	1.0644	−0.5776	15.5130	−2.0587	−3.4329	0.0258	0.0080
11. ALPS	0.0438	2.2695	−0.4057	7.5794	−4.4044	−5.9682	0.0193	0.0073
12. ETHO	0.0371	1.2920	−0.3905	13.1914	−2.4952	−3.8768	0.0287	0.0096
13. ESG	0.0391	1.2425	−0.6550	17.1434	−2.3962	−4.1678	0.0315	0.0094
14. ERTH	0.0158	1.4111	−0.8597	11.8960	−2.7500	−4.3259	0.0112	0.0037
15. XJR	0.0434	1.4232	0.0062	3.5048	−2.7461	−3.0847	0.0305	0.0141
16. CTEC	−0.0026	2.5181	0.2064	4.0658	−4.9381	−5.3799	−0.0010	−0.0016

Notes: This table reports the unconditional moments (mean, standard deviation, skewness and kurtosis, respectively) for the log returns (in percentages) of each of the sampled ESG funds that are used in this study (listed in Table 1). The last four columns show the value at risk (VaR), modified VaR (MVaR), Sharpe ratio, and modified Sharpe ratio, respectively (see Equations (1)–(4)).

While not directly comparable given the funds' unequal sample ranges, we can see that CTEC and ALPS have the highest downside risks (VaR) while not necessarily offering the highest Sharpe ratio for investors, relatively speaking. Across the sixteen ESG funds, the average VaR and Sharpe ratios are, respectively, −2.755 and 0.020. However, considering that these ESG fund returns' distributions deviate from a theoretically normal distribution, and thus carry heightened skewness and kurtosis risk for investors, it is possible that these VaR and Sharpe ratios downplay their actual downside risks.

Given the non-Gaussian behavior of their returns, it is useful to incorporate information content beyond what we observe in their first two unconditional moments. As Signer and Favre (2002) show, VaR estimations that neglect higher moment risks, such as excessive skewness and kurtosis ("fat tails"), may downplay the actual downside risks posed by the underlying asset returns in question. From a behavioral finance perspective, tail risk, and investors' perception of such risks, can have an impact on their risk aversion (Lemperiere et al. 2017).

In order to gain preliminary insights into the price behaviors of the sampled ESG funds, Table 2 also shows each of their modified VaR (MVaR) estimates and modified Sharpe ratios, respectively (Gregoriou and Gueyie 2003). Using similar notation as with the VaR, the MVaR can be expressed in the following way:

$$\mathrm{MVaR} = W\left[\mu - \left\{z_c + \frac{1}{6}\left(z_c^2 - 1\right)S + \frac{1}{24}\left(z_c^3 - 3z_c\right)K - \frac{1}{36}\left(2z_c^3 - 5z_c\right)S^2\right\}\sigma\right] \quad (1)$$

where W denotes the value of the portfolio invested in the ESG fund, z_c is the critical value for the probability $(1-\alpha)$ and is -1.96 for a 95% probability, μ reflects the mean return, σ is the unconditional standard deviation of the return series, S is the unconditional skewness of the return series, and K is the unconditional excess kurtosis of the return series. The physical (unconditional) skewness and kurtosis of the respective ESG funds' returns are calculated in the following way:

$$S = \frac{1}{T}\sum\nolimits_{t=1}^{T}\left(\frac{R_t - \overline{R}}{\sigma}\right)^3 \quad (2)$$

$$K = \frac{1}{T}\sum\nolimits_{t=1}^{T}\left(\frac{R_t - \overline{R}}{\sigma}\right)^4 - 3 \quad (3)$$

After estimating our sampled funds' MVaR, we proceed to estimate respective modified Sharpe ratios (see footnote (6)):

$$\text{Modified Sharpe Ratio} = (R_{\mathrm{t}} - r_{\mathrm{f}})/\mathrm{MVaR} \quad (4)$$

When comparing MVaR with VaR estimates, we see that in each of the sampled ESG funds, there is a higher possibility for downside risks (MVaR) when incorporating skewness and kurtosis. As a result, we see an overall deterioration in their reward-to-risk profiles (modified Sharpe ratios).

A key theme here is that, despite the growing interest in ESG funds, they do carry downside risks which investors need to understand and quantify. These summary statistics lead to the next questions that are critical in this study: Given the ESG funds' downside risks and price volatilities, are herding behaviors present in such markets and, if so, what impact do they exert on ESG asset prices? In addition, what role does aggregate investor sentiment play? The next section proceeds to build a framework that can be used to shed light on these questions.

3. Analytical Framework

To explore the extent to which herding behaviors are present in ESG markets, this study builds a framework based on the models of Merton (1980), Shiller (1984), and Sentana and Wadhwani (1992). The purpose is to see, firstly, whether herding behaviors are present in such markets and, secondly, if so, to detect the manner in which these herding traders trade. In other words, do they buy shares in ESG funds when there are recent price increases and sell during recent price declines? If this is the case, these traders engage in "trend-chasing", or "follow-the-herd", types of behaviors and are often referred to as "positive-feedback" traders in the literature (Sentana and Wadhwani 1992). On the other hand, if they sell shares when there are recent price increases and buy during recent price declines, they are referred to as "negative-feedback" traders. In this case, such traders may be engaging in contrarian trading or have some expectation of mean reversion in the underlying asset's price integrated into their trading strategy. Sections 3.1 and 3.2 discuss the frameworks used to detect herding, while Section 3.2 integrates TEU into the analysis. By integrating TEU into the analysis, we can decipher whether aggregate investor sentiment plays any role in herding behaviors.

3.1. Modeling Herding Behavior

Building upon the theoretical and empirical models of Merton (1980), Shiller (1984), and Sentana and Wadhwani (1992), the framework in this study assumes the presence of two types of heterogeneous investors. The first, and consistent with classical portfolio theory, are mean-variance (MV) optimizers who trade (or re-balance) their portfolios in order to achieve a maximum value in their mean-variance expected utility (Merton 1980).

Their buy and sell decisions are based on the first two moments of the assets' returns. Specifically, their demand function can be expressed as follows:

$$MV_t = \left[E_{t-1}(R_t) - r_f\right] / (\theta * Var(R_t));\ \theta > 0\ or\ \theta < 0 \quad (5)$$

whereby MV_t denotes the fraction of shares within a given ESG fund that these mean-variance optimizers hold at time t. $E(.)$ is an expectations operator, whereby $E_{t-1}(R_t)$ is the expected return that is conditional on the information set available to the market as of $t-1$. The risk-free rate is denoted by r_f, as discussed in footnote (6). The coefficient θ reflects relative risk aversion and, consistent with asset pricing theory, should be positive and statistically significant. Another interpretation of θ is the sign of the risk–return tradeoff for the asset in question. A positive sign would be theoretically expected if investors were rational mean-variance optimizers. However, and as is discussed later on, this is not always the case. In addition, and a priori, there is no expectation to believe that these sampled ESG funds have a positive risk–return tradeoff, especially given aforementioned studies that show how investors may have a preference for ESG investments regardless of their underlying risk–return profiles (Eccles et al. 2017; Kräussl et al. 2024). The conditional variance of each ESG fund's returns at time t is denoted by $Var(R_t)$. Therefore, and if we assume that the coefficient θ is positive and statistically significant, the product of $\theta * Var(R_t)$ represents the risk premium at time t. The mean-variance optimizers' demand for ESG funds is thus determined by the degree of volatility risk, $Var(R_t)$, whereby their demand increases when their expected returns, $E_{t-1}(R_t) - r_f$, also increase.

The second group of investors, which is also the focal point of our study, exhibit herding-type (or feedback) trading strategies. These herding $(Herd)$ investors may engage in strategies such as "trend chasing" or "momentum" behaviors, whereby their current demand for ESG funds depends on lagged returns, R_{t-1}. Their demand function can thus be expressed as follows:

$$Herd_t = \rho\left(R_{t-1} - r_f\right);\ \rho > 0\ or\ \rho < 0 \quad (6)$$

where $Herd_t$ denotes the fraction of shares in the respective ESG fund that they hold at time t. As can be seen from Equation (6), past (lag) returns are of primary importance in determining their demand for the underlying asset. This is not necessarily an over-simplification of their behaviors, especially considering the plethora of investment and social media websites, as well as trading platforms, that allow investors to share momentum-type investment tips or offer built-in features which allow them to automate their preferred momentum strategies.

The coefficient ρ is important in telling us the direction and statistical significance of such herding behaviors. For example, when the coefficient ρ is positive and significant, it indicates that herding investors are following "positive-feedback", or "trend-chasing" momentum strategies by buying during recent price increases and selling during recent price decreases. As discussed, this type of behavior deviates from what is assumed in modern portfolio theory, whereby investors make buy and sell decisions to optimize their mean-variance expected utility. It is important to note, however, that although such behavior may be considered irrational, especially if investors are attempting to copy one another's trades, as often happens in online financial forums, it may also be rationally explainable. For example, a negative price shock in the market naturally has a higher probability of triggering electronic stop-loss orders en bloc. This scenario would naturally be a catalyst for positive-feedback trading behaviors.

Regardless of the reason, this is a form of herding that produces undesirable features in the market, such as price bubbles and excess volatility. If, however, the coefficient ρ is negative and significant, this shows that traders are buying during recent price decreases and selling during recent price increases. A negative and significant sign for ρ may be the result of contrarian-type behaviors or an expectation of mean reversion integrated into the trading strategies of traders. At any rate, this too is a form of (negative) feedback trading.

Following Sentana and Wadhwani (1992), in market equilibrium, and given Equations (5) and (6), we assume that at any given time these two heterogeneous groups of investors hold all available shares of a given ESG fund,

$$MV_t + Herd_t = 1 \tag{7}$$

By substituting Equations (5) and (6), respectively, into Equation (7), we can state the following:

$$\left[E_{t-1}(R_t) - r_f\right] / (\theta * Var(R_t)) + \rho\left(R_{t-1} - r_f\right) = 1 \tag{8}$$

Equation (8) can now be re-expressed as an equation containing a stochastic residual, if we set the following: $r_t = R_{t-1} - r_f$ and $r_t + \varepsilon_t = E_{t-1}(R_t) - r_f$. When both of these are substituted into Equation (8), we can express the following:

$$r_t = \theta\sigma_t^2 - \rho(\theta * Var(r_t)\Big)(r_{t-1}) + \varepsilon_t \tag{9}$$

As discussed earlier, and consistent with modern portfolio theory and the notion that investors seek to optimize their mean-variance expected utility, we expect to see a positive and significant sign for θ. If we do see this, it is evidence of a positive risk–return tradeoff in the context of Merton (1980).

Focusing our attention on the parameter term $-\rho(\theta * Var(r_t))(r_{t-1})$ can help us decipher the impact of any feedback trading, positive or negative, within the dynamics of each ESG fund's return series. For example, if positive-feedback trading is present (i.e., ρ is positive), then this will induce a negative autocorrelation pattern in returns. Such negative autocorrelation is commensurate to the degree of conditional volatility, $Var(r_t)$. For example, herding behaviors (positive-feedback trading) during periods of high price volatility cause greater autocorrelation compared to low price volatility periods. Conversely, a negative and significant sign for ρ (negative-feedback trading) would result in positive autocorrelation, since we now have $-(-\rho(\theta * Var(r_t))(r_{t-1}))$. Again, and in this scenario, the extent of the positive autocorrelation will depend on $Var(r_t)$.

Consistent with Lo and MacKinlay (1990), we can algebraically simplify Equation (9), and, in order to account for any autocorrelation due to non-synchronous trading and other such market frictions, express it in the following way:

$$r_t = b_0 + b_1 Var(r_t) + (b_2 + b_3 Var(r_t))(r_{t-1}) + \varepsilon_t \tag{10}$$

Equation (10) is now a more tractable model that can be estimated in order to detect the presence of herding (feedback) behaviors in our sampled ESG funds. We will refer to Equation (10) as our "base model". This model still has not integrated rises and declines in TEU, which we discuss in the proceeding sub-section. In the case of Equation (10), $b_1 = \theta$ and $b_3 = -\rho(\theta)$. The constant term, b_0, may serve to account for information not contained within the other coefficients. It is important to note that Equation (10) simplifies to the classical Merton (1980) intertemporal capital asset pricing model (ICAPM) in the event that herding (feedback) traders are not present (i.e., $b_3 = 0$).

Finally, another consideration that needs to be made is the use of a conditional volatility model to estimate Equation (10). Following, among others, Lo and MacKinlay (1988) and Nelson (1991), this study utilizes AR(1)-EGARCH(1,1) to extract time-series estimates from the respective ESG funds' raw AR(1)-fitted return series, R_t:[7]

$$\ln\left(\sigma_t^2\right) = a_0 + a_1\left|\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right| + a_2\left(\frac{\epsilon_{t-1}}{\sigma_{t-1}}\right) + a_3\ln\left(\sigma_{t-1}^2\right) \tag{11}$$

whereby the term $|\epsilon_{t-1}/\sigma_{t-1}|$ is the absolute value of the standardized innovations. The coefficients a_2 and a_3 represent volatility asymmetry and persistence (Koutmos 2011; Nelson 1991).

When estimating ESG funds' conditional variance using Equation (11), an important consideration to make is the assumption for the distribution of the standardized innovations. While a standard normal distribution is often used, a potential drawback to this is that standardized GARCH-derived innovations may display thicker tails than a theoretical normal distribution. Thus, this study estimates the conditional variance using the generalized error distribution (GED), which has the following density function:

$$f(\mu_t, \sigma_t, v) = (v/2)[\Gamma(3/v)]^{1/2}[\Gamma(1/v)]^{-3/2}(1/\sigma_t)exp\left(-[\Gamma(3/v)/\Gamma(1/v)]^{v/2}\left|\varepsilon_t\middle|\sigma_t\right|\right) \quad (12)$$

whereby $\Gamma(.)$ is the gamma function. v denotes a scale parameter that is endogenously estimated. For example, and when $v = 2$, the GED will yield a normal distribution. In addition, and for $v = 1$, we have a Laplace distribution. Finally, the log likelihood over each sampled fund is expressed as follows:

$$L(\theta) = \sum_{t=1}^{T} \log f(\mu_t, \sigma_t, v) \quad (13)$$

whereby the conditional mean and standard deviation are denoted as μ and σ, respectively. Given that there are nonlinearities in the parameters of Equation (13), numerical maximization methods are needed. This study utilizes the algorithm of Berndt et al. (1974) for model estimations.

3.2. Gauging the Impact of Twitter Economic Uncertainty

In order to incorporate the information content of TEU and to gauge whether fluctuations in investor optimism and pessimism play any role in herding behaviors, we modify Equation (10) (our base model). As discussed, this study integrates the Baker et al. (2021) TEU index, given that fluctuations in investor sentiment can very well have an impact on how traders behave. This index is arguably a forward-looking proxy for sentiment that is constructed using the Twitter API to extract all available English tweets containing a keyword that is related to uncertainty. The following four keywords are considered, respectively: "uncertain", "uncertainties", and "uncertainty". Figure 2 shows a time-series plot of TEU from 1 June 2011 to 21 April 2023. The starting period of 1 June 2011 is the earliest starting period among all the sampled funds (DFSIX, ICLN, and ERTH). As can be seen from Figure 2, TEU reached its record high at the height of the COVID-19 pandemic, and while it reached a low point in 2021, it seems to be on the rise again in recent months. Another point worth noting is the rise in TEU during 2011, when the European debt crisis featured prominently in the financial press.

To incorporate TEU, Equation (10) is modified to integrate increases and decreases in this index. Using Sentana and Wadhwani (1992) as our theoretical foundation, and motivated by, among others, Chau et al. (2011) and Chau et al. (2016), we re-cast Equation (10) to allow for the inclusion of a dummy variable, D_t, to account for whether there is a rise $(D_t = 1)$ or decline $(D_t = 0)$ in TEU relative to the previous trading day:

$$\begin{aligned} r_t = b_{0,D}D_t + b_{0,ND}(1 - D_t) + b_{1,D}D_t Var(r_t) + b_{1,ND}(1 - D_t)Var(r_t) \\ +D_t(b_{2,D} + b_{3,D}Var(r_t))(r_{t-1}) + (1 - D_t)(b_{2,ND} + b_{3,ND}Var(r_t))(r_{t-1}) + \varepsilon_t \end{aligned} \quad (14)$$

As in Equation (10), Equation (14) is estimated using the EGARCH specification in Equation (11). In addition, the GED distribution for the EGARCH innovations (Equation (12)) and the log likelihood (Equation (13)) are utilized in order to maintain consistency. To distinguish it from Equation (10), and for the purposes of this study, we will refer to Equation (14) as our "extended model".

Interpretations for the coefficients in Equation (14) are qualitatively analogous to our base model. The important distinction now is whether the coefficients are estimated during a time when investor sentiment is deteriorating (i.e., TEU is rising, $D_t = 1$), or when it is improving (i.e., TEU is declining, $D_t = 0$). In all, the following parameters contain the subscript D: $b_{0,D}$ (the constant term), $b_{1,D}$ (which reflects the behavior of mean-variance optimizing traders), $b_{2,D}$ (the autocorrelation coefficient), and $b_{3,D}$ (the behavior of herding traders), respectively. Again, all these parameters are estimated during a time when there are rises in TEU. Conversely, parameters with the subscript ND (no dummy) represent (and with a similar interpretation) the trading days for which $D_t = 0$, whereby TEU is declining.

Through estimating Equation (14), we can detect whether the coefficients exhibit similar signs and degrees of significance across periods of rising and falling sentiment. If in the extended model we see similar signs with the base model and no significance for the parameters which contain a dummy variable, we can conclude that traders in ESG markets may not be influenced by fluctuations in investor sentiment when making their buy and sell decisions. If we do see differences in parameter estimates between the base model and extended model, or if we see that parameters which do contain a dummy variable are significant, this gives us some evidence that investor sentiment does play a role in traders' behaviors in ESG markets.

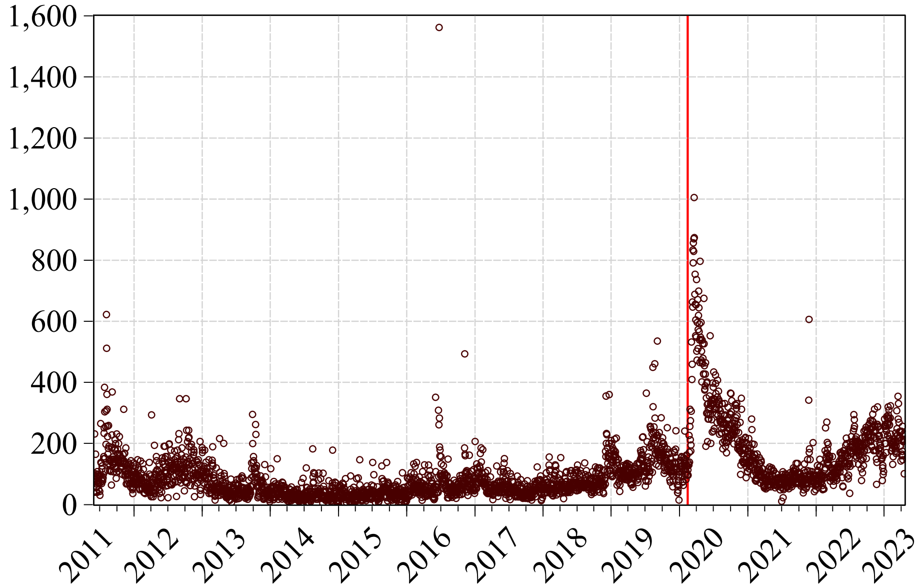

Figure 2. Time-series plot of Twitter-based economic uncertainty. Notes: This figure shows a time-series plot of the daily Twitter-based economic uncertainty (TEU) index of Baker et al. (2021) that is used in this study. The sample range is from 1 June 2011 to 21 April 2023. The vertical red line denotes when the World Health Organization (WHO) announced the official name for "COVID-19" on 11 February 2020 (see https://www.cdc.gov/museum/timeline/covid19.html).

4. Discussion of Findings

This section discusses coefficient estimates for the "base" herding model in Equation (10) and the "extended" herding model in Equation (14), which integrates TEU in order to gauge the impact fluctuating investor sentiment and uncertainty have on herding behaviors. Broadly speaking, and as discussed, the motivation for exploring herding behavior in ESG markets is as follows. First, given that these markets are rapidly growing in terms of their size and importance, they are likely to have a growing influence on our financial system and its future development. Second, herding behaviors can have an impact on the evolution of assets' prices. For example, as shown in Equations (8) and (9), the autocorrelation structure in asset returns can very much depend on the type of herding (positive- or negative-feedback trading) as well as the degree of price volatility. Third, while we typically see herding behaviors in traditional asset markets, such as equity markets and indexes, it is of interest to see whether such trading behaviors exist in ESG markets. In the words of Devenow and Welch (1996), "…imitation and mimicry are perhaps among our most basic instincts…investors are influenced by the decisions of other investors…" (p. 603). Finally, it is of interest to ascertain (and quantify) whether fluctuations in the daily Baker et al. (2021) TEU index, which is used to proxy for investor sentiment and uncertainty, plays a role in herding activity. The regression equations in Equations (10) and (14), respectively, have the advantage of being empirically tractable and can be applied to a range of various asset markets.

Results for the base model (Equation (10)) are shown in Table 3. These results serve as a good starting point for our discussion, prior to examining whether TEU plays a role in herding (as shown in Table 4). In the case of our base model, the parameters of primary interest are b_1 and b_3, which show the nature of the risk–return tradeoff and whether (and in what direction) herding is present, respectively.

Table 3. Herding model estimates without TEU.

Index Fund	Base Model Parameters			
	b_0	b_1	b_2	b_3
1. ESGU	0.0920 ** (2.732)	−0.0483 ** (−3.952)	0.0093 (0.314)	−0.0199 ** (−10.214)
2. ESGV	0.1234 ** (2.550)	−0.0580 ** (−4.069)	0.0254 (0.715)	−0.0201 ** (−8.619)
3. ESGD	0.0367 (1.203)	−0.0234 * (−1.794)	0.0116 (0.395)	−0.0176 ** (−6.917)
4. DFSIX	0.0421 * (1.718)	−0.0115 (−1.062)	0.0187 (0.865)	−0.0147 ** (−7.048)
5. FITLX	0.0845 ** (2.409)	−0.0349 ** (−3.632)	−0.0150 (−0.493)	−0.0138 ** (−9.068)
6. VSGX	0.1960 (1.177)	−0.1376 (−1.119)	−0.5669 (−0.727)	0.2976 (0.521)
7. ICLN	0.0354 (0.848)	−0.0127 (−1.257)	0.1103 ** (4.719)	−0.0135 ** (−6.958)
8. EFAX	−0.0081 (−0.214)	0.0145 (0.613)	0.0287 (0.837)	−0.0445 ** (−6.440)
9. XVV	−0.0042 (−0.058)	0.0241 (0.630)	−0.0220 (−0.306)	0.0090 (0.357)
10. SDG	0.1668 ** (4.527)	−0.1473 ** (−5.302)	0.0078 (0.274)	−0.0493 ** (−9.876)
11. ALPS	0.0722 (0.852)	−0.0085 (−0.820)	0.1069 ** (2.799)	−0.0081 ** (−4.729)
12. ETHO	0.0622 * (1.832)	−0.0201 * (−1.871)	0.0187 (0.664)	−0.0118 ** (−5.617)
13. ESG	0.0935 ** (2.824)	−0.0365 ** (−3.989)	0.0028 (0.097)	−0.0147 ** (−8.239)
14. ERTH	0.0150 (0.455)	−0.0036 (−0.323)	0.0886 ** (3.800)	−0.0185 ** (−7.499)
15. XJR	−0.2148 (−1.097)	0.1283 (1.349)	−0.0255 (−0.232)	0.0141 (0.324)
16. CTEC	−0.1513 (−0.498)	0.0194 (0.419)	0.2213 ** (2.113)	−0.0204 * (−1.682)

Notes: This table reports maximum likelihood estimates for the "base" herding model in Equation (10) for the sampled ESG funds that are explored in this study. The conditional variance is estimated using the EGARCH model in Equation (11). Parentheses show t-statistics, whereby (*) and (**) denote significance at the 10% and 5% levels, respectively.

Table 4. Herding model estimates with TEU.

Index Fund	$b_{0,D}$	$b_{0,ND}$	$b_{1,D}$	$b_{1,ND}$	$b_{2,D}$	$b_{2,ND}$	$b_{3,D}$	$b_{3,ND}$
1. ESGU	0.1270 ** (2.640)	0.0239 (0.505)	−0.1741 ** (−9.224)	0.0989 ** (4.982)	0.0134 (0.287)	−0.0257 (−0.691)	−0.0113 ** (−2.596)	−0.0070 ** (−2.721)
2. ESGV	0.1912 ** (2.737)	−0.0144 (−0.206)	−0.1725 ** (−7.736)	0.0953 ** (3.964)	0.0147 (0.258)	−0.0196 (−0.437)	−0.0124 ** (−2.264)	−0.0051 (−1.593)
3. ESGD	0.0569 (1.279)	−0.0120 (−0.281)	−0.1604 ** (−7.173)	0.1294 ** (6.277)	0.0489 (1.030)	−0.0556 (−1.501)	−0.0047 (−0.611)	−0.0010 (−0.327)
4. DFSIX	0.0824 ** (2.375)	−0.0043 (−0.126)	−0.1135 ** (−7.397)	0.0899 ** (5.860)	0.0218 (0.629)	−0.0019 (−0.067)	−0.0156 ** (−3.290)	−0.0067 ** (−2.731)
5. FITLX	0.0977 ** (1.979)	0.0327 (0.673)	−0.1316 ** (−8.883)	0.0833 ** (5.434)	−0.0041 (−0.086)	−0.0544 (−1.431)	−0.0086 ** (−2.420)	−0.0033 * (−1.675)
6. VSGX	−0.4374 (−0.875)	0.1850 (0.596)	0.2507 (0.686)	−0.0506 (−0.223)	−2.8512 (−1.346)	0.2657 (0.397)	2.0217 (1.272)	−0.3093 (−0.651)
7. ICLN	0.0796 (1.289)	−0.0405 (−0.685)	−0.0618 ** (−3.951)	0.0461 ** (3.145)	0.1250 ** (3.184)	0.0914 ** (2.977)	−0.0171 ** (−3.709)	−0.0083 ** (−3.589)
8. EFAX	0.0241 (0.429)	−0.0827 (−1.556)	−0.1191 ** (−3.275)	0.1807 ** (5.353)	0.1068 * (1.858)	−0.0173 (−0.398)	−0.0674 ** (−4.060)	−0.0215 ** (−2.665)
9. XVV	−0.2619 ** (−2.517)	0.2395 ** (2.839)	0.1311 * (1.726)	−0.0766 (−1.160)	−0.0521 (−0.382)	0.0102 (0.131)	0.0463 (0.644)	−0.0186 (−0.660)
10. SDG	0.3597 ** (6.256)	−0.1117 * (−1.881)	−0.4366 ** (−9.270)	0.2247 ** (4.465)	−0.0449 (−0.935)	−0.0151 (−0.418)	−0.0128 (−0.943)	−0.0085 (−1.176)
11. ALPS	0.1599 (1.233)	−0.0195 (−0.162)	−0.0579 ** (−3.294)	0.0412 ** (2.679)	0.0497 (0.732)	0.1141 ** (2.256)	−0.0047 (−0.884)	−0.0052 ** (−2.505)
12. ETHO	0.1232 ** (2.591)	−0.0114 (−0.243)	−0.1347 ** (−8.842)	0.0981 ** (6.253)	−0.0082 (−0.181)	0.0057 (0.162)	−0.0039 (−0.815)	−0.0026 (−1.028)
13. ESG	0.1130 ** (2.454)	0.0497 (1.074)	−0.1119 ** (−9.069)	0.0522 ** (3.656)	0.0222 (0.466)	−0.0428 (−1.167)	−0.0104 ** (−3.266)	−0.0073 ** (−3.133)
14. ERTH	0.0524 (1.080)	−0.0553 (−1.189)	−0.0703 ** (−4.103)	0.0791 ** (4.848)	0.1013 ** (2.579)	0.0750 ** (2.484)	−0.0253 ** (−4.167)	−0.0101 ** (−3.446)
15. XJR	−0.5256 * (−1.815)	0.0801 (0.300)	0.2489 * (1.744)	0.0185 (0.145)	−0.1422 (−0.620)	0.0450 (0.339)	0.0556 (0.563)	−0.0107 (−0.211)
16. CTEC	−0.4557 (−1.038)	0.1679 (0.396)	0.0521 (0.769)	−0.0159 (−0.247)	0.2197 (1.614)	0.1861 (1.092)	−0.0224 (−1.460)	−0.0136 (−0.670)

Notes: This table reports the maximum likelihood estimates for the "extended" herding model in Equation (14) for the sampled ESG funds that are explored in this study. The conditional variance is estimated using the EGARCH model in Equation (11). Parentheses show t-statistics whereby (*) and (**) denote significance at the 10% and 5% levels, respectively.

At the 5% level of statistical significance, five out of the sixteen sampled ESG funds (ESGU, ESGV, FITLX, SDG, and ESG, respectively) show a negative sign for the parameter b_1. At the 10% level of significance, two of the sixteen show a negative sign (ESGD and ETHO). The remaining funds show weak evidence of any risk–return relation. While more work is needed in deciphering the risk–return tradeoffs of various ESG markets and investments, the evidence herein shows that ESG markets exhibit several of the same risk–return qualities which traditional asset markets show. Namely, and as is well-documented in prior studies, these markets show evidence of a "volatility feedback effect", which theorizes that rises in investors' required rate of return (due to rises in perceived risk) put downward pressure on underlying assets' prices (Campbell and Hentschel 1992; French et al. 1987; Koutmos 2015). This is an interesting finding, since despite the potentially distinct investor clientele which ESG markets attract, they appear to exhibit some similar risk–return features in their price changes (Eccles et al. 2017; Kräussl et al. 2024).

The statistical significance, and signs, of the parameter b_3 show consistent evidence in support of the notion that herding behaviors are present and have an impact on these sampled ESG funds' price changes. Specifically, and at the 5% level of statistical significance, twelve out of the sixteen funds have a negative sign for b_3. Of the remaining funds, CTEC shows a negative sign, albeit at the 10% level of significance. As discussed, a negative sign for b_3 (i.e., positive-feedback trading) indicates bandwagon, or trend-chasing, behaviors whereby investors buy more shares of the asset during recent price increases and sell during recent price decreases. Such behavior leads to a negative sign for b_3 as well as a negative autocorrelation pattern in their price changes that is commensurate to the level of conditional volatility observed on the given trading day.

The results for the extended model (Equation (14)) show a more granular picture of the funds' risk–return tradeoffs and herding behaviors during periods of rising and falling TEU. These results are shown in Table 4. As in the base model, the primary parameters of interest are b_1 and b_3. Unlike the base model, however, we will now see, using the dummy variable D_t, whether there are changes in the natures of the parameters when there is a rise $(D_t = 1)$ or decline $(D_t = 0)$ in TEU.

In the case of b_1, an interesting and consistent pattern emerges. In all the sampled ESG funds (with the exception of VSGX, XVV, XJR, and CTEC), it can be seen that rises and declines in TEU can be directly linked with investors' risk aversion. With the exception of those few funds, all the ESG funds exhibit a positive risk–return tradeoff during trading days when TEU declines $(D_t = 0)$ and a negative risk–return tradeoff during trading days when TEU rises $(D_t = 1)$. These findings are statistically significant at the 5% level at least. They show support for the notion that TEU can serve as a forward-looking proxy to investor sentiment and that this sentiment is linked with investors' willingness to take risks.

While TEU is powerful in influencing the ESG funds' risk–return tradeoff, the evidence also shows it may exacerbate the degree of herding (positive-feedback trading). In six of the sixteen ESG funds (ESGU, DFSIX, ICLN, EFAX, ESG, and ERTH), the parameter $b_{3,D}$ is statistically significant at the 5% level at least. When comparing the sizes of the coefficient estimates, $b_{3,D}$ are larger in size relative to $b_{3,ND}$. This shows that a deterioration in investor sentiment (i.e., rises in TEU) can fuel herding behaviors in these funds. An interesting exception is the case of ALPS, whereby herding behaviors are detected in $b_{3,ND}$ but not $b_{3,D}$.

An overall view of the coefficients in Tables 3 and 4 lends credence to the following observations. First, herding behaviors, and specifically, positive-feedback trading, are present in these markets despite differences they may have in their investor clientele (relative to traditional asset markets such as equity markets). Second, the risk–return tradeoff is shown to be negative when not accounting for rises and declines in TEU (Equation (10)). When these rises and declines are accounted for (Equation (14)), it appears that this relation becomes more nuanced, showing instead that periods of investor pessimism potentially drive this negative sign. From the perspective of investors and regulators, the findings herein suggest that ESG markets, and their constituent assets' prices, can be prone to the same types of feedback trading pressures which can afflict traditional asset markets. In addition, and for investors seeking particular risk premia within ESG markets, it is important for them to understand how social media sentiment can play a role in these assets' mean-variance relations. In addition, such sentiment can very well amplify feedback trading within these markets.

5. Concluding Remarks

In recent years, interest and attention to ESG investing has grown among retail and institutional investors as well as policymakers and regulators. This study explores some of the budding literature in this field and builds an empirically tractable model in order to gauge the extent to which herding behaviors are present in ESG markets. Using a sample of some of the largest and most popular ESG funds available to investors, it shows that, similar to what we see in traditional asset markets, herding behaviors are indeed present in such markets. In addition, this study builds an extended model that integrates fluctuations in investor sentiment. For this purpose, the TEU index by Baker et al. (2021) was utilized. The results show that, while herding behaviors are generally consistently present in such markets, economic uncertainty (investor pessimism) can potentially exacerbate such herding. In addition, and while ESG funds generally show a negative risk–return tradeoff, as is often identified in traditional asset markets, it appears that economic uncertainty stemming from social media can very much impact this tradeoff in ESG markets.

Future research into ESG markets can take several avenues based on the significance of the findings herein. Firstly, it is shown here that the herding behaviors we typically see in traditional asset markets also exist in ESG markets. This leads to the question of *are ESG markets integrated with other asset markets?* If they are integrated, this has implications in terms of investors' diversification opportunities in such markets. Secondly, more comprehensive and empirical investigations are needed, specifically on the nature of the risk–return tradeoff in ESG markets. The preliminary evidence herein shows that this tradeoff can very much change depending on fluctuations in investor sentiment. Thirdly, and given the aforementioned questions, it is worth exploring whether investors are provided with material incremental benefits (in terms of diversification and risk management), given the ESG funds' expense ratios (management fees) which they are subject to. Finally, future research should propose novel proxies for herding and feedback trading that are specific to ESG markets and their potentially unique investor clientele. As discussed earlier, several proxies and modeling approaches can be utilized to detect herding-type behaviors, such as feedback trading, within financial markets. Future research should look into discovering more such models to decipher how investors behave within ESG markets.

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Data Availability Statement: The data presented in this are available in Morningstar (https://www.morningstar.com), Fidelity (https://www.fidelity.com), Vanguard (https://investor.vanguard.com), BlackRock (https://www.blackrock.com), Invesco (https://www.invesco.com), and the ETF Database (https://etfdb.com). Data on Twitter Economic Uncertainty is available at Economic Policy Uncertainty (https://www.policyuncertainty.com/index.html).

Conflicts of Interest: The author declares no conflict of interest.

Notes

1 The current PRI Strategic Plan for 2021–24 is publicly available here: https://www.unpri.org/about-us/pri-2021-24-strategy (accessed on 1 April 2024).

2 More information, including reporting and assessment responsibilities which signatories must commit to, is publicly available here: https://www.unpri.org/signatories (accessed on 1 April 2024).

3 On 14 April 2022, Elon Musk began acquiring Twitter, and, by 28 October 2022, this acquisition was completed. Twitter is now known as "X". For purposes of this study, "Twitter" and "X" may be used interchangeably. Statistics on US adult usage of Twitter (X) are publicly available from the Pew Research Center here: https://www.pewresearch.org/short-reads/2023/07/26/8-facts-about-americans-and-twitter-as-it-rebrands-to-x/ (accessed on 1 April 2024).

4 See more information on company 'ESG risk ratings' from Morningstar here: https://www.sustainalytics.com/esg-ratings (accessed on 1 April 2024).

5 See Morningstar's 2023 Annual US Fund Fee Report here: https://www.morningstar.com/lp/annual-us-fund-fee-study (accessed on 1 April 2024).

6 The 1-month treasury maturity is used to calculate the daily holding period return of the risk-free rate, r_f. The calculation is based on duration, assuming that yields to maturity (YTM) correspond to bonds' par value. By doing so, the 1-month yield, expressed in daily terms as a holding period return, can be compared to changes in other daily return series.

7 Several other GARCH variants are also entertained, such as the standard symmetric GARCH, as well as asymmetric GJR-GARCH. The results are qualitatively consistent to what is reported when using the EGARCH specification in Equation (11). A (1,1) specification is estimated in view of the fact that others also show that lower order GARCH models are sufficient in modeling the conditional variance of asset returns (Bollerslev et al. 1992). These results, as well as various GARCH diagnostic tests, are not tabulated for brevity but available upon request.

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