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Attention, ESG, and Retail Investor Stock Holdings

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ABSTRACT
This study examines retail investors' stock purchase-, hold-, and sell-decisions based on two factors: how much attention the stocks get and their environmental, social, and governance (ESG) ratings. We use Google search data, ESG ratings from five different providers, and various market indicators to account for overall climate change concerns, environmental awareness, and market sentiment. We discover that retail investors' purchase-, hold-, and sell-decisions are related to a stock's abnormal Google search volume, ESG ratings, returns, analyst recommendations, and market sentiment. Importantly, this study is the first to identify factors that influence retail investors' decisions to hold or sell stocks.

KEYWORDS
Attention; ESG; Google search volume; Investor behavior; Sustainability

JEL CODES
G11; G12; G14; G24

Introduction

In their seminal paper, Barber and Odean (2008) find that retail investors tend to buy stocks that attract their attention. These are stocks that are in the news, have high abnormal trading volumes, and extreme returns. Barber and Odean (2008) suggest that because people have limited cognitive resources, they are unable to monitor, evaluate, and rank thousands of stocks. As a result, retail investors narrow their choice set to those stocks that catch their attention and buy only stocks from that set.

However, it is difficult to identify what attracts investors' attention. Da, Engelberg, and Gao (2011) point out that news coverage, stock turnover, and returns are only indirect proxies for investor attention, based on the assumption that retail investors actually pay attention when a stock's return or turnover is extreme or when the stock's name is mentioned in the news media. In contrast, Google search volume is an advanced, direct measure of attention that is related to stock returns (Cziraki, Mondria, and Wu 2021; Da, Engelberg, and Gao 2011, 2015). In this sense, we define the attention-grabbing features of a stock as all information that can draw investors' attention to this stock and potentially trigger an investment decision. Moreover, we use the abnormal Google search volume for a company provided by Google Trends as attention measure.

Interestingly, Starks (2023) begins her presidential address to the American Finance Association with the words "While sustainable finance has been drawing increased attention from institutional and retail investors […]" (p. 1837). This statement suggests that it is not only the most recent and frequently changing information, such as stock returns, that may attract the attention of retail investors. Instead, the sustainability characteristics of stocks may also be a relevant filter to limit the choice set, at least for those investors with a preference for stocks with high ESG ratings (Bauer, Ruof, and Smeets 2021; Brodback, Guenster, and Mezger 2019; Horn 2023). It is therefore not surprising that sustainability information significantly influences investment flows (Baily et al. 2024; Benson and Humphrey 2008; Bialkowski and Starks 2016; Hartzmark and Sussman 2019; Latino, Pelizzon, and Rzeznik 2021).

Sustainability and attention-grabbing information are not isolated from each other. A firm's ESG ratings are a predictor of its future news (Serafeim and Yoon 2023), and ESG-related news can have an influence on stock returns (Capelle-Blancard and Petit 2019). However, it is unclear how retail investors weight ESG ratings and attention-grabbing stock characteristics in investment decisions. Are stocks with high ESG ratings and unspectacular returns bought on net or overlooked by retail investors? Do retail investors buy

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stocks with attention-grabbing features and low ESG ratings?

This study aims to answer these questions. We use the securities holdings statistics of the German central bank, which is a representative sample of retail investors' stock holdings. The database covers all securities holdings of retail investors with portfolios at German banks at the end of a month. The sample period runs from January 2013 to December 2019. We analyze monthly changes in aggregate stock ownership, i.e. whether a stock is net bought, held, or net sold by retail investors in a given month. Thus, our study provides a different perspective than recent studies using retail broker trading data (e.g. Barber et al. 2022; Welch 2022). Our focus is less on extreme price movements of a few stocks and more on the aggregate behavior of all retail investors, also including those with high inertia (see e.g. Bonaparte and Cooper 2009; Brunnermeier and Nagel 2008), to assess the existence and the economic impact of attention-induced trading and ESG preferences for the entire retail sector.

We use abnormal Google search volume from Google Trends, stock returns, absolute and maximum returns, abnormal turnover, analyst ratings, and ESG ratings from five sources as explanatory variables. We also consider how investor preferences for sustainable stocks (Ardia et al. 2023; Horn et al. 2023; Pástor, Stambaugh, and Taylor 2022) and market sentiment, measured by investors' greed and fear (Da, Engelberg, and Gao 2015), change over time.

The present study follows the approach of Barber and Odean (2008) and utilizes an attention measure to construct portfolios. This approach enables us to assess the efficacy of abnormal Google search volume as a metric for measuring retail investors' attention and to delve into the repercussions of attention-induced trading for the collective of all German retail investors. Utilizing a range of analytical techniques, including panel logit and panel multinomial logit regression analyses, we seek to identify the impact of additional attention-grabbing stock features, ESG ratings, and other pertinent control variables on the purchase-, hold-, and sell-decisions of retail investors.

The evidence presented herein indicates a correlation between the ESG ratings, returns, and analyst recommendations of stocks, as well as other attention-grabbing features that are proxied by abnormal Google search volume and market sentiment, and the purchase-, hold-, and sell-decisions of retail investors in the same month. Portfolio sorting reveals a positive correlation between abnormal Google search volume and stock returns in the same month, but not in the following month. Logit regressions demonstrate that retail investors exhibit a net buying tendency toward stocks characterized by elevated abnormal Google search volume, diminished returns, augmented trading volume, and recent analyst downgrades. Investors demonstrate a propensity to acquire equities with elevated ESG ratings during periods characterized by heightened climate change concerns, and subsequently divest during periods of diminished concern. This lends further credence to the hypothesis that retail investors' preferences for sustainability are unstable. As retail investors' propensity for greed increases, they net purchase more stocks while selling more stocks in times of greater fear. Furthermore, stocks that are rarely googled are much more likely to be neither net sold nor net purchased by retail investors. Investors tend to sell stocks with low search volume, higher returns, and recent analyst upgrades. The utilization of Google Trends data has revealed that the search volume of the initial search term suggested by Google in the *Business News* category exhibits a stronger correlation with the investment decisions of retail investors than the overall search volume of a designated search term.

This study makes several contributions to the extant literature. Firstly, to the best of our knowledge, our study is the first to combine ESG characteristics of stocks with their attention-grabbing features and market-wide measures of climate change concerns, environmental awareness, and sentiment to explain retail investors' investment decisions. Secondly, by identifying stock features that are significantly correlated with hold- and sell-decisions, our work extends previous studies of attention-driven trading that find significant determinants of purchase-decisions. Thirdly, we find further support for the trading patterns identified by Barber and Odean (2008) and Barber et al. (2022) among the entire population of German retail investors.

The findings of this study have implications for both researchers and practitioners. Firstly, we find further evidence that retail investors' attention is drawn to certain stocks, which are more likely to be net purchases by retail investors. Secondly, we find that preferences for ESG investments and climate change hedging motives also play a role. Thirdly, we additionally identify stock characteristics that are correlated with sell- and hold-decisions. Fourthly, the monthly dataset is not sufficiently frequent to facilitate effective forecasting of retail investors' investment decisions. Consequently, financial authorities and researchers can utilize high-frequency Google search volume data to identify stocks that attract retail investors' attention, for instance, as an indicator of potential market disruptions. It may be advantageous to focus on the search volume of the *Business News* category rather than the overall search volume.

The remainder of the paper is structured as follows. The subsequent section will be dedicated to a review of the extant literature. Data, variables, and methodology are described in the "Data and methodology" section. The "Results and discussion" section summarizes and discusses the results of the empirical analysis. We conclude and provide implications and paths for further research in the "Conclusion" section.

Literature review

Attention-driven trading

Traditional financial theories posit that investors have access to all pertinent information and the capacity to prioritize it during analysis and decision-making processes (Hou, Peng, and Xiong 2009; Yang et al. 2021). However, the cognitive processing capacity of the human brain is limited, rendering investor attention a rare resource (Barber and Odean 2008; Hou, Peng, and Xiong 2009; Pashler and Johnston 1998; Yang et al. 2021; Yuan 2015). Moreover, the information environment has undergone substantial changes in recent years, with investors confronted with an overwhelming volume of information, a digital environment, and numerous distractions such as social media messages or push notifications (Arnold, Pelster, and Subrahmanyam 2022; Barber et al. 2022; Yang et al. 2021). According to Kahneman (1973), an excess of information can result in a state of "attentional poverty", characterized by the failure to pay adequate attention to crucial details due to their obscurity within the overwhelming amount of information (Kahneman 1973; Yang et al. 2021).

The investment decisions of retail investors exhibit patterns that can be explained by their limited cognitive processing capacity. Barber and Odean (2008) posit that investors encounter greater ease in evaluating a limited number of investment alternatives than in evaluating a vast array of options across multiple dimensions. Consequently, investors are more likely to consider investment options that attract attention when making purchase decisions, while disregarding options that attract less attention (Barber and Odean 2008; Odean 1999). This phenomenon underscores the notion that attention plays a pivotal role in investor decision-making (Hou, Peng, and Xiong 2009). Investors tend to allocate their attention to local stocks, stocks with extreme returns, abnormally high trading volume, news coverage, and a high market capitalization (Barber and Odean 2008; Gargano and Rossi 2018; Odean 1999; Yang et al. 2021). However, the specific stock selected for purchase depends on investors' individual preferences (Barber and Odean 2008; Odean 1999). In contrast, the authors did not observe attention-driven selling behavior, as retail portfolios consist of a limited number of shares and retail investors do not engage in short selling (Barber and Odean 2008).

In light of these findings, Da, Engelberg, and Gao (2011) advanced a novel approach to measuring investors' stock-specific attention using Google search volume. It is acknowledged that news coverage, stock turnover, and returns serve as indirect proxies for investor attention. This is predicated on the assumption that retail investors exhibit heightened attention when a stock's return or turnover reaches an extreme level or when the stock's name is featured in news media. In contrast, Google search volume offers a direct and advanced measure of attention. The work of Da, Engelberg, and Gao (2011, 2015) and Cziraki, Mondria, and Wu (2021) shows that an increase in Google search frequency serves as a harbinger of an impending escalation in stock prices, followed by relative underperformance in the following year. In the context of a more digitalized information environment, Google search volume emerges as a more precise indicator of attention compared to the indirect measures proposed by Barber and Odean (2008). In Germany, Google's search engine market share is approximately 90%.

Recent observations have revealed that fintech brokerage or mobile applications may influence trading behavior through gamification, simplicity, and commission-free trading (Barber et al. 2022). These applications offer distinctive features, such as "top movers lists," that motivate particularly inexperienced users to engage in attention-driven trading. This phenomenon has the potential to adversely impact future returns, and its influence on market returns is a subject of concern (Seasholes and Wu 2007). Conversely, enhanced transparency or platform outages have been shown to curtail attention-based trading, thereby enhancing investment returns (Barber et al. 2022; Gao et al. 2024).

Seasholes and Wu (2007) and Yuan (2015) conducted a series of studies on the temporal dynamics of market-wide attention and the impact of attention-grabbing events. They find that specific market-wide attention events, such as record levels of the Dow Jones, front-page articles about the stock market, or recent stock performance, increased investor attention and led to higher trading activity. Consequently, the individual effects observed by Barber and Odean (2008) become more pronounced in the context of such events, leading retail investors to purchase previously non-owned attention-grabbing stocks (Seasholes and Wu 2007; Yuan 2015). Consequently, attention-based trading behavior may exert an influence on market returns (Yuan 2015). On the one hand, high investor attention in up markets can promote price overreactions; on the other hand, limited investor attention leads to underreactions of stock prices to earning news (Hou, Peng, and Xiong 2009).

A substantial body of research has examined the impact of investor attention within the cross section of stocks or in the context of market-attention in general (see Barber et al. 2022; Barber and Odean 2008; Da, Engelberg, and Gao 2011; Hirshleifer, Lim, and Teoh 2011; D. Luo 2014; Peress and Schmidt 2020; Yang et al. 2021; Yuan 2015). Concurrent studies have examined the influence of attention triggers on investors' risk taking (see, for example, Arnold, Pelster, and Subrahmanyam 2022) and the role of social media (Shen et al. 2019). In contrast to the extant literature, the present study focuses on the aggregate behavior of all retail investors, including those with high inertia (see, for example, Bonaparte and Cooper 2009; Brunnermeier and Nagel 2008). The objective is to assess the existence and the economic impact of attention-induced trading for the entire retail sector.

ESG and investment behavior

Since the 21st United Nations Conference of the Parties (COP21) in December 2015, ESG-topics have gained significant prominence in the media and, consequently, have become a focal point for investors (Pelster, Horn, and Oehler 2024), particularly in regard to the environmental dimension (Benuzzi, Klaser, and Bax 2024). The predominant incentives and motives for considering ESG criteria in investment decisions are non-pecuniary aspects, hedging climate risks, and higher expected returns (Giglio et al. 2025; Riedl and Smeets 2017). Consequently, investments associated with ESG criteria, such as mutual funds with high ESG ratings, experience increased inflows when investors perceive ESG risk as relevant (e.g., Hartzmark and Sussman 2019; Kim and Yoon 2023; Scherer and Hasaj 2023). Investors have been observed to be willing to accept lower returns in order to obtain non-pecuniary benefits of ESG investments (M. Baker, Egan, and Sarkar 2022; Barber, Morse, and Yasuda 2021; Bauer, Ruof, and Smeets 2021; Gutsche and Ziegler 2019).

However, the preferences of investors for ESG investments may be subject to change over time (D'Hondt, Merli, and Roger 2022; Giglio et al. 2025; Horn et al. 2023). These preferences are influenced by various factors, including the environmental awareness of the investors and their individual characteristics (see, for example, Assaf et al. 2024; Brodback, Guenster, and Mezger 2019; Dabbous, Horn, and Croutzet 2023; D'Hondt, Merli, and Roger 2022; Starks 2023). Choi, Gao, and Jiang (2020) posit that investors modify their beliefs concerning climate change during periods of anomalous warmth in their environment, resulting in heightened attention to climate change and subsequent outperformance of firms with lower carbon intensity. Baily et al. (2024) posit that mutual funds with superior sustainability ratings experience heightened inflows during periods of heightened climate change concern. Consequently, investors allocate capital to stocks with higher ESG ratings in the context of rising climate concerns (Baily et al. 2024; Fiordelisi, Galloppo, and Paimanova 2023). Pástor et al. (2021), Pástor, Stambaugh, and Taylor (2022) and Pedersen, Fitzgibbons, and Pomorski (2021) posit that an escalation in investor demand for ESG investments will culminate in heightened short-term returns, subsequently giving way to diminished returns over time (see also Ardia et al. 2023; Engle et al. 2020). Li, Watts, and Zhu (2024) observe that retail investors reallocate their portfolio capital only when the ESG news appears important for stock performance. However, the interpretation of ESG ratings as a reliable indicator of a company's ESG risk is hindered by several factors. These include the presence of conflicting ratings from different providers, the issue of greenwashing, and the lack of comprehensive information, which impedes the ability of retail investors to accurately assess the ESG risk of their investments and the financial implications of ESG events (Horn 2024).

Data and methodology

Securities holdings statistics of the German central bank

The securities holdings statistics of the German central bank (SHS-Base plus; https://doi.org/10.12757/SHSBaseplus.05122206) include micro data on securities holdings from December 2005 to the present. From December 2005 to December 2012, the data is reported on a quarterly basis. Since January 2013, financial institutions domiciled in Germany have been reporting securities that they hold for their customers on a monthly basis. Given the focus of our study on investor attention, we have elected to utilize only monthly data. The final point in time for the sample period is December 2019, a time shortly before the advent of the Covid-19 pandemic. This external shock considerably draws attention to pandemic-related topics, which should be of negligible relevance in other times. Consequently, the analysis is based on monthly data from January 2013 to December 2019.

Due to the implementation of the Statistical Disclosure Control (SDC) protocol by the Deutsche Bundesbank, it was necessary to omit certain observations from the analysis. The SDC mandates that results be based on a minimum of five distinct financial institutions. Consequently, a stock must be held in the portfolios of retail investors at a minimum of five financial institutions to be included in the analysis. Furthermore, the combined stock holdings of retail investors with portfolios at the two largest financial institutions may not exceed 85% of the holdings of all German retail investors in that stock. Given the substantial sample size of over 1500 financial institutions, the impact of the SDC restrictions is rendered negligible for the purposes of our analysis.

For each stock i, we sum up the aggregate holdings in Euros of all customers of all institutions covered in the SHS-Base plus per month t ($Holdings_{i,t}$). Following Fecht, Hackethal, and Karabulut (2018), we compute the share that the customers in the SHS-Base plus hold of a stock i ($Share_{i,t}$) by dividing $Holdings_{i,t}$ through the market capitalization of the stock in month t ($MCap_{i,t}$).

$$Share_{i,t} = \frac{Holdings_{i,t}}{MCap_{i,t}} \tag{1}$$

We are particularly interested in changes in retail investors' aggregated stock holdings from one month to the next ($\Delta Share_{i,t}$). We expect that small changes occur just because of noise. These changes are only of minor interest. Instead, our focus is on significant aggregated stock purchases and sales. Hence, we introduce a noise barrier (*NoiseBarrier*) that helps us differentiate between large, relevant changes and minuscule variations in stock holdings. We introduce dummy variables to indicate such significant purchases and sales.

$$DummyBuy_{i,t} = 1 \text{ if } \Delta Share_{i,t} > NoiseBarrier \tag{2}$$

$$DummySell_{i,t} = 1 \text{ if } \Delta Share_{i,t} < 0 - NoiseBarrier \tag{3}$$

$$DummyHold_{i,t} = 1 \text{ if } NoiseBarrier \geq \Delta Share_{i,t} \leq 0 - NoiseBarrier \tag{4}$$

$$\text{with } \Delta Share_{i,t} = Share_{i,t} - Share_{i,t-1} \tag{5}$$

We use these dummies as dependent variables in our analysis, corresponding to the aim of our study, which is to identify features that make retail investors buy or sell stocks rather than trying to estimate the exact amount by which retail investors increase or decrease their holdings. The latter would be influenced by several microstructure issues (free float, availability and use of derivatives and market makers, cross-listings of stocks etc.) and even retail investors' place of residence (see e.g. Baltzer, Stolper, and Walter 2015; Cziraki, Mondria, and Wu 2021), in combination with their investable wealth and demographics (Sicherman et al. 2016), that can be hardly controlled for due to some restrictions for the use of the SHS-Base plus.

The SHS-Base plus contains highly confidential data that must not leave the German central bank. Computations have been conducted during a guest researcher stay at the German central bank. Data for control variables must be selected in advance and transferred to the central bank. It is not possible to get a list of all securities covered in a time period. Hence, we had to preselect the stocks for the analysis.

Stock data

Due to the given restrictions, we focus on all stocks that have been listed at least once in the following indices. S&P/ASX Australia All Ordinaries, Hang Seng (Hong Kong), S&P/NZX 50 (New Zealand), Straits Times (Singapore), MSCI Europe All Cap, TOPIX (Japan), MSCI North America All Cap. With this selection, we cover all developed stock markets around the globe. Some Asian mid- and small-cap stocks may be missing. However, these stocks are hardly held by German investors. The stock price and daily total return data are from Thomson Reuters Datastream and survivorship-bias free.

ESG ratings data

We use the overall ESG rating scores of five rating providers: ISS oekom, MSCI KLD,[1] Sustainalytics, Refinitiv (previously Asset 4), and Vigeo Eiris. Some rating providers include negative screens in their overall score. To make the ratings comparable with regard to content, we isolate the negative screen scores from the overall rating, leaving us with the overall score excluding negative screens (for better readability, this is referred to as the ESG rating in the following). To make the ESG ratings numerically comparable, we follow Berg et al. (2021), Oehler and Horn (2022), and Serafeim and Yoon (2023), and apply normalized ratings (z-scores) with a mean value of 0 and a standard deviation of 1.

$$ESGRating\_Z_{i,j,t} = \frac{ESGRating_{i,j,t} - \overline{ESGRating_{j,t}}}{\sigma_{ESGRating_{j,t}}} \quad (6)$$

with $\overline{ESGRating}_{j,t}$ as the mean and $\sigma_{ESGRating_{j,t}}$ as the standard deviation of the ESG ratings assigned by rating provider j in month t.

Higher values of $ESGRating\_Z_{i,j,t}$ indicate better ESG-performance, i.e., lower unmanaged ESG risk and, hence, more sustainable companies. We do not adjust the ratings for industry sectors, since Berg et al. (2021) show that the ESG ratings hardly depend on industry sectors. It is unclear to which ESG rating(s) German retail investors have access. To account for this uncertainty, we consider the z-scores of the individual ESG ratings separately and we also compute the average ESG rating per stock and month ($MeanESGZ_{i,t}$) as the market's consensus view (Berg, Kölbel, and Rigobon 2022; Oehler and Horn 2022).

$$MeanESGZ_{i,t} = \overline{ESGScore\_Z}_{i,t} \quad (7)$$

In addition, we follow Christensen, Serafeim, and Sikochi (2022), Oehler and Horn (2022), and Serafeim and Yoon (2023) by measuring disagreement between rating agencies as the standard deviation of the z-scores ($StdESGZRatings_{i,t}$).

$$StdESGZRatings_{i,t} = \sigma_{ESGScore\_Z_{i,t}} \quad (8)$$

Stock data and ESG rating data are matched by the ISIN. If the rating providers do not include the ISIN in their dataset, matching is done with the Ticker symbol.

Attention measures

Following Barber and Odean (2008) we use attention measures that are based on abnormal trading volume and stock returns. Abnormal trading volume of stock i in month t ($AVolume_{i,t}$) is computed as follows:

$$AVolume_{i,t} = \frac{Volume_{i,t}}{\overline{Volume}_{i,t}} \quad (9)$$

$$\text{with } \overline{Volume}_{i,t} = \sum_{d=t-12}^{t-1} \frac{Volume_{i,d}}{12} \quad (10)$$

$Volume_{i,t}$ is the trading volume of stock i in month t in US dollars. The return of stock i in month t ($Return_{i,t}$) is defined as the return from the closing price of the month t-1 to the closing price of the month t. We also include the absolute value of $Return_{i,t}$ ($AbsReturn_{i,t}$), the maximum daily return of stock i in month t ($MaxReturn_{i,t}$), and the price of a stock at the end of a month ($Price_{i,t}$) as control variables (see e.g. Bali, Cakici, and Whitelaw 2011; Kumar 2009).

We adopt the approach of Da, Engelberg, and Gao (2011) to compute abnormal Google search volume for a company i in month t ($ASVI_{i,t}$). Google Search Volume (SVI)is gathered with the pytrends library.[2] Pytrends offers a number of parameters that can be configured to optimize the search process. These include the ability to specify a search category, the country for which search volume data is to be gathered, and the option to enable or disable Google's search suggestions. In this study, we opted for "Germany" as the country of interest, given that the SHS-Base plus encompasses shareholdings of customers residing in Germany. The overall search volumes and those categorized as News, Business News, Business Finance, and Investing were downloaded. For the previous queries, the search volume for the search term that was entered, as well as for the first search term that Google suggests when entering a search term, is downloaded. In contrast to the United States, ticker symbols are not widely used or recognized by retail investors in Germany. A preliminary test revealed that the number of individuals in Germany who utilize Google to search for ticker symbols is minimal, which resulted in Google Trends not providing a search volume index for the majority of ticker symbols. Hence, we use the company names as search term and adjust the approach of Da, Engelberg, and Gao (2011) for a monthly search volume index as follows.

$$ASVI_{i,t} = \ln(SVI_{i,t}) - \ln[Med(SVI_{i,t-1}, \ldots, SVI_{i,t-6})] \quad (11)$$

Further controls

Changes in analysts' stock price forecast may significantly draw retail investors' attention. Therefore, we use data from the Institutional Brokers Estimate System (I/B/E/S) as control variables. More specifically, we include the number of analysts that cover a stock ($NumEst_{i,t}$) and the number of analysts that revised the price forecasts upwards ($NumUp_{i,t}$) and downwards ($NumDown_{i,t}$) in the previous month. We assume that retail investors are more familiar with stocks with a higher market capitalization ($Mcap_{i,t}$) (see Gargano and Rossi 2018). Further control variables address the levels of climate change concerns, related policy uncertainty, and environmental awareness among the population. More specifically, we use the Media Climate Change Concerns Index ($MCCCI_t$) (Ardia et al. 2023; Pástor, Stambaugh, and Taylor 2022), Climate Policy Uncertainty (CPU_t) index (Gavriilidis 2021), Global Economic Policy Uncertainty Index ($GEPU_t$) (S. R. Baker, Bloom, and Davis 2016), Environmental Awareness Index (EAI_t) (Dabbous, Horn, and Croutzet 2023; Horn et al. 2023), and the VDAX ($VDAX_t$), which is the German pendant to the volatility index VIX of the US stock market. In addition, we create interacted values of $MCCCI_t$, CPU_t, and EAI_t with the mean ESG rating of a stock, since retail investors may, e.g., invest stronger in high ESG stocks in times of high climate change concerns to hedge against climate risks.

Da, Engelberg, and Gao (2015) develop the FEARS index based on Google search volume and show its predictive power for equity fund flows. Gao, Ren, and Zhang (2020) develop a FEARS and a GREED index for several countries, and provide native-language search terms that can be used to construct the indices for different countries. We use their search terms and compute economy-related FEARS ($Fears\_Economic_t$) and GREEDS ($Greads\_Economic_t$) indices as well as non-economy related FEARS ($Fears\_NonEco_t$) and GREEDS ($Greads\_NonEco_t$) indices for Germany. Other studies may use other economic indicators such as consumer confidence indices, unemployment rates, and GDP growth rates. However, we would argue that these economic indicators are likely to form the basis of retail investors' expectations and thus their sentiment. Therefore, the FEARS and GREED index should be sufficient to capture retail investors' stock market expectations.

Descriptive statistics

Our full sample consists of 276,758 stock-month observations. Descriptive statistics for these observations are reported in Table 1. On average, the holdings of German retail investors per stock and month are worth 49 million Euros. However, the holdings show a wide dispersion, as indicated by a standard deviation of 435 million Euros and a maximum value of 16,640 million Euros. Moreover, for about a quarter of all observations, the holdings of the retail investors are worth less than one million Euros. The proportion of stocks held by German retail investors varies between zero and 93%. However, for about three quarters of all observations, the share of German retail investors is less than 0.1%. The changes in the share are rather small (0.001% on average). There is a small imbalance between net purchases and net sales (51 versus 47%), indicating that purchases are slightly more frequent than sales. In only about 2% of the observations do stocks not change from one month to the next. Several restrictions reduce the size of the sample analyzed. If only stocks with a market capitalization of at least one billion euros are considered, the sample shrinks by about 70,000 observations. Google search volume is not available for about 100,000 observations, i.e. the respective company names have not been searched enough to create a search volume index. ESG ratings are only available for about 156,000 observations. However, the descriptive statistics strongly suggest that most of the dropped observations are of negligible importance, as the respective stocks were hardly held by retail investors in the respective month.

The correlations shown in Table 2 indicate that retail investors invest larger amounts in high ESG, high market capitalization, and German companies. This leads to a relative overweight in German and high ESG companies and a relative underweight in high market capitalization stocks, as the latter tend to be from the United States.

Figure 1 plots the number of stocks with ESG ratings per rating provider. The figure includes double counts, e.g. if a stock was rated by both ISS and Refinitiv, the stock is counted as rated by both ISS and Refinitiv. Over time, more stocks have been rated. It is important to note that the rating providers

Table 1. Descriptive statistics ($N = 276{,}758$).

	Mean	Std. dev.	Min	p25	p50	p75	Max
$Holdings_{i,t}$ in million Euros	49	435	0	0	1	4	16,640
$Share_{i,t}$ in percent	0.74	4.42	0.00	0.01	0.03	0.10	93.43
$\Delta Share_{i,t}$ in percent	0.001	0.214	−24.766	−0.001	0.00	0.001	21.149
$DummyBuy_{i,t}$	0.51	0.50	0	0	1	1	1
$DummySell_{i,t}$	0.47	0.50	0	0	0	1	1
$Mcap_{i,t}$ in billion Euros	10	20	0	1	3	9	136

Notes: We provide mean, minimum (min), maximum (max), 25th-percentile (p25), 50th-percentile (p50), and 75th-percentile (p75) values as well as the standard deviation (Std. dev.).
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

Table 2. Correlations.

	$Holdings_{i,t}$	$Share_{i,t}$	$\Delta Share_{i,t}$
$Holdings_{i,t}$	1.000		
$Share_{i,t}$	0.408***	1.000	
$\Delta Share_{i,t}$	0.007	−0.010	1.000
$MeanESGZ_{i,t}$	0.180***	0.044***	0.003
$StdESGZRatings_{i,t}$	−0.025***	−0.036***	0.003
$ASVI_{i,t}$	−0.008	−0.012*	0.010
$Return_{i,t}$	0.002	−0.004	−0.055***
$AVolume_{i,t}$	−0.006	−0.013*	−0.006
$Fears\_Economic_t$	−0.002	−0.005	0.007
$Greads\_Economic_t$	−0.001	−0.003	−0.004
$Fears\_NonEco_t$	−0.001	−0.000	−0.004
$Greads\_NonEco_t$	0.002	0.006	−0.006
EAI_t	−0.000	−0.002	−0.002
$MCCCI_t$	0.008	0.015**	−0.001
CPU_t	0.009	0.029***	−0.003
$GEPU_t$	0.005	0.019***	0.003
$VDAX_t$	−0.002	−0.019***	0.004
$AbsReturn_{i,t}$	−0.019***	0.031***	0.011*
$MaxReturn_{i,t}$	−0.037***	0.033***	−0.005
$Mcap_{i,t}$	0.257***	−0.044***	0.005
$German_{i,t}$	0.418***	0.758***	−0.007

Notes: We provide Pearson correlation coefficients and their significance levels. The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively.
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

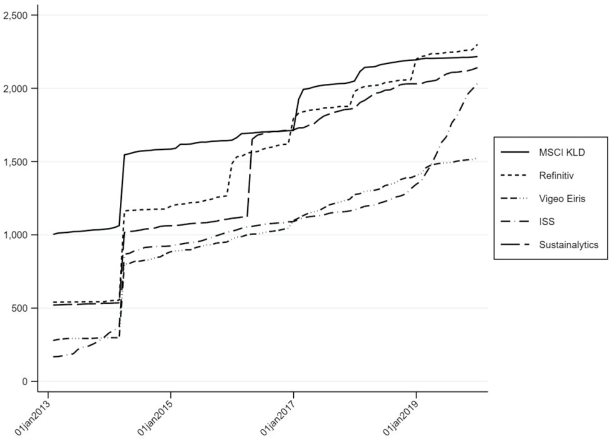

Figure 1. Number of ESG ratings per provider.

tended to specialize in a geographic region when they started. Although MSCI KLD provided most of the ratings for our sample, the largest share is for US companies. As German investors are home biased, the ratings of Refinitiv, Vigeo Eiris and ISS may be more important as these providers provide the most ratings for European stocks. Sustainalytics is the dominant provider for Japanese stocks. However, in non-tabulated regressions, we find significant relationships between all ESG ratings and changes in stock ownership, depending on the model used. Therefore, we would refrain from calling any particular ESG rating more relevant. In these regressions, we also find that the model fit is best when we use the mean ESG rating instead of the individual ratings as the independent variable. Therefore, we only present the latter results in detail.

Methodology

We winsorized extreme values at the 1% and 99% boundaries except for the variables $Holdings_{i,t}$, $Share_{i,t}$, and $\Delta Share_{i,t}$.

Since Da, Engelberg, and Gao (2011, 2015) and Gao, Ren, and Zhang (2020) focus on stock returns and not on security transactions, the form of the relation between $ASVI_{i,t}$ and retail investors' purchase- and sell-decisions is unclear. We tackle this problem by creating polynomial variables of degree N (e.g., $ASVI_{i,t}$, $ASVI^2_{i,t}$, $ASVI^3_{i,t}$, … $ASVI^N_{i,t}$) and use Recursive Feature Elimination to select the most important variables. For this procedure, a sub-sample is randomly divided into a training and a test dataset (50:50). As a robustness check, we use the Boruta algorithm, a random forest based method, to iteratively remove features that are statistically less relevant than a random sample. The most important variables are then used in portfolio analyses (following Barber and Odean 2008) as well as in regression analyses to analyze the relationship between the attention features, ESG ratings, control variables, and the investment decisions of retail investors. The Wooldridge test shows no significant autocorrelation. A Hausman specification test favors a fixed effects model. To avoid heteroskedasticity problems, we opt for robust standard errors. Therefore, we run our regressions as panel logit and panel multinomial logit regressions with stock-fixed effects and robust standard errors.

The regression models are run in a descriptive and a predictive setting. The descriptive setting shows correlations between the independent variables in month t and retail investors' purchase- and sell-decisions in the same month. In the predictive setting, we use the independent variables at month $t-1$ to predict the purchase- and sell-decisions of retail investors in the next month t.

Results and discussion

The unreported results of the recursive factor elimination show that the $ASVI_{i,t}$ for the first search term suggested by Google in the *Business News* category is by a small margin the most accurate predictor of $DummyBuy_{i,t}$. Therefore, we use the latter specification of $ASVI_{i,t}$ in the following. First, we use $ASVI_{i,t-1}$ to sort stocks in portfolios following Barber and Odean (2008). We then use $ASVI_{i,t}$ as an explanatory variable in panel regression analyses. We introduce $NoiseBarrier = 0.0002$ to divide the observations into about three thirds: $DummyBuy_{i,t}$ equals 1 in 39% of the observations and $DummySell_{i,t}$ equals 1 in 32% of the observations. The remaining observations show no significant net buying or selling by German retail investors, i.e. $DummyHold_{i,t} = 1$. Preliminary analyses showed that a lower noise barrier leads to more diluted results, probably due to more noise. We refrain from further increasing the noise barrier to limit overfitting of our models.

Portfolio sorts

Portfolio sorts on $ASVI_{i,t-1}$ are applied to the sample of stocks with complete control variables (see Appendix Table A1) and to stocks with complete control variables and a market capitalization of at least one billion Euros. The results for the latter are presented in Table 3.[3] Following Barber and Odean (2008), we provide results for the two vingtile portfolios with the highest and lowest $ASVI_{i,t-1}$. We also construct a portfolio that includes the remaining stocks with negative $ASVI_{i,t-1}$ (abnormally low search volume), a portfolio of stocks with $ASVI_{i,t-1} = 0$ (which is usually the case when there is no search for the firm name for several months), and a portfolio that includes the remaining stocks with positive $ASVI_{i,t-1}$ (abnormally high search volume). The portfolios reveal some interesting patterns. The portfolio of the 5% of stocks with the lowest (highest) $ASVI_i$ in t-1 shows the lowest (highest) mean $ASVI_i$ in the following month t. According to t-tests, the difference in $ASVI_{i,t}$ between the 1st and 20th vingtile portfolio is statistically significant at the one per mill level, i.e. stocks with abnormally low (high) search volume in month t-1 also have abnormally low (high) search volume in month t. For stocks that are not in the two extreme vingtile portfolios, i.e. the 1st vingtile and the 20th vingtile portfolio, we do not observe a consistent effect.

We find two significant patterns between abnormal Google search volume and stocks' market capitalization. First, on average, stocks with $ASVI_{i,t-1} = 0$, i.e. no (abnormal) search volume, have a significant lower market capitalization than the stocks in the remaining portfolios with a significance at the one per mill level. Second, stocks in the two extreme vingtile portfolios have a significantly lower market capitalization than the stocks with non-zero $ASVI_{i,t-1}$. Hence, portfolios of stocks with non-zero and non-extreme abnormal search volume usually have the highest market capitalization.

ESG ratings are positively correlated with market capitalization (Drempetic, Klein, and Zwergel 2020). We observe the same correlation among our portfolios for the mean ESG rating as well as for all five individual ESG ratings considered. Thus, portfolios of stocks with non-zero and non-extreme search volumes tend to include stocks with higher ESG ratings. Comparing the two extreme vingtile portfolios, we find that the portfolio with the highest abnormal search volume consists of stocks with lower ESG ratings than the portfolio with the lowest abnormal search volume. The difference is significant at the one per mill level for the mean ESG score ($t = 12.35$) as well as for each of the five individual ESG scores (t-statistics ranging from 7.75 to 10.87). We do not find significant differences between the five ESG ratings with respect to these patterns. Therefore, the portfolio analysis does not provide any evidence that the ESG ratings of one provider are more or less relevant for German retail investors.

Portfolio returns are computed using equally weighted returns and indicate a correlation between abnormal search volume and returns. The equally weighted return in t-1 ($Return_{i,t-1}$) of all portfolios with positive $ASVI_i$ in t-1 is 1.40%, while the corresponding return of all portfolios with negative $ASVI_i$ in $t-1$ is 0.84%. This difference is significant at the one per mill level ($t = 6.70$). The return difference between the two extreme vingtile portfolios is 0.33% and significant at the 5% level ($t = 2.02$). We observe a similar pattern for the portfolio performance, measured by the monthly Sharpe Ratio. The Sharpe Ratio of stocks with positive $ASVI_i$ in t-1 is significantly higher. The difference in the Sharpe Ratio between the two extreme vingtile portfolios is .043 (=0.224–0.181) and statistically significant at the 5% level ($t = 2.39$). However, there is no clear relation between $ASVI_i$ in t-1 and portfolio returns and performance in t. Da, Engelberg, and Gao (2011) find such a relation between their attention measure and the stock returns in the following two weeks. The corresponding outperformance is more than 30 basis points. Barber et al. (2022) document such a relation for high attention stocks for the following month (see also Bijl et al. 2016). The underperformance of high-herding stocks in the following month ranges between 2% and 20%, depending on the herding identification filter. There are at least two possible reasons why we do not observe this relation between attention and stock returns. First, our dataset may not be frequent

Table 3. Portfolio sorts on abnormal Google search volume in month t − 1 ($ASVI_{i,t-1}$); only stocks with market capitalization of at least one billion Euro.

	1st vingtile (5% stocks with lowest $ASVI_{i,t-1}$)	2nd vingtile	Remaining stocks with negative ASVI	Stocks with $ASVI_{i,t-1}=0$	Remaining stocks with positive ASVI	19th vingtile	20th vingtile (5% stocks with highest $ASVI_{i,t-1}$)	T-test highest vs. lowest
$ASVI_{i,t-1}$	−2.75	−1.41	−0.29	0	0.48	2.17	3.60	
	(0.41)	(0.59)	(0.24)	(0)	(0.36)	(0.66)	(0.45)	
$ASVI_{i,t}$	−0.66	−0.09	−0.20	0.38	−0.22	0.26	0.47	1.13***
	(1.80)	(1.29)	(0.92)	(1.09)	(1.07)	(1.50)	(1.76)	
$Return_{i,t-1}$	0.93	0.99	0.72	1.12	1.46	1.36	1.26	0.33**
	(8.48)	(8.07)	(7.95)	(8.34)	(8.92)	(8.94)	(9.51)	
$Return_{i,t}$	0.99	1.08	0.93	1.08	0.99	1.21	0.96	−0.03
	(8.81)	(8.36)	(8.56)	(8.45)	(8.34)	(8.41)	(8.67)	
$SharpeRatio_{i,t-1}$	0.18	0.18	0.15	0.20	0.24	0.23	0.22	0.046**
	(0.99)	(0.98)	(0.98)	(0.99)	(1.01)	(1.01)	(1.02)	
$SharpeRatio_{i,t}$	0.19	0.22	0.20	0.21	0.21	0.22	0.18	−0.004
	(1.00)	(1.01)	(1.00)	(1.00)	(0.99)	(1.00)	(0.99)	
$\Delta Share_{i,t}$	0.000	−0.003	0.003	0.000	0.003	0.001	0.000	
	(0.019)	(0.102)	(0.284)	(0.055)	(0.281)	(0.052)	(0.045)	
$DummyBuy_{i,t}$	0.41	0.43	0.49	0.32	0.50	0.43	0.40	
	(0.09)	(0.09)	(0.08)	(0.04)	(0.07)	(0.09)	(0.09)	
$DummySell_{i,t}$	0.37	0.38	0.41	0.29	0.38	0.33	0.32	
	(0.10)	(0.09)	(0.08)	(0.05)	(0.08)	(0.10)	(0.08)	
$DummyHold_{i,t}$	0.21	0.19	0.11	0.40	0.13	0.25	0.28	
	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.07)	(0.07)	
$Share_{i,t}$	0.09	0.47	2.03	0.11	1.52	0.20	0.08	
	(0.29)	(2.91)	(5.57)	(1.34)	(4.76)	(1.84)	(0.86)	
$Holdings_{i,t}$ (mio. €)	13	81	273	22	229	38	8	
	(77)	(740)	(963)	(390)	(964)	(504)	(70)	
$Mcap_{i,t}$ in bn. €	13.5	19.7	30.7	9.0	28.8	14.0	10.1	
	(19.1)	(26.9)	(39.5)	(15.7)	(37.6)	(20.0)	(15.7)	
$MeanESGZ_{i,t-1}$	0.24	0.47	0.65	0.04	0.60	0.27	0.08	−0.17***
	(0.81)	(0.86)	(0.89)	(0.74)	(0.90)	(0.80)	(0.75)	
$StdESGZRatings_{i,t-1}$	0.58	0.61	0.62	0.56	0.62	0.59	0.57	
	(0.28)	(0.29)	(0.30)	(0.28)	(0.30)	(0.28)	(0.29)	
$ESG\_JSS_{i,t-1}$	0.15	0.43	0.64	−0.08	0.59	0.20	−0.01	−0.16***
	(0.92)	(0.99)	(1.01)	(0.83)	(1.02)	(0.93)	(0.83)	
$ESG\_MSCIKLD_{i,t-1}$	0.42	0.66	0.82	0.14	0.77	0.47	0.25	−0.17***
	(1.08)	(1.17)	(1.22)	(0.94)	(1.21)	(1.09)	(1.02)	
$ESG\_Sustainalytics_{i,t-1}$	0.34	0.58	0.79	0.09	0.73	0.39	0.17	−0.18***
	(1.03)	(1.10)	(1.10)	(0.94)	(1.11)	(1.03)	(0.95)	
$ESG\_Refinitiv_{i,t-1}$	0.34	0.58	0.73	0.04	0.68	0.40	0.15	−0.19***
	(0.95)	(0.94)	(0.99)	(0.91)	(0.99)	(0.93)	(0.93)	
$ESG\_Vigeo_{i,t-1}$	0.21	0.36	0.51	0	0.47	0.23	0.06	−0.15***
	(0.91)	(0.95)	(0.97)	(0.84)	(0.97)	(0.91)	(0.84)	
$NumEst_{i,t}$	14	15	17	12	16	14	12	
	(7)	(7)	(8)	(6)	(8)	(7)	(6)	
$NumEst_{i,t-1}$	13	15	17	12	16	14	12	
	(7)	(7)	(8)	(6)	(8)	(7)	(6)	

Notes: We provide mean values and their respective standard deviations (in parentheses) for portfolios constructed by sorting stocks on their abnormal Google search volume in month t − 1 ($ASVI_{i,t-1}$). The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively.
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

enough, i.e., we cannot run a strategy that shorts high attention stocks on a daily basis. Second, our approach may not be focused enough to identify bubble events that typically occur in very few stocks, such as meme stocks (Pedersen 2022). We consider several thousand stocks and the behavior of all German retail investors, i.e. we certainly cover the stocks with the extreme attention and price movements in the 20th vingtile portfolio. However, even in the latter portfolio, the share of one or two stocks is so small that it has no significant impact on the portfolio return in month t. This further underscores that our study provides a different perspective than studies using retail broker trading data.

Although the portfolios have significantly different ESG ratings, we do not observe significant relationships between (mean) ESG ratings and portfolio returns and performance. Our results thus support the findings of Horn and Oehler (2024), who show that long-short portfolios based on ESG ratings do not outperform the market on average, and that portfolio sorts based on different ESG ratings yield portfolios that do not differ significantly in terms of performance.

$\Delta Share_{i,t}$ is positive on average for stocks with positive abnormal search volume in t-1. For the sample of stocks with complete control variables (see Appendix Table A1), these positive mean values are significantly different from zero with a statistical significance at the 1% level (mean: 0.005, t-statistic: 2.65), further supporting the findings of Barber and Odean (2008). For the sample of stocks with complete control variables and a market capitalization of at least one billion Euros, the mean values are not different from zero at statistically significant levels. This indicates that high abnormal search volumes are particularly associated with relatively high net purchases by retail investors of small cap stocks. Such a pattern is typical of gambling by some retail investors (Bali et al. 2021; Barber et al. 2022; Han and Kumar 2013; Oehler and Schneider 2022) and meme stock bubbles (Pedersen 2022) but is unlikely to have a considerable impact in terms of absolute amounts of money invested by the aggregate household sector. Oehler and Schneider (2022), also utilizing the SHS-Base with a special focus on gambling behavior, conclude that the amount invested in lottery stocks does not seem to be particularly relevant.

When the abnormal search volume is zero, it is much more likely that retail investors are neither net sellers nor net buyers of the stock. 40% of the stocks are net held in the portfolio with $ASVI_{i,t-1} = 0$. This is a much higher percentage than in any of the other portfolios (each difference is significant at the one per mill level) and a at the one per mill level significantly higher percentage than the net purchases (32%) and net sales (29%) in the same portfolio.

Stocks with extreme abnormal search volume or $ASVI_{i,t-1} = 0$ are those with the lowest market capitalization, the lowest absolute and relative holdings among retail investors, and the lowest ESG ratings. This reiterates the need to introduce a stock market capitalization cutoff to eliminate outliers associated with micro- and small-cap stocks. Therefore, we only include stocks with a market capitalization of 1 billion Euros in the following analysis.

Regression analysis

In Table 4, we present the results of panel logit regressions with stock-fixed effects, where we regress $DummyBuy_{i,t}$ and $DummySell_{i,t}$ on the aforementioned independent variables. In the descriptive setting, stocks with higher abnormal Google search volume, lower returns, higher trading volume, and recent analyst downgrades are more likely to be net bought by retail investors. This provides further support for their preferences for contrarian strategies (Barber and Odean 2000; Grinblatt and Keloharju 2000, 2001; Kaniel et al. 2012; Komai, Koyano, and Miyakawa 2018; C. Luo et al. 2022; Yuan 2015; see Galariotis 2014 for a summary) and is consistent with the observation of Barber et al. (2022) that active retail investors also trade past loser stocks heavily. In addition, we find that stocks with higher mean ESG ratings are more likely to be bought during periods of higher climate change concerns but lower environmental awareness (see also Baily et al. 2024). The probability of net purchases is also higher when the economic sentiment is more greedy and less fearful.

In the predictive setting, we find that higher abnormal Google search volume, lower returns, and higher trading volume of a stock in month $t-1$ are significantly associated with a higher probability that retail investors will be net buyers of that stock in month t.

Regarding the descriptive setting for net sold stocks, we find that higher mean ESG ratings are associated with a higher probability of a stock being sold by retail investors, except in periods of high climate change concerns and high climate policy uncertainty. The latter may indicate climate change hedging motives (Engle et al. 2020). Therefore, we cannot support the finding of Moss, Naughton, and Wang (2024) that ESG disclosure is irrelevant for German retail

Table 4. Panel logit regression analyses.

	$DummyBuy_{i,t}$		$DummySell_{i,t}$	
	descriptive	predictive	descriptive	predictive
	(1)	(2)	(3)	(4)
$MeanESGZ_{i,t}$	−0.145*	0.002	0.395***	0.235***
	(0.063)	(0.063)	(0.064)	(0.064)
$StdESGZRatings_{i,t}$	−0.052	−0.033	−0.115*	−0.055
	(0.044)	(0.043)	(0.045)	(0.044)
$EAI_t*MeanESGZ_{i,t}*10^{-2}$	−0.157**	0.107*	0.102*	−0.032
	(0.050)	(0.049)	(0.052)	(0.051)
$MCCCI_t*MeanESGZ_{i,t}$	0.138***	0.043	−0.102**	−0.068
	(0.038)	(0.038)	(0.039)	(0.038)
$CPU_t*MeanESGZ_{i,t}*10^{-3}$	0.021	−0.347	−0.500**	−0.018
	(0.186)	(0.184)	(0.190)	(0.187)
$ASVI_{i,t}$	0.041***	0.029***	−0.033***	−0.0252**
	(0.01)	(0.006)	(0.007)	(0.007)
$Return_{i,t}$	−0.019***	−0.0129***	0.016***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)
$AVolume_{i,t}$	0.109***	0.095***	0.110***	0.027
	(0.019)	(0.018)	(0.019)	(0.019)
$Fears\_Economic_t$	−0.173***	0.092*	0.136**	−0.008
	(0.040)	(0.040)	(0.041)	(0.041)
$Greads\_Economic_t$	0.329***	0.083*	0.081*	−0.003
	(0.039)	(0.038)	(0.040)	(0.040)
$Fears\_NonEco_t$	0.212***	−0.176***	−0.008	0.258***
	(0.029)	(0.029)	(0.029)	(0.030)
$Greads\_NonEco_t$	−0.072*	0.129***	0.146***	−0.049
	(0.033)	(0.034)	(0.034)	(0.035)
EAI_t*10^{-2}	−0.126*	−0.141**	0.277***	0.014
	(0.052)	(0.051)	(0.053)	(0.053)
$MCCCI_t$	0.146***	−0.034	−0.299***	0.027
	(0.034)	(0.034)	(0.035)	(0.035)
CPU_t*10^{-2}	0.101***	−0.136***	0.168***	0.22***
	(0.026)	(0.025)	(0.026)	(0.026)
$GEPU_t*10^{-2}$	0.052	0.209***	−0.152***	−0.167***
	(0.029)	(0.029)	(0.029)	(0.030)
$VDAX_t$	0.011***	−0.005*	0.005*	0.892***
	(0.002)	(0.002)	(0.002)	(0.212)
$AbsReturn_{i,t}*10^{-2}$	1.05***	0.924***	0.042	−0.384*
	(0.149)	(0.147)	(0.153)	(0.151)
$MaxReturn_{i,t}*10^{-2}$	0.246	0.406	0.684*	0.696*
	(0.337)	(0.336)	(0.339)	(0.339)
$Price_{i,t}*10^{-2}$	0.328***	0.361***	−0.135*	−0.187***
	(0.053)	(0.001)	(0.054)	(0.0541)
$Mcap_{i,t}*10^{-12}$	0.07	4.84**	2.79	−6.06***
	(1.76)	(1.77)	(1.84)	(1.84)
$NumEst_{i,t}*10^{-2}$	0.653	1.11*	0.001	−0.133
	(0.439)	(0.435)	(0.445)	(0.442)
$NumUp_{i,t}$	−0.008**	−0.012***	0.020***	0.009**
	(0.003)	(0.003)	(0.003)	(0.003)
$NumDown_{i,t}$	0.080***	0.031***	−0.062***	−0.033***
	(0.004)	(0.004)	(0.004)	(0.004)
N	78.877	78.788	79.066	78.981

Notes: We provide regression coefficients and their respective standard errors (in parentheses) for panel logit regression analyses with stock-fixed effects using $DummyBuy_{i,t}$ (columns (1) and (2)) and $DummySell_{i,t}$ (columns (3) and (4)) as dependent variables. Columns (1) and (3) provide results for the descriptive setting with dependent and independent variables at month t. Columns (2) and (4) provide results for the predictive setting with dependent variables at month t and independent variables at month t − 1. The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively. Example: Regressing $DummyBuy_{i,t}$ on the full regression model in the descriptive setting yields a coefficient of −0.145 of the stocks' mean ESG rating ($MeanESGZ_{i,t}$) with a statistical significance at the 5% level.
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

investors. Stocks with higher Google search volume are less likely to be sold. Retail investors tend to sell stocks with higher returns and recent analyst upgrades. This may indicate that retail investors prefer to realize gains rather than losses (Shefrin and Statman 1985), and supports the findings of Yuan (2015). We observe more net sales during periods of fearful economic sentiment and high environmental awareness. The latter finding is consistent with Anderson and Robinson's (2022) observation that households with stronger environmental values are less invested in the stock market. It seems plausible that retail investors divest as their environmental awareness increases and as they observe potential conflicts between their sustainability values and some companies. Moreover, stocks with high trading volumes are more likely to be net sold. Combined with our finding that higher trading volume is also associated with a higher probability of net purchases, the role of trading volume seems contradictory. Our interpretation is that the results reflect, to some extent, an endogeneity problem: For stocks with higher trading volumes, retail investors are more likely to change their holdings in these stocks to an extent that exceeds our noise barrier than for stocks with low trading volumes. We will explore this issue in more detail in the multinomial panel logit regression analyses below.

In the predictive setting, we find that stocks with higher mean ESG ratings and returns and lower abnormal Google search volume in month t − 1 are more likely to be sold in month t.

Unreported results indicate that the findings on the impact of the mean ESG rating in the regressions described above are not driven by the rating of a particular provider. Thus, none of the ratings appear to be significantly more important than the others. In addition, we find that the model fit is best when we use the mean ESG rating rather than the individual ratings. Therefore, we do not report results for individual ESG ratings in the regression analyses.

The results of the multinomial panel logit regression analyses with stock-fixed effects presented in Table 5 indicate a significant correlation of both ESG-related and attention-grabbing characteristics of stocks with the purchase-, hold-, and sell-decisions of retail investors in the same month. The model provides correct estimates for more than 43% of the observations, i.e. it has good explanatory power. Compared to net-purchased stocks, net-sold stocks have a higher mean ESG-rating. The latter correlation is reversed during periods of high climate change concerns and is not driven by the ESG ratings of a particular provider. Net bought stocks have significantly higher abnormal Google search volume and significantly lower returns than net sold stocks or stocks with no significant

Table 5. Multinomial panel logit regression analyses (descriptive setting).

	$DummySell_{i,t}$	$DummyHold_{i,t}$
	(1)	(2)
$MeanESGZ_{i,t}$	0.293***	−0.317**
	(0.061)	(0.099)
$StdESGZRatings_{i,t}$	−0.045	0.257***
	(0.043)	(0.076)
$EAI_t*MeanESGZ_{i,t}*10^{-2}$	0.187**	0.089
	(0.058)	(0.072)
$MCCCI_t*MeanESGZ_{i,t}$	−0.190***	−0.102
	(0.044)	(0.062)
$CPU_t*MeanESGZ_{i,t}*10^{-3}$	−0.165	0.374
	(0.244)	(0.355)
$ASVI_{i,t}$	−0.048***	−0.036***
	(0.008)	(0.010)
$Return_{i,t}$	0.020***	0.015***
	(0.002)	(0.002)
$AVolume_{i,t}$	−0.028	−0.435***
	(0.025)	(0.035)
$Fears\_Economic_t$	0.186***	0.119*
	(0.045)	(0.055)
$Greads\_Economic_t$	−0.160***	−0.665***
	(0.047)	(0.055)
$Fears\_NonEco_t$	−0.117***	−0.356***
	(0.034)	(0.040)
$Greads\_NonEco_t$	0.117**	−0.033
	(0.037)	(0.045)
EAI_t*10^{-2}	0.244***	−0.058
	(0.063)	(0.072)
$MCCCI_t$	−0.216***	0.109*
	(0.043)	(0.053)
CPU_t*10^{-2}	0.054	−0.391***
	(0.031)	(0.039)
$GEPU_t*10^{-2}$	−0.131***	0.147***
	(0.035)	(0.042)
$VDAX_t$	−0.003	−0.022***
	(0.003)	(0.003)
$AbsReturn_{i,t}*10^{-2}$	0.0186	−2.59***
	(0.187)	(0.230)
$MaxReturn_{i,t}*10^{-2}$	0.753	−2.03***
	(0.417)	(0.582)
$Price_{i,t}*10^{-2}$	−0.126***	−0.464***
	(0.0208)	(0.0634)
$Mcap_{i,t}*10^{-12}$	−5.25***	−8.54***
	(0.70)	(1.56)
$NumEst_{i,t}*10^{-2}$	0.679**	−1.81***
	(0.222)	(0.539)
$NumUp_{i,t}$	0.017***	−0.008
	(0.004)	(0.005)
$NumDown_{i,t}$	−0.079***	−0.073***
	(0.005)	(0.006)
N		

Notes: We provide regression coefficients and their respective standard errors (in parentheses) for multinomial panel logit regression analyses with stock-fixed effects in the descriptive setting with dependent and independent variables at month t. Observations with $DummyBuy_{i,t} = 1$ serve as base outcome. Results for $DummySell_{i,t} = 1$ in relation to the base outcome are reported in column (1). Results for $DummyHold_{i,t} = 1$ in relation to the base outcome are reported in column (2). The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively.

Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

change in ownership. Not surprisingly, the latter stocks are also traded less frequently than stocks with significant ownership changes. Furthermore, the trading volume of net sold and net bought stocks does not differ significantly, i.e. the negative relationship between trading volume and the net holding dummy is mechanical. Consistent with previous sentiment literature, we observe significantly more reductions in holdings during periods of greater economic fear and fewer reductions in holdings when the economic greed index is high (see Kumar and Lee 2006). It is important to note, however, that e.g. Kumar and Lee (2006) and Barber, Odean, and Zhu (2009) use such order imbalances to measure sentiment. In contrast, we use a sentiment measure based on Google Trends and show that order imbalances are indeed correlated with retail investor sentiment. Down(up)grades by stock analysts are significantly correlated with net purchases (sales) by retail investors. Thus, at first glance, our observation differs from the findings of McLean, Pontiff, and Reilly (2024) and Welagedara, Deb, and Singh (2017). However, we have to take into account the monthly frequency of our data. In particular, Welagedara, Deb, and Singh (2017) provide evidence of overreactions and price reversals following analyst downgrades. Our results may capture this long-term reversal rather than the short-term overreaction caused by retail trading in the direction of analyst recommendations.

As illustrated in Table 6, the results of multinomial panel logit regression analyses with stock-fixed effects in the predictive setting are presented. In this setting, the independent variables correspond to month t − 1, while the dependent variables correspond to month t. Although the coefficients for variables such as stocks' mean ESG rating, return, and trading volume are identified as statistically significant, the model is unable to correctly predict a sufficient proportion of observations. The model's capacity to accurately predict the purchase-, hold-, and sell-decisions of retail investors in the subsequent month is only 20%, indicating its inadequacy for such predictions. The implementation of machine learning, specifically the Boruta algorithm, did not result in a substantial enhancement of the model's suitability for prediction. The conspicuously divergent explanatory power observed between descriptive and predictive settings can be attributed to the rapid reaction time exhibited by certain retail investors. It appears that new information is processed expeditiously, resulting in a significant correlation between Google search volume in one month and investment decisions in the same month, but not in the subsequent month. This suggests that, in response to new information, retail investors promptly conduct Google searches for additional information and then rapidly determine whether to purchase, sell, or hold the stocks in question. Once this information

Table 6. Multinomial panel logit regression analyses (predictive setting).

	$DummySell_{i,t}$ (1)	$DummyBuy_{i,t}$ (2)
$MeanESGZ_{i,t}$	0.593***	0.377***
	(0.095)	(0.097)
$StdESGZRatings_{i,t}$	−0.194*	−0.188*
	(0.076)	(0.075)
$EAI_t{*}MeanESGZ_{i,t}{*}10^{-2}$	0.036	0.103
	(0.077)	(0.073)
$MCCCI_t{*}MeanESGZ_{i,t}$	−0.118*	0.022
	(0.059)	(0.061)
$CPU_t{*}MeanESGZ_{i,t}{*}10^{-3}$	−0.385	−0.598
	(0.335)	(0.335)
$ASVI_{i,t}$	−0.017	0.016
	(0.009)	(0.009)
$Return_{i,t}$	0.006***	−0.011***
	(0.002)	(0.002)
$AVolume_{i,t}$	0.205***	0.277***
	(0.033)	(0.032)
$Fears\_Economic_t$	0.079	0.167**
	(0.056)	(0.052)
$Greads\_Economic_t$	0.103	0.109*
	(0.053)	(0.050)
$Fears\_NonEco_t$	0.271***	−0.035
	(0.039)	(0.038)
$Greads\_NonEco_t$	0.038	0.182***
	(0.048)	(0.044)
$EAI_t - {*}10^{-2}$	−0.110	−0.154*
	(0.073)	(0.068)
$MCCCI_t$	0.027	−0.059
	(0.050)	(0.050)
$CPU_t{*}10^{-2}$	0.231***	−0.010
	(0.038)	(0.038)
$GEPU_t{*}10^{-2}$	−0.104*	0.155***
	(0.046)	(0.045)
$VDAX_t$	0.006	−0.003
	(0.003)	(0.003)
$AbsReturn_{i,t}{*}10^{-2}$	1.13***	2.06***
	(0.237)	(0.233)
$MaxReturn_{i,t}{*}10^{-2}$	4.04***	3.39***
	(0.560)	(0.569)
$Price_{i,t}{*}10^{-2}$	0.208***	0.459***
	(0.055)	(0.058)
$Mcap_{i,t}{*}10^{-12}$	0.697	7.06***
	(1.58)	(1.64)
$NumEst_{i,t}{*}10^{-2}$	3.71***	3.98***
	(0.553)	(0.548)
$NumUp_{i,t}$	−0.007	−0.019***
	(0.004)	(0.004)
$NumDown_{i,t}$	−0.026***	0.011
	(0.006)	(0.006)
N		

Notes: We provide regression coefficients and their respective standard errors (in parentheses) for multinomial panel logit regression analyses with stock-fixed effects in the predictive setting with dependent variables at month t and independent variables at month t − 1. Observations with $DummyHold_{i,t} = 1$ serve as base outcome. Results for $DummySell_{i,t} = 1$ in relation to the base outcome are reported in column (1). Results for $DummyBuy_{i,t} = 1$ in relation to the base outcome are reported in column (2). The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively.
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.

processing is complete, it appears to have no discernible impact on subsequent investment decisions.

Conclusion

We conducted an analysis of one of the most extensive stock holdings datasets, the SHS-Base plus of the German central bank, to evaluate prior conclusions that retail investors exhibit a tendency to prioritize attention-grabbing stocks in their investment decision-making processes (Barber et al. 2022; Barber and Odean 2008). The SHS-Base plus encompasses all securities holdings of retail investors with portfolios at German banks at the end of a month, thereby serving as a representative sample of the stock holdings of the retail sector in Europe's largest economy. The sample period under consideration extends from January 2013 to December 2019.

The findings of this study demonstrate a correlation between the ESG ratings, returns, analyst recommendations, and other notable events, as indicated by abnormal Google search volume, and the purchase-, hold-, and sell-decisions of retail investors within the same month. However, the rapidity of information processing suggests that the aforementioned stock characteristics may not be suitable for predicting retail investors' investment decisions in the subsequent month.

This study makes several contributions to the extant literature. Firstly, to the best of our knowledge, our study is the first to combine the ESG characteristics of stocks with their attention-grabbing features and market-wide measures of climate change concerns, environmental awareness, and sentiment to explain retail investors' investment decisions. This is important because both ESG issues and information overload, which creates attentional poverty, are dominant aspects in financial decisions. Secondly, our study extends previous research on attention-driven trading by identifying stock characteristics that are significantly correlated with decisions to hold and sell. Consequently, our findings contribute to a more comprehensive understanding of investment decision-making. Thirdly, our findings provide further validation for the trading patterns identified by Barber and Odean (2008) and Barber et al. (2022) among the broader population of German retail investors. Consequently, our study demonstrates that these trading patterns are not exclusive to investors utilizing online platforms and brokers but are prevalent among the broader population of retail investors.

The findings of this study have implications for both researchers and practitioners. Firstly, our research provides further evidence that certain stocks garner the attention of retail investors, and these stocks are more likely to be purchased by retail investors. This phenomenon, among others, lends support to the notion that price bubbles may arise as a consequence. Secondly, our research indicates that preferences for ESG investments and climate change hedging motives also play a role. Given the consideration of these factors by investors, initiatives aimed at financing biodiversity or establishing a nature-positive financial system are likely to garner attention and receive consideration (The Paulson Institute, The Nature Conservancy, and the Cornell Atkinson Center for Sustainability 2020; World Economic Forum 2021). However, our findings align with those of previous studies, which indicate an absence of significant differences in the relevance of ESG rating providers. Consequently, a prevailing consensus among retail investors within our sample regarding the assessment of sustainability remains elusive, and there is no indication of a preferred rating provider. Thirdly, we identify stock characteristics that are correlated with sell- and hold-decisions. The findings of this study necessitate further research to either substantiate or refute our results. Fourthly, the monthly datasets may not be sufficiently frequent to effectively forecast retail investors' investment decisions. Furthermore, financial authorities and researchers can utilize high-frequency Google search volume data to identify stocks that attract retail investors' attention, serving as an indicator of potential market disruptions. A potential avenue for further exploration lies in the analysis of the search volume of the *Business News* category, as opposed to the utilization of the aggregate search volume.

Further research can take advantage of these findings and address some limitations of our study. Kozak, Nagel, and Santosh (2018) subsume all attention-grabbing features, ESG preferences, market-wide concern measures, etc. as sentiment affecting asset prices. Ehsani and Linnainmaa (2022) show that this type of sentiment drives factor momentum. Chen et al. (2022) show that investor attention can predict the stock market risk premium. Researchers could analyze whether there is a direct link between attention-grabbing stock features, transactions of retail investors (which should correspond to sentiment investors) driven by sentiment/attention, and factor momentum/market risk premium. While Google search volume is a suitable attention measure for German investors, it is important to note that Google might not be the only source for a direct attention measure, as other search engines are more popular in other countries. Consequently, further research might employ diverse search engines or social media platforms to develop novel attention measures. These measures can then be tested among different populations to elaborate on the generalizability of our findings beyond the German market.

Notes

1. Please note that the MSCI KLD ratings are usually not provided with an overall rating score. We follow the approach of Horn (2023) to compute the score.
2. See https://github.com/GeneralMills/pytrends.
3. Results for portfolio sorts on the full sample are not systematically different, however, appear a little bit more diluted. This indicates that retail investors' holdings in stocks with low market capitalization are more influenced by noise (which is not surprising). Therefore, we focus on the less noisy sample of stocks with a market capitalization of at least one billion Euros.

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Appendix

Table A1. Portfolio sorts on abnormal Google search volume in month t − 1 ($ASVI_{i,t-1}$).

	1st vingtile (5% stocks with lowest $ASVI_{i,t-1}$)	2nd vingtile	Remaining stocks with negative ASVI	Stocks with $ASVI_{i,t-1}=0$	Remaining stocks with positive ASVI	19th vingtile	20th vingtile (5% stocks with highest $ASVI_{i,t-1}$)	T-test highest vs. lowest
$ASVI_{i,t-1}$	−2.77	−1.42	−0.29	0.00	0.49	2.17	3.63	
	(0.41)	(0.59)	(0.24)	(0.00)	(0.36)	(0.66)	(0.45)	
$ASVI_{i,t}$	−0.67	−0.10	−0.21	0.35	−0.22	0.28	0.47	1.14***
	(1.81)	(1.30)	(0.93)	(1.06)	(1.09)	(1.50)	(1.78)	
$Return_{i,t-1}$	0.61	0.75	0.52	0.88	1.31	1.42	1.13	0.52**
	(9.56)	(8.86)	(8.65)	(9.84)	(9.83)	(10.21)	(10.95)	
$Return_{i,t}$	0.73	0.96	0.80	0.86	0.80	1.06	0.83	0.10
	(10.08)	(9.17)	(9.36)	(9.95)	(9.20)	(9.45)	(10.14)	
$SharpeRatio_{i,t-1}$	0.14	0.14	0.12	0.16	0.21	0.21	0.19	0.046**
	(1.00)	(0.98)	(0.97)	(1.00)	(1.01)	(1.02)	(1.01)	
$SharpeRatio_{i,t}$	0.15	0.18	0.17	0.16	0.18	0.18	0.15	0.004
	(1.00)	(1.00)	(1.00)	(1.00)	(0.99)	(1.00)	(1.00)	
$\Delta Share_{i,t}$	0.001	0.000	0.002	0.001	0.006	0.007	0.002	0.001
	(0.079)	(0.201)	(0.460)	(0.092)	(0.462)	(0.147)	(0.118)	
$DummyBuy_{i,t}$	0.43	0.44	0.49	0.34	0.50	0.43	0.41	
	(0.08)	(0.08)	(0.08)	(0.04)	(0.07)	(0.08)	(0.08)	
$DummySell_{i,t}$	0.38	0.38	0.41	0.31	0.39	0.34	0.34	
	(0.09)	(0.08)	(0.08)	(0.05)	(0.07)	(0.09)	(0.08)	
$DummyHold_{i,t}$	0.19	0.18	0.10	0.35	0.11	0.22	0.25	
	(0.05)	(0.06)	(0.03)	(0.04)	(0.03)	(0.06)	(0.06)	
$Share_{i,t}$	0.38	1.12	3.72	0.22	2.92	0.46	0.26	
	(2.95)	(5.82)	(10.43)	(2.30)	(9.24)	(3.64)	(2.51)	
$Holdings_{i,t}$ (mio. €)	11	72	242	17	204	33	7	
	(71)	(685)	(898)	(335)	(898)	(462)	(62)	
$Mcap_{i,t}$ (bn. €)	11.3	16.9	26.6	6.7	24.9	11.9	8.0	
	(18.1)	(25.8)	(38.1)	(14.0)	(36.3)	(19.0)	(14.5)	
$MeanESGZ_{i,t-1}$	0.13	0.37	0.54	−0.10	0.50	0.17	−0.04	−0.17***
	(0.84)	(0.89)	(0.93)	(0.74)	(0.94)	(0.82)	(0.77)	
$StdESGZRatings_{i,t-1}$	0.57	0.61	0.62	0.54	0.62	0.58	0.55	
	(0.29)	(0.31)	(0.32)	(0.29)	(0.31)	(0.29)	(0.29)	
$ESG\_JSS_{i,t-1}$	0.16	0.44	0.64	−0.07	0.59	0.21	0.00	−0.16***
	(0.94)	(1.02)	(1.03)	(0.84)	(1.04)	(0.95)	(0.85)	
$ESG\_MSCIKLD_{i,t-1}$	0.28	0.52	0.67	−0.02	0.62	0.33	0.11	−0.17***
	(1.06)	(1.17)	(1.23)	(0.90)	(1.22)	(1.08)	(0.99)	
$ESG\_Sustainalytics_{i,t-1}$	0.23	0.48	0.68	−0.03	0.63	0.30	0.04	−0.18***
	(1.04)	(1.11)	(1.12)	(0.92)	(1.12)	(1.03)	(0.95)	
$ESG\_Refinitiv_{i,t-1}$	0.22	0.48	0.61	−0.07	0.58	0.29	0.03	−0.19***
	(0.98)	(0.98)	(1.03)	(0.91)	(1.02)	(0.96)	(0.94)	
$ESG\_Vigeo_{i,t-1}$	0.19	0.33	0.46	−0.02	0.43	0.22	0.04	−0.15***
	(0.91)	(0.95)	(0.98)	(0.84)	(0.98)	(0.91)	(0.84)	
$NumEst_{i,t}$	12	13	15	10	15	12	11	
	(7)	(7)	(8)	(6)	(8)	(7)	(7)	
$NumEst_{i,t-1}$	12	13	15	10	15	12	11	
	(7)	(7)	(8)	(6)	(8)	(7)	(6)	

Notes: We provide mean values and their respective standard deviations (in parentheses) for portfolios constructed by sorting stocks on their abnormal Google search volume in month t − 1 ($ASVI_{i,t-1}$). The symbols ***, **, and * denote statistical significance at the 1‰, 1%, and 5% level, respectively.
Source: Research Data and Service Centre (RDSC) of the Deutsche Bundesbank, Securities Holdings Statistics Base plus, January 2013 to December 2019, own calculations.