Behavioural finance in sustainable finance: could socially responsible investors be more rational than conventional ones?

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Abstract

This paper investigates the exposure of sustainable and non-sustainable firms' stocks to behavioral biases. We use the behavioral three-factor model of Daniel et al. (2020) to identify behavioral biases in both the short and long term. Evidence is provided for firms from European Union countries over the period January 2004 to December 2022. The main results show that stock prices of firms with high environmental, social, and governance (ESG) scores are not exposed to behavioral biases while those of firms with low ESG scores exhibit behavioral biases. In particular, stock prices of bottom ESG ranked firms are affected by an overconfidence bias. The results hold for different market states. These findings suggest that stock prices of firms with high ESG standards are better valued than those of firms with low ESG standards. This is consistent with superior disclosure quality and reduce information asymmetry for this type of firms. Overall, we find that stock prices of ESG-aware firms are more aligned with the efficient market hypothesis.

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1. Introduction

Behavioral biases, such as overconfidence and investor inattention, have been shown to affect the decision-making of individuals (Gao et al., 2021). While behavioral finance literature has studied the existence of behavioral biases in the asset prices of conventional firms, the presence of behavioral biases in asset prices of sustainable firms remains unstudied. In this paper we fill this gap and investigate the exposure of sustainable and non-sustainable firms' stocks to behavioral biases.

Between the 1950s and 1970s, leading academics such as Markowitz, Sharpe, Lintner, Modigliani and Miller, established the principles of neoclassical finance. Their studies, grounded in the concepts of market efficiency and investor rationality, have functioned as an instrument for investment and financing decisions over the years. Individuals base their decisions on a number of axioms and, since returns on assets can be assumed to be normally distributed, the decision parameters are μ (return) and σ (risk). This approach is underpinned by a rigorous scientific background[1]. Neoclassical finance evolved from the prevailing requirement for more sophisticated methodologies and instruments to manage sizable corporate entities and investments (Gómez-Bezares, 2017). Traditionally, developments in finance have emerged in response to shifting demands. In recent decades, finance has continued evolving, with one notable feature: the tendency of a growing number of investors to go beyond the financial utility of their decisions and to pursue a non-financial utility that reflects their social values. Financial market participants have progressively adopted sustainability aspects by including criteria such as environmental, social and governance (ESG) factors in their decision-making processes. According to the Global Sustainable Investment Review (GSIR, 2022), $30.3 trillion is invested globally in sustainable investing assets. Since 2020, there has been a 20% increase in sustainable assets under management in Canada, Europe, Japan, Australia and New Zealand.

Derwall et al. (2011) distinguish between two types of investors in today's markets: (1) profit-seeking investors and (2) values-driven investors, i.e. investors who are purely profit-seeking and investors who integrate social and environmental preferences into their investment decisions. This new context, in which part of investors include non-purely financial aspects in decision-making, has challenged the validity of certain neoclassical finance assumptions; in particular it has at least one important implication: rational deviations by investors from utility optimization based on the return-risk trade-off lead to equilibrium outcomes that deviate from the efficient frontier of portfolio theory and the CAPM, even without considering behavioral biases (van Dooren and Galema, 2018). Furthermore, if investor behavior and preferences are considered, as Zahera and Bansal (2018) argue, the expected utility theory and the efficient market hypothesis are not able to solve the problem in specific situations.

Research in behavioral finance has addressed the effects of preferences and psychological factors on decision-making. This research suggests that, in addition to the particular preferences that investors have for certain assets that are unrelated to financial compensation,

[1] Portfolio theory: Markowitz (1952); Market model: Sharpe (1963); Asset Pricing Model (CAPM): Sharpe (1964), Lintner (1965), Black (1972); Financial structure: Modigliani and Miller (1958; 1963); etc.

different psychological phenomena make it difficult for them to be fully rational. As a consequence, they do not behave in accordance with the Von Neumann-Morgenstern axioms on unknown wealth distributions. Chandra and Thenmozhi (2017) collect some of the behavioral biases that arise in investor decision making which are relevant to asset prices. An example takes place during the process of searching for information: the investor tries to reduce the risk of excessive information and thus the associated uncertainty. There are also social and herding factors that lead investor to use non-fundamental company information for decision making. Hou et al. (2015) investigate about 80 pricing anomalies and conclude that almost half are significant in explaining stock returns. Daniel et al. (2020) associate 34 of the anomalies previously identified by Hou et al. (2015) to both short-term and long-term investor behavior. These authors document, for example, that investors' attention is limited to new information resulting in a delay in price response to information.

In the area of sustainable investments, findings of Barberis and Shleifer (2003) suggest that the activity of value-driven investors could lead to mispricing and inefficiencies in asset management. These investors incorporate into their decision making a preference for particular types of assets, a rejection of investing in others, and attend to emotions associated with their desire to address specific social conflicts, environmental concerns, etc. This approach could make sustainable assets overvalued for the interest of sustainable investors. However, an alternative stance is that socially responsible investors quickly incorporate any new information that appears in the market into share prices since they are expected to follow more closely the practices and activities of the firms in which they invest. In such circumstances, stock prices of sustainable firms would become less exposed to mispricing due to biases such as limited investor attention. This is consistent with previous research suggesting that firms with high ESG standards tend to exhibit higher disclosure quality, suffer from less information asymmetries, and be attractive to a larger investor base (Giese, et al., 2019; Wang et al., 2024).

While the behavioral finance literature has studied how behavioral biases can affect stock prices of conventional firms, as far as we known, there is no previous evidence on the existence of behavioral biases on asset prices of sustainable firms. We aim to fill this gap. We address questions such as: Could the behavioral biases identified by previous research explain the performance of sustainable firms? Could sustainable firms be more exposed to mispricing? Could sustainable firms be even better valued than non-sustainable ones? To do so, we evaluate whether stock prices of top ESG ranked firms are equally exposed to behavioral biases, if any, as those of bottom ESG ranked firms. We follow a portfolio approach and then the behavioral three-factor model of Daniel et al. (2020) is used to identify behavioral biases in both the short and long term. This model adds two behavioral factors to the market factor, which attempt to explain a long-term valuation error (overconfidence bias) and a short-term value error (limited attention bias). Our data covers firms from European Union countries over the period January 2004 to December 2022. The main results show that stock prices of firms with high ESG scores are not exposed to behavioral biases while those of firms with low ESG scores exhibit behavioral biases. In particular, stock prices of bottom ESG ranked firms are affected by an overconfidence bias. These findings indicate that stock prices of firms with high ESG standards are better valued than those of firms with low ESG standards. Paradoxically, we find that stock prices of

ESG-aware firms are more aligned with the efficient market hypothesis.

We also investigate whether asset prices are affected by behavioral biases to a greater extent under different market states. Daniel et al. (2001) claim that, for instance, overconfidence may become strong and evident in bull markets. In these markets, with high returns and low volatility, investors are particularly prone to overconfident and optimistic about the prospects (Hwang et al., 2021). Findings of Chuang and Lee (2006) confirm that overconfidence exists, and its effect is more prevalent in bull markets than in bear markets. Novelty, we assess whether biased investor behavior in different market states is confirmed for both sustainable and non-sustainable firms. Our results show that, in the European market, investors' exposure to behavioral biases remains consistent regardless of whether the market is in a bull or bear period. Specifically, only firms with the poorest ESG valuations are susceptible to the overconfidence bias, irrespective of the prevailing market conditions.

Our paper provides first evidence on the impact of behavioral biases on sustainable and non-sustainable asset prices. Our findings have a twofold contribution. On the one hand, it contributes to the existing literature on the effect of behavioral biases on asset pricing. And, on the other hand, it sheds light on ESG preferences on pricing efficiency. Individual investment behavior has been shown to be influenced by psychological attitude. We focused on assessing whether the stock prices of firms characterized by high and low ESG scores exhibit comparable susceptibility to behavioral biases.

The remainder of the paper is organized as follow: Section 2 discusses the literature on socially responsible investing, behavioral finance, and the connection between them. Section 3 introduces the data, section 4 presents the empirical implementation, and section 5 draws the conclusion.

2. Background

2.1 Behavioral finance

A behavioral asset pricing model aims to analyze the impact of individuals' beliefs and preferences on asset prices. Some of the most well-known behavioral concepts are, for example, overconfidence (the belief that investors know more than they really do), and overoptimism (the overestimation of their own capabilities due to a sense of control). The specific effects of investor behavior and sentiment on stock returns have been studied both theoretically and empirically. As an alternative to the theory of rational investors and market efficiency, Kahneman and Tversky (1979) propose the prospect theory in which they introduce psychological factors to improve the decision-making process of economic agents. Thaler (1980) argues that investors do not deliberately act irrationally, but act under the influence of behavioral biases that often lead them to make suboptimal decisions. Several studies have provided empirical evidence that investor sentiment systematically influences stock returns and thus plays a key role in determining stock prices[2]. Doukas et al. (2002) show that investors tend to extrapolate their information disproportionately into the future,

[2] Chandra and Thenmozhi (2017) provide a review and synthesis on the evolution and current development of behavioral models for asset pricing as an alternative approach to pricing using classical models in the financial literature.

that they behave too optimistically, and that they exhibit a tendency to overreact. Through a natural experiment, Gao et al. (2021) find that investors turn overconfident after winning a purely luck-driven event. Cooper et al. (2008) document that investors suffer from an investor limited attention; they do not react adequately to the information contained in companies' financial statements. Bhalla (2012) and Spyrou (2013) evidence herding behavior which causes that much of the relevant information can be discounted in advance, leading to a distorted pricing mechanism.

Several authors have developed empirical asset pricing models that consider behavioral biases. For example, Hirshleifer and Jiang (2010) construct a valuation error factor by going long on stocks that repurchase their own shares and short on stocks that make new issues. They discuss the practice of managers when deciding whether the firms they manage should issue or purchase their own shares. These authors suggest that external financing and repurchase decisions by firms can provide relevant information. Corporate managers make financing decisions to exploit mispricing of the firms they manage. Firms tend to issue equity or debt when they are overvalued, and to repurchase equity or retire debt when they are undervalued. Daniel et al. (2020) also develop a model in which two factors related to investor behavior are included: a financing factor, which captures long-term valuation errors, and an inattention factor, which captures short-term valuation errors. Consistent with the argument of Hirshleifer and Jiang (2010), these authors state that, if a firm is overvalued, it will issue its own shares, whereas, if it is undervalued, it will buy them back. They suggest that managers who do not share the market expectations and observe a mispricing exploit it in the interest of shareholders. Additionally, these authors also note the existence of a limited investor attention bias. Firms that experience positive earnings surprises subsequently earn higher returns than those with negative earnings surprises. This pattern reflects the lagged response of prices to information.

There are a number of studies examining the impact of behavioral biases on asset prices or asset returns, thus contributing to the literature on behavioral asset valuation. Such literature, as can be seen, has been concerned with assessing behavioral biases on conventional asset valuation, i.e. without considering sustainability aspects. However, there is no previous literature addressing the existence of behavioral biases in asset prices in an SRI context.

2.2 Socially responsible investing

Most of the debate in the SRI literature revolves around the impact of social and environmental screening on portfolio financial performance[3]. By means of a meta-analysis, Hornuf and Yüksel (2023) provide evidence that, on average, SRI does not outperform or underperform the market portfolio. A strand of the literature has focused on the financial performance of SRI investment funds. Most of these studies (e.g., Bauer et al., 2005; Cortez et al., 2009, Bebchuk et al., 2013; Kamil et al., 2014; Boo et al., 2017) find no significant differences between the performance of SRI mutual funds and conventional funds, or the market in general. However, Derwall et al. (2011), Hammami and Oueslati (2017), and

[3] A discussion at the theoretical level on the effects of corporate social responsibility (CSR) practices on firms has been obviated for the sake of brevity. A review in detail can be found in Liang and Renneboog (2017) and Gillan et al. (2021), for example.

Reddy et al. (2017) show that SRI funds outperform the market, while Bauer et al. (2007), Lee et al. (2010), and Nainggolan et al. (2016) documented that these funds underperform the market. In a recent systematic literature review of the main studies analyzing the relative performance of SRI equity funds versus their conventional counterparts, Meyers et al. (2023) conclude that most empirical studies show a non-statistically significant difference in the relative financial performance of SRI funds. Another area of SRI research has addressed the performance of socially responsible indexes versus conventional market indexes. While most initial studies (e.g., Schröder, 2007; Statman, 2006) conclude that the performance of social indices does not differ statistically from conventional indices, more recent research (Cunha et al., 2020) has provided evidence of heterogeneous performance of SRI indices in different geographic regions[4]. A body of research explores the effects of SRI on the performance of synthetic portfolios formed from the social characteristics of firms. Most studies conclude that the consideration of sustainability aspects in the portfolio selection process does not impact portfolio performance (Auer and Schuhmacher, 2016; Badía et al., 2022; Carvalho and Areal, 2016; Eccles et al., 2014; Halbritter and Dorfleitner, 2015; Mollet and Ziegler, 2014; Yen et al., 2019)[5]. Finally, a new trend of research evaluates the effects of green investments on financial performance. Tang and Zhang (2020) provide evidence on the impact of green bond issuance. They find a positive stock price sensitivity to the issuance of green bonds. Flammer (2021) also evaluates the response of green bond issuances and find that there is a positive reaction from investors.

This previous literature on the effects of SRI on financial performance has mainly used multi-factor models such as the three, and five-factor Fama-French models along with the Carhart model. These models, while simple to apply and interpret -and the factors are easy to obtain, are based on investor rationality, and return and risk as decision parameters. However, as noted above, a number of behavioral biases can affect investor rationality, and a significant proportion of investors include ESG dimensions in their decision parameters. Such considerations prompt us to investigate whether SRI assets are exposed to behavioral biases and whether the inclusion of ESG dimensions in the decision parameters has an effect on the valuation of firms. In doing so, we use the behavioral model of Daniel et al. (2020).

2.3 Sustainability and behavior

This study arises in response to the lack of evidence on the impact of behavioral biases on ESG asset valuation. However, from an asset allocation perspective, previous studies have been concerned with assessing the impact of behavioral biases on asset managers, specifically on managers of sustainable investment funds. This approach makes it possible to show the extent to which investment fund managers are exposed to different behavioral biases. One of the biases that has been studied on sustainable investment fund managers is the disposition effect, consisting of the tendency to sell appreciated (gaining) stocks too early and to hold depreciated (losing) stocks too long. Summers and Duxbury (2012) suggest that specific emotional states trigger the disposition effect: regret after a money loss leads

[4] For a detailed review of studies on the performance of socially responsible indexes, see Cunha et al. (2020).

[5] A review of the literature concerned with evaluating the effects of SRI using synthetic portfolios can be found in Badía et al. (2020).

losers to hold, while euphoria after a gain leads winners to sell. Several explanations have been suggested on why this effect may exist for sustainable investors. For example, Boumda et al. (2021) suggest that, since SRI investors value social utility, SRI fund managers may be more willing to hold on to losing stocks if they believe that the social value outweighs the financial loss. Another assessed bias among SRI fund managers is herd behavior. Herding becomes because investors ignore their own personal views and decide to follow the decisions of others (Spyrou, 2013). Behavioral theory relates herding to psychological biases since investors operate based on unstable emotions and beliefs, leading to price movements away from fundamentals (Litimi et al., 2016). Lobato et al. (2023) examine the herding behavior of socially responsible exchange traded funds in comparison to conventional ones during extreme markets conditions and find that SRI investors herd during special periods. This response can be seen as a rational strategy, as it underlines the idea that adherence to socially responsible business behavior is a clear indicator of sound business judgment. Consequently, it reflects a company's ability to effectively navigate unforeseen shocks, such as a pandemic. In addition, investors' herd behavior can be attributed, in part, to the inherent challenges arising from information scarcity. These challenges make it particularly difficult for investors to arrive at accurate financial assessments when faced with unforeseen events (Clark et al., 2015). Other types of biases such as cognitive dissonance or investor sentiment have been also studied (Chang et al., 2016; Heimer, 2016; Patterson, 2022). Overall, these studies have highlighted the existence of behavioral biases among sustainable investors. It is therefore to be expected that the prices of assets in which they invest are affected by behavioral biases. This study attempts to shed light on this issue.

3. Data

This study assesses the exposure of sustainable and non-sustainable firms' stocks to behavioral biases. To identify sustainability, we use the ESG score provided by Thomson Reuters Refinitiv ESG (Refinitiv, 2022). The Refinitiv ESG scoring scheme classifies companies on the basis of more than 630 different ESG metrics. Refinitiv's ESG scores provide a comprehensive and transparent measure of a firm's relative ESG performance, engagement and effectiveness. It includes 10 main themes: emissions, environment, product innovation, human rights, shareholders, etc. Refinitiv's ESG scores are data-driven and consider the most material industry metrics. As part of its calculation rating method, scores are based on the relative performance of ESG factors with the company's sector (for environmental and social) and country of incorporation (for governance).

We analyze a dataset of firms from 19 European Union countries: Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherland, Poland, Portugal, Romania, Slovenia, Spain, and Sweden[6]. The sample comprises stocks assessed in terms of ESG performance by Refinitiv in these countries, covering a total of 1332 firms in the period from January 2004 to December 2022 (228 months = 19 years). We use the entire Refinitiv universe and both active and inactive

[6] No firms from the following European Unión countries are present in our sample due to the lack of ESG information provided by Refinitiv: Bulgaria, Cyprus, Croatia, Estonia, Latvia, Lithuania, Malta and Slovakia.

stocks are included, so our results are not affected by survivorship bias. Table 1 shows the evolution of ESG scores every three years. As expected, increasing percentiles lead to an upward trend in the average ESG score. Moreover, increments between percentiles are reasonably stable over the period, providing data robustness. This is especially important considering the portfolio approach we use to study the existence of biases in firms with different ESG scores. Consistent with Badía et al. (2020), the number of rated firms is progressively growing, reflecting the increasing market demand for ESG information. Overall, there is a broadly positive evolution in average ESG scores over time. This reflects that firms are generally getting better ESG ratings which suggests that firms are becoming more aware of ESG issues.

Table 1. Evolution of ESG scores over time

Date	P10	P20	P30	Median	P70	P80	P90	Mean	SD	n. of firms
Jun-04	15.18	19.64	25.00	37.43	48.29	52.83	64.05	37.94	18.39	255
Jun-07	18.59	25.31	32.43	44.86	58.94	65.66	73.35	45.58	20.30	338
Jun-10	22.29	32.92	41.24	54.76	66.18	70.96	78.83	52.55	20.73	388
Jun-13	27.28	37.07	45.45	57.03	68.55	73.98	78.97	55.33	19.57	402
Jun-16	31.73	42.88	49.24	60.29	71.26	76.77	82.36	58.62	18.97	443
Jun-19	27.85	38.31	45.44	57.40	68.60	74.26	80.12	55.61	19.83	863
Jun-22	29.98	41.53	49.40	60.59	71.48	76.53	82.10	58.56	19.36	981

This table summarizes the percentile values and descriptive statistics on the ESG score of the firms in the sample at the end of June every three years over the period analyzed: January 2004 to December 2022.

4. Empirical implementation

4.1 Portfolio formation

To examine whether stock prices of firms are exposed to behavioral biases, we follow a portfolio approach and then use the behavioral model of Daniel et al. (2020). For each year, we form two value weighted portfolios of stocks based on firms ESG ratings in the previous year. One portfolio comprises stocks with the top ESG rated firms, and other includes those with the bottom ESG rated firms. As in prior studies (e.g., Auer, 2016; Badía, et al., 2020; Carvalho and Areal, 2016), we use different cut-offs to form portfolios (10, 20 and 30%) in order to evaluate portfolios that are more or less restricted with respect to ESG criteria. In the spirit of Fama and French (1993), we also form zero-investment portfolios to identify significant differences between firms with different ESG characteristics. This consists of going long on top ESG firms and short on bottom ones. Monthly discrete stock returns are computed based on the total return series (in Euro) from the Thomson Reuters Datastream database. In line with Cooper et al. (2004) and Asem (2009), in order to minimize non-trading and microstructure-induced biases, we excluded stocks whose prices are below 1€ at the beginning of the holding period and those with a steady price for two consecutive months. Table 2 presents average ESG values of portfolios with different cut-offs over the period under analysis. The average ESG scores of the top and bottom portfolios for different cut-offs confirm the sizeable difference between firms in terms of ESG. For instance, in 2022, firms in the bottom 10% (B10) portfolio, i.e. those with the worst ESG values, score an average of 20.89, while firms in the top 10% (T10) portfolio, i.e. those with the best ESG values, score 86.62, which represents an average difference of more than 65 points.

Accordingly, the less stringent the ESG constraint, the smaller the ESG differences between firm. In this sense, the lowest case of stringency corresponds to the comparison between the firms in the B30 and those in the T30. In 2022, the average gap remains substantial at more than 45 points.

Table 2 Mean ESG values of top- and bottom-rated portfolios

Date	T10	B10	T20	B20	T30	B30
Jun-04	72.39	10.24	64.83	13.90	60.13	16.65
Jun-07	78.78	12.76	73.69	17.33	69.92	21.25
Jun-10	83.93	14.72	79.45	21.25	75.83	26.55
Jun-13	84.36	18.52	80.34	25.80	77.26	31.07
Jun-16	85.88	22.14	82.68	29.65	79.67	35.23
Jun-19	85.15	17.98	81.04	25.69	77.73	31.15
Jun-22	86.62	20.89	82.85	28.73	79.85	34.41

This table summarizes average ESG values for the top (T) and bottom (B) portfolios every three years at the 10%, 20% and 30% cut-off level. The full period analyzed is from January 2004 to December 2022.

Table 3 presents the descriptive statistics of portfolio monthly returns with different cut-offs over the period under analysis. All portfolios, both top and bottom, obtain a positive average monthly return for the full period. Firms in bottom portfolios for the different cut-offs obtain a higher mean return than firms in top portfolios, although standard deviation is also higher. This is consistent with a risk/return trade-off.

Table 3. Descriptive statistics of portfolio returns

	T10	B10	L-S10	T20	B20	L-S20	T30	B30	L-S30
Mean	0.0053	0.0062	-0.0010	0.0055	0.0071	-0.0016	0.0053	0.0070	-0.0017
SD	0.0455	0.0540	0.0341	0.0448	0.0487	0.0247	0.0449	0.0478	0.0216
t-mean	0.1157	0.1154	-0.0285	0.1220	0.1452	-0.0651	0.1173	0.1466	-0.0811
Median	0.0101	0.0139	-0.0037	0.0110	0.0129	-0.0018	0.0095	0.0128	-0.0025
Skewness	-0.3418	-0.3949	-0.2255	-0.3713	-0.3995	-0.1553	-0.4268	-0.5123	-0.2636
Ex.Kurtosis	1.7653	4.7647	4.7180	1.6282	3.3505	1.8361	1.5869	2.9620	0.9344

This table presents descriptive statistics for the top (T), bottom (B) and long-short (L-S) portfolios at the 10%, 20% and 30% cut-off level. t-mean ratio is the mean value divided by SD. The long-short portfolio is formed by subtracting the returns of the bottom-ranked portfolio from the returns of the top-ranked portfolio. The full period analyzed is from January 2004 to December 2022.

4.2 Portfolio exposure to behavioral biases

In order to identify behavioral biases in asset prices, we use the multi-factor model proposed by Daniel et al. (2020)[7]. This model introduces two behavioral factors in addition to the market factor, which attempt to capture a long-term valuation error (overconfidence bias) and a short-term valuation error (limited attention bias). The model is as follows:

$$r_{pt} = \alpha_p + \beta_{mp} Mkt_t + \beta_{FINp} FIN_t + \beta_{PEADp} PEAD_t + \varepsilon_{pt} \quad \text{(Eq.1)}$$

where r_{pt} is the euro excess return (the return in excess of the ten years German Treasury bill

[7] The model has been used, among others, in following prior studies: Edeling et al., (2021), Hou et al., (2021), Liu et al., (2022).

rate) of portfolio *p* in month *t*, and Mkt_t is the excess return of the value-weighted market portfolio in month *t*. The remaining independent variables are the financing factor (*FIN)* and the post earnings announcement drift (*PEAD)*. As described below, we form factors consistent with Daniel et al. (2020) using all sampled firms. In this model α_p is the intercept - also the estimated abnormal performance of portfolio *p*, and β_{mp}, β_{FINp}, and β_{PEADp} represent the estimated coefficients associated with the different factors. Finally, e_{pt} is the zero-mean residuals.

4.2.1 The FIN factor

One of the factors that the model introduces alongside the market is the FIN factor. Based on the intuition from the model of Stein (1996), this factor captures long-horizon mispricing. Firms' managers aware of mispricing of their firms can attempt to arbitrage this mispricing via issuance/repurchase of their own stocks. If investors were fully rational, the firm's financing decision would not predict future returns. As shown by Daniel et al. (1998), the market does not fully impound the information contained in a firm's decision to issue or repurchase equity, leading to return predictability. This factor is based on the 5-year composite share issuance (CSI) measures of Daniel and Titman (2006) and the 1-year net share issuance (NSI) of Pontiff and Woodgate (2008).

Daniel and Titman's (2006) 5-year CSI measure is the firm's 5-year growth in market equity not attributable to the stock returns. Issuance activity, as seasoned issues, the exercise of employee stock options, and equity-financed acquisitions, will increase the issuance measure. Activity such as share repurchases or cash dividends will decrease the issuance measure. Splits and stock dividends leave the composite issuance measure unchanged as they do not affect the market capitalization or the return. The CSI measure is as follow:

$$CSI_t = log\ (ME_t/ME_{t-5}) - r(t - 5,t) \quad \text{(Eq.2)}$$

For CSI in June of year *t*, ME_t is the market equity at the end of June in year t, ME_{t-5} is the market equity at the end of June in year *t-5*, and *r(t - 5,t)* is the cumulative log return on the stock from end of June in year *t–5* to end of June in year *t*.

Pontiff and Woodgate's (2008) 1-year NSI measure is identical to CSI except that NSI uses a 1-year horizon and excludes cash dividends:

$$NSI_{t-1} = log\ (\text{split-adjusted shares outstanding}_t/\text{split-adjusted shares outstanding}_{t-1}) \quad \text{(Eq.3)}$$

Once the CSI and NSI are calculated, at the end of each June, we assign firms to one of the two size groups (small "S" and big "B") based on whether that firm's market equity is below or above the June median size breakpoint. Independently, we sort firms into one of the three financing groups (low "L", middle "M", or high "H") based on the NSI and the CSI, respectively, using 20% and 80% breakpoints. The three financing groups are created based on an index of NSI and CSI rankings. If a firm belongs to the high (low) group by both the NSI and the CSI rankings, or to the high (low) group by one ranking while missing the other, the firm is assigned to the high (low) financing group "H" ("L"). In all other cases, firms are assigned to the middle financing group ("M"). Then, six portfolios (SL, SM, SH, BL, BM, and BH) are formed based on the intersections of size and financing groups. Value-weighted portfolios are calculated for each month from July to the next June, and the portfolios are rebalanced at the end of the next June. The FIN factor is formed by going long in firms with low issuance activity and short in firms with high issuance activity. The FIN factor return each month is calculated as the average return of the low financing portfolios (SL and BL) minus average return of the high financing portfolios (SH and BH):

$$FIN=(r_{SL}+r_{BL})/2-(r_{SH}+r_{BH})/2 \qquad \text{(Eq.4)}$$

4.2.2 The PEAD factor

The other factor that the model adds is the PEAD. This factor captures short-horizon mispricing. Firms that experience positive earnings surprises subsequently earn higher returns than those with negative ones. Empirical literature argues that this fact reflects delayed price response to information and that market underreaction is due to limited investor attention (e.g. Hirschleifer et al., 2009). Based on Chan et al. (1996), earning surprise is measured as the 4-day cumulative abnormal return (CAR) around the most recent earnings announcement date:

$$CAR = \sum_{d=-2}^{d=1}(R_{i,d} - R_{m,d}) \qquad \text{(Eq.5)}$$

Where $R_{i,d}$ is stocks *i's* return on day d and $R_{m,d}$ is the market return on day *d* relative to the earnings announcement date. To form the PEAD portfolio, we sort on *CAR* from the most recent announcement. A firm is excluded from the portfolio if no earnings are announced in the past 6 months.

At the beginning of month *t*, we assign firms to one of the two size groups (small "S" and big "B") based on whether that firm's market equity is below or above the median size breakpoint. Independently, we sort firms into one of the three earnings surprise groups (low "L", middle "M", or high "H") based on CAR_i at the end of month *t–1*, using 20% and 80% breakpoints. Six portfolios (SL, SM, SH, BL, BM, and BH) are formed based on the intersections of size and financing groups. Value-weighted portfolios are calculated for the current month. The PEAD factor is formed by going long in firms with positive earnings surprises and short in firms with negative surprise. The PEAD factor return each month is calculated as the average return of the high earnings surprise portfolios (SH and BH) minus the average return of the low earnings surprise portfolios (SL and BL).

$$PEAD=(r_{SH}+r_{BH})/2-(r_{SL}+r_{BL})/2 \qquad \text{(Eq.6)}$$

Table 4 reports summary statistics of the three factors of the model over the period under analysis. Panel A shows that Mkt factor offers the highest average monthly premium, although with the highest standard deviation. Meanwhile, the average premium of the PEAD factor is close to the Mkt, while the standard deviation is far lower. As a result, the monthly t-mean ratio for the PEAD factor is the highest. As an important point, panel B shows that the level of correlation between the FIN and the PEAD factor is low. This means that they capture different sources of mispricing. Both behavioral factors also show a low level of correlation with the Mkt factor.

Table 4. Descriptive statistics of model factors

Panel A. Statistics	Mkt	FIN	PEAD
Mean	0.0049	0.0027	0.0062
SD	0.0418	0.0170	0.0169
t-mean	0.1166	0.1616	0.3672
Median	0.0108	0.0010	0.0059
Skewness	-0.5144	0.2467	-0.2106
Ex. Kurtosis	1.6252	2.5542	1.0723
Panel B. Correlations	**Mkt**	**FIN**	**PEAD**
Mkt	1.0000		
FIN	-0.2133	1.0000	
PEAD	-0.1005	-0.0593	1.0000

This table reports descriptive statistics for the three factors. Panel A shows statistics of the three factors over the full sample period: January 2004 to December 2022. Panel B displays pairwise correlation levels.

Table 5 reports the results of the model estimations for the top, bottom and long-short portfolios at the different cut-off levels over the full sample period. Our results show that bottom-ranked ESG portfolios at different ESG stringency levels (10, 20, and 30%) are exposed to the FIN factor. The FIN factor is negative and statistically significant, meaning that stock prices of firms in these portfolios are affected by a long-term mispricing. This result confirms the idea that investors investing in bottom-ranked ESG firms are influenced by an overconfidence bias. This is a relevant finding since, on the contrary, top-ranked ESG portfolios are not exposed to the FIN factor. Results of the long-short portfolios confirm statistically significant differences in the portfolio exposure to the FIN factor between top- and bottom-ranked ESG portfolios. Our results also show that portfolios are not exposed to the PEAD factor. This finding suggests that for European firms there is not a short-term behavioral bias related to investor limited attention.

Our findings reveal that portfolios comprising stocks with the top-rated ESG firms are not affected by behavioral biases, whereas portfolios including stocks with the bottom-rated ESG firms exhibit behavioral bias associated with overconfidence. These results allow us to discard that sustainable firms are more exposed to mispricing, while accepting that these firms are even better valued than non-sustainable ones. This result is novel; no previous studies distinguish between sustainable and non-sustainable firms. Indeed, our results allow us to fine-tune those of Daniel et al. (2020). They find that firms in the US market are exposed to both behavioral factors. However, we find that, for the European market, only firms with the worst ESG valuations are exposed to one of the behavioral biases, in particular, the overconfidence bias. This result suggests that European investors are less affected by behavioral biases previously identified for other markets.

Table 5. Regression estimates of portfolios

	α		β_{Mkt}		β_{FIN}		β_{PEAD}	R^2 Adj.
T10	0.0002		1.0343	***	0.0479		-0.0141	0.8944
	(0.1558)		(29.8054)		(0.6624)		(-0.2242)	
B10	0.0035		1.0417	***	-0.4831	***	-0.1652	0.7307
	(1.5853)		(16.2147)		(-4.8154)		(-1.1255)	
L-S10	-0.0033		-0.0074		0.5310	***	0.1511	0.0620
	(-1.2935)		(-0.0854)		(3.9535)		(0.8308)	
T20	0.0003		1.0360	***	0.0406		-0.0043	0.9248
	(0.3478)		(33.5415)		(0.6894)		(-0.0890)	
B20	0.0043	*	0.9965	***	-0.5127	***	-0.1145	0.8327
	(2.5622)		(21.7919)		(-5.8553)		(-1.1667)	
L-S20	-0.0040	*	0.0394		0.5533	***	0.1102	0.1286
	(-2.0762)		(0.6239)		(5.6756)		(0.8457)	
T30	0.0003		1.0413	***	0.0022		-0.0131	0.9398
	(0.3320)		(40.7351)		(0.0414)		(-0.3547)	
B30	0.0032	*	1.0071	***	-0.4100	***	-0.0024	0.8481
	(2.2311)		(23.7946)		(-4.5484)		(-0.0251)	
L-S30	-0.0030		0.0342		0.4122	***	-0.0106	0.0892
	(-1.9335)		(0.6510)		(3.9470)		(-0.0915)	

This table shows the estimates of the three-factor model of the Daniel et al. (2020) for the top (T), bottom (B) and long-short (L-S) portfolios at the 10%, 20% and 30% cut-off level. The long-short portfolio is formed by subtracting the returns of the bottom-ranked portfolio from the returns of the top-ranked portfolio. The model (eq. 1) is estimated by OLS based on the heteroscedasticity and autocorrelation adjusted errors of Newey and West (1987). Values in brackets are the *t*-statistics. Asterisks represent statistically significant coefficients at the 0.1% (***), 1% (**) and 5% (*) significance levels. The full period analyzed is from January 2004 to December 2022.

4.3 Behavioral biases under different market conditions

The full period under analysis covers different market states (e.g. the international financial crisis and the European sovereign debt crisis). We exploit the opportunity to test whether behavioral biases are likely to be more prevalent in bull or bear markets. Market states are determined in the spirit of the Pagan and Sossounov (2003) approach. A month candidate for peak is identified when the maximum price of the month is higher than the maximum prices of the eight previous and the eight posterior months. A month candidate for trough is identified when the minimum price of the month is lower than the minimum prices of the eight previous and the eight posterior months. When consecutive peaks are identified, only highest is considered, and when consecutive troughs are identified, only lowest is considered. Consistent with the literature, we identify bear periods as those with a downtrend in the stock market index of at least 20% from peak to trough. The Eurostoxx 600 is used as the index. Table 6 shows the bear market episodes during the period 2004-2022; all other periods are considered bullish.

We observe a bear period associated with the international financial crisis (from 2007 to 2009). The downtrend from February 2011 to September 2011 can be attributed to the Euro sovereign debt crisis. The decline phase from April 2015 to February 2016 can be connected to the general stock market selloff, prompted to the Chine stock market turbulence and the Greek debt default in June 2015. The bear market of 2020 is associated with the COVID-19 pandemic. Furthermore, we observe another bear market period from January 2022 to September 2022, which can be connected with global pandemic-related supply chain disruptions and Russia's invasion of Ukraine.

Table 6. Bear market states

Start date	Index value (Points)	End date	Index value (Points)	Change in market index	Length of bear period (days)
2007/6	400.31	2009/3	157.97	-60.54	647
2011/2	291.16	2011/9	214,89	-26.20	217
2015/4	414.06	2016/2	303.58	-26.68	302
2020/2	433.90	2020/3	279.66	-35.55	28
2022/1	494.35	2022/9	382.89	-22.55	267

This table identifies periods of bear market identified in the spirit of the Pagan and Sossounov (2003) procedure. The sample period studied is from January 2004 to December 2022. The index used is the Eurostoxx 600. Consistent with the literature, we require the rise (fall) of the market being greater (less) than either 20%. We test the window breadth for eight, nine and ten months and obtain the same results.

Table 7 reports the results of the model estimations for the top, bottom and long-short portfolios at the different cut-off levels over the full sample period, considering different market states. Our findings align with those presented earlier in Table 5. Specifically, the FIN factor is negative and statistically significant for all bottom-ranked ESG portfolios at different ESG stringency levels (10, 20, and 30%). This implies that stock prices of firms in these portfolios are subject to long-term mispricing, during both bullish and bearish periods. Overconfidence bias influences investors investing in bottom-ranked ESG firms, independent on the market state. Results of the long-short portfolios confirm statistically significant differences in the portfolio exposure to the FIN factor between top- and bottom-ranked ESG portfolios. Notably, our results indicate that portfolios are not exposed to the PEAD factor, in either bear or in bull periods. Moreover, investor limited attention bias does not impact European firms, irrespective of the prevailing market state.

In summary, our research reveals behavioral biases do not differentially affect asset prices across different market states. These results support the conclusion that European sustainable firms are better valued than their non-sustainable counterparts.

Table 7. Regression estimates of portfolios in different market states

	α BEAR	α BULL	β_{Mkt} BEAR	β_{Mkt} BULL	β_{FIN} BEAR	β_{FIN} BULL	β_{PEAD} BEAR	β_{PEAD} BULL
T10	0.0023	-0.0016	1.0053 ***	1.0927 ***	0.0908	0.0131	0.1601	-0.0426
	(0.5954)	(-1.4105)	(14.1417)	(26.3568)	(0.4954)	(0.1592)	(1.3029)	(-0.5925)
B10	0.0040	0.0039	0.8972 ***	1.0345 ***	-0.9494 *	-0.3340 **	-0.5455	-0.0998
	(0.6675)	(1.8770)	(6.8974)	(10.3384)	(-2.4524)	(-2.6078)	(-1.9884)	(-0.5052)
L-S10	-0.0017	-0.0055 *	0.1082	0.0581	1.0402 *	0.3471 *	0.7056 *	0.0571 *
	(-0.2210)	(-2.3299)	(0.6127)	(0.4545)	(2.0893)	(1.9948)	(2.1325)	(0.2336)
T20	0.0035	-0.0012	1.0401 ***	1.0758 ***	0.0925	0.0248	0.0871	-0.0142
	(0.9914)	(-1.3115)	(16.9684)	(35.8520)	(0.4692)	(0.3951)	(0.6460)	(-0.2754)
B20	0.0035	0.0041 *	0.8365 ***	1.0283 ***	-0.9164 ***	-0.3519 ***	-0.2465	-0.1333
	(0.8985)	(2.5684)	(11.2859)	(15.6762)	(-4.3912)	(-3.9009)	(-1.4297)	(-1.0222)
L-S20	0.0000	-0.0053 **	0.2036	0.0474	1.0089 **	0.3767 **	0.3336	0.1192
	(0.0007)	(-3.0097)	(1.7754)	(0.5927)	(3.3947)	(3.3553)	(1.5126)	(0.7429)
T30	0.0031	-0.0006	1.0456 ***	1.0656 ***	-0.0049	0.0071	0.0437	-0.0302
	(1.0459)	(-0.7471)	(20.8133)	(42.2603)	(-0.0313)	(0.1268)	(0.4125)	(-0.6731)
B30	0.0062	0.0031 *	0.8942 ***	1.0250 ***	-0.8418 ***	-0.2382 **	-0.1179	-0.0358
	(1.5323)	(2.1076)	(13.0510)	(18.5744)	(-5.2792)	(-3.0039)	(-0.6138)	(-0.3241)
L-S30	-0.0032	-0.0037 *	0.1514	0.0406	0.8368 ***	0.2452 *	0.1615	0.0056
	(-0.6518)	(-2.2688)	(1.6467)	(0.6363)	(3.8864)	(2.2664)	(0.7055)	(0.0415)

This table shows the estimates of the three-factor model of the Daniel et al. (2020) for the top (T), bottom (B) and long-short (L-S) portfolios at the 10%, 20% and 30% cut-off level, in different market states. The long-short portfolio is formed by subtracting the returns of the bottom-ranked portfolio from the returns of the top-ranked portfolio. The model (eq. 1) is estimated by OLS based on the heteroscedasticity and autocorrelation adjusted errors of Newey and West (1987). Values in brackets are the *t*-statistics. Asterisks represent statistically significant coefficients at the 0.1% (***), 1% (**) and 5% (*) significance levels. The full period analyzed is from January 2004 to December 2022.

5. Conclusions

In this paper, we address the exposure of stocks of sustainable and non-sustainable firms to behavioral biases. Whereas research in behavioral finance has explored behavioral biases that may affect the stock prices of conventional firms, there is no previous evidence on the existence of behavioral biases in the stock prices of sustainable firms. We follow a portfolio approach and evaluate whether stock prices of top ESG ranked firms are equally exposed to behavioral biases, if any, as those of bottom ESG ranked firms. To identify behavioral biases in both the short and long term, the three-factor behavioral model of Daniel et al. (2020) is used. Our data includes firms in European Union countries for the period January 2004 to December 2022.

The results revel that stock prices of firms with high ESG scores are not exposed to behavioral biases while those of firms with low ESG scores exhibit behavioral biases. In particular, stock prices of bottom ESG ranked firms are affected by an overconfidence bias. These results are consistent with the idea of sustainable investors follow more closely the practices and activities of the firms in which they invest and quickly incorporate any new information that appears in the market into share prices. This evidence implies that stock prices of firms with high ESG standards are better valued than those of firms with low ESG standards. The results are irrespective of the prevailing market states. Our findings allow to discard that sustainable firms are more exposed to mispricing, while accepting that sustainable firms are even better valued than non-sustainable ones. Paradoxically, we conclude that stock prices of ESG-aware firms are more aligned with the efficient market hypothesis.

Our results have major implications in terms of resource allocation and are important for both practitioners and academics. The central problem of the economy is resource allocation (Copeland et al., 2005) and the market is the institution primarily responsible for solving it (Fama, 1970). In doing so, stock prices must properly reflect all available information. As behavioral finance research has shown, a number of behavioral biases can affect the proper pricing of assets, directly affecting the efficient allocation of resources and thus compromising the smooth functioning of economies. Our findings reveal that in Europe stock prices of firms with high ESG scores are not exposed to behavioral biases, signaling a good allocation of resources.

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