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The power of ethical words

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Abstract

In this research, we analyse the impact of the inclusion of ethical expressions in the prospectuses of socially responsible (SR) mutual funds on money flows. We contribute to the existing literature by proposing a text-based measure that integrates three attributes that are relevant to whether clients are attracted: exclusiveness, intensity and lexical diversity. We analyse a sample formed of 266 SR US equity mutual funds in the period 1999–2019. Our findings show that both the proposed indicator and other alternative partial proxies based on textual data have a positive impact on the money flows of the SR funds. This effect is more relevant in the case of SR mutual funds belonging to smaller families. Besides, persistence in money flows is more intense for SR mutual funds that are more attractive because of their ethical expressions. Another finding shows that return-chaser behaviour occurs among all SR investors, independently of the level of text attractiveness of the mutual funds in which they invest, revealing that they take into account both financial and non-financial outcomes. Our results indicate that policymakers should control fund prospectus information, given its importance for investors' decisions. In addition, managers should be especially cautious with the information provided in prospectuses because of its impact on investor decisions.

KEYWORDS
money flows persistence, money fund flows, return-chaser behaviour, socially responsible (SR) mutual funds, textual persuasion strategies

1 | INTRODUCTION

The widespread development of the socially responsible (SR) mutual fund industry over recent decades has allowed SR funds to become important collective vehicles for investment in the financial markets (El Ghoul et al., 2023; Erragragui & Lagoarde-Segot, 2016; Muñoz, 2020). This growth has also enhanced the competition to attract money flows from increasingly ESG-conscious[1] investors. Among other corporate strategies, SR funds deal with market competition through product differentiation. One of the primary sources of SR fund differentiation for investors is the ESG policy of the fund and the ESG practices described in the fund prospectus. The fund prospectus is commonly the first piece of information considered for investment decisions, and it must be accessible and understandable to all investors (Kostovetsky & Warner, 2020). Hence, apart from financial information based on fundamentals such as returns or holdings, the ESG information provided in the fund prospectus may be essential to attract and retain investors; that is, it is not only quantitative data but also qualitative information that may be a significant predictor of SR fund flows.

With regard to the influence of quantitative data on fund flows, previous studies find that past returns, portfolio holdings, portfolio

rebalancing decisions, return-chasing behaviours, stock market conditions and macroeconomic variables have diverse effects on mutual fund flows (Fong et al., 2018; Jotikasthira et al., 2012; Li et al., 2015; Puy, 2016; Qureshi et al., 2017; Raddatz & Schmukler, 2012, among others). Nonetheless, the SR mutual fund literature finds that SR fund flows are less sensitive to financial results than conventional fund flows (Benson & Humphrey, 2008; Bollen, 2007; In et al., 2014; Renneboog et al., 2011). Whether or not SR mutual fund flows are less sensitive to financial matters, the non-financial utility found in aspects such as the ESG information in the fund prospectus might be relevant to SR fund flows. Nevertheless, the relationship between ESG information in fund prospectuses and fund flows is an underexplored area in the literature.

The number of text analyses based on the information shared with investors is growing (Loughran & McDonald, 2016), and earlier studies examined product differentiation based on text-based indicators in fund prospectuses (Alda et al., 2022; Kostovetsky & Warner, 2020). Kostovetsky and Warner (2020) find that text-based uniqueness in fund prospectuses can predict flows for young conventional funds. Alda et al. (2022) find that differentiation in the text of prospectuses attracts flows, especially for younger SR funds and for funds belonging to smaller families. However, unlike this paper, the aforementioned works do not consider the influence of specialized vocabulary on SRI (Socially Responsible Investment) and ESG matters.

Furthermore, the broad universe of SR categories and the specialization of funds according to diverse ESG themes (climate change, water, religious matters, social rights, labour conditions, fossil fuel divestment, tobacco exclusions, military/weapon exclusions and anti-corruption, among many others) result in diverse ESG text in prospectuses, providing additional opportunities to analyse whether funds with specialized ESG vocabulary and ESG wording patterns are able to differentiate themselves from funds in other SR categories as well as from funds in the same SR category. This paper considers these concerns, and analyses the value in attracting and retaining investors of ESG wording and ESG expressions in the prospectus of an SR fund. We propose a score that captures attractiveness to investors by considering three ESG wording parameters (ESG intensity, ESG exclusiveness and ESG lexical diversity). In addition, considering that the US mutual fund industry is the most globally competitive market (according to US Sustainable Investment Forum [USSIF] records [USSIF, 2022]), we study this topic for a US mutual fund sample.

Our findings indicate that funds that include more, more diverse and more exclusive ESG expressions in their fund prospectus attract more flows than competing funds. Our research contributes to the academic literature with three textual indicators of product differentiation (based on intensity, exclusiveness and lexical diversity). In addition, persuasive strategies based on text are more relevant in attracting money flows for mutual funds belonging to smaller mutual fund families. Our results identify patterns in money flow determinants, helping managers gain a better understanding of the behaviour of investors. Specifically, investors demonstrate persistence and return-chaser behaviour, since they put their money in funds in which they have already invested and select mutual funds that have performed well in the past. Our further analyses offer interesting findings for policymakers controlling fund prospectus information because the inclusion of sustainability terms in the fund name, unlike ESG expressions in the fund prospectus, does not increase money flows. Besides, we find a positive relationship between mutual funds' ESG scores and their scores for our ESG investor attractiveness text measure, which means that the mutual fund companies in our sample show a true commitment to ESG issues instead of opportunistic greenwashing behaviour. Finally, our results are robust regarding the impact of the ESG investor attractiveness score on flows after controlling for load fees and also if we perform a quintile/decile portfolio analysis based on the ESG investor attractiveness score.

The rest of the paper is structured as follows. The second section describes the text-based measures and establishes the research hypotheses. The third section presents the data and methods. The fourth section includes our main empirical findings. Finally, the fifth section displays the main conclusions.

2 | TEXT-BASED MEASURES AND RESEARCH HYPOTHESES

2.1 | Proposed text-based measure

The previous literature demonstrates an influence of advertisement strategies on investment intention related to mutual funds and, specifically, on investor flows (see, for example, Dey et al., 2015 or Gallaher et al., 2015). Moreover, based on the fact that advertising techniques can be classified into three groups (Romanova & Smirnova, 2019) (those pertaining to logical reasoning, those presenting a positive image of the company and those involving an emotional component [persuasive advertising]), one might consider a mutual fund prospectus to be an advertisement that provides the investor with relevant information about the investment. The text of a prospectus is easier for the investor to process and can be a more visible product differentiator than other characteristics such as portfolio holdings or return data (Alda et al., 2022; Kostovetsky & Warner, 2020). Further, given that persuasive advertising seeks to attract consumers to purchase specific goods or services by appealing to their emotions and/or general sensibilities, we might consider an SR mutual fund prospectus to be an even more powerful persuasive advertising instrument since it contains information about ESG investments that would match the views of like-minded SR investors. An SR investor is expected to be more sensitive about fund investments that have a positive ESG impact, and accordingly, investors may react more strongly to this type of information which matches with their emotions and, indeed, offers a more positive image of the fund.

This reasoning led us to develop our novel text-based measure of investor attraction. For this purpose, we consider three factors

influencing SR investors' behaviour and their predisposition to put their money into this type of socially conscious fund:

1. ESG *exclusiveness*. As is widely known, exclusivity attracts the most sophisticated consumers who are looking for a differentiated product. Chandon et al. (2022) point out that exclusiveness is built on five closely related concepts: uniqueness, differentiation, inhibition, dominance and salience. The first of these, uniqueness, refers to the absence of comparable brands; differentiation refers to the implicit association with one specific product; inhibition occurs when one brand inhibits the recall of others; dominance occurs when most consumers associate a product with a specific brand; and salience refers to the high level of prominence in memory that makes one brand stand out from its competitors. For this specific case, we take Manning and Schutze's (Manning & Schutze, 1999) approach as a starting point. This approach is based on a weighting scheme that considers the frequency with which words (expressions) appear in the documents (prospectuses) analysed. On the basis of this idea, we measure ESG fund exclusiveness as the quotient of the total number of funds with prospectuses containing ethical expressions in year t in the sample (N) and the number of funds in which the ethical expression j occurs at least once in year t (n_j) in the fund prospectuses. Funds with an ethical expression that only occurs in a small number of fund prospectuses (the prospectus section selected) are more likely to be different from other funds with ethical expressions that are used in a large number of fund prospectuses. The quotient will be higher when an ethical expression appears less often in the fund sample analysed (that is, the quotient shows the *exclusiveness* of the ethical expression in the fund sample). Note that the maximum value of this quotient will be N, which would indicate that only one fund prospectus contains the ethical expression j, corresponding to a situation of maximum exclusiveness; by contrast, the minimum value of this measure is 1, which corresponds to a situation of zero exclusiveness since expression j appears in all the fund prospectuses analysed.
2. ESG *intensity*: Repetition is a basic strength factor of cognition. Repetition makes it easier for a consumer to recall and record a product characteristic in their memory (Musté et al., 2015). Chang (2009) explores the effectiveness of repetition strategies for narrative advertising and finds that repetition makes a narrative easier to comprehend and more persuasive. Here, we approximate the ESG intensity or repetition by the frequency of ESG mentions, that is, the number of all occurrences of the ESG expression j in the prospectus of fund i in year t. The higher the ESG intensity, the stronger the expected response from SR investors, taking into account that linguistic resources involving the repetition of some elements/expressions are inherent to the strategy of persuasion.
3. ESG *lexical diversity*: Previous studies on lexical diversity in the field of applied linguistics have documented a positive relationship between lexical diversity, the holistic quality of written or spoken discourses and language proficiency (Yu, 2010). Considering the prospectus as the most important advertising factor for a mutual fund, the writing and wording are of special interest for the fund marketer, and this is even more relevant for an SR fund because the prospectus is aimed at SR investors who are especially sensitive to the ESG activities of the fund. This type of investor, theoretically, prioritizes optimal environmental, social and governance outcomes. We consider that the higher the ESG lexical diversity in the fund prospectus, the greater the investor perceives the fund's commitment to the environment and society to be. We approximate the ESG fund lexical diversity by the number of different (not repeated) ESG expressions appearing in the prospectus of fund i in year t.

Thus, we consider the three dimensions (exclusiveness, intensity and lexical diversity) to construct our novel text-based measure of investor attraction (1)[2]:

$$ESG\_Investor\_attraction\_Score_{i,t} = \sum_{j=1}^{M}\left(ESG\_intensity^{j}_{i,t} \times ESG\_exclusiveness^{j}_{i,t}\right) \times ESG\_lexical\,diversity_{i,t} \quad (1)$$

Note that intensity and exclusiveness are obtained for each ESG expression j, and hence to build the investor attraction score for fund i, we need to add these components for all expressions j appearing in the prospectus of fund i in year t ($j = 1, \ldots M$).[3]

The score is calculated by considering all the SR mutual funds together and by controlling for the Morningstar ESG investment strategies.[4] This is done because an SR fund following negative screens for the tobacco sector and another fund investing in renewable energies could obtain different scores. However, the ESG investor attraction score might not completely explain the different inflow volumes that these funds would receive because the fact that the two funds represent different ESG concerns would also have an impact on their inflows. Thus, for a given year t and for each ESG strategy, we first obtain the score for each fund applying that particular ESG category (note that now N and n_j are restricted by the number of funds following the specific ESG strategy) and we then obtain a unique score for each fund and year by averaging the scores obtained by that fund in all the ESG strategies in which the fund is involved, as in expression (2):

$$ESG\_Investor\_attraction\_Score^{*}_{i,t} = \sum_{k=1}^{P}\frac{\left(ESG\,Investor\,attraction\,Score^{k}_{i,t}\right)}{P} \quad (2)$$

where k refers to the Morningstar ESG strategies followed by fund i ($k = 1, \ldots P$).

In addition, in the analyses conducted in the following sections, we consider other partial investor attraction measures with the aim of checking the robustness of our findings. Thus, we calculate the exclusiveness score separately. For this purpose, first, based on

Manning and Schutze's (1999) approach, we obtain the logarithm of the quotient of N and n_j as follows:

$$w_{i,t}^{j} = \log(N / n_j) \tag{3}$$

where $w_{i,t}^{j}$ is the exclusiveness of the ESG expression j in fund i in year t with regard to the other funds in the sample in year t, and N and n_j have been defined previously. The weight (w) will be higher when an ethical expression appears less often in the fund sample analysed (that is, it shows the *exclusiveness* of the ethical expression in the fund sample).[5]

Next, we calculate $w_{i,t}^{j}$ for all j expressions appearing in the prospectus for fund i in year t (from $j = 1, \ldots M$).

We then obtain the *fund exclusiveness* score (4) as the average of all $w_{i,t}^{j}$; that is, the average weights of all the j expressions appearing in the prospectus of fund i in year t:

$$ESG\_fund\_exclusiveness\_score_{i,t} = \sum_{j=1}^{M} \frac{w_{i,t}^{j}}{M} \tag{4}$$

Additionally, we compute the exclusiveness score controlling for the Morningstar ESG strategies, as we explained above for the investor attraction score. We follow the same procedure:

$$ESG\_fund\_exclusiveness\_Score_{i,t}^{*} = \sum_{k=1}^{P} \frac{ESG\_fund\_exclusiveness\_score_{i,t}^{k}}{P} \tag{5}$$

Lastly, the *number of ESG expressions* in one fund prospectus (ESG fund intensity) and the *number of unique ESG expressions* (not repeated) in a particular fund prospectus (ESG fund lexical diversity) are considered as additional partial investor attraction measures.

2.2 | Research hypotheses

The utility function of SR mutual fund investors depends on both financial and non-financial attributes (Bollen, 2007). The determinants of the money flows of investors in SR mutual funds constitute a relevant research topic in the academic literature. Most previous studies have focused on the relationship between money flows and past financial outcomes. However, more recently, we can find academic articles analysing the impact on money flows of different mutual funds' ESG commitment indicators. Most of these articles find a positive relationship between these two dimensions. Thus, Ammann et al. (2019) find that mutual funds with higher sustainability ratings attract larger money flows. In the field of experimental economy, Hartzmark and Sussman (2019) document a positive relationship between sustainability and money flows in the mutual fund industry. Reboredo and Otero (2021) point out that investors allocate more money to funds with lower climate-related transition risks. Becker et al. (2022) find that a better ESG label leads to larger net fund inflows. El Ghoul and Karoui (2021) point out that changing a fund's name to include sustainability-related terms increases money flows. Fang and Parida (2022) find that highly sustainable funds attract significantly more investment. On the other hand, among the few authors finding different empirical evidence, Sokolov et al. (2022) control for non-linear drivers and interactions between input factors and obtain the result that sustainability has little power to predict fund flows.

Beyond its ESG score and name as indicators of the ESG commitment of a mutual fund, we consider that one of the more noticeable signals for investors of a mutual fund's sustainability commitment could be the information provided in the fund prospectus, as we have explained in the previous section. We hypothesize that SR mutual funds with prospectuses containing more exclusive, intense, and lexically diverse ethical expressions will be able to attract more money flows. For this reason, our first research hypothesis is as follows:

> **RH1:** SR mutual funds with higher text scores attract more inflows.

The previous literature has analysed the impact of different text-based scores on mutual funds' money flows. Kostovetsky and Warner (2020) find that text-based differentiation is more relevant for mutual funds belonging to smaller families and for younger funds. Smaller families have fewer resources to compete in expenses and/or reputation and have to use text differentiation to attract investors' attention. The rate of starting new funds is higher in smaller mutual fund families, meaning that they have more innovation and product differentiation (Kostovetsky & Warner, 2020; Sirri & Tufano, 1993). Younger funds have to stand out in order to compete for money flows with more consolidated mutual funds. Besides, mutual fund families have incentives to differentiate their new funds to avoid cannibalizing the market share of their existing products and to attract investors with new profiles (Gaspar et al., 2006; Khorana & Servaes, 2012). Alda et al. (2022) obtain similar empirical evidence in the case of SR funds.

The above reasons lead us to hypothesize that the two dimensions of family size and fund age could have an impact on the empirical results for RH1. Thus, we propose the following research hypotheses:

> **RH2:** The impact of text-based measures on fund flows is more relevant for funds from smaller families.

> **RH3:** The impact of text-based measures on fund flows is more relevant for younger funds.

The mutual fund literature has proved the existence of money flow persistence. Cashman et al. (2014) explain that investors are likely to invest more in mutual funds if they already own such shares. These authors find that fund flows are a better predictor of future fund flows than performance. Other authors find a positive

correlation between current and subsequent money flows (Del & Tkac, 2002; Keswani & Stolin, 2008; Warther, 1995; among others). Muñoz (2019) obtains similar empirical evidence in the case of SR mutual funds. El Ghoul and Karoui (2017) argue that a fund that is highly committed to CSR (Corporate Social Responsibility) principles will cater to more loyal investors and will be less worried about other matters such as financial performance or risk, so investors will show greater persistence in money flows. Like El Ghoul and Karoui (2017), we hypothesize that the persistence of flows should be more intense for mutual funds with higher text scores, since SR mutual fund investors would face difficulties in finding alternatives that meet their non-financial concerns. Besides, persuasion through text could cater to more loyal investors (Alda et al., 2022). Thus, we propose the following research hypothesis:

> **RH4:** Persistence of money flows is more intense for SR mutual funds with higher text scores.

Investors in SR mutual funds take into account both the financial and non-financial outcomes of their portfolios. The empirical evidence obtained in the previous literature is mixed. Benson and Humphrey (2008) find that money flows for SR funds are less sensitive to past returns than those for conventional funds. These authors explain that the lower number of alternatives fulfilling the non-financial concerns of investors makes it more likely that these investors will purchase more shares in funds in which they have already invested. Although Bollen (2007) identifies that SR investors' utility function depends on both financial and non-financial dimensions, he finds that SR mutual fund investors are more (less) sensitive to past positive (negative) returns, meaning that these investors may be more sensitive to performance variations because of the higher uncertainty caused by the short history of SR funds in comparison to conventional ones. Renneboog et al. (2011) find that the type of ESG strategy followed can have an impact on the relationship between flows and past returns in the SR mutual fund industry. Specifically, whereas the implementation of sin/ethical and social screens reduces the flow sensitivity to past returns, the integration of environmental issues into investment strategies enhances the flow–return sensitivity when past returns are positive. These results show the heterogeneity of the investor clientele for SR funds. Muñoz (2019) provides empirical evidence of return-chaser behaviour among investors in SR mutual funds. However, the influence of lagged returns on money flow decisions could be less intense for certain investor profiles. For example, Muñoz (2019) finds that values-driven investors are less influenced by past performance when making their investment decisions. El Ghoul and Karoui (2017) point out that funds holding a higher ESG portfolio repel performance-chasing investors and attract socially conscious ones. In this regard, these authors find that an increase in the CSR portfolio score weakens the flow–performance relationship. Following the reasoning of El Ghoul and Karoui (2017), we hypothesize that those investors holding shares in funds with higher text scores present weaker return-chaser behaviour since they are more loyal to these funds and face greater difficulties in finding good alternatives that meet their non-financial concerns. Thus, we pose the following research hypothesis:

> **RH5:** Return-chaser behaviour is lower for SR mutual funds with higher text scores.

3 | DATA AND METHODS

3.1 | Data

From the Morningstar database, we obtain the actively-managed and non-indexed SR mutual funds investing in domestic and global equity assets domiciled in the US market with "YES" in the Socially Conscious label[6] from January 1999 to October 2019. We collect information on monthly returns, monthly total net assets (TNA), inception date, net expense ratio, turnover ratio, advisor name and SR investment strategy indicators (representing different screens and SR strategies; see endnote 3). The sample analysed is free of survivorship bias because we include those funds that disappeared before October 2019. To examine the ESG expressions included in the fund prospectuses, we search the prospectuses on the webpages of the selected funds; however, prospectuses are common for all share classes belonging to the same fund. Hence, we work at the mutual fund level and aggregate all share classes by fund, following the method proposed by Renneboog et al. (2011). When we searched for the fund prospectuses, some were not available; as a result, the final fund sample is restricted to 266 SR mutual funds.

From the fund prospectuses obtained, we search the "principal investment strategies" (PIS) section. From the PIS sections of all the funds, we eliminate all words and expressions not related to ESG vocabulary and obtain the ESG expressions used for each fund. From these ESG expressions, we create a list with all ESG expressions appearing in the fund prospectuses analysed, resulting in our ESG expression sample. This is the information that we use to compute the different text measures explained in the previous section. We found it more appropriate to consider ESG expressions and not only ESG words because some words only acquire an ESG meaning when they form part of an expression; for example, the word "change" does not suggest an ESG meaning, but if it is considered as part of the expression "climate change," then it does. Figure 1 plots the more frequent ESG expressions in our sample.

We develop other variables at the fund level. We define fund size (Size) as the log of the fund's monthly total net assets (expressed in $ millions). We also consider the size of the fund's family (Family Size), defined as the log of the monthly total net assets of all SR funds belonging to the same family (expressed in $ millions). The net expense ratio (NER) and the turnover ratio (TR) are directly collected from Morningstar.[7] The fund age (Age) is computed as the number of years since the inception date of the oldest share class of the fund. Additionally, we compute the percentage of total net assets belonging to institutional share classes (INST) and the number of

FIGURE 1 ESG expression cloud. This figure shows the ESG expression cloud for those expressions appearing at least 20 times in the analysed prospectuses. The total number of non-repeated ESG expressions in these prospectuses is 2006. The size of each item represents its frequency. *Source*: Own elaboration from TagCrowd (TagCrowd.com).

SR strategies followed by the fund (Number SR Strategies). Relative monthly flows (Flows) are computed according to this expression:

$$Flows_{i,t} = \frac{\left[TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})\right]}{TNA_{i,t-1}} \quad (6)$$

where $TNA_{i,t}$ is the total net assets of fund i at the end of month t, $TNA_{i,t-1}$ is the total net assets of fund i at the end of month $t-1$ and $r_{i,t}$ is the net monthly return of fund i in month t. Following Kostovetsky and Warner (2020), we winsorize the relative monthly flows at the 1% and 99% levels.

We also assess whether portfolio holdings influence money flows by analysing portfolio similarity. For this purpose, we calculate the portfolio similarity (Overlap) based on fund holdings (Kostovetsky & Warner, 2020). To calculate this measure, we obtain the annual portfolio holding weights of the analysed funds from the Morningstar database.[8] Following Kostovetsky and Warner (2020), we calculate the cosine similarity between the holdings of two funds (the cosine similarity between two vectors is the dot product of the two vectors scaled by the product of the magnitudes of the two vectors). In this way, we obtain the cosine similarity between the holding weights of each fund-year observation and the holding weights of each other fund in the same SR category. We then average this pairwise measure across all other funds in an SR category annually to obtain the measure Portfolio Overlap.

Table 1 presents the main summary statistics of all the variables involved across the models, and Tables 2a and 2b provide the correlation matrix.

3.2 | Methods

Given the nature of our data, we perform ordinary least squares (OLS) regressions with time controls and standard errors clustered at the fund level. We perform several analyses to explain the money flows into SR funds. First, we set out the base model, including all controls at the fund level:

$$\begin{aligned} FLOWS_{i,t} = {} & \alpha_0 + \beta_1 FLOWS_{i,t-1} + \beta_2 RET_{i,t-1} + \beta_3 SIZE_{i,t-1} + \beta_4 FAM_{SIZE_{i,t-1}} \\ & + \beta_5 AGE_{i,t-1} + \beta_6 ESG\_STRAT_{i,t-1} + \beta_7 TR_{i,t-1} + \beta_8 NER_{i,t-1} \\ & + \beta_9 INST_{i,t-1} + \beta_{10} OVERLAP_{i,t-1} + TIME\_CONTROLS + \varepsilon_{i,t} \end{aligned} \quad (7)$$

Then, we add the different text measures explained in Section 2 to the base model, testing RH1; that is, we analyse the impact of these text indicators on the money flows into the SR funds.

$$Flows_{i,t} = BASE\ MODEL + \beta_{11} TEXT\_MEASURE_{i,t-1} + \varepsilon_{i,t} \quad (8)$$

Kostovetsky and Warner (2020) and Alda et al. (2022) find that text differentiation could be especially relevant for younger funds and funds belonging to smaller families. Thus, to analyse RH2 and RH3, we interact these funds' characteristics with the different text measures by using mean-centred variables to avoid multicollinearity problems (see Aiken et al., 1991).

$$\begin{aligned} Flows_{i,t} = {} & BASE\ MODEL + \beta_{11} TEXT\_MEASURE_{i,t-1} \\ & + \beta_{12} TEXT\_MEASURE_{i,t-1} * FAM_{SIZE_{i,t-1}} + \varepsilon_{i,t} \end{aligned} \quad (9)$$

$$\begin{aligned} Flows_{i,t} = {} & BASE\ MODEL + \beta_{11} TEXT\_MEASURE_{i,t-1} \\ & + \beta_{12} TEXT\_MEASURE_{i,t-1} * AGE_{i,t-1} + \varepsilon_{i,t} \end{aligned} \quad (10)$$

TABLE 1 Summary statistics.

	Obs.	Mean	Std. dev.	10th percentile	50th percentile	90th percentile
Flows (%)	30,608	0.6956	5.2693	−2.5177	−0.0988	4.4057
Return (%)	30,608	0.5719	4.8483	−5.4578	0.9377	5.9189
Size	30,608	5.7753	1.9379	3.2224	5.9263	8.2916
Family Size	30,608	8.6975	2.1599	5.9657	9.3705	11.2315
Age	30,608	10.5976	10.5385	1.5096	8.2219	21.1068
N° SR Strategies	30,608	3.0857	3.4832	1.0000	1.0000	8.0000
TR	30,608	0.6778	0.7147	0.1500	0.5000	1.3014
NER (%)	30,608	1.5062	1.1685	0.6585	1.2516	2.3980
INST (%)	30,608	0.4064	0.3670	0.0000	0.2789	0.9826
Overlap	30,608	0.0656	0.0469	0.0143	0.0526	0.1375
Ethical expressions (Intensity)	30,608	14.1473	26.1647	1.0000	5.0000	34.0000
Ethical expressions (not repeated) (lexical diversity)	30,608	9.2093	14.9519	1.0000	4.0000	23.0000
ESG exclusiveness score	30,608	1.3336	0.4537	0.7801	1.3593	1.9150
ESG attractiveness score	30,608	−0.0736	0.8595	−0.3632	−0.3230	0.2697
ESG exclusiveness score*	30,608	1.0368	0.4282	0.4863	1.0220	1.6165
ESG attractiveness score*	30,608	−0.1876	0.5867	−0.4959	−0.3362	0.1017

Note: This table reports the summary statistics of the variables considered in all the models, showing information for the relative monthly flows, the monthly return, the size (measured as the log of the total net assets expressed in $ millions), the family size (measured as the log of the total net assets, expressed in $ millions, managed by funds belonging to the same family), the age of the fund (measured in years from the inception date of the oldest share class), the number of socially responsible strategies followed by the fund, the turnover ratio (TR), the net expense ratio (NER), the percentage of the total net assets linked to share classes marketed to institutional investors (INST), the portfolio overlap, the number of ethical expressions, the number of non-repeated ethical expressions, the ESG exclusiveness score, the ESG attractiveness score, the ESG exclusiveness score computed when controlling for SR strategies and the ESG attractiveness score computed when controlling for SR strategies.

TABLE 2A Correlation matrix (Part I).

	Flows	Return	Size	Family size	Age	No. SR strategies	TR	NER	INST
Return	**0.0541**								
Size	**−0.1612**	0.0091							
Family size	**−0.0875**	**0.0156**	**0.4899**						
Age	**−0.1495**	0	**0.3742**	**0.1745**					
SR Strategies	0.0057	−0.004	**−0.122**	**−0.3126**	**0.0305**				
TR	**0.031**	−0.0104	**−0.1456**	**−0.0435**	**−0.0902**	−0.0032			
NER	**0.3537**	**0.1015**	**−0.2439**	**−0.0751**	**−0.1457**	**0.023**	**0.1671**		
INST	**0.0601**	−0.0006	**−0.0351**	**−0.0159**	**−0.176**	**−0.1139**	**−0.1353**	**−0.16**	
Overlap	**−0.0628**	**−0.0113**	**0.268**	**−0.0287**	**0.1587**	**−0.0359**	**−0.0411**	**−0.2115**	**−0.0189**
Ethical expressions	**0.0348**	0.0002	**−0.0636**	**−0.1332**	**0.0504**	**0.7054**	**−0.0687**	−0.0035	**−0.0414**
Ethical expressions (not repeated)	**0.025**	−0.0005	**−0.0907**	**−0.1375**	**0.0508**	**0.742**	**−0.044**	**0.0149**	**−0.077**
ESG exclusiveness score	0.005	−0.0019	**−0.0473**	**−0.1758**	**0.0451**	**0.328**	**−0.0896**	**−0.0761**	**−0.0428**
ESG attractiveness score	**0.041**	0.0035	**−0.0616**	**−0.0853**	**0.0195**	**0.5962**	**−0.0504**	0.0051	**−0.0104**
ESG exclusiveness score*	0.0016	0.0025	**0.0267**	**0.0224**	**0.0372**	**−0.1251**	**−0.1052**	**−0.0757**	−0.0074
ESG attractiveness score*	**0.0545**	0.0045	**−0.0564**	**−0.0528**	0.0056	**0.4706**	**−0.0481**	**0.0139**	0.0014

Note: Significant correlations at 10% are highlighted in bold.

TABLE 2B Correlation matrix (Part II).

	Overlap	Ethical expressions	Ethical expressions (not repeated)	ESG exclusiveness score	ESG attractiveness score	ESG exclusiveness score*
Ethical expressions	0.0055					
Ethical expressions (not repeated)	**−0.0364**	**0.9633**				
ESG exclusiveness score	**0.1058**	**0.37**	**0.387**			
ESG attractiveness score	**−0.0266**	**0.9399**	**0.8992**	**0.3116**		
ESG exclusiveness score*	**0.1191**	**0.0734**	**0.0824**	**0.8336**	**0.0574**	
ESG attractiveness score*	**−0.0122**	**0.8933**	**0.8569**	**0.304**	**0.9512**	**0.1439**

Note: Significant correlations at 10% are highlighted in bold.

In the base model, we include the one-month-lagged monthly flows and returns. This allows us to control for persistence in money flows and return-chaser behaviour. In order to analyse how the different text measures impact these phenomena (RH4 and RH5), we interact the text measures with these fund characteristics. Again, we use mean-centred variables to avoid multicollinearity problems.

$$Flows_{i,t} = BASE\ MODEL + \beta_{11} TEXT\_MEASURE_{i,t-1} + \beta_{12} TEXT\_MEASURE_{i,t-1} * FLOWS_{i,t-1} + \varepsilon_{i,t} \quad (11)$$

$$Flows_{i,t} = BASE\ MODEL + \beta_{11} TEXT\_MEASURE_{i,t-1} + \beta_{12} TEXT\_MEASURE_{i,t-1} * RET_{i,t-1} + \varepsilon_{i,t} \quad (12)$$

4 | EMPIRICAL FINDINGS AND DISCUSSION

4.1 | Main empirical findings

Table 3 reports the estimated coefficients of the base model and Equation (8), testing RH1 for the different text measures.

Model 1 reports the estimated coefficients only for the control variables. The diagnostic tests show the reliability and validity of the model. Thus, the model *F*-test validates the reliability of independent variables, and the mean VIF points out the absence of multicollinearity problems.[9] We observe that money flows are persistent, since the estimated coefficient of the one-month lagged monthly flow is positive and significant. This result aligns with the previous academic literature documenting this phenomenon (see, among others, Cashman et al. (2014)). The estimated coefficient on the one-month lagged monthly return is also positive and significant, revealing that the SR mutual fund investors in our sample select those funds that have performed well in the past—that is, they behave as return-chasers. This means that SR mutual fund investors take into account not only non-financial issues but also financial ones when making their investment decisions. Muñoz (2019) finds similar empirical evidence. Other relevant controls for our research hypotheses are the family size and the age of the fund. The estimated coefficient for the family size proxy is negative but non-significant. In the case of age, the estimated coefficient is negative and significant, which could be explained by the ability of younger funds to adapt flexibly to changes in the market and by their stronger commitment to perform well to survive, which would attract investors' attention (Ferreira et al., 2013). For the other control variable results, we highlight two striking results. First, we obtain the result that the net expense ratio has a positive impact on money flows—that is, more expensive funds attract more money flows. This finding was also obtained by Alda et al. (2022), who explain that SR mutual fund investors do not consider price as a relevant factor in the fund selection process. This would reflect the idea that SR investors are willing to pay more for investing in a fund that meets their non-financial concerns (In et al., 2014). Second, mutual funds with greater portfolio-holding overlap attract more money flows. This means that SR fund investors do not take into account differentiation in portfolio holdings as a relevant feature when selecting a mutual fund. This result could also reflect the fact that most mutual fund investors probably do not analyse portfolio holdings in fund selection because they may find it hard to extract conclusions about fund differentiation from this type of information (Alda et al., 2022; Kostovetsky & Warner, 2020).

Models 2–7 add the different textual variables to the base model. Model 2 considers the number of ethical expressions included in a fund's prospectus (intensity); model 3 considers the number of non-repeated ethical expressions (lexical diversity); models 4 and 5 include the ESG exclusiveness score and the ESG investor attractiveness score, respectively, computed considering all SR funds in the sample as the reference group; models 6 and 7 include the same textual proxies as models 4 and 5, but computed controlling for the ESG strategy. In all cases, the LR Chi test points out the relevance of including the different textual variables in the base model. In all cases, the estimated coefficients for the textual variables[10] are positive and significant, meaning that the inclusion of more ethical expressions, more exclusive ethical expressions and more diverse expressions attracts money flows. Further, the scores computed when controlling for ESG strategies provide more significant coefficients (models 5 and 7) than the scores for the same variables computed considering all SR funds (models 4 and 6). These findings align with the previous literature showing that persuasion from textual information in SR fund prospectuses attracts investors' interest and that SR funds should differentiate themselves from other SR funds applying the same ESG strategies

TABLE 3 Impact of ethical expressions on money flows.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Ethical expressions		0.010*** (3.07)					
Ethical expressions (not repeated)			0.013** (1.98)				
ESG exclusiveness score				0.238* (1.92)			
ESG attractiveness score					0.240*** (3.00)		
ESG exclusiveness score*						0.223* (1.79)	
ESG attractiveness score*							0.350*** (3.2)
Flows_lagged	0.332*** (12.07)	0.330*** (12.03)	0.331*** (12.06)	0.332*** (12.06)	0.331*** (12.08)	0.332*** (12.06)	0.330*** (12.09)
Return_lagged	0.034*** (4.84)	0.034*** (4.83)	0.034*** (4.84)	0.034*** (4.81)	0.034*** (4.83)	0.034*** (4.82)	0.034*** (4.82)
Size	−0.137*** (−4.11)	−0.127*** (−3.64)	−0.127*** (−3.69)	−0.135*** (−4.03)	−0.130*** (−3.77)	−0.135*** (−4.02)	−0.128*** (−3.7)
Family size	−0.021 (−0.66)	−0.037 (−1.13)	−0.034 (−1.03)	−0.017 (−0.54)	−0.035 (−1.09)	−0.021 (−0.65)	−0.035 (−1.1)
Age	−0.018** (−2.34)	−0.019** (−2.49)	−0.019** (−2.51)	−0.018** (−2.37)	−0.018** (−2.34)	−0.018** (−2.37)	−0.018** (−2.46)
Number of SR strategies	−0.003 (−0.22)	−0.059** (−2.13)	−0.047 (−1.54)	−0.013 (−0.8)	−0.041* (−1.83)	0.001 (0.04)	−0.034* (−1.68)
Turnover ratio (TR)	−0.149** (−2.52)	−0.123** (−2.09)	−0.134** (−2.27)	−0.138** (−2.29)	−0.137*** (−2.37)	−0.139** (−2.29)	−0.134** (−2.33)
Net expense ratio (NER)	1.077*** (11.57)	1.081*** (11.57)	1.079*** (11.59)	1.084*** (11.66)	1.079*** (11.54)	1.081*** (11.64)	1.078*** (11.5)
Institutional	0.941*** (6.12)	0.906*** (6.09)	0.930*** (6.15)	0.952*** (6.14)	0.910*** (6.07)	0.958*** (6.15)	0.908*** (6.07)
Overlap	3.191*** (2.94)	2.951*** (2.77)	3.159*** (2.92)	2.947*** (2.67)	3.121*** (2.94)	2.954*** (2.67)	3.063*** (2.88)
Intercept	0.260 (0.54)	0.354 (0.72)	0.309 (0.64)	−0.051 (−0.1)	0.475 (0.95)	0.025* (1.79)	0.489 (0.98)
Time controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2526	.2538	.2532	.2529	.2535	.2529	.2537
F-test	41.2***	41.09***	40.18***	39.77***	41.32***	40.01***	41.89***

(Continues)

TABLE 3 (Continued)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
VIF	1.24	1.42	1.47	1.25	1.34	1.23	1.28
LR test		48.53***	23.69***	14.72***	39.04***	12.73***	47.07***
Obs.	30,608	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients for models 1–7, with their standard errors clustered at the fund level. Model 1 is the base model with controls (one-month lagged flow, one-month lagged return, fund size, family size, fund age, number of SR strategies followed by the fund, turnover ratio, net expense ratio, percentage of total net assets linked to share classes targeted at institutional investors and portfolio overlap). Models 2/3/4/5/6/7 add to the base model each one of the proxies related to the ethical expressions in the prospectus (number of ethical expressions, number of non-repeated ethical expressions, ESG exclusiveness score, ESG attractiveness score, ESG exclusiveness score* and ESG attractiveness score*). Also reported are the model *R*-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF testing for multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare models 2–7 with model 1) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

(see Alda et al., 2022; Kostovetsky & Warner, 2020). This empirical evidence leads us not to reject RH1.

Tables 4 and 5 report the results for the models that allow us to test RH2 and RH3 (Equations 9 and 10).

Kostovetsky and Warner (2020) and Alda et al. (2022) point out that textual differentiation could be especially relevant for mutual funds that belong to smaller families and that are younger. Table 4 reports the results from the models, including the interaction term between the different textual variables and the size of the fund family. The estimated coefficients for the interaction terms are negative and significant for the number of ethical expressions (intensity) (model 8), the number of non-repeated ethical expressions (lexical diversity) (model 9) and for the ESG attractiveness scores computed both when controlling for and when not controlling for ESG strategies (models 13 and 11). This means that the positive impact of these textual variables documented in Table 3 diminishes as the family size grows. Larger mutual fund families have more resources and can employ them to attract money flows, so the persuasive techniques using ESG information included in the fund's prospectus are less necessary. This leads us not to reject RH2. Table 5 reports the results for the models, including the interaction term between age and the different textual variables. In these analyses, we observe that none of the interaction terms has a significant estimated coefficient. This means that, in our sample, the age of the fund does not have an impact on the relationship between the textual variables and money flows shown in Table 3, and, thus, we reject RH3. This last result could reflect the fact that, despite the important growth in recent years, the SR mutual fund industry is still a non-competitive market and, consequently, mutual funds can maintain, over time, the advantages of persuasion strategies (In et al., 2014).

Tables 6 and 7 report the results that allow us to test RH4 and RH5 (Equations 11 and 12).

We hypothesized that the persistence of flows should be greater for those funds that are more attractive, according to the textual indicators, because these funds could attract more loyal investors; these investors perceive the fund to be more attractive because it is more difficult for them to find an alternative that meets their non-financial concerns. To test this, we interact the lagged flows with the textual variables. We obtain positive and significant coefficients for the interaction terms in the models, including the ESG exclusiveness score computed when controlling for ESG strategy (model 24) and the ESG investor attractiveness score computed both when considering all the SR funds and when controlling for ESG strategy (models 23 and 25, respectively). This leads us not to reject RH4. Table 7 reports the results, including the interaction term between the lagged return and the textual variables. We hypothesized that return-chaser behaviour should be weaker for the most attractive funds. The estimated coefficients for the interaction terms are non-significant (except in model 30, which achieves a positive and significant coefficient, contrary to what we expect). This shows return-chaser behaviour for investors investing in both the most and

TABLE 4 Interaction between family size and ethical expressions proxies.

	Model 8	Model 9	Model 10	Model 11	Model 12	Model 13
Family size	−0.046 (−1.43)	−0.041 (−1.25)	−0.023 (−0.71)	−0.043 (−1.37)	−0.025 (−0.81)	−0.041 (−1.37)
Ethical expressions	0.008*** (2.93)					
Ethical expressions (not repeated)		0.012** (2.04)				
ESG exclusiveness score			0.244* (1.96)			
ESG attractiveness score				0.161** (2.54)		
ESG exclusiveness score*					0.221* (1.75)	
ESG attractiveness score*						0.192** (2.07)
Family_Size * Textual proxy	−0.005** (−2.15)	−0.007* (−1.69)	0.058 (0.88)	−0.164** (−2.02)	0.046 (0.68)	−0.265*** (−3.01)
Funds' characteristics and time controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2548	.2538	.2531	.2549	.253	.2558
F-test	41.90***	39.46***	40.52***	42.48***	40.8***	44.3***
VIF	1.41	1.44	1.24	1.34	1.22	1.29
LR test	43.02***	25.13***	4.61**	54.74***	2.6	84.71***
Obs.	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients with standard errors clustered at the fund level for the models testing the interaction effect between the family size and the different proxies of ethical expressions. Models 8/9/10/11/12/13 include the interaction between family size and the number of ethical expressions/number of non-repeated ethical expressions/ ESG exclusiveness score/ ESG attractiveness score/ESG exclusiveness score*/ESG attractiveness score*. We use mean-centred variables in the interaction to avoid multicollinearity problems. Also reported are the model *R*-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF evaluating multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare each model with its corresponding model in Table 3 without interaction term) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

least attractive funds, consistent with the results of Bollen (2007), who points out that the utility function of SR mutual fund investors depends on both financial and non-financial concerns. This leads us to reject RH5.

From a practitioner's point of view, the results obtained in this section are relevant for mutual fund companies seeking strategies to attract investors' interest. The empirical findings obtained reveal that the use of ESG terms in the prospectus is a powerful tool for competing in the SR mutual fund industry, especially for small companies. Besides, the empirical evidence related to return-chaser behaviour and flow persistence allows mutual fund managers to gain a better understanding of the decisions of SR mutual fund investors.

4.2 | Further research analyses

In this section,[11] we perform a plethora of further research analyses to give robustness to our previous findings and to enlarge upon our main empirical evidence.

4.2.1 | Impact of load fees on money flows

First, for the results provided in Table 3, we control for the fee structure of the mutual fund. The models constructed in the previous section include among the controls the net expense ratio of the fund, which mainly encompasses management fees, administrative fees and operating costs. However, we now control for the presence of load fees, which may have an impact on investors' flows. Front-end load fees are the fees imposed directly on investors when they purchase or redeem shares in a fund. Barber et al. (2005) explain that mutual fund investors are more sensitive to front-end load fees (*in-your-face fees*) than they are to operating expenses (those included in the net expense ratio). We use two proxies to control for load fees. First, we build a dummy variable that takes the value of 1 when the funds have at least one share class that charges load fees to investors and 0 otherwise. Second, we consider the percentage of total net assets in the fund belonging to share classes charging load fees.[12] The results are shown in Table 8.

As can be seen in all the models reported in Table 8, the estimated coefficient for the load variable is negative and significant, meaning

TABLE 5 Interaction between funds' Age and ethical expressions proxies.

	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19
Age	−0.0183** (−2.51)	−0.0193*** (−2.76)	−0.0196*** (−2.73)	−0.0175** (−2.2)	−0.0185** (−2.49)	−0.0179** (−2.51)
Ethical expressions	0.0101*** (3.12)					
Ethical expressions (not repeated)		0.0129* (1.96)				
ESG Exclusiveness Score			0.2486* (1.96)			
ESG Attractiveness Score				0.2350*** (3.13)		
ESG Exclusiveness Score*					−0.0185* (1.8)	
ESG Attractiveness Score*						0.3462*** (3.23)
Age * Textual proxy	−0.0001 (−0.34)	0.0000 (0.11)	0.0077 (0.5)	−0.0057 (−0.89)	0.0052 (0.35)	−0.0023 (−0.22)
Funds' characteristics and time controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2538	.2532	.253	.2536	.2529	.2537
F-test	40.73***	39.75***	39.69***	40.74***	39.35***	41.39***
VIF	1.41	1.46	1.27	1.32	1.22	1.28
LR test	0.79	0.09	0.98	2.91*	0.42	0.28
Obs.	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients with standard errors clustered at the fund level for the models testing the interaction effect between the fund's age and the different proxies of ethical expressions. Models 14/15/16/17/18/19 include the interaction between the fund's age and the number of ethical expressions/number of non-repeated ethical expressions/ESG exclusiveness score/ESG attractiveness score/ESG exclusiveness score*/ESG attractiveness score*. We use mean-centred variables in the interaction to avoid multicollinearity problems. Also reported are the model *R*-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF evaluating multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare each model with its corresponding model in Table 3 without interaction term) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

that those funds for which load fees are more relevant show lower money flows. This result is similar to that previously obtained by Barber et al. (2005), who explain that mutual fund investors are more sensitive to front-end load fees than to operating expenses, since the former are more obvious and salient. With regard to the estimated coefficients for the text-based measures, we obtain similar results to those reported in Table 3, except for the exclusiveness scores (models 35 and 37), where the estimated coefficients remain positive but become non-significant when load proxies are incorporated into the models. However, it is necessary to point out that before controlling for load fees, the estimated coefficients for these text-based measures were only significant at the 10% level, since exclusiveness was the component of our overall score with the weakest impact on money flows.

4.2.2 | Quintile and decile portfolio approach

Second, in addition to the regression approach, we use an alternative methodological framework based on the comparison of the money flows of the top and bottom quintile and top and bottom decile portfolios of funds, formed based on the different text-based proxies. The results are shown in Tables 9 and 10.

We obtain mixed empirical evidence. For the quintile analysis (Table 9), we do not detect significant differences in the money flows of the quintile portfolios, except in the case of the ESG investor attractiveness score*. That is, for the most complete proposed indicator, the mutual funds in the top quintile achieve greater monthly money flows (0.862%) than those in the bottom quintile (0.611%). This result is aligned with that obtained using the regression framework. In the decile analyses (Table 10), focusing on significant differences, we observe that the top decile portfolio money flows (1.052%) are greater than those achieved by the bottom decile portfolio (0.700%) in the ESG investor attractiveness score*. For the number of ethical expressions, the top decile portfolio (1.224%) shows significantly higher net money flows than the bottom decile portfolio (0.789%). These two results are aligned with those from the regression analyses shown in Table 3. However, for the ESG exclusiveness score and the ESG exclusiveness score*, the top decile portfolios (0.700%/0.318%) achieve significantly lower money flows than the bottom decile portfolios (1.108%/0.818%). This result is

TABLE 6 Impact of ethical expressions proxies in flows' persistence.

	Model 20	Model 21	Model 22	Model 23	Model 24	Model 25
Flow_lagged	0.3290*** (12.33)	0.3302*** (12.38)	0.3314*** (12.39)	0.3287*** (12.53)	0.3289*** (12.57)	0.3255*** (12.45)
Ethical expressions	0.0087*** (3.02)					
Ethical expressions (not repeated)		0.0120*** (2.0)				
ESG exclusiveness score			0.2476** (2.00)			
ESG attractiveness score				0.1768** (2.53)		
ESG exclusiveness score*					0.3289** (2.07)	
ESG Attractiveness Score*						0.2484** (2.39)
Textual proxy * Flow_lagged	0.0014 (1.31)	0.0022 (1.08)	0.0803 (1.62)	0.0524* (1.92)	0.1246** (2.17)	0.0673** (2.12)
Funds' characteristics and time controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.255	.2541	.2544	.2558	.2557	.2561
F-test	40.73***	38.96***	38.28***	42.84***	38.16***	43.68***
VIF	1.4	1.43	1.23	1.32	1.21	1.27
LR test	51.65***	37.81***	61.14***	91.81***	115.73***	95.75***
Obs.	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients with standard errors clustered at the fund level for the models testing the interaction effect between the lagged fund's flow and the different proxies of ethical expressions. Models 20/21/22/23/24/25 include the interaction between the lagged fund's flow and the number of ethical expressions/ number of non-repeated ethical expressions/ESG exclusiveness score/ ESG attractiveness score/ESG exclusiveness score*/ESG attractiveness score*. We use mean-centred variables in the interaction to avoid multicollinearity problems. Also reported are the model *R*-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF evaluating multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare each model with its corresponding model in Table 3 without interaction term) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

contrary to that obtained from the regression approach. In this regard, it is necessary to note two points. First, among the different text-based measures included in Table 3, the ESG exclusiveness scores are those that show the weakest impact on money flows (the estimated coefficients are positive and are only significant at 10%, becoming non-significant when controlling for load fees in Table 8). Second, the multivariate regression analysis allows us to include a set of relevant controls that are more difficult to include in a portfolio methodological approach. In sum, the quintile/decile portfolio analyses confirm the empirical evidence for the most complete text-based measure and reveal the need to deepen the study of some of the dimensions covered in our proposed score, such as the exclusiveness component, which could be performed in further research.

4.2.3 | Sustainability-related appellations in funds' names

Third, in our main empirical analyses, we focus on the ESG expressions included in the prospectuses of the mutual funds. However, beyond the prospectus, a relevant way to attract investors could be through the name used by the mutual fund company to market the fund. For example, Cooper et al. (2005) find that mutual funds that change their names to reflect a current "hot" style subsequently obtain abnormal money flows. Karoui and El Ghoul (2022) find that those funds with names closer to those of their families attract more money flows. Within the ESG sphere, El Ghoul and Karoui (2021) find that those funds that change their names to include sustainability-related appellations experience a subsequent increase in fund flows. We therefore test whether the presence of sustainability-related expressions in the fund's name has an impact on money flows in our sample. Following El Ghoul and Karoui (2021), we identify a set of keywords in the fund names related to sustainability terms.[13] We build a set of dummy variables, one for each of these keywords, that adopt the value of 1 if the fund name includes the keyword and 0 otherwise. We regress the money flows on the control variables and these dummies. The results are provided in Table 11.

We obtain mixed empirical evidence according to the sustainability-related terms considered. For the "impact" and "thematic" terms,

TABLE 7 Impact of ethical expressions proxies in returns' chaser behaviour.

	Model 26	Model 27	Model 28	Model 29	Model 30	Model 31
Rent_lagged	0.0340*** (4.83)	0.0341*** (4.84)	0.0343*** (4.85)	0.0339*** (4.82)	0.0349*** (4.93)	0.0339*** (4.82)
Ethical expressions	0.0100*** (3.07)					
Ethical expressions (not repeated)		0.0129** (1.98)				
ESG exclusiveness score			0.2378* (1.92)			
ESG attractiveness score				0.2401*** (3.0)		
ESG exclusiveness score*					0.2229* (1.79)	
ESG attractiveness score*						0.3505*** (3.21)
Textual * Rent_lagged	−0.0001 (−0.43)	0.0001 (0.24)	0.0175 (1.08)	−0.0032 (−0.33)	0.0332** (2.19)	−0.0003 (−0.02)
Funds' characteristics and time controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2538	.2532	.253	.2535	.2531	.2537
F-test	40.14***	39.1***	38.64***	40.37***	38.95***	41.11***
VIF	1.39	1.43	1.23	1.31	1.21	1.26
LR test	0.3	0.06	2.12	0.26	6.75***	0.00
Obs.	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients with standard errors clustered at the fund level for the models testing the interaction effect between the lagged monthly return and the different proxies of ethical expressions. Models 26/27/28/29/30/31 include the interaction between the lagged monthly return and the number of ethical expressions/number of non-repeated ethical expressions/ESG exclusiveness score/ESG attractiveness score/ESG exclusiveness score*/ESG attractiveness score*. We use mean-centred variables in the interaction to avoid multicollinearity problems. Also reported are the model *R*-squared, the model *F*-test assessing the reliability of independent variables, the mean VIF evaluating multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare each model with its corresponding model in Table 3 without interaction term) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

the estimated coefficient for the dummy name variable is negative and significant, meaning that the funds whose names include these terms show lower money flows. Conversely, the funds whose names include the "social" term show greater money flows (the estimated coefficient for the dummy name variable is positive and significant). For the remaining terms and also for the dummy variable, considering all the sustainability-related terms together, the estimated coefficients are not significant. These results indicate that the inclusion of sustainability-related terms in the fund names of our sample has no clear effect on money flows. This result is different from the results achieved by El Ghoul and Karoui (2021); however, it is important to point out two aspects. First, while El Ghoul and Karoui (2021) analyse the impact of fund name changes on subsequent money flows, we are studying the impact of sustainability terms in the fund name on the money flows that the mutual fund achieves over its life. Second, our database is based on SR mutual funds, whereas El Ghoul and Karoui (2021) consider a sample of US domestic equity mutual funds, including both conventional and SR mutual funds. Further research should shed light on how different dimensions of a fund's name can play a role in money flow dynamism.

4.2.4 | ESG scores of portfolio holdings and text-based measures

Fourth, we want to determine whether our text-based scores reflect a real commitment of the mutual fund to ESG issues or, conversely, whether they are reflecting greenwashing practices. With this aim in mind, we regress the ESG scores for the mutual fund portfolios[14] on the control variables and our text-based measures. The results are reported in Table 12.

The results are mixed and depend on the text-based measure considered. In the case of the exclusiveness score indicators, the estimated coefficients are non-significant; that is, this dimension is not related to holding a more sustainable portfolio. However, considering the number of ethical expressions, the number of ethical expressions (non-repeated) and the attractiveness scores, the estimated coefficients are positive and significant. This means that mutual funds with a higher record for these text-based scores achieve a higher Portfolio Sustainability Score (i.e. these funds hold portfolios formed by companies with better ESG scores). In this way, the commitment of the mutual funds in our sample to ESG issues is embodied in the information

TABLE 8 Load fees impact on money flows.

	Model 32	Model 33	Model 34	Model 35	Model 36	Model 37	Model 38
Loads	−0.659*** (−3.54)	−0.709*** (−3.81)	−0.691*** (−3.74)	−0.618*** (−3.34)	−0.705*** (−3.84)	−0.619*** (−3.35)	−0.691*** (−3.76)
Ethical expressions		0.011*** (3.4)					
Ethical expressions (not repeated)			0.014** (2.23)				
ESG exclusiveness score				0.187 (1.56)			
ESG attractiveness score					0.258*** (3.29)		
ESG exclusiveness score*						0.165 (1.39)	
ESG attractiveness score*							0.367*** (3.37)
Flows_lagged	0.331*** (11.88)	0.328*** (11.84)	0.329*** (11.87)	0.330*** (11.88)	0.329*** (11.89)	0.330*** (11.88)	0.328*** (11.9)
Return_lagged	0.034*** (4.79)	0.034*** (4.78)	0.034*** (4.78)	0.034*** (4.77)	0.034*** (4.77)	0.034*** (4.78)	0.034*** (4.77)
Size	−0.149*** (−4.73)	−0.140*** (−4.26)	−0.139*** (−4.29)	−0.147*** (−4.63)	−0.143*** (−4.38)	−0.147*** (−4.62)	−0.141*** (−4.31)
Family size	−0.007 (−0.23)	−0.023 (−0.72)	−0.021 (−0.64)	−0.005 (−0.16)	−0.021 (−0.68)	−0.008 (−0.24)	−0.022 (−0.69)
Age	−0.013* (−1.81)	−0.013** (−2.0)	−0.013** (−2.02)	−0.013* (−1.87)	−0.012* (−1.8)	−0.013* (−1.87)	−0.013* (−1.93)
Number of SR strategies	−0.002 (−0.16)	−0.062** (−2.33)	−0.049* (−1.71)	−0.010 (−0.63)	−0.043** (−1.99)	0.000 (0.03)	−0.034* (−1.77)
Turnover ratio (TR)	−0.132** (−2.23)	−0.103* (−1.73)	−0.115* (−1.93)	−0.125** (−2.07)	−0.117** (−2.02)	−0.125** (−2.08)	−0.115** (−1.99)
Net expense ratio (NER)	1.101*** (11.49)	1.107*** (11.53)	1.105*** (11.54)	1.105*** (11.57)	1.105*** (11.5)	1.103*** (11.54)	1.104*** (11.46)
Institutional	0.565*** (3.02)	0.500*** (2.67)	0.535*** (2.86)	0.597** (2.52)	0.505*** (2.7)	0.601*** (3.15)	0.512*** (2.74)
Overlap	2.974*** (2.71)	2.702** (2.51)	2.930*** (2.68)	2.797** (2.52)	2.884*** (2.7)	2.812** (2.53)	2.830*** (2.64)
Intercept	0.684 (1.34)	0.816 (1.56)	0.757 (1.46)	0.413 (0.79)	0.944* (1.77)	0.484 (0.93)	0.944* (1.78)
Time controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2536	.255	.2543	.2539	.2547	.2538	.549
F-test	40.99***	41.81***	40.65***	39.67***	41.84***	39.82***	42.26***
VIF	1.37	1.55	1.59	1.39	1.47	1.37	1.42
LR test		55.21***	27.87***	8.91***	45.16***	6.85***	51.48***
Obs.	30,608	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS estimated coefficients with their standard errors clustered at the fund level for the models shown in Table 3 but incorporating the load fee structure variable. Model 32 is the base model that considers controls (one-month lagged flow, one-month lagged return, fund size, family size, fund age, number of SR strategies followed by the fund, turnover ratio, net expense ratio, percentage of total net assets linked to share classes targeted at institutional investors and portfolio overlap). Models 33/34/35/36/37/38 add to the base model each proxy related to the ethical expressions in the prospectus (number of ethical expressions, number of non-repeated ethical expressions, ESG exclusiveness score, ESG attractiveness score, ESG exclusiveness score* and ESG attractiveness score*). Also reported are the model R-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF testing multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models (we compare models 33–38 with model 32) and the number of observations.

***Significant at 1%; **significant at 5%; *significant at 10%.

TABLE 9 Portfolio money flows. Quintile analysis.

	Mean	*SD*	10th percentile	Median	90th percentile	Mean difference test
Ethical expressions BQ	0.736	1.252	−0.526	0.584	2.201	
Ethical expressions TQ	0.704	1.321	−0.900	0.634	2.304	−0.2979
Ethical expressions (non_repeated) BQ	0.939	0.939	−0.278	0.725	2.426	
Ethical expressions (non_repeated) TQ	0.840	1.318	−0.714	0.711	2.486	−0.8447
ESG exclusiveness score BQ	0.965	2.095	−0.844	0.561	3.003	
ESG exclusiveness score TQ	0.807	1.272	−0.716	0.706	2.396	−1.0895
ESG attractiveness score BQ	0.912	1.445	−0.410	0.613	2.520	
ESG attractiveness score TQ	0.811	1.281	−0.737	0.791	2.408	−0.8681
ESG exclusiveness score* BQ	0.782	2.706	−0.876	0.501	2.170	
ESG exclusiveness score* TQ	0.482	1.384	−1.154	0.509	2.003	−1.4959
ESG attractiveness score* BQ	0.611	1.518	−0.996	0.380	2.184	
ESG attractiveness score* TQ	0.862	1.473	−0.870	0.664	2.569	(1.9811)**

Note: This table shows the summary statistics of money flows from different portfolios formed with mutual funds belonging to the bottom quintile (BQ) and the top quintile (TQ) for each period according to the different text-based measures considered across the models. Also included is the mean test between the money flows (expressed as a percentage) of the TQ and BQ portfolios for each text-based measure.

**significant at 5%;

TABLE 10 Portfolio money flows. Decile analysis.

	Mean	*SD*	10th percentile	Median	90th percentile	Mean difference test
Ethical expressions BD	0.789	1.509	−0.526	0.535	2.225	
Ethical expressions TD	1.224	1.671	−0.653	0.901	3.609	(2.9177)***
Ethical expressions (non_repeated) BD	1.002	1.518	−0.342	0.725	2.474	
Ethical expressions (non_repeated) TD	1.110	1.716	−0.750	0.820	3.652	0.7056
ESG exclusiveness score BD	1.108	2.976	−1.047	0.680	3.530	
ESG exclusiveness score TD	0.700	1.972	−1.320	0.415	3.140	(−1.7963)*
ESG attractiveness score BD	1.056	2.750	−0.673	0.697	3.082	
ESG attractiveness score TD	1.024	1.732	−0.945	0.688	3.447	(−0.1476)
ESG exclusiveness score* BD	0.818	2.874	−1.003	0.594	2.845	
ESG exclusiveness score* TD	0.318	1.732	−1.565	0.026	2.798	(−2.3126)**
ESG attractiveness score* BD	0.700	1.827	−1.147	0.515	2.579	
ESG attractiveness score* TD	1.052	1.670	−0.750	0.733	3.543	(2.3622)**

Note: This table shows the summary statistics of money flows from different portfolios formed with the mutual funds belonging to the bottom decile (BD) and the top decile (TD) for each period according to the different text-based measures considered across the models. Also included is the mean test between the money flows (expressed as a percentage) of the TD and BD portfolios for each text-based measure.

***Significant at 1%; **significant at 5%; *significant at 10%.

provided to investors through their prospectuses, and we can discard the concern that our proposed scoring method reflects greenwashing practices. These results are of interest to policymakers and regulators, who have to monitor the market to detect and correct opportunistic behaviours that could harm investors' interests.

5 | CONCLUSIONS

Recently, the academic literature has shown the effectiveness of differentiation strategies based on textual descriptions included in prospectuses in the mutual fund industry. Differentiation measures based on text are noticed more by investors in comparison with other differentiation proxies based on mutual funds' fundamentals, such as portfolio holdings. In this research, we analyse the impact on SR mutual funds' money flows of including ethical expressions in their prospectuses. To do this, we propose a textual measure that integrates three attributes that are relevant in attracting investors' attention: intensity, exclusiveness and lexical diversity. We analyse a sample of 266 US mutual funds investing in equity from 1999 to 2019. Our empirical findings allow us to confirm that those funds that include more ethical expressions, more diverse expressions and

TABLE 11 Presence of sustainability-related terms in fund names.

	Model 39: Environmental	Model 40: ESG	Model 41: Impact	Model 42: Responsible	Model 43: Social	Model 44: Sustainable	Model 45: Thematic	Model 46: All terms
Dummy_name	0.448 (1.34)	−0.075 (−0.36)	−0.700** (−2.39)	−0.418 (−1.25)	0.783* (1.72)	−0.094 (−0.44)	−0.431** (−2.39)	−0.127 (−1.09)
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.2526	.2526	.253	.2526	.253	.2526	.2527	.2527
F-test	41.14***	40.13***	40.54***	40.32***	39.97***	42.33***	41.34***	41.53***
VIF	1.22	1.23	1.24	1.23	1.24	1.23	1.23	1.25
LR test	0.76	0.26	18.90***	1.58	15.59***	0.9	3.71*	3.91**
Obs.	30,608	30,608	30,608	30,608	30,608	30,608	30,608	30,608

Note: This table reports the OLS-estimated coefficients with standard errors clustered at the fund level for the models with a dummy variable added to the base model identifying funds with names including some of the following keywords: environmental, ESG, impact, responsible, social, sustainable and thematic. For the sake of brevity, we only report the estimated coefficient for the dummy variable reflecting the presence of the keywords in the fund name. We also report the model *R*-squared, the model *F*-test assessing the reliability of the independent variables, the mean VIF testing multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models and the number of observations.
***Significant at 1%; **significant at 5%; *significant at 10%.

TABLE 12 Portfolio sustainability scores.

	Model 47: Ethical expressions	Model 48: Ethical expressions (non_repeated)	Model 49: ESG exclusiveness score	Model 50: ESG attractiveness score	Model 51: ESG exclusiveness score*	Model 52: ESG attractiveness score*
Text_based_measure	0.00022** (2.05)	0.00049** (2.35)	0.00145 (0.28)	0.00459* (1.66)	0.00021 (0.04)	0.00691* (1.72)
Time controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	.1761	.181	.1593	.1699	.159	.1705
F-test	24.39***	24.44***	23.3***	24.29***	23.3***	24.41***
VIF	1.39	1.43	1.29	1.34	1.27	1.31
LR test	183.40***	237.03***	3.28*	116.47***	0.06	122.78***
Obs.	8958	8958	8958	8958	8958	8958

Note: This table reports the OLS estimated coefficients with standard errors clustered at the fund level for the models, in which the dependent variable is the Portfolio Sustainability Score and the explanatory variables include the fund controls and the text-based measures. For the sake of brevity, we only report the estimated coefficient for the text-based indicators. We also report the model *R*-squared, the model *F*-test assessing the reliability of independent variables, the mean VIF testing multicollinearity problems, the likelihood (LR Chi test) comparing the goodness-of-fit between models and the number of observations.
***Significant at 1%; **significant at 5%; *significant at 10%.

a greater number of ESG expressions that are different from the ESG expressions in the prospectuses of other competing funds can attract more money flows.

We then perform a set of additional analyses. First, we show that persuasive strategies based on text are more relevant in attracting money flows for mutual funds belonging to smaller mutual fund families. This result is not striking, given that smaller mutual fund families have fewer resources to attract money flows using alternative strategies. We also observe that age does not shorten the impact of textual persuasion on money flows. This means that, despite the important growth experienced by the SR mutual funds industry in recent years, it continues to be a non-competitive market, and, consequently, the advantages arising from persuasive strategies can be maintained over time.

Additionally, we identify two common patterns in money flow determinants: (i) investors invest in shares from funds that they already own (persistence), and (ii) investors select mutual funds that performed well in the past (return-chaser behaviour). We analyse how textual persuasion measures influence these two phenomena. We obtain the result that money flow persistence is more intense for more attractive funds. This could reflect the fact that more attractive funds cater to more loyal investors and that these investors have greater problems finding alternative funds that meet their non-financial concerns. In the case of the return-chaser behaviour, we find that this behaviour occurs

for both the most and the least attractive funds, meaning that SR fund investors appreciate both financial and non-financial performance.

Our further analyses show that, in general, the inclusion of sustainability terms in the fund name does not increase money flows, and that the funds with higher results for our proposed text score hold portfolios formed of stocks with better records on ESG issues. We also find that the impact of the ESG investor attractiveness score on fund flows does not change when we include a control for load fees. Finally, our main regression results are confirmed by the analysis of quintile/decile portfolios based on the ESG investor attractiveness score.

Our findings are interesting because we provide the academic literature with a new textual measurement of fund prospectus information to quantify SRI product differentiation based on intensity, exclusiveness and lexical diversity. Managers can now better understand the relevant attributes that attract the attention of investors, and policymakers can better control the type of information provided in fund prospectuses, ensuring investors' safety.

This study suffers from certain weaknesses that, at the same time, constitute avenues for further research. Data availability obliged us to focus on the US SR mutual fund industry. It would be of interest to perform similar analyses in other markets in which institutional features could reveal additional insights. Besides, we focus on equity mutual funds; however, it could be very interesting to analyse the drivers of money flows for bond funds, which is a less commonly analysed topic in the academic literature. It could also be of interest to develop new measures of differentiation/attractiveness based on text. For example, it could be interesting to analyse the differences in the prospectus paragraphs that explicitly provide information on the risks borne by investors. In this regard, the growing field of natural language processing and artificial intelligence techniques for processing textual data could be very useful.

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CONFLICT OF INTEREST STATEMENT

No conflicts of interest.

DATA AVAILABILITY STATEMENT

Requests for data availability will be considered by the authors.

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ENDNOTES

[1] Environmental, social and governance (ESG).

[2] To avoid our findings being affected by the changing number of funds each year, we standardize the ESG investor attraction score.

[3] Our proposed ESG investor attraction score is tested in Appendix 1.

[4] Morningstar categorizes funds into different ESG strategies. We consider all ESG strategies with which our analysed funds are involved. Thus, we consider the following sustainable investment ESG strategies: ESG engagement, ESG incorporation, Environmental Sector Overall, Gender & Diversity, Low Carbon/Fossil-Fuel Free, Community Development, Environmental and Impact themes. We also consider the following 'Employs Exclusions' ESG strategies: Norms-based screening, Abortion, Adult entertainment, Alcohol, Animal Testing, Controversial Weapons, Gambling, GMOs, Military Contracting, Nuclear, Pesticides, Small Arms, Thermal Coal, Tobacco and Other.

[5] The maximum value of $w_{i,t}^{j}$ is log(N), and this value would indicate that only one fund prospectus contains the ethical expression j, which corresponds to a situation of maximum exclusiveness; by contrast, the minimum value of this measure is 0, which would indicate a situation of zero exclusiveness since expression j would appear in all the fund prospectuses analysed.

[6] According to Morningstar, this label "is allocated to funds that invest according to non-economic guidelines. Such funds may make investments based on such issues as environmental responsibility, human rights, or religious views. A socially conscious fund may take a pro-active stance by selectively investing in, for example, environmentally-friendly companies, or firms with good employee relations. This group also includes funds that avoid investing in companies involved in promoting alcohol, tobacco, or gambling, or in the defense industry".

[7] This information is only available on a yearly basis; however, the other variables in our sample are obtained on a monthly basis. Following the previous literature, we make the assumption that these values are the same for all months of the year t (Muñoz, 2019).

[8] All share classes of a fund possess the same portfolio holdings.

[9] The conclusions from the model F-test and mean VIF hold across all the models.

[10] The estimated coefficients can be interpreted as elasticities. For example, in model 2, the estimated coefficient for the number of ethical expressions variable shows that a one-unit increase in the number of ethical expressions leads to an increase of 0.010% in money flows.

[11] We thank the two anonymous referees and the associate editor for the comments and suggestions that we include in this section.

[12] For the sake of brevity, we only report the results for the second proxy. However, the empirical evidence remains very similar when using the other proxy. These results are available from the authors upon request.

[13] Specifically, these keywords are Environmental (2 funds), ESG (14 funds), Impact (7 funds), Responsible (2 funds), Social (7 funds), Sustainable (21 funds) and Thematic (2 funds). In total, we identified 55 funds in our sample whose names explicitly include these keywords.

[14] We obtain the Portfolio Sustainability Scores (available from August 2012) from the Morningstar database. These scores are computed from the ESG performance of the stocks held by the funds, using information from Sustainalytics.

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APPENDIX 1

INVESTOR ATTRACTION SCORE COMPONENTS: VALIDATION TESTS

Panel A: ESG exclusiveness validation test

Fund ID	Ethical expression	ESG Intens. (1)	ESG Lex. Div. (2)	*n*	*N*	ESG Exclus. (3)	(1) × (3)	Σ(1) × (3)	ESG IAS
F1	Humman Suffering	1	1	**2**	64	**32**	32	32	**32**
F2	ESG accountability	1	1	**1**	64	**64**	64	64	**64**

Panel B: ESG intensity validation test

Fund ID	Ethical expression	ESG Intens. (1)	ESG Lex.div. (2)	*n*	*N*	ESG Exclus. (3)	(1) × (3)	Σ(1) × (3)	ESG IAS
F1	Humman Suffering	**1**	1	2	64	32	32	32	**32**
F3	Humman Suffering	**2**	1	2	64	32	64	64	**64**

Panel C1: ESG lexical diversity validation test 1

Fund ID	Ethical expression	ESG Intens. (1)	ESG Lex. Div. (2)	*n*	*N*	ESG Exclus. (3)	(1) × (3)	Σ(1) × (3)	ESG IAS
F1	Humman Suffering	1	**1**	2	64	32	32	32	**32**
F4	Handguns	1	**2**	2	64	32	32	64	**128**
	Workplace safety	1		2		32	32		

Panel C2: ESG lexical diversity validation test 2

Fund ID	Ethical expression	ESG Intens. (1)	ESG Lex. Div. (2)	*n*	*N*	ESG Exclus. (3)	(1) × (3)	Σ(1) × (3)	ESG IAS
F3	Humman Suffering	2	**1**	2	64	32	64	64	**64**
F4	Handguns	1	**2**	2	64	32	32	64	**128**
	Workplace safety	1		2		32	32		

Appendix 1 reports a battery of validation tests to check the correct specification of the proposed ESG Investor Attraction score measure. In panel A, the ESG Exclusiveness component is validated; in panel B, the ESG Intensity component is validated; and in panel C, the ESG Lexical Diversity component is validated. The first column of each panel reports the Fund ID that we have selected to compute the three validation tests. In the second column, the ethical expressions included in each fund prospectus are shown. Note that each validation test requires us to select funds with different characteristics. The third column shows the ESG intensity score, computed as the repetition frequency of the ESG expression *j*. The fourth column reports the ESG lexical diversity score, which is computed as the number of different (not repeated) ESG expressions in the fund prospectus considered. In column 5, we report the number of funds for which each ethical expression *j* is included in the prospectus, that is, n_j. In column 6, we show the number of funds with prospectuses containing some ethical expressions each year, *N*. In column 7, we report the ESG exclusiveness score as the quotient N/n_j. In columns 8 and 9, the different calculations needed to obtain the ESG Investor Attraction Score (IAS) are reported. Finally, the ESG Investor Attraction Score is displayed in column 10.

(1) First, to check the exclusiveness component (panel A), we consider two funds, each with only one ESG expression. One of the expressions only appears in the prospectus of the fund studied, while the other expression also appears in another fund's prospectus. In this case, the more exclusive fund obtains a higher score than the other. (2) Second, to test the intensity component (panel B), we compare two funds, each with only one ESG expression in its prospectus, with both expressions also appearing in another fund's prospectus, so the exclusiveness component has the same scoring for both funds; however, this ESG expression appears twice in one of the fund prospectuses and only once in the other prospectus.

We find that the fund with higher intensity achieves a higher score than the other fund. (3) Third, to check the lexical diversity component (panel C1), we compare two funds, one of them with only one ESG expression and the other with two ESG expressions. However, in both cases, each ESG expression appears only once in the fund prospectus (the intensity is the same), and, in both cases, each ESG expression appears in two fund prospectuses (the exclusiveness is the same). We find the investor attraction score of the fund with greater lexical diversity is higher than the investor attraction score of the other fund. Note that panel C1 reveals that the ESG lexical diversity component has both a direct and an indirect impact on the IAS: (i) *indirectly* because those funds with more non-repeated ESG expressions achieve a higher value for $\Sigma(1) \times (3)$; and (ii) *directly* because we subsequently multiply $\Sigma(1) \times (3)$ by the lexical diversity measure. However, consideration of the direct effect is necessary because it allows us to control for situations such as the one shown in panel C2. Concretely, we compare one fund with only one ESG expression appearing twice in the prospectus versus another fund with two ESG expressions appearing once. In this case, all the ESG expressions appear in two fund prospectuses (the exclusiveness is the same). Without considering the direct effect of lexical diversity, both funds would obtain the same score. However, we consider that these funds should not be equally attractive for investors since the fund with two different expressions should be able to attract more money flows than the other because it represents more ESG concerns.

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