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The limited role of sustainability in mutual fund investor decisions: A machine learning approach

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ABSTRACT

Despite the growth in the supply of socially responsible investment products, the weight of environmental, social and governance (ESG) factors in the decisions of mutual fund investors remains under-researched. We conducted a study relating fund flows to past returns, ESG performance and other financial variables using data from 3,767 US mutual funds from 2015 to 2021. First, we aimed to assess the importance of ESG performance in investment decisions. Next, we studied whether ESG performance is increasingly important or has reached its limit. Finally, we developed decisional models to predict the flows raised by each investment fund, its financial return and ESG performance. We used logistic regression, neural networks, random forest and gradient boosting decision trees. We found that the investors consider ESG performance, but the factors that matter most are past growth, mutual fund fees and past returns. Our models predicted the money raised by the funds, obtaining accuracy rates of around 70%. In addition to confirming that "past financial return does not guarantee future financial return," we found that "past ESG performance guarantees future ESG performance," which may be of interest to socially responsible investors.

1. Introduction

Conventional portfolio theory states that investments should be made based on risk-adjusted financial returns (Fama, 1970; Mansour et al., 2019; Markowitz, 1952; Zopounidis et al., 2015), and this is how rational investors should make decisions in financial markets (Miller & Modigliani, 1961). However, many investment decisions are driven by other motivations and investors' cognitive biases, as behavioral finance theories proved (Kahneman & Tversky, 1979; Thaler, 1980). Socially responsible investing (SRI) provides another example of going beyond the risk-return trade-off, as these investors incorporate environmental, social and governance (ESG) concerns into their decisions (Bilbao-Terol et al., 2012; Calvo et al., 2016; Pedersen et al., 2021). Therefore, portfolio selection progressively requires multi-criteria decision support methods (Aouni et al., 2018; Chen et al., 2021; Li et al., 2022). Thus, we aimed to analyze mutual fund investment decisions by comparing the importance of past returns (and other variables) versus ESG performance, to study whether ESG performance is increasingly important, and to develop decision models that predict whether a mutual fund will attract money, as well as its financial return and social performance.

Our study was firstly motivated by the desire to investigate whether the heightened emphasis on ESG performance within the mutual funds industry results in tangible shifts in investor decision making due to the substantial discourse concerning the relevance of ESG criteria or whether traditional financial variables exert more influence. Secondly, the study was inspired by the lack of comprehensive investigations testing whether the prominence of the social component is progressively increasing or remaining static. This gap in knowledge served as pivotal motivation for our research. Thirdly, the majority of studies, rooted in their explanatory nature, have resorted to linear regression models (Ammann et al., 2019; Guercio & Tkac, 2008; Reboredo & Otero, 2021), often overlooking the potential of machine learning approaches, known for their heightened predictive accuracy. This encouraged us to use state-of-the-art methodologies. Finally, the notion of "smart money" is currently being studied in the context of investors' search for profit (Feng et al., 2014; Zheng, 1999), which led us to investigate whether a similar phenomenon exists in the search for social returns.

The paper addresses four research questions. First, we explored the factors that mutual fund investors take into account. It is particularly interesting to study whether investors consider ESG performance to be more or less important than past fund returns. The debate on financial market decisions has a long pedigree. The hypothesis of efficient

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financial markets with rational investors dominated financial theory (Fama, 1970). However, prospect theory showed the imperfections of financial markets and the inconsistencies of decision-makers (Barberis, 2013). The nonrationality of decision-makers favored the development of financial decision support systems, which have the advantage of not being affected by human emotions (Bhandari et al., 2008). Previous research identified the importance of past returns as a factor that investors look for when choosing a mutual fund (Guercio & Tkac, 2008; Sirri & Tufano, 1998). Other studies examined relevant aspects of investors' decisions, such as mutual fund fees (Servaes & Sigurdsson, 2022), risk aversion (Dorn & Huberman, 2010), herd behavior (Nofsinger & Sias, 1999), and investment style (Cremers et al., 2019). Some researchers studied the influence of social aspects on investment decisions (Bauer et al., 2021; Bollen, 2007; Reboredo & Otero, 2021; Renneboog et al., 2011), concluding that socially responsible investors may behave differently from other investors. Environmentally and socially conscious investors are even more willing to sacrifice financial returns to invest in sustainable investment products than their counterparts (Gutsche & Ziegler, 2019; Riedl & Smeets, 2017). This may explain why SRI flows are less sensitive to past negative returns than conventional ones (Renneboog et al., 2011). Moreover, some studies suggest that the volatility of SR investments is significantly lower than that of conventional assets (Albuquerque et al., 2018; Bollen, 2007). Previous studies paid attention to the relationship between labeling a fund as sustainable and the flows it receives (Ammann et al., 2019; Hartzmark & Sussman, 2019). Despite these studies, the weight of social considerations in mutual fund investment decisions remains unclear.

Our study contributes to the growing literature by comparing the relative importance of past returns and other financial variables versus ESG performance. We found that investors take ESG into account, but past returns trump sustainability in mutual fund investment decisions. Past growth is the most important variable for mutual fund investors, which can be explained by herd behavior (Nofsinger & Sias, 1999). Investors are attracted to funds that have grown in the past. It seems that the mutual fund industry is influenced by the Matthew effect (Merton, 1968), as funds with higher inflows grow even more. The fund fee is a relevant aspect for investors; this finding may be associated with the growth of passive management (Cremers & Petajisto, 2009), which can be interpreted as a sign of rationality in financial decision-making, being underpinned by the efficient market hypothesis. The importance of past return for investors is well known (Guercio & Tkac, 2008; Sirri & Tufano, 1998). They often suffer from extrapolation bias, as past return does not guarantee future return (Malkiel, 2005). Therefore, our study corroborates the existence of biases identified by prospect theory (De Bondt & Thaler, 1985; Kahneman & Tversky, 1979). As expected, volatility matters, which is explained by the fact that mutual fund clients like diversification, as opposed to those who buy a few stocks on their own (Dorn & Huberman, 2010). The relationship between fund size and fund growth is negative, confirming that larger funds have greater difficulty in continuing to grow (Chen et al., 2004).

Society's concern for ESG issues has taken hold and investors have also begun to value sustainability when choosing mutual funds (Bauer et al., 2021). Our second research question was whether the increase in ESG concerns that society has been experiencing in recent years translated into a greater weight of ESG in investment decisions. Motivation could be social, but also financial if there is a positive relationship between social and financial performance. The mantra "doing good leads to doing well" is heard so often that it seems reasonable to expect many investors to include ESG criteria when selecting funds. However, empirical studies showed mixed results (Badía et al., 2020; Flammer, 2021; Galema et al., 2008; Halbritter & Dorfleitner, 2015; Hawn et al., 2018; Hong & Kacperczyk, 2009; Krüger, 2015; Muñoz et al., 2014). Flammer (2021) concluded that the market responds positively to the announcement of green bond issuance, while Hawn et al. (2018) found that investors punished companies that were added to the Dow Jones Sustainability Index. Krüger (2015) showed that the market responds strongly negatively to negative social-related events and weakly negatively to positive ones. Similar inconclusive results were also obtained in studies that analyzed whether SRI funds outperform conventional ones (Galema et al., 2008; Hong & Kacperczyk, 2009; Muñoz et al., 2014) or whether high-rated portfolios constructed based on ESG outperformed low-rated portfolios (Badía et al., 2020; Halbritter & Dorfleitner, 2015). Our study contributes to this literature by showing that the low importance of ESG scores was maintained during the period under analysis (2015 to 2021).

Our third research question aimed to develop a decision model to predict the flows raised by each mutual fund. Previous studies identified key factors for investment decisions (Ammann et al., 2019; Guercio & Tkac, 2008; Reboredo & Otero, 2021), but they are not predictive models. These studies used regression analysis and found statistically significant relationships, but they do not provide information on the relevant performance measures in forecast verification. Other studies used advanced techniques for selecting funds (Chen & Ren, 2022; Deboeck, 1998; DeMiguel et al., 2023; Vo et al., 2019), but their objective was not to identify the factors that explain the subscription or redemption of funds carried out by investors. Our empirical study examined US equity mutual funds from 2015 to 2021. We used logistic regression as a baseline model to predict the flows raised by each mutual fund, and various machine learning tools (random forest, gradient boosting decision trees and neural networks) because of their ability to predict with remarkable accuracy in highly nonlinear ways. We performed a temporal validation of the models splitting the data into two periods, the first being the training sample and the second the test sample.

Previous studies investigated the determinants of fund flows (Guercio & Tkac, 2008; Reboredo & Otero, 2021). Our study contributes to this literature by proposing predictive models of fund flows using machine learning tools, providing performance measures, and employing intertemporal validation to assess their predictive power. Random forest (RF) obtained the best performance, with an accuracy of around 70 % in the sample test. The importance of each variable was examined by analyzing the SHapley Additive exPlanations (SHAP) and Permutation Feature Importance (PFI) values. The type of mutual fund and the type of clientele can affect decision-making. For example, in funds labeled as sustainable, the model's accuracy was as high as 74.86 %. The model fitted better in the subsample of funds targeting individual investors rather than institutional investors, who may consider other aspects.

Our fourth research question was whether investors who invested in the funds that received the most flows made the right decision (in financial and social terms). To do this, we compared their financial returns with that of the average mutual fund. Previous research obtained inconclusive results (Feng et al., 2014; Zheng, 1999). Some studies found a "smart money" effect (Zheng, 1999). However, other studies found that only institutional investors showed a "smart money" effect while individual investors showed a "dumb money" effect (Feng et al., 2014), the latter in line with the efficient market hypothesis that states that it is impossible to predict movements in stock prices (Fama, 1970). These findings led us to explore whether a similar phenomenon exists in the search for social returns. In the period under investigation, we did not find a clear relationship between past returns and future returns, a finding that supports the efficient market hypothesis (Fama, 1970; Markowitz, 1952). However, the objectives of some investors are not limited to the search for financial but also social returns. Our study contributes to the literature by finding that past ESG performance explains future ESG performance. The adjusted R2 of the model that predicts the fund's sustainability score one year later based on the current sustainability score was 0.74. Investors who choose to acquire funds that meet ESG criteria are not guaranteed a financial return (like other investments), but at least the association between past ESG performance and future ESG performance is very strong, so the social return is largely guaranteed.

The study has practical implications for fund managers, regulators, and investors. Being able to predict flows is important because it helps to understand how investors make decisions. The study helps fund managers to better understand what their clients look for. As ESG performance is not as relevant as expected, perhaps they should change the sales pitch. It does not appear to be a problem with access to information as Morningstar provides a free, intuitive 1-to-5 globe rating system on ESG performance. Perhaps investors think that there is a negative relationship between social and financial performance and they must choose between one or the other. The fund's sales force should emphasize that high ESG performance implies less risk of a reputational crisis and that the performance of socially responsible funds does not differ statistically from that obtained by conventional mutual funds (Hamilton et al., 1993). In fact, we found a positive and statistically significant association between past ESG performance and future financial performance. However, the association was very weak, with negligible predictive power. It is useful for the regulator to know the reasons for fund flows. The model can help the supervisor to detect and predict trends in flow movements. The persistence of investor biases calls for increased financial literacy. The paper is also useful for investors. Individual investors focus on irrelevant aspects (past financial return is often not predictive of future financial return) and place little value on social aspects (past ESG performance is predictive of future ESG performance). However, it is difficult to get investors to avoid biases, as they are predisposed to listen to the sirens' songs (Buffett, 2016). One solution is to let a decision support system make the financial decisions.

2. Literature review and model development

The efficient market hypothesis and prospect theory stand out among the theories that can help to understand how investors make financial decisions. The efficient market hypothesis proposed that current stock prices fully reflect available information about the value of the firm; hence, the past cannot be used to predict the future in any meaningful way (Fama, 1965). In other words, there is no way to beat the market using this information, because stock prices follow a random walk rather than a predictable path; hence, a rational investor should not analyze past information. The efficient market hypothesis is based on two assumptions: investors are fully rational decision-makers who do not behave erratically, and there are no information asymmetries. According to the efficient market hypothesis, it does not matter what you buy; therefore, a quite rational position would be to buy mutual funds with the lowest fees. In fact, many investors consider mutual fund fees when it comes to investment (Servaes & Sigurdsson, 2022), which is fully justified given the negative relation between fees and fund performance (Gil-Bazo & Ruiz-Verdú, 2009). Passive funds, which replicate a benchmark index to match its performance, are becoming increasingly popular, as opposed to active funds, which require frequent trading to try to outperform the benchmark index (Cremers et al., 2019). The more actively the fund is managed, the more trades it undertakes and the higher the costs it incurs. Conversely, passive management has low fees because it performs fewer transactions than active management. Assets under management by US passive funds exceeded those of active funds for the first time in September 2019 (Gittelsohn, 2019). Considering the above, it is expected that mutual fund fees and investment strategy will be factors explaining fund flows.

However, the efficient market hypothesis is a theoretical model that does not explain some market anomalies, such as the possibility of beating the market by identifying undervalued companies (Basu, 1977). Prospect theory was developed to explain how people decide, not how they should decide (Kahneman & Tversky, 1979). Prospect theory is central to behavioral finance by explaining that the cause of these anomalies is the behavioral biases of financial decision-makers. One of the most important biases is the overreaction of investors to information, who react disproportionately to new information and cause the stock price to change in an unjustified way (De Bondt & Thaler, 1985). Other cognitive biases explain why investors prefer funds that were profitable in the past. For example, the extrapolation bias consists of believing that past performance is the best indicator for predicting future performance (Chen et al., 2007). Investors are heavily influenced by past returns in their purchase decisions (Barber and Odean, 2013) but some of them experience the opposite effect – the Gambler's Fallacy – and think that a trend will reverse (Huber et al., 2010). Although it has been shown that past returns do not guarantee future returns (Malkiel, 2005), and the opposite may be true (De Bondt & Thaler, 1985), decision-makers tend to invest in mutual funds that have had above-average returns (Guercio & Tkac, 2008; Sirri & Tufano, 1998). For all these reasons, it is expected that past performance will be a factor in explaining fund flows.

Another factor that can explain why a fund receives flows from investors is the fund's past growth. Herd behavior may be an explanatory factor, as the tendency to imitate what other investors do is well documented in the capital markets (Nofsinger & Sias, 1999). Many investors mimic the behavior of other investors so that increases in fund size can explain future fund growth. It is expected that the increases in size experienced by the fund will explain future fund flows. However, the size of the fund limits its growth because the larger the fund, the greater the difficulties in continuing to grow (Chen et al., 2004). Investors exhibit different patterns in the face of risk. While high risk-taking may reveal narcissism in some investors (Campbell et al., 2004), risk-averse investors show a stronger tendency to invest in mutual funds as a way to ensure that their portfolios are highly diversified (Dorn & Huberman, 2010). Given the risk aversion of fund investors, low volatility is expected to be a factor behind fund flows.

Including social aspects in decision-making means adding a constraint to the decisional model, so that an investor seeking sustainable investments would have lower financial returns, all other things being equal. However, from the stakeholder theory approach (Freeman, 1984), it can be argued that those companies that stand out for their ESG performance signal high managerial quality, which can translate into favorable financial performance and may reduce the high costs that emerge during corporate social crises or environmental disasters (Renneboog et al., 2008). Nevertheless, literature reviews found little evidence that the risk-adjusted returns of ESG funds differ substantially from conventional funds (Plagge & Grim, 2020; Renneboog et al., 2008). Bollen (2007) studied the behavior of social investors, finding that they are more loyal than other investors, which is explained because they seem to derive utility from being exposed to the social attribute. Investors value sustainable investments and, indeed, react to the availability of sustainability ratings (Ammann et al., 2019). Whether or not social investors pay a premium for ethics, it seems undeniable that there are investors willing to invest in ESG funds, therefore it is expected that ESG performance will be a factor explaining fund flows. Analysts' ratings can also have an impact on fund flows (Armstrong et al., 2019), as well as the macroeconomic conditions of the economy and financial markets (Chen & Qin, 2017). Taking into account all of the above factors, we modeled decisions on mutual funds as a function of the past return, risk, ESG performance, fund size, previous size increase, investment strategy, management fees, analysts' ratings, and macroeconomic conditions.

3. Methodology

3.1. Sample and data collection

Our data about mutual funds were sourced from the Morningstar Direct Mutual Fund (MDMF) database, which encompasses U.S. open-end mutual funds. Morningstar is one of the largest providers of information for mutual fund investors. The MDMF database provides a comprehensive range of information, including fund names, returns, size, age, expense ratios, turnover ratios, investment styles, and other fund characteristics, along with ESG variables. To narrow our focus, we applied standard filters to the MDMF database, concentrating on share classes of equity mutual funds domiciled and commercialized in the

Table 1
Description of the variables used.

Variables	*Definition*
Dependent variables	
$Flow_{t+n}$	The percentage change in the total net assets (TNA) of a share class over the next N months (N = 1, 3, 6 or 12) (see Equation (1).
$DFlow_{t+n}$	A dummy variable obtained by transforming the cumulative flow ($Flow_{t+n}$), where 1 indicates that the cumulative flow was greater than the median and 0 otherwise.
$Return_{t+n}$	Financial return over the next N months (N = 1, 3, 6 or 12).
$ESGscore_{t+n}$	Asset-weighted average of the company ESG scores (environmental, social, and governance) for the covered holdings in a portfolio over the next N months (N = 1, 3, 6 or 12). Morningstar changed the calculation method from September 2019, measuring the degree to which a company may be at risk driven by social factors. The data were transformed to maintain consistency in the series (Source: Morningstar; Code: portfolio corporate sustainability score).
Social independent variable	
ESGscore	Environmental, social, and governance (ESG) score for the current period
Financial independent variables	
Yield	Fund cumulative net return in the previous 12 months (Source: Own elaboration from Morningstar; Code: Return).
Volatility	Standard deviation of the previous 12 months' return (Source: Own elaboration from Morningstar; Code: Return).
Alpha	The previous 12-month excess return generated by the fund, relative to the Fama–French five-factor model, as per Equation (3) (Fama & French, 2015).
logTNA	The logarithm in base 10 of the total net assets of the individual share classes (Source: Morningstar; Code: net assets – share class (monthly)).
Fees	The percentage of fund assets used to pay for operating expenses and management fees, including 12b-1 fees, administrative fees, and all other asset-based costs incurred by the fund, except brokerage costs (Source: Morningstar; Code: annual report net expense ratio).
Turnover	Fund's trading activity, which is computed by taking the lesser of purchases or sales and dividing by average monthly net assets (Source: Morningstar; Code: turnover ratio %).
RatingInd	Morningstar Analyst Rating, which assigns ratings on a five-tier scale, encompassing three positive ratings of Gold, Silver, and Bronze, a Neutral rating, and a Negative rating. (Source: Morningstar; Code: Morningstar Medalist Rating).
Flow	The percentage change in the total net assets (TNA) of a share class (see Equation (1).
Macroeconomic control variables	
Tb3	Three-month T-Bill rate (Source: Refinitiv-Eikon)
Def	Return spread between the high-yield bond index and the intermediate government bond index (Source: Refinitiv-Eikon)
Option	Return spread between the GNMA index and intermediate government bond index (Source: Refinitiv-Eikon)
Stk	Excess return on the SP500 stock index (Source: Refinitiv-Eikon)
Vix	Implied market volatility index (Source: Refinitiv-Eikon)

United States from January 2015 to December 2021.

The start date was chosen because Morningstar began reporting ESG ratings of fund portfolios in January 2015. We chose listed and delisted share classes to avoid survivorship bias. Our initial sample comprised 20,184 share classes belonging to 5,330 funds. However, not all share classes had complete data on the study variables. After data cleaning, we analyzed 12,776 share classes from 3,767 funds. Table 1 shows the financial and nonfinancial variables used and their definition.

We estimate the following three models to explain the money flows Equation (1), the return Equation (2) and the ESGscore Equation (3) achieved by funds.

$$\begin{aligned} Flow_{it+n} = {} & \alpha_i + \beta_1 \times ESGscore_{it} + \beta_2 \times Yield_{it} + \beta_3 \times Volatility_{it} \\ & + \beta_4 \times Flow_{it} + \beta_5 \times \log TNA_{it} + \beta_6 \times Fees_{it} \\ & + \beta_7 \times Turnover_{it} + \beta_8 \times RatingInd_{it} + \beta_9 \times Macro_{it} + \varepsilon_{it+n} \end{aligned} \tag{1}$$

$$\begin{aligned} Return_{it+n} = {} & \alpha_i + \beta_1 \times ESGscore_{it} + \beta_2 \times Yield_{it} + \beta_3 \times Volatility_{it} \\ & + \beta_4 \times Flow_{it} + \beta_5 \times \log TNA_{it} + \beta_6 \times Fees_{it} \\ & + \beta_7 \times Turnover_{it} + \beta_8 \times RatingInd_{it} + \beta_9 \times Macro_{it} + \varepsilon_{it+n} \end{aligned} \tag{2}$$

$$\begin{aligned} ESGscore_{it+n} = {} & \alpha_i + \beta_1 \times ESGscore_{it} + \beta_2 \times Yield_{it} + \beta_3 \times Volatility_{it} \\ & + \beta_4 \times Flow_{it} + \beta_5 \times \log TNA_{it} + \beta_6 \times Fees_{it} \\ & + \beta_7 \times Turnover_{it} + \beta_8 \times RatingInd_{it} + \beta_9 \times Macro_{it} + \varepsilon_{it+n} \end{aligned} \tag{3}$$

Our study had three groups of dependent variables: the flow in the next N months ($Flow_{t+n}$), the return in the next N months ($Return_{t+n}$), and the sustainability score in the next N months ($ESGscore_{t+n}$).

We first obtained the money flow of share class *i* (*Flow*) following Equation (4) (Bollen, 2007; Guercio & Tkac, 2008).

$$Flow_{it} = \frac{TNA_{it} - TNA_{it-1}(1 + Return_{it})}{TNA_{it-1}} \tag{4}$$

where TNA_{it} is the total net assets of a share class *i* in month *t*, and $Return_{it}$ measures the net revaluation suffered by the assets of share class *i* in month *t*.

Return measures the financial return of each share class. *ESGscore* measures the overall environmental, social, and governance performance according to Morningstar, and captures the scores obtained by the fund's portfolio holdings. Morningstar changed its methodology as of September 2019 and now the interpretation is the opposite: A high value means high social risk. Therefore, we used min–max normalization to homogenize the time series of this variable. In addition, Morningstar communicates ESG information with a one-month lag. Therefore, we delayed all portfolio scores by one month.

Regarding the independent variables, *Yield* shows the cumulative net return of the fund in the last 12 months. *Volatility* measures the risk of the investment in the last 12 months. The return adjusted for risk (*Alpha*) provides a measure of the fund's outperformance or underperformance and was obtained as the excess return over the last 12 months on the Fama–French five-factor model following Equation (5) (Fama & French, 2015).

$$\begin{aligned} r_{it} = {} & Alpha_i + \beta_{MKT} MKT_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \beta_{RMW} RMW_t \\ & + \beta_{CMA} CMA_t + \varepsilon_{it} \end{aligned} \tag{5}$$

where r_{it} is the return of share class *i* in period *t*, and $Alpha_i$ shows the excess return over the risk factors: market effect (*MKT*), size effect (*SMB*), value effect (*HML*), profitability (*RMW*), and investment style (*CMA*).

LogTNA is the logarithm of the TNA of the share class and measures the size of the class. The fees of each share class were measured by calculating the percentage of share class assets used to pay operating expenses and management fees (*Fees*). The turnover ratio measured the fund's trading activity and was calculated by taking the lower of purchases or sales and dividing it by the average monthly net assets (*Turnover*) (Elton et al., 2010). A high value of this variable reflects an investment strategy that involves more trading than holding, which increases costs for investors. Morningstar analysts use a five-tier scale (*RatingInd*) encompassing three positive ratings of gold, silver, and bronze, a neutral rating, and a negative rating. This rating serves as a summary expression of Morningstar's forward-looking analysis of a fund (Armstrong et al., 2019).

The equations include the usual variables examined in the financial literature on investment funds, in which the use of lagged flows is well established (Coval & Stafford, 2007; Del Guercio & Tkac, 2008; Fant & O'Neal, 2000; Reboredo & Otero, 2021).

The macroeconomic conditions encompass the 3-month T-Bill rate (*Tb3*), the return spread between the high-yield bond index and the

Table 2
Descriptive statistics of the variables.

	mean	std	min	25 %	50 %	75 %	max	#
ESGScore	59.22	11.68	2.62	52.08	59.74	67.50	99.68	489,885
Yield	13.63 %	19.67 %	−40.26 %	0.12 %	10.29 %	23.18 %	135.77 %	489,885
Volatility	4.57 %	1.81 %	0.76 %	3.21 %	4.33 %	5.78 %	14.05 %	489,885
Alpha	−0.06 %	0.76 %	−5.35 %	−0.43 %	−0.07 %	0.27 %	5.07 %	489,885
logTNA	7.76	1.25	3.73	6.99	7.87	8.66	10.63	489,885
Fees	1.10 %	0.50 %	0.00 %	0.78 %	1.04 %	1.37 %	2.72 %	489,885
Turnover	54.75 %	47.96 %	1.63 %	24.00 %	41.64 %	70.00 %	338.80 %	489,885
RatingInd	2.58	1.10	1.00	2.00	2.00	3.00	5.00	489,885
Flow	−0.31 %	6.36 %	−40.18 %	−1.76 %	−0.50 %	0.51 %	80.50 %	489,885
$Flow_{t+1}$	−0.35 %	6.28 %	−40.18 %	−1.76 %	−0.51 %	0.49 %	80.50 %	489,885
$Flow_{t+3}$	−0.41 %	6.16 %	−40.18 %	−1.78 %	−0.53 %	0.46 %	80.50 %	457,341
$Flow_{t+6}$	−0.49 %	6.08 %	−40.18 %	−1.82 %	−0.56 %	0.42 %	80.50 %	413,037
$Flow_{t+12}$	−0.58 %	5.76 %	−40.18 %	−1.84 %	−0.60 %	0.37 %	80.50 %	336,673
$Return_{t+1}$	0.98 %	5.09 %	−30.63 %	−1.58 %	1.41 %	3.79 %	23.46 %	489,885
$Return_{t+3}$	0.97 %	5.20 %	−30.63 %	−1.66 %	1.46 %	3.84 %	23.46 %	457,341
$Return_{t+6}$	0.99 %	5.36 %	−30.63 %	−1.78 %	1.53 %	4.00 %	23.46 %	413,037
$Return_{t+12}$	1.24 %	5.24 %	−30.63 %	−1.37 %	1.71 %	4.09 %	23.46 %	336,673
$ESGscore_{t+1}$	59.47	11.73	2.62	52.28	60.08	67.78	99.68	489,885
$ESGscore_{t+3}$	59.86	11.76	0.63	52.62	60.59	68.14	99.68	478,412
$ESGscore_{t+6}$	60.21	11.73	0.00	52.99	61.09	68.41	99.68	446,411
$ESGScore_{t+12}$	61.14	11.47	0.00	53.90	62.22	68.95	99.68	384,352
Tb3	0.08 %	0.08 %	−0.01 %	0.01 %	0.05 %	0.15 %	0.31 %	84
Def	0.29 %	2.09 %	−11.82 %	−0.45 %	0.56 %	1.37 %	3.82 %	84
Option	−0.04 %	0.49 %	−1.48 %	−0.25 %	−0.03 %	0.17 %	1.73 %	84
Stk	1.29 %	4.21 %	−12.35 %	−0.04 %	1.87 %	3.63 %	12.82 %	84
Vix	0.03	0.30	−0.46	−0.14	−0.02	0.11	1.35	84

intermediate government bond index, (*Def*), the return spread between the GNMA index and intermediate government bond index (*Option*), the excess return on the SP500 stock index (*Stk*), and the implied market volatility index (*Vix*). Macroeconomic variables were obtained from Refinitiv-EIKON database.

The presence of outliers affects to both the estimated coefficients of regressions and the convergence of machine learning methods that rely on gradient descent. Winsorizing is a common practice when utilizing financial data to reduce the impact of outliers, extreme values, and data errors (Drechsler et al., 2021; Fee et al., 2006; Henry & Koski, 2017). To limit the influence of extreme outliers we winsorized the financial variables each month at the 1th and 99th percentile, which is the threshold most commonly used by researchers with financial data.

3.2. Preliminary analysis

Table 2 shows descriptive statistics of the variables and Table 3 shows the results of a Pearson correlation analysis. The correlation coefficient between flows and the independent variables was very low, as was the correlation between future financial return and the independent variables. By contrast, the correlation between past and future ESG performance variables was very high, with a value of 0.82 with a 12-month lag between the two variables, meaning that the funds maintain ESG scores over time. As for the independent variables, the correlation coefficient between *Def* and *Stk* was 0.76 and between *Alpha* and *Yield* was 0.32, which could suggest the presence of multicollinearity. Although multicollinearity may not affect predictive power, the effect of each independent variable on the dependent variable could be miscalculated, producing inaccurate and unstable regression coefficients (Myers, 1990). We opted to remove *Alpha* from the regression analysis and use only *Yield* as a measure of return, because it is observable and easily understood by investors. We also removed *Def* from the regression analysis.

4. Results

4.1. Factors explaining the purchase of funds

Our first research question aimed to study the factors that explain why an investor buys a fund, and in particular to compare the relative importance of past returns versus ESG performance. Table 4 presents the results of exploratory analysis and an independent T-test to compare the differences between funds that received flows above the median and those that did not. Investors subscribed to funds with a higher past return, better ESG performance and smaller fund size but which had increased in size, had lower volatility, lower fees, and lower turnover ratio. The mean differences were statistically significant for all variables. Focusing on the flows received in the following month, *Flow* showed the largest mean differences: Funds, where flows increased above the median, had previously grown by 1.04 %, while funds whose flows increased below the median had previously decreased by −1.66 %. *Fees* also showed highly significant differences in means. Differences in *logTNA*, *Yield*, and *RatingInd* were also high. Statistically significant but modest mean differences were observed for *ESGscore, Volatility*, and *Turnover*. The results were similar if the dependent variable measured the flows in the following 3, 6, and 12 months. It should be noted that the macroeconomic control variables take the same values in each of the funds in a given month and therefore do not differ between the two groups.

We performed a panel data regression model of Equation (1) to study the factors that explain investors' flows. The Hausman test (Hausman, 1978) indicated a preference for the fixed-effect model over the random-effect model, with a p-value below 1 %. We analyzed the multicollinearity between the variables by using the variance inflation factor (VIF). All variables had VIF values below the acceptable cutoff of 5.0, indicating that multicollinearity was absent. Financial data can be sensitive to departures from regression assumptions. Therefore, we conducted several robustness tests.

Heteroscedasticity does not cause bias or inconsistency in the estimators, but it does render the standard errors and test statistics invalid, even with large sample sizes (Wooldridge, 2019). The modified Wald test was used to diagnose the heteroscedasticity in the errors. This test rejected the null hypothesis of homoscedasticity and consequently, we employed cluster-robust standard errors. D'Agostino-Belanger-D'Agostino K-squared normality test was used to assess normality. The results did not support the normality assumption. Despite applying winsorization and standardization techniques to the variables, achieving complete normality remained elusive. We used the Ramsey specification test to

Table 3
Pearson's correlation matrix between variables.

	(0)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)
(0) *ESGScore*	1.00																									
(1) *Yield*	0.19	1.00																								
(2) *Volatility*	0.09	−0.07	1.00																							
(3) *Alpha*	−0.01	0.32	−0.04	1.00																						
(4) *logTNA*	−0.01	0.06	−0.09	0.05	1.00																					
(5) *Fees*	−0.09	−0.06	−0.01	−0.03	−0.38	1.00																				
(6) *Turnover*	−0.07	−0.03	0.06	−0.02	−0.21	0.23	1.00																			
(7) *RatingInd*	0.04	0.05	−0.10	0.07	0.38	−0.30	−0.27	1.00																		
(8) *Flow*	0.01	0.09	−0.02	0.08	−0.01	−0.10	−0.01	0.05	1.00																	
(9) *Flow$_{t+1}$*	0.01	0.09	−0.02	0.08	−0.05	−0.10	−0.01	0.05	0.24	1.00																
(10) *Flow $_{t+3}$*	0.02	0.07	0.00	0.08	−0.05	−0.10	−0.01	0.05	0.18	0.20	1.00															
(11) *Flow $_{t+6}$*	0.03	0.06	0.02	0.07	−0.06	−0.10	−0.01	0.04	0.14	0.15	0.18	1.00														
(12) *Flow $_{t+12}$*	0.03	0.02	0.04	0.05	−0.07	−0.11	−0.01	0.02	0.11	0.11	0.13	0.14	1.00													
(13) *Return $_{t+1}$*	0.06	−0.07	0.24	0.03	0.00	−0.02	−0.01	0.01	−0.01	0.03	0.03	0.02	0.02	1.00												
(14) *Return $_{t+3}$*	0.05	−0.10	0.19	−0.01	0.01	−0.03	0.00	0.00	−0.00	−0.01	0.03	0.02	0.03	−0.03	1.00											
(15) *Return $_{t+6}$*	0.10	−0.00	0.09	−0.05	0.01	−0.02	−0.00	0.01	−0.01	−0.00	−0.00	0.03	0.02	0.03	−0.06	1.00										
(16) *Return $_{t+12}$*	0.04	−0.02	0.06	−0.04	0.00	−0.02	−0.00	−0.00	−0.00	−0.01	−0.01	−0.00	0.03	−0.06	−0.17	−0.01	1.00									
(17) *ESGscore $_{t+1}$*	0.99	0.19	0.11	0.00	−0.01	−0.09	−0.07	0.04	0.01	0.01	0.02	0.03	0.03	0.06	0.06	0.07	0.02	1.00								
(18) *ESGscore $_{t+3}$*	0.96	0.17	0.15	0.02	−0.02	−0.08	−0.06	0.03	0.01	0.01	0.02	0.03	0.03	0.07	0.07	0.06	0.05	0.97	1.00							
(19) *ESGscore $_{t+6}$*	0.92	0.14	0.22	0.03	−0.03	−0.08	−0.05	0.01	0.00	0.01	0.02	0.03	0.03	0.08	0.06	0.08	0.10	0.94	0.96	1.00						
(20) *ESGscore $_{t+12}$*	0.82	−0.01	0.28	0.05	−0.06	−0.07	−0.02	−0.03	−0.00	−0.00	0.01	0.02	0.03	0.06	0.11	0.10	0.07	0.84	0.87	0.92	1.00					
(21) *Tb3*	−0.42	−0.48	−0.20	−0.02	−0.08	0.04	0.04	−0.09	−0.02	−0.01	−0.02	−0.03	−0.01	−0.05	−0.05	−0.11	0.02	−0.41	−0.39	−0.31	−0.12	1.00				
(22) *Def*	0.05	0.19	0.11	0.00	0.01	−0.00	−0.01	0.01	0.02	0.00	0.00	0.01	−0.00	−0.09	−0.12	0.05	−0.03	0.05	0.04	0.04	−0.01	−0.44	1.00			
(23) *Option*	−0.00	0.03	−0.04	−0.03	0.01	0.00	−0.01	0.01	0.00	0.02	0.01	0.00	−0.01	0.10	−0.01	−0.15	0.05	0.01	−0.03	−0.04	−0.09	0.11	−0.26	1.00		
(24) *Stk*	0.07	0.22	0.13	0.04	−0.00	−0.01	0.00	−0.01	0.03	0.00	0.00	0.01	0.01	−0.11	−0.06	−0.01	−0.09	0.08	0.05	0.07	0.04	−0.32	0.76	−0.25	1.00	
(25) *Vix*	0.00	−0.17	−0.05	−0.06	−0.00	−0.00	0.00	0.00	−0.02	−0.01	0.01	−0.00	0.00	−0.07	0.19	0.17	0.18	−0.01	0.03	0.02	0.06	0.17	−0.50	0.08	−0.78	1.00

evaluate the adequacy of the model's functional form. This test determines whether there are any omitted nonlinear relationships between the independent variables and the dependent variable. The results of Ramsey's test rejected the null hypothesis, indicating that incorporating omitted nonlinear terms could improve the regression model's performance but not to a satisfactory extent in terms of the interpretability of the results. Given this consideration, we made the decision to avoid introducing additional complexity into the model. The use of panel data regression with fixed effects mitigate potential endogeneity issues arising from omitted variables (Rakowski & Yamani, 2021; Pástor et al., 2015).

Table 5 shows the results of 3 panel data regression specifications for each of the four time periods analyzed for the dependent variable *Flow$_{t+n}$* (N = 1, 3, 6, and 12 months). Specification 1 used *ESGscore* as the independent variable. The goodness of fit of the model was low (adjusted R2 was 0.09 for *Flow$_{t+1}$*). Specification 2 used financial variables as the independent variables, and the adjusted R2 was 0.15 for *Flow$_{t+1}$*. Specification 3 added the *ESGscore* variable to specification 2, i.e., it is the full model and the adjusted R-squared remained the same. The results were very similar when the flows of the following periods were considered.

Thus, regarding the first research question, although ESG performance obtained a statistically significant coefficient, it does not explain much of the flows achieved by mutual funds.

4.2. The evolution of investors' concern about ESG issues

Our second research question aimed to study the evolution of investors' concern about ESG performance, compared to all other factors. We analyzed the evolution of the importance of each independent variable by estimating Equation (1) through a rolling regression. This is a time series modeling technique used to analyze how the coefficients of variables change over time. The regressions were carried out from December 2015 until December 2021 with a rolling window of 12 months, totaling 61 regressions for Flow_{t+12}. The remaining regressions for Flow_{t+6}, Flow_{t+3}, and Flow_{t+1}, followed the same procedure. We obtained a time series of standardized regression coefficients. We chose to use standardized regression coefficients rather than the traditional non-standardized coefficients to determine the relative importance of explanatory variables, in line with the two first research questions. The relative size of these coefficients indicates the comparative influence of the independent variables in the model. Fig. 1 shows the evolution of the standardized beta coefficients for the financial and social variables during the analyzed period. The average standardized beta coefficient for *ESGscore* (0.10) was significantly lower than the coefficients for *Yield* (0.77), *Fees* (-0.81), *RatingInd* (0.20), and *Volatility* (0.15).

Investors may take ESG performance into account, but past returns, Morningstar Analyst Rating, and mutual fund fees are much more important. However, the interpretation of coefficients in a multivariate regression can be misleading, and its utilization is a subject of debate (Bring, 1994). Therefore, the use of general dominance weights is recommended to complement the analysis (Jung & Suh, 2019), which indicates the importance of the variable for the goodness of fit of the model (Tonidandel & LeBreton, 2011). Fig. 2 shows the evolution of the general dominance weights. No major variations were observed during the period analyzed. The average dominance weight for *ESGscore* (0.55) was significantly lower than the weights for *Fees* (23.98), *Yield* (7.01), *RatingInd* (2.32), and *Volatility* (0.88). Both the analysis of the standardized coefficients and the analysis of the general dominance weights revealed that ESG performance was never highly relevant for investors, although its importance fluctuated, which suggests that sentiment toward sustainability varies over time (Pástor et al., 2021; Pedersen et al., 2021).

Table 4
T-test of mean differences between funds that increased their flows over the next 1, 3, 6, and 12 months above the median ($DFlow_{t+n} = 1$) and those that did not ($DFlow_{t+n} = 0$).

	$DFlow_{t+1}$			$DFlow_{t+3}$			$DFlow_{t+6}$			$DFlow_{t+12}$		
	D = 1	D = 0	Test	D = 1	D = 0	Test	D = 1	D = 0	Test	D = 1	D = 0	Test
ESGscore	59.51	58.93	17.38***	59.34	58.73	17.89***	59.14	58.48	18.89***	58.59	57.96	17.66***
Yield	14.82 %	12.44 %	42.45***	13.97 %	11.85 %	37.09***	12.25 %	10.67 %	27.40***	8.03 %	7.14 %	20.33***
Volatility	4.52 %	4.61 %	−17.35***	4.51 %	4.60 %	−15.85***	4.49 %	4.57 %	−12.32***	4.26 %	4.30 %	−6.54***
logTNA	7.62	7.90	−76.92***	7.64	7.91	−75.53***	7.66	7.94	−71.46***	7.71	7.98	−63.54***
Fees	1.02 %	1.19 %	−120.74***	1.02 %	1.19 %	−118.93***	1.01 %	1.19 %	−115.81***	1.00 %	1.19 %	−107.61***
Turnover	53.61 %	55.89 %	−16.68***	53.09 %	55.63 %	−18.12***	52.59 %	55.21 %	−17.91***	51.63 %	54.29 %	−16.61***
RatingInd	2.67	2.49	57.82***	2.68	2.51	52.74***	2.69	2.53	45.20***	2.70	2.59	30.25***
Flow	1.04 %	−1.66 %	152.26***	0.88 %	−1.48 %	126.53***	0.77 %	−1.34 %	105.16***	0.56 %	−1.20 %	80.85***
#	244,924	244,961		228,652	228,689		206,502	206,535		168,318	168,355	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

4.3. A decision model for predicting mutual fund flows

Our third research question aimed to develop decision models to predict the flows raised by each mutual fund. In this study, we used the dummy dependent variable $DFlow_{t+n}$ to calculate accuracy and other absolute performance measures. We adopted a viewpoint that resembles a real case of an observer trying to predict which funds will increase their flows, using one year's past information from a set of independent variables. We divided the sample into a training sample and a test sample. The training sample included for each share class all the information of the dependent and independent variables, in different periods, from January 2015 to December 2018. The test sample included data from January 2019 to December 2021. Therefore, the test made it possible to perform a temporal validation of the results, which is very convenient.

Predictions were performed with logistic regression (LR), random forest (RF), extreme gradient boosting (XGBoost), and multilayer perceptron neural network (MLP). We used cross-validation for training, splitting the training sample into 5 K-folds. We used the *scikit-learn* machine learning library to build and test the RF and MLP models (Pedregosa et al., 2011) and the *xgboost* package for XGBoost (Chen & Guestrin, 2016). For RF, the following hyperparameters were optimized: n_estimators (100,200); max_depht (5, 10); max_features (1, 0.333, 0.666); and bootstrap (True). For XGBoost, the following hyperparameters were optimized: max_depth (1, 3, 5); subsample (0.5, 0.75, 1) learning_rate (0.005, 0.025, 0.05, 0.1,0.3); n_estimators (1000), early_stopping_rounds (5); objective='reg:logistic'. For MLP, the following hyperparameters were optimized: hidden_layer_sizes [(10, 10), (25, 10), (25, 25), (50, 25), (50, 50), (10, 25), (25, 50)]; max_iter (1500), n_iter_no_change (5). The rest of the hyperparameters used were those selected by default by both the *scikit-learn* and *xgboost* libraries.

Table 6 shows several performance measures (accuracy, sensitivity, specificity, precision, F-score, and area under the curve (AUC)) for each model and dependent variable analyzed (fund flows over the next 1, 3, 6, and 12 months). When considering the AUC criterion, RF obtained the best results, slightly better than XGBoost. When considering the accuracy criterion, RF obtained the best results compared to the other techniques and successfully predicted the future flows collected by the funds with an accuracy ranging from 65.4 % to 70.4 % for the test sample. The prediction accuracy of XGBoost ranked from 63.6 % to 68.8 % and that of MLP ranked from 63.6 % to 67.5 %. LR performed the worst with a prediction accuracy ranging from 61.6 % to 63.2 %.

Different explainable machine learning approaches can be used to interpret the results of black-box techniques such as RF, XGBoost, and MLP (Carta et al., 2022; Moreira et al., 2021). Table 7 shows the results of the SHapley Additive exPlanations (SHAP) over the test sample and the permutation feature importance (PFI) techniques. SHAP uses a game-theory-based approach to calculate individual contributions of the variables in the prediction model. The SHAP values show the contribution of the variable to the output of the model for a given share class *i* in period *t*. However, the calculation of SHAP values is computationally demanding, thus we only calculated them for 5 % of the test sample randomly selected. PFI randomly shuffles the values of each variable in the model to assess its effect on model performance. Thus, the PFI value shows the importance of the variable on the model's accuracy.

When using the SHAP technique averaged over the four periods, the most significant variables were *Flow* (35.28 %) and *LogTNA* (18.6 %), with *Fees* (14.4 %), *Yield* (12.91 %), *RatingInd* (2.95 %) and *Volatility* (1.87 %) following in importance. The least important variables were *ESGscore* (1.31 %) and *Turnover* (1.91 %). The results of the PFI analysis were consistent with the previous one. Note how the relative importance of some variables decreases as time increases. For example, current returns (*Yield*) influence decisions made one month later, but have little influence on decisions made one year later.

Not all investors can access all types of funds as some are reserved for institutional investors. The behavior of an individual investor managing a small amount of money may differ from that of an institutional investor managing a large pension fund. Table 8 shows Morningstar's classification of funds, based on the type of investor (institutional or individual), type of fund (sustainable or non-sustainable fund), and type of fees and minimum investment required (different share classes). The table shows for each subsample the accuracy and the relevant variables according to the RF technique and SHAP. The accuracy of the prediction increased significantly when segmented by fund type. Overall, the importance of the variables was maintained in each of the samples. When predicting fund flows purchased by individual investors, the accuracy of the model scored 1.95 points above the accuracy of institutional funds, up to 71.33 % (on average). Accuracy in predicting sustainable fund flows exceeded that of nonsustainable funds by 6.23 points, to 74.31 % (on average). The highest accuracy was obtained when using class B funds (funds that have lower investment minimums and carry a deferred-load sales charge), which reached 82.35 % (on average), and the minority class T (tax-deferral vehicle), which reached 88.23 % (on average). By contrast, the accuracy of class D funds (typically carried by broker-sold fund shops) barely reached 54.93 % (on average). The variables hardly changed their position in the relative importance ranking.

4.4. The right decisions

In this subsection, we studied whether investors' decisions were successful. First, we analyzed whether funds that received flows above the median performed better than those that received flows below the median in terms of financial return. For this purpose, we performed a T-test and a Kruskal–Wallis test to compare the return of both groups, which is shown in Table 9. To carry out this study, we accumulated the flows received, as well as the returns, at 3, 6, and 12 months. Funds that received flows above the median obtained higher returns over the next months than those that received flows below the median. The differences were statistically significant but rather small in magnitude. In the

Table 5

Panel data regression analysis with fixed effects for the flows over the next 1, 3, 6, and 12 months. Reported values are non-standardized coefficients with cluster-robust standard errors between parentheses.

	Flow $_{t+1}$			Flow $_{t+3}$			Flow $_{t+6}$			Flow $_{t+12}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.0177***	0.2684***	0.2789***	0.0016	0.2941***	0.3012***	−0.0065***	0.2880***	0.2909***	−0.0199***	0.2450***	0.2415***
	(0.0009)	(0.0097)	(0.0097)	(0.0011)	(0.0103)	(0.0103)	(0.0011)	(0.0095)	(0.0096)	(0.0013)	(0.0094)	(0.0094)
ESGscore	−0.0001***		−0.0002***	−0.0001***		−0.0001***	0.0001***		−0.0001**	0.0003***		0.0001***
	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)
Yield		0.0177***	0.0199***		0.0111***	0.0125***		0.0085***	0.0091***		−0.0047***	−0.0052***
		(0.0009)	(0.0009)		(0.0008)	(0.0009)		(0.0008)	(0.0009)		(0.0013)	(0.0013)
Volatility		−0.1674***	−0.1431***		−0.1440***	−0.1269***		−0.1026***	−0.0950***		−0.0455***	−0.0568***
		(0.0093)	(0.0097)		(0.0092)	(0.0097)		(0.0085)	(0.0092)		(0.0093)	(0.0103)
logTNA		−0.0358***	−0.0356***		−0.0386***	−0.0384***		−0.0379***	−0.0378***		−0.0310***	−0.0310***
		(0.0012)	(0.0012)		(0.0012)	(0.0012)		(0.0012)	(0.0012)		(0.0011)	(0.0011)
Fees		0.4688**	0.3610		0.1648	0.0983		0.4485**	0.4276*		−0.0981	−0.0778
		(0.2198)	(0.2209)		(0.2158)	(0.2163)		(0.2182)	(0.2186)		(0.2883)	(0.2884)
Turnover		−0.0036***	−0.0037***		−0.0040***	−0.0040***		−0.0024***	−0.0024***		−0.0010	−0.0010
		(0.0007)	(0.0007)		(0.0007)	(0.0007)		(0.0007)	(0.0007)		(0.0009)	(0.0009)
RatingInd		0.0039***	0.0038***		0.0037***	0.0036***		0.0024***	0.0024***		0.0000	0.0000
		(0.0002)	(0.0002)		(0.0002)	(0.0002)		(0.0002)	(0.0002)		(0.0003)	(0.0003)
Flow		0.1147***	0.1142***		0.0509***	0.0505***		0.0170***	0.0169***		0.0002	0.0003
		(0.0041)	(0.0041)		(0.0030)	(0.0030)		(0.0027)	(0.0027)		(0.0029)	(0.0029)
TB3		−0.8397***	−1.5385***		−1.9051***	−2.3534***		−3.2611***	−3.4195***		−3.3034***	−3.1205***
		(0.1745)	(0.1956)		(0.1836)	(0.2009)		(0.1886)	(0.2047)		(0.1901)	(0.2004)
Opt		0.1309***	0.1344***		0.1285***	0.1294***		0.0538***	0.0556***		0.1075***	0.1033***
		(0.0160)	(0.0159)		(0.0173)	(0.0173)		(0.0160)	(0.0161)		(0.0171)	(0.0171)
Stk		−0.0388***	−0.0427***		0.0063**	0.0038(0.0032)		−0.0169***	−0.0178***		0.0022 (0.0034)	0.0029
		(0.0035)	(0.0035)		(0.0032)			(0.0031)	(0.0032)			(0.0034)
Vix		−0.0056***	−0.0056***		0.0028***	0.0028***		−0.0009**	−0.0009**		0.0007	0.0006
		(0.0005)	(0.0005)		(0.0005)	(0.0005)		(0.0005)	(0.0005)		(0.0005)	(0.0005)
#	760,285	491,702	491,702	724,957	461,254	461,254	675,403	418,024	418,024	588,320	342,719	342,719
Adj R2	0.0906	0.1521	0.1523	0.09	0.1442	0.1444	0.0895	0.1425	0.1425	0.0924	0.1398	0.1398

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Fig. 1. Evolution of the beta standardized coefficients of the rolling regression.

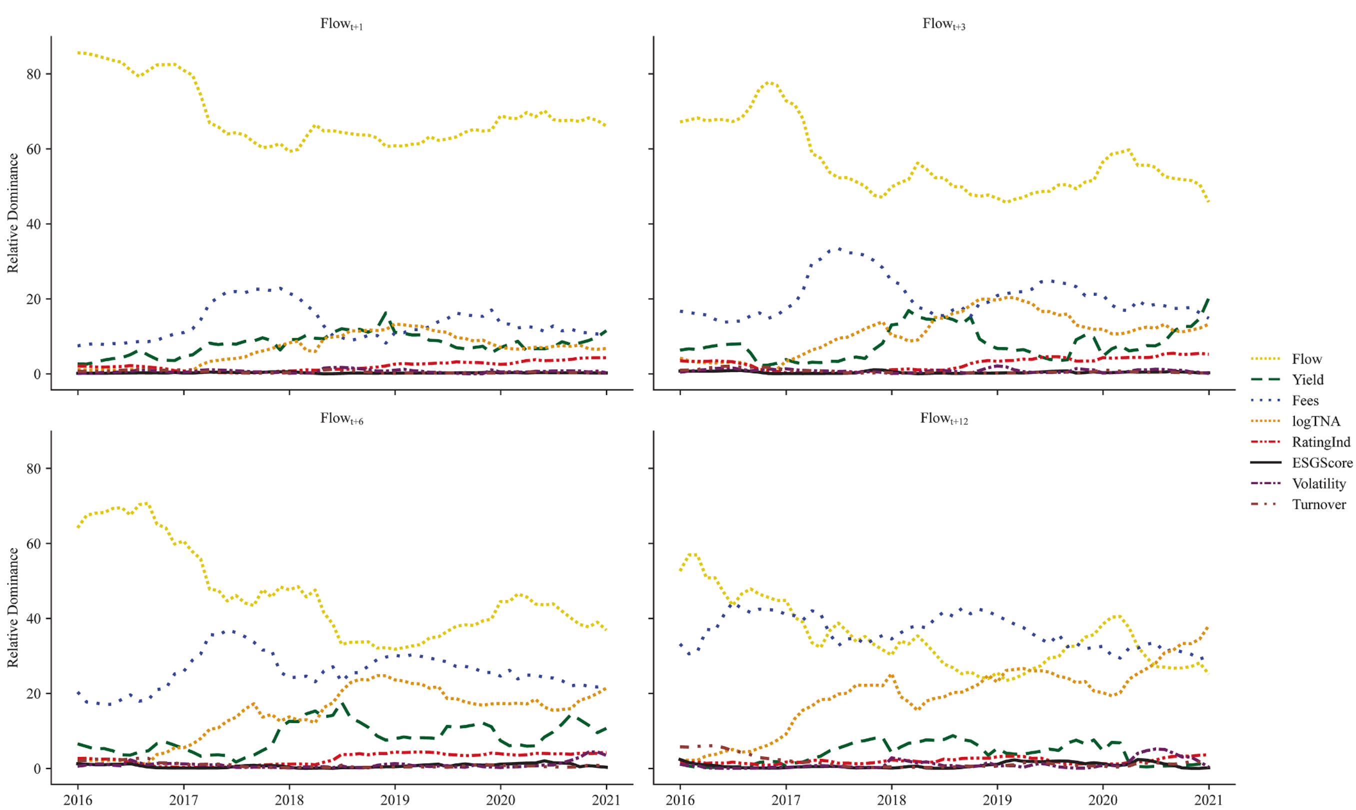

Fig. 2. Evolution of the contribution of each independent variable to the R2 of the rolling regression using dominance analysis.

Table 6

Performance of different techniques in predicting mutual fund flows over the next 1, 3, 6, and 12 months.

		$DFlow_{t+1}$				$DFlow_{t+3}$				$DFlow_{t+6}$				$DFlow_{t+12}$			
		LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP
Training Sample	*Accuracy*	66.01 %	73.27 %	72.77 %	72.35 %	64.89 %	71.33 %	70.51 %	70.38 %	63.83 %	69.49 %	69.06 %	68.29 %	63.14 %	69.11 %	68.94 %	67.50 %
	Sensitivity	63.40 %	73.01 %	72.91 %	70.78 %	62.55 %	71.15 %	70.82 %	72.01 %	61.62 %	69.47 %	69.59 %	68.03 %	61.06 %	71.24 %	70.54 %	70.26 %
	Specificity	68.62 %	73.53 %	72.64 %	73.93 %	67.22 %	71.51 %	70.20 %	68.75 %	66.04 %	69.52 %	68.52 %	68.54 %	65.21 %	66.97 %	67.34 %	64.73 %
	Precision	66.86 %	73.39 %	72.71 %	73.06 %	65.59 %	71.40 %	70.38 %	69.75 %	64.45 %	69.50 %	68.86 %	68.38 %	63.68 %	68.34 %	68.36 %	66.60 %
	F-score	65.08 %	73.20 %	72.81 %	71.90 %	64.03 %	71.27 %	70.60 %	70.86 %	63.00 %	69.48 %	69.22 %	68.20 %	62.34 %	69.76 %	69.43 %	68.38 %
	AUC	71.58 %	80.33 %	79.92 %	79.13 %	70.29 %	78.27 %	77.34 %	76.84 %	69.01 %	76.47 %	76.06 %	74.59 %	68.17 %	75.79 %	75.96 %	73.62 %
Test Sample	*Accuracy*	63.23 %	70.39 %	68.78 %	65.22 %	62.17 %	68.58 %	67.85 %	67.50 %	62.10 %	66.99 %	64.25 %	65.24 %	61.62 %	65.44 %	63.64 %	63.58 %
	Sensitivity	57.28 %	74.47 %	78.65 %	66.07 %	52.56 %	71.91 %	75.09 %	72.36 %	55.38 %	70.06 %	75.87 %	70.07 %	51.64 %	67.06 %	66.47 %	63.03 %
	Specificity	69.17 %	66.31 %	58.90 %	64.38 %	71.77 %	65.26 %	60.60 %	62.64 %	68.82 %	63.91 %	52.63 %	60.42 %	71.60 %	63.83 %	60.81 %	64.14 %
	Precision	64.94 %	68.89 %	65.76 %	64.98 %	64.94 %	67.45 %	65.65 %	65.99 %	63.90 %	66.03 %	61.66 %	63.94 %	64.39 %	64.97 %	62.93 %	63.73 %
	F-score	60.87 %	71.57 %	71.62 %	65.52 %	58.10 %	69.61 %	70.05 %	69.03 %	59.33 %	67.98 %	68.02 %	66.87 %	57.31 %	66.00 %	64.65 %	63.38 %
	AUC	68.61 %	76.83 %	75.95 %	74.49 %	67.42 %	74.63 %	74.07 %	73.55 %	66.95 %	72.77 %	70.71 %	70.49 %	66.08 %	70.96 %	68.71 %	68.27 %

Table 7

Results of the relative variable importance analysis (as percentage of total) for each machine-learning method. Panel A: SHapley Additive exPlanations (SHAP) values. Panel B: permutation feature importance (PFI) values.

Panel A	$Dflow_{t+1}$				$Dflow_{t+3}$				$Dflow_{t+6}$				$Dflow_{t+12}$			
	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP
ESGscore	0.16 %	0.50 %	3.54 %	0.92 %	0.22 %	0.80 %	0.84 %	1.34 %	1.10 %	1.10 %	2.58 %	0.80 %	1.93 %	0.96 %	2.95 %	1.19 %
Yield	20.70 %	3.49 %	13.76 %	21.40 %	19.88 %	4.13 %	13.88 %	11.67 %	15.96 %	7.06 %	20.99 %	10.85 %	10.26 %	3.16 %	14.35 %	14.97 %
Volatility	0.11 %	0.69 %	1.37 %	2.26 %	1.36 %	0.80 %	1.87 %	1.33 %	1.44 %	1.30 %	3.13 %	1.61 %	1.09 %	2.29 %	5.25 %	4.07 %
logTNA	25.16 %	15.38 %	14.59 %	11.73 %	25.69 %	16.38 %	15.54 %	12.21 %	25.77 %	18.24 %	15.77 %	12.90 %	28.01 %	22.78 %	19.96 %	17.54 %
Fees	18.68 %	8.50 %	10.14 %	4.88 %	19.75 %	11.76 %	12.17 %	17.35 %	21.77 %	13.78 %	14.62 %	12.50 %	25.42 %	13.91 %	13.43 %	11.73 %
Turnover	0.35 %	1.47 %	1.75 %	1.35 %	0.36 %	2.10 %	2.47 %	1.25 %	0.74 %	2.48 %	2.61 %	2.87 %	0.89 %	2.76 %	3.23 %	3.90 %
RatingInd	7.88 %	1.49 %	1.62 %	2.51 %	7.49 %	1.49 %	1.41 %	1.50 %	8.15 %	1.54 %	1.26 %	2.48 %	5.41 %	0.81 %	1.23 %	0.90 %
Flow	10.77 %	66.10 %	47.52 %	30.31 %	9.00 %	60.54 %	45.30 %	36.90 %	9.12 %	51.58 %	33.19 %	41.29 %	8.74 %	49.87 %	31.62 %	32.57 %
Macros	16.20 %	2.39 %	5.70 %	24.63 %	16.25 %	1.99 %	6.50 %	16.45 %	15.95 %	2.91 %	5.85 %	14.70 %	18.24 %	3.46 %	7.97 %	13.12 %

Panel B	$Dflow_{t+1}$				$Dflow_{t+3}$				$Dflow_{t+6}$				$Dflow_{t+12}$			
	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP	LR	RF	XGBoost	MLP
ESGscore	0.02 %	−0.14 %	−0.96 %	−0.22 %	−0.00 %	0.16 %	−0.13 %	−0.00 %	0.11 %	−0.25 %	−1.31 %	−0.11 %	0.25 %	0.04 %	−1.62 %	−0.31 %
Yield	10.58 %	0.10 %	1.23 %	4.65 %	10.32 %	−0.15 %	2.75 %	0.94 %	7.38 %	−0.67 %	1.95 %	0.91 %	3.46 %	−1.26 %	−3.21 %	−1.70 %
Volatility	−0.11 %	−0.12 %	−0.96 %	−0.13 %	−0.41 %	−0.05 %	−0.25 %	−0.06 %	−0.30 %	−0.13 %	0.01 %	−0.47 %	−0.16 %	−1.06 %	0.27 %	1.82 %
logTNA	32.38 %	18.51 %	20.62 %	18.50 %	36.46 %	19.40 %	20.83 %	20.51 %	40.20 %	23.77 %	24.64 %	24.43 %	45.87 %	28.77 %	35.57 %	32.93 %
Fees	22.99 %	4.75 %	9.16 %	3.62 %	24.93 %	6.87 %	9.80 %	13.48 %	29.20 %	9.18 %	15.19 %	10.55 %	31.37 %	13.54 %	18.11 %	11.39 %
Turnover	−0.04 %	−0.07 %	−0.08 %	−0.01 %	0.00 %	−0.09 %	−0.13 %	−0.07 %	−0.05 %	−0.16 %	0.24 %	−0.64 %	0.06 %	−0.51 %	−0.23 %	0.17 %
RatingInd	5.23 %	0.30 %	0.36 %	1.59 %	4.49 %	0.40 %	0.30 %	−0.20 %	3.74 %	0.52 %	0.30 %	0.20 %	2.93 %	0.08 %	−0.07 %	−0.17 %
Flow	22.39 %	76.57 %	68.07 %	65.95 %	18.08 %	73.42 %	63.42 %	58.03 %	14.32 %	67.21 %	56.79 %	66.73 %	11.40 %	60.91 %	53.81 %	54.75 %
Macros	6.56 %	0.11 %	2.57 %	6.05 %	6.13 %	0.04 %	3.40 %	7.37 %	5.40 %	0.53 %	2.19 %	−1.59 %	4.82 %	−0.51 %	−2.63 %	1.14 %

Table 8
Accuracies using RF and SHAP values for the subsamples obtained from Morningstar's fund classification (test sets). The descriptions of share class types are available on https://morningstardirect.morningstar.com/clientcomm/Share_Class_Types.pdf.

Subsample		$DFlow_{t+1}$	$DFlow_{t+3}$	$DFlow_{t+6}$	$DFlow_{t+12}$	AvgObsTrain	AvgObsTest	Average of the SHAP values
Institutional	No	71.33 %	69.72 %	68.15 %	66.62 %	137,531	96,320	Flow (52.39 %), logTNA (20.03 %), Fees (13.71 %), Yield (5.39 %), Macros (2.93 %), Turnover (2.47 %), Volatility (1.54 %), ESGScore (0.92 %), RatingInd (0.62 %)
	Yes	69.62 %	67.40 %	66.63 %	64.38 %	69,476	50,508	Flow (56.52 %), logTNA (14.17 %), Fees (7.41 %), Yield (5.64 %), Macros (5.31 %), RatingInd (4.99 %), Turnover (2.25 %), Volatility (2.09 %), ESGScore (1.61 %)
Sustainable Fund	No	70.76 %	68.78 %	66.98 %	65.77 %	197,389	139,951	Flow (56.70 %), logTNA (17.45 %), Fees (12.15 %), Yield (4.83 %), Macros (2.80 %), Turnover (2.34 %), Volatility (1.40 %), RatingInd (1.40 %), ESGScore (0.93 %)
	Yes	74.86 %	74.79 %	74.72 %	72.85 %	8,510	6,874	Flow (31.87 %), Fees (23.11 %), logTNA (16.14 %), Macros (7.37 %), Turnover (7.17 %), ESGScore (4.18 %), Yield (3.59 %), Volatility (3.39 %), RatingInd (3.19 %)
Share Class Type	A	69.18 %	66.29 %	62.28 %	62.44 %	28,791	19,927	Flow (45.57 %), logTNA (16.32 %), Yield (11.25 %), Fees (10.27 %), Macros (6.05 %), Turnover (4.36 %), Volatility (2.25 %), ESGScore (1.97 %), RatingInd (1.97 %)
	Adv	66.15 %	66.21 %	63.53 %	64.29 %	6,534	4,395	Flow (44.23 %), logTNA (13.63 %), Macros (10.43 %), Yield (9.04 %), Fees (8.34 %), Turnover (5.98 %), Volatility (4.03 %), ESGScore (2.64 %), RatingInd (1.67 %)
	B	82.30 %	83.04 %	83.32 %	80.73 %	2,54	1,400	Fees (36.36 %), Flow (15.81 %), logTNA (14.62 %), Macros (12.25 %), Volatility (6.52 %), RatingInd (4.55 %), Yield (3.75 %), Turnover (3.16 %), ESGScore (2.96 %)
	C	77.34 %	78.57 %	77.31 %	73.63 %	25,614	17,421	Flow (38.94 %), logTNA (30.06 %), Yield (11.34 %), Macros (6.05 %), Fees (4.91 %), Volatility (3.40 %), Turnover (2.46 %), ESGScore (1.70 %), RatingInd (1.13 %)
	D	59.91 %	56.30 %	52.05 %	51.44 %	627	403	Macros (22.20 %), Flow (22.07 %), logTNA (18.78 %), Yield (9.76 %), ESGScore (7.32 %), Turnover (6.22 %), Fees (5.85 %), Volatility (5.61 %), RatingInd (2.20 %)
	Inst	69.84 %	68.00 %	66.02 %	64.36 %	56,521	40,023	Flow (56.13 %), logTNA (14.78 %), Yield (7.39 %), Fees (6.60 %), Macros (5.35 %), Turnover (3.30 %), RatingInd (2.36 %), ESGScore (2.04 %), Volatility (2.04 %)
	Inv	69.78 %	66.80 %	65.45 %	63.89 %	10,178	6,973	Flow (36.25 %), logTNA (26.94 %), Yield (8.89 %), Macros (8.75 %), Volatility (4.86 %), Fees (4.44 %), Turnover (4.03 %), ESGScore (2.92 %), RatingInd (2.92 %)
	M	72.44 %	66.12 %	65.91 %	65.38 %	1,684	1,073	Flow (48.87 %), Turnover (10.61 %), Macros (10.13 %), logTNA (7.23 %), Yield (6.91 %), ESGScore (5.95 %), Fees (5.31 %), Volatility (3.54 %), RatingInd (1.45 %)
	N	65.53 %	67.68 %	65.28 %	64.50 %	2,725	1,712	Flow (33.89 %), Fees (14.25 %), logTNA (14.12 %), Macros (12.07 %), Yield (8.73 %), Volatility (6.03 %), Turnover (5.13 %), ESGScore (3.34 %), RatingInd (2.44 %)
	No Load	66.56 %	64.15 %	62.17 %	60.49 %	8,967	6,250	Flow (47.68 %), logTNA (11.25 %), Macros (8.16 %), Volatility (7.88 %), Yield (7.17 %), Fees (4.92 %), Turnover (4.92 %), RatingInd (4.92 %), ESGScore (3.09 %)
	Other	71.08 %	68.24 %	67.02 %	65.80 %	16,832	13,049	Flow (54.50 %), logTNA (14.05 %), Fees (10.99 %), Macros (5.95 %), Turnover (4.89 %), Volatility (2.90 %), Yield (2.90 %), RatingInd (2.29 %), ESGScore (1.53 %)
	Retirement	68.68 %	67.32 %	67.16 %	66.52 %	40,767	30,330	Flow (39.66 %), logTNA (27.53 %), Fees (14.15 %), Macros (6.22 %), Yield (5.60 %), Turnover (2.02 %), Volatility (1.71 %), ESGScore (1.71 %), RatingInd (1.40 %)
	S	71.30 %	72.51 %	71.36 %	72.27 %	4,874	3,646	logTNA (34.27 %), Flow (33.53 %), Macros (8.61 %), Turnover (5.34 %), Volatility (4.60 %), Fees (4.60 %), Yield (4.45 %), ESGScore (3.12 %), RatingInd (1.48 %)
	T	90.12 %	87.82 %	86.58 %	88.40 %	344	221	logTNA (33.73 %), Flow (26.51 %), Macros (10.84 %), Turnover (9.64 %), Yield (6.02 %), Fees (6.02 %), Volatility (4.82 %), ESGScore (2.41 %), RatingInd (0.00 %)

Table 9
T-test of mean differences between funds that increased their flows in the next N months above the median ($DFlow_{t+n} = 1$) and those that did not ($DFlow_{t+n} = 0$). Return $_{t+n}$ (cumulative) measures the cumulative return of the fund in the next N months. ESGscore $_{t+n}$ (average) measures the mean ESG score in the next N months.

		$DFlow_{t+1}$			$DFlow_{t+3}$ (cumulative)			$DFlow_{t+6}$ (cumulative)			$DFlow_{t+12}$ (cumulative)		
		D = 1	D = 0	Test	D = 1	D = 0	Test	D = 1	D = 0	Test	D = 1	D = 0	Test
$Return_{t+n}$	Mean	1.01 %	0.95 %	4.0^{***}	3.17 %	2.83 %	13.3^{***}	6.83 %	5.99 %	22.2^{***}	16.14 %	14.00 %	31.7^{***}
(cumulative)	Median	1.41 %	1.40 %	7.1^{**}	3.50 %	3.27 %	131.2^{***}	6.44 %	5.65 %	426.7^{***}	13.74 %	11.46 %	1069.0^{***}
$ESGscore_{t+n}$	Mean	59.76	59.18	17.3^{***}	59.82	59.23	17.1^{***}	59.91	59.35	15.8^{***}	60.21	59.70	13.3^{***}
(average)	Median	60.46	59.70	302.2^{***}	60.50	59.75	299.1^{***}	60.53	59.91	247.1^{***}	60.79	60.21	188.9^{***}

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 10
Panel data regression analysis with fixed effects for the return over the next 1, 3, 6, and 12 months. Reported values are non-standardized coefficients with cluster-robust standard errors between parentheses.

	Return $_{t+1}$			Return $_{t+3}$			Return $_{t+6}$			Return $_{t+12}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	−0.0097***	0.0490***	0.0575***	0.0010***	0.0321***	0.0450***	−0.0327***	0.0380***	−0.0066**	−0.0289***	0.0174***	−0.0054**
	(0.0003)	(0.0028)	(0.0028)	(0.0003)	(0.0023)	(0.0024)	(0.0005)	(0.0023)	(0.0027)	(0.0005)	(0.0026)	(0.0027)
ESGscore	0.0003***		−0.0002***	0.0001***		−0.0002***	0.0007***		0.0009***	0.0007***		0.0005***
	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)
Yield		−0.0259***	−0.0242***		−0.0369***	−0.0343***		−0.0076***	−0.0160***		−0.0237***	−0.0269***
		(0.0004)	(0.0004)		(0.0004)	(0.0004)		(0.0004)	(0.0004)		(0.0007)	(0.0007)
Volatility		0.8367***	0.8562***		0.4926***	0.5237***		0.1483***	0.0295***		0.1500***	0.0779***
		(0.0041)	(0.0041)		(0.0032)	(0.0032)		(0.0025)	(0.0048)		(0.0034)	(0.0044)
logTNA		−0.0068***	−0.0066***		−0.0038***	−0.0035***		−0.0045***	−0.0054***		−0.0016***	−0.0021***
		(0.0003)	(0.0003)		(0.0002)	(0.0002)		(0.0003)	(0.0003)		(0.0003)	(0.0003)
Fees		−0.0351	−0.1219		−0.7693***	−0.8901***		0.1947**	0.5229***		−0.0215	0.1086
		(0.0968)	(0.0980)		(0.1149)	(0.1176)		(0.0795)	(0.0947)		(0.1189)	(0.1223)
Turnover		−0.0059***	−0.0059***		0.0017***	0.0017***		0.0023***	0.0022***		−0.0023***	−0.0025***
		(0.0003)	(0.0003)		(0.0004)	(0.0004)		(0.0003)	(0.0003)		(0.0004)	(0.0004)
RatingInd		0.0003**	0.0003**		−0.0009***	−0.0010***		0.0000	0.0001		0.0000	0.0000
		(0.0001)	(0.0001)		(0.0001)	(0.0001)		(0.0002)	(0.0002)		(0.0001)	(0.0001)
Flow		0.0049***	0.0045***		0.0068***	0.0062***		−0.0073***	−0.0055***		−0.0028**	−0.0022
		(0.0011)	(0.0011)		(0.0011)	(0.0011)		(0.0012)	(0.0012)		(0.0014)	(0.0014)
Tb3		−7.5265***	−8.0891***		−4.5370***	−5.3513***		−6.0731***	−3.5856***		0.1498**	1.3228***
		(0.0841)	(0.0919)		(0.0631)	(0.0772)		(0.0702)	(0.1000)		(0.0655)	(0.0765)
Opt		0.3456***	0.3485***		0.2236***	0.2252***		−1.0446***	−1.0717***		0.8007***	0.7738***
		(0.0075)	(0.0076)		(0.0072)	(0.0072)		(0.0076)	(0.0075)		(0.0081)	(0.0080)
Stk		−0.5705***	−0.5736***		0.1667***	0.1621***		0.1784***	0.1922***		0.1866***	0.1912***
		(0.0021)	(0.0021)		(0.0017)	(0.0018)		(0.0018)	(0.0019)		(0.0025)	(0.0025)
Vix		−0.0791***	−0.0791***		0.0527***	0.0528***		0.0541***	0.0537***		0.0517***	0.0510***
		(0.0003)	(0.0003)		(0.0003)	(0.0003)		(0.0004)	(0.0004)		(0.0004)	(0.0004)
#	760,285	491,702	491,702	724,957	461,254	461,254	675,403	418,024	418,024	588,320	342,719	342,719
Adj R2	0.0055	0.1746	0.1749	0.0072	0.0852	0.0858	0.0001	0.0664	0.0728	0.0041	0.0277	0.0296

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

Table 11
Panel data regression analysis with fixed effects for the ESGscore over the next 1, 3, 6, and 12 months. Reported values are non-standardized coefficients with cluster-robust standard errors between parentheses.

	ESGScore $_{t+1}$			ESGScore $_{t+3}$			ESGScore $_{t+6}$			ESGScore $_{t+12}$		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	1.169***	52.715***	2.163***	3.722***	50.178***	5.279***	8.287***	45.581***	8.957***	21.643***	42.368***	21.638***
	(0.0177)	(1.1419)	(0.1052)	(0.0513)	(1.1482)	(0.2874)	(0.1043)	(1.1434)	(0.5254)	(0.2209)	(1.1826)	(0.8956)
ESGscore	0.981***		0.950***	0.941***		0.850***	0.867***		0.712***	0.645***		0.431***
	(0.0003)		(0.0006)	(0.0009)		(0.0015)	(0.0018)		(0.0026)	(0.0039)		(0.0042)
Yield		10.835***	0.665***		11.912***	3.015***		14.211***	6.896***		10.069***	6.964***
		(0.1460)	(0.0172)		(0.1474)	(0.0451)		(0.1546)	(0.0834)		(0.2188)	(0.1861)
Volatility		137.896***	21.774***		177.044***	70.792***		239.484***	143.421***		293.975***	232.274***
		(1.8600)	(0.1818)		(1.9481)	(0.5454)		(2.1069)	(1.0435)		(2.1454)	(1.5291)
logTNA		1.209***	0.074***		1.221***	0.233***		1.035***	0.315***		0.954***	0.489***
		(0.1297)	(0.0108)		(0.1304)	(0.0293)		(0.1297)	(0.0530)		(0.1331)	(0.0971)
Fees		−559.553***	−43.628***		−525.306***	−92.404***		−396.543***	−114.007***		−307.102***	−193.021***
		(47.8803)	(4.6148)		(47.5985)	(13.1068)		(47.3821)	(24.5473)		(49.2570)	(39.2424)
Turnover		−0.199	−0.046***		−0.316**	−0.193***		−0.221	−0.259***		−0.317**	−0.469***
		(0.1496)	(0.0135)		(0.1460)	(0.0386)		(0.1441)	(0.0729)		(0.1493)	(0.1178)
RatingInd		−0.161***	−0.026***		−0.172***	−0.061***		−0.172***	−0.109***		−0.224***	−0.231***
		(0.0570)	(0.0046)		(0.0551)	(0.0119)		(0.0529)	(0.0211)		(0.0500)	(0.0359)
Flow		−2.706***	−0.203***		−2.517***	−0.415***		−1.961***	−0.489***		−1.294***	−0.736***
		(0.1802)	(0.0413)		(0.1809)	(0.0752)		(0.1814)	(0.1068)		(0.1739)	(0.1465)
Tb3		−3,353.445***	−9.443**		−2,702.784***	208.775***		−928.474***	1,181.139***		1,132.664***	2,233.313***
		(34.8693)	(4.1003)		(32.3408)	(10.8569)		(31.5854)	(22.4223)		(35.1121)	(37.0895)
Opt		41.720***	24.940***		−53.478***	−67.951***		−92.162***	−98.901***		−44.761***	−69.816***
		(1.0481)	(0.4595)		(0.9474)	(0.6279)		(1.2784)	(1.0699)		(0.9687)	(1.0594)
Stk		−18.804***	−0.251***		−22.650***	−5.282***		−12.057***	1.238***		6.057***	10.365***
		(0.1487)	(0.0632)		(0.1628)	(0.0957)		(0.1630)	(0.1270)		(0.2610)	(0.2364)
Vix		0.043*	−0.167***		0.607***	0.261***		1.435***	1.333***		4.118***	3.617***
		(0.0258)	(0.0092)		(0.0254)	(0.0123)		(0.0315)	(0.0174)		(0.0449)	(0.0335)
#	760,285	491,702	491,702	747,706	480,221	480,221	713,744	448,149	448,149	645,815	385,904	385,904
Adj R2	0.9782	0.8045	0.9765	0.9347	0.8030	0.9382	0.8701	0.8117	0.9032	0.7434	0.8390	0.8711

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

1-month case, the average returns were 1.01 % versus 0.95 %. When considering 12 months, cumulative returns were 16.14 % and 14 %, respectively. The same study was carried out with the ESG performance. We obtained the average ESG scores at 3, 6, and 12 months. Funds that received flows above the median obtained higher ESG scores over the next months than those that received flows below the median. The differences were statistically significant, but also very small in magnitude. In the 1-month case, the means were 59.76 versus 59.18. By incorporating ESG aspects, this finding could go beyond the "smart money effect," meaning that investors can predict the performance of mutual funds and invest accordingly (Feng et al., 2014; Zheng, 1999), and be considered a case of "smart and virtuous money effect."

We ran Equation (2), which is a regression model taking $Return_{t+n}$ as the dependent variable. Table 10 provides the panel data regression results with fixed effects. Most of the variables obtained statistically significant coefficients. However, the adjusted R2 was 0.004 for the following 12 months' return, which indicates low goodness of fit. In the period under investigation, past ESG performance ($ESGscore_t$) was positively associated with the future financial return ($Return_{t+n}$), but the predictive power was very small. Analyzing the standardized coefficients of the regression (not reported in the table), it was found that the only variable that explains the return is volatility – the well-known relationship between profitability and risk. The association between past financial return ($Yield_t$) and future financial return ($Return_{t+n}$) was negative.

However, the objective of some socially responsible investors may be to achieve ESG performance and therefore the right decision will be to choose funds that will achieve the highest ESG score in the near future. We ran several specifications of a panel data regression model taking future *ESGscore* as the dependent variable (Equation (3). Table 11 shows the results of the regressions with fixed effects. The adjusted R2 of the model ranged from 0.98 (one month later) to 0.74 (one year later), indicating high goodness of fit. Although several variables had statistically significant coefficient values, the variable with the highest predictive power was *ESGscore*. In other words, past ESG scores predicted future ESG scores.

5. Discussion and conclusions

This study aimed to analyze mutual fund investor decisions, particularly to compare the importance of ESG performance with past returns and other financial variables. We modeled fund flows as a function of the past return, ESG performance, volatility, size, past growth, turnover ratio, managerial fees, Morningstar analysts' rating, and macroeconomic conditions. Although there is a great deal of interest in SRI (Ammann et al., 2019; Vo et al., 2019), we found that ESG concerns are not as important in predicting investment decisions as past performance, past growth, and managerial fees. We used statistical and machine learning models to predict future flows raised by the funds, future short-term returns, and ESG scores.

In particular, our first research question analyzes the importance of ESG aspects for the decision-makers. Following previous studies, we found that individual investors take ESG criteria into account (Ammann et al., 2019; Plagge & Grim, 2020; Renneboog et al., 2008). However, we found that the weight of ESG scores in mutual fund purchasing decisions is small and the predictive ability of ESG variables is very low. It is particularly relevant that the high interest that industry and academia seem to show in ESG performance does not correspond to the low interest currently shown by investors.

In addition, our second research question analyzes whether ESG concerns are becoming increasingly important and we studied the evolution of the importance of each variable by analyzing standardized regression coefficients and general dominance weights. We found that ESG performance has not played an increasingly important role in explaining the investment decisions of US mutual fund investors from 2015 to 2021.

Our third research question was to develop predictive models using logistic regression and machine learning techniques (RF, MLP, and XGBoost). We developed a predictive model that achieves approximately 70 % accuracy in forecasting future fund flows. RF outperforms the other machine learning techniques although the results are quite similar.

The fourth research question analyzed the outcome of the decisions made by investors. We found that the funds that received the most flows obtained slightly higher returns than the others did, at least in the short term. Finally, we developed decision models to predict both the financial returns and ESG performance. Complementing the well-established statement that "past (financial) performance does not guarantee future results," our study contributes by finding that "investing in a fund that meets ESG criteria guarantees that the fund will continue to perform well socially," because most mutual funds that obtain a high ESG score retain it, at least in the short term. The explanation for this ESG persistence is simple: There are no abrupt changes in ESG scores and the fund that performs well in the ESG rankings continues to do so in subsequent periods. Individual investors would do well to support their financial choices by using decisional systems to avoid behavioral biases and increase returns, both in financial and social terms.

The paper has some limitations. Morningstar's ESG scores began in 2015. The lack of ESG scores for mutual funds until recently limits the robustness of the study's findings. The period analyzed was not long enough to draw robust conclusions on whether ESG concerns decreased or increased largely. Our study does not address the outcome of long-term decisions, but rather the time frame covers 1, 3, 6, and 12 months. Future studies are needed to understand the impact of decisions over the long term, in different financial periods, and financial markets other than the US. We consider the results robust due to the large sample size, relevant predictive variables, and consistent findings obtained through multiple analytical techniques. All of these techniques produced very similar results: investors do consider ESG criteria when making investment decisions, but they give them significantly less weight than financial variables. However, we must acknowledge that the financial data exhibit departures from regression assumptions, which could affect the estimation of the results. Another limitation of the study refers to the accuracy of the models in predicting flows – about 70 % – which is not very high. Much remains unexplained, which calls for future studies that include other types of nonfinancial variables. Accuracy increased when segmented by type of fund, which gives us a clue as to where to focus the subsequent studies. In this regard, not only the financial management of the fund may be important. Other factors may explain why a fund attracts investors, such as the sales force efforts, investment in advertising, popularity in financial social networks, a high ranking on Internet search engines, and the current media attention (Sirri & Tufano, 1998).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Carlos Serrano-Cinca reports financial support was provided by Spanish Ministry of Education. Carlos Serrano-Cinca reports financial support was provided by Government of Aragon. Carlos Serrano-Cinca reports financial support was provided by the European Regional Development Fund. Laura Andreu reports financial support was provided by University of Zaragoza.

Data availability

Data will be made available on request.

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