Can US equity funds time ESG score updates?

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ABSTRACT

This paper derives the implications of a time gap between the publication of the disaggregated ESG information and the final ESG scores. We use early ESG raw data to reconstruct the scores of MSCI and build a portfolio long in the stocks which ESG score will be upgraded and short in the stocks which ESG score will be downgraded We show that because ESG information is material for financial performance, asset managers can trade on this disaggregated ESG information, before it is known to every player on the market and gain from it. Consistent with the idea that ESG scores incorporates fundamentals which are predictive of performance, we find that timing the announcement of ESG scores yields a significant 0.22 % monthly alpha. Additionally, we identify a subsample corresponding to 13.8 % of the active equity funds which use this strategy and confirm that these funds have a tendency to trade stocks prior to changes in ESG scores.

1. Introduction

The Global Sustainable Investment Alliance (GSIA) emphasized the growing share of asset under management aligned with sustainability principles, now representing about $5.59 trillion globally, i.e. 18.44% of professionally managed assets[1]. According to this report, “ESG integration” is the main investment strategy deployed in the US to invest sustainably throughout the period 2016-2022. This consists of using environmental, social and governance (ESG) indicators to filter the investment universe and/or assess the performance of a stock. Proponents of this strategy get support from recent academic literature (Gompers et al., 2019; Pedersen et al., 2021; Edmans et al., 2021) demonstrating that ESG scores account for fundamental information which are predictive of future profitability. Given the low frequency with which ESG scores are published and refreshed (most of time, once a year), should ESG rating be related to future unpriced performance, this could create opportunities for asset managers who would dedicate resources to produce their home-made rating and anticipate a future appreciation or deterioration of the sustainability performance of a stock.

Our paper investigates the relevance of published ESG scores in deploying investment strategies and the capacity of asset managers to time updates in these scores. For performing our analysis, we use MSCI data[2] which provide an interesting setting as they update the constituents of the scores such as carbon emission, gender diversity metrics, … (hereafter called the “raw data” to ESG scores) a few months, up to one years, before updating their final scores. The aggregation process into scores is subject to a checking process which consists of multiple committees and thus, take a few months to complete. Our experiment on the MSCI setting shows that it is possible to anticipate the changes in MSCI ESG scores and to reconstruct ESG scores ex-ante by using the information present in the updated raw data. We construct a strategy which takes a long position at the time of a predicted upgrade and a short position at the time of a downgrade. We reverse these positions either when the update is realized or after a year. This strategy captures an ESG momentum and outperforms the market by 0.22 %. In addition, we show that 13.8 % of the active equity funds are exposed to this strategy and that these funds display on average excess returns 0.76% higher than their counterparts. These funds are

[1] Global Sustainable Investment Alliance. (2024). *Global Sustainable Investment Review 2024*. Retrieved from https://www.gsi-alliance.org

[2] ESG scores are widely used in the literature (Pedersen et al., 2021; Chatterji et al., 2016). Moreover, recent studies have started using the raw data as well (Berg et al., 2021).

then shown to have bought stocks in the months prior to an upgrade and have sold stocks in the month prior to a downgrade.

To construct predicted scores, we use a lasso algorithm, calibrated using 5-fold cross-validation, and which we train on all the available past raw data. Only Aoudi et Ma (2024), D'amato et al. (2022) and Del Vitto et al., 2023) have performed a similar exercise, yet we differ from these studies which primary goal is to assess the feasibility of a reproduction of the ESG scores using the raw data while we test the possibility to reconstruct the ratings using all past information and contemporaneous raw data. While they train their algorithm on a subsample of stocks and test on the remaining set, we use only past information to do the prediction, as would an asset manager at each time t. In addition, these two papers focus on the scores produced by Refinitiv, which is more closely related to the raw data, while the score we use, produces by MSCI, are more processed.

Our contribution is threefold. First, we contribute to the literature on the materiality of ESG scores for financial performance and its potential for the construction of investment strategies. Among the information aggregated in the ESG scores are variables which have an impact on future profitability – including, but not limited to employee satisfaction (Edmans, 2011), good governance (Gompers et al., 2015), and energy efficiency (Porter and Van der Linde, 1995). As a consequence, ESG scores should also be predictive of future profitability as demonstrated by Pedersen et al. (2021). However, accounting for sustainability information remains difficult, and as a consequence, ESG scores remains relatively opaque (Larcker et al., 2022; Christensen et al., 2022) and may not be immediately fully accounted for by the market leading to investment opportunities. Related to that, Berg et al. (2025) develops a method to remove the noise from the ESG ratings and show that it improves the link with financial performance. In this article, we confirm that the information present in the ESG scores has a material impact on the returns and show that the opacity of the ESG scores leads to investment opportunities.

We also contribute to a recent strand of literature which documents a momentum effect linked to ESG information such as ESG scores and ESG controversies. In particular, Capelle-Blanchard and Petit (2017) documents a market reaction after the announcement of negative ESG news. Serafeim and Yoon (2021) further elaborate on this result by showing that the market reacts more to news which are material and have an impact on the firm' value. As for the ESG scores, Pastor et al. (2020) show that the growing demand for high ESG stocks lead to a continuous increase in prices. Building on these results, Pedersen et al. (2021) show that there exist unpriced opportunities in the ESG ratings leading to abnormal returns. This effect translates to the investment funds as shown by an enhanced performance of the funds with an active engagement in ESG stocks (Dimson et al. 2015). Closely related, Ceccarelli et al. (2025) show that the funds which invest in the quarter prior to an upgrade in the ESG scores display higher financial performance. We confirm that an ESG momentum exists, in particular prior to the announcement of the rating, and we discuss its implications. In particular, we show that abnormal returns can be obtained by anticipating the changes in ESG scores.

This paper eventually contributes to the literature on the investment strategies which can be adopted by investment funds in order to achieve sustainable but also financial performance. The existing literature on the investment strategies linked to ESG scores is mainly focused on the trading behavior of the funds after a change in ESG ratings. In particular, Berg et al. (2024) show that the funds adapt their holdings after a change in ESG score. Closely related, Rzeznik et al. (2022) use a natural experiment to show that institutional investors care about ESG scores and react to their changes. We improve on this literature by showing that the reaction of funds to ESG score changes does not only happen after the announcement, but also ahead of it, using previously published ESG information.

The remainder of this paper is organized as follows. Section 2 describes the data used, including our sample of stocks and funds, and the ESG information retrieved from MSCI. Section 3 details the portfolio's construction and conducts a performance analysis of our ESG timing portfolio. Section 4 identifies the funds that follow the strategy and analyzes their trading behavior. Finally, section 5 concludes.

2. Data

2.1. Stock level data: ESG raw data, ESG scores, and financial data

Our sample consists of stocks traded on the US stock exchanges (New York Stock Exchange, AMEX, or NASDAQ) – excluding stocks issued by financial companies.[3] – sourced from the Compustat/CRSP merged database. We collect stock's ESG scores (normally distributed on a scale from 0 to 10) and raw data (corresponding to 106 variables assessing the exposure and management of the issuers regarding issues such as carbon footprint, water consumption, human capital, corruption…) from the ESG rating agency MSCI. MSCI provides an interesting setting as they update their ESG data monthly, contrary to other providers, which proceed to annual updates. According to their website and

[3] Stocks traded on the US stock exchanges correspond to exchange codes 11, 12, and 14. Following Fama and French (1996), we remove financial companies corresponding to sic codes 6000 to 6999, as these companies may display specific behaviors and impact our results. Finally, we ensure the stocks are associated with a non-negative price.

documentation, MSCI process consists of continuously collecting data from annual reports, investor presentations and financial and regulatory filings in order to extract key metrics measuring the company exposure to environmental, social and governance factors[4]. These key metrics corresponding to what we call "raw data" are monitored continuously throughout the year with potential updates, if needed, at the end of every month. However, ESG score updates only occur after an analytical review, at the time of an "MSCI ESG Research rating action" which concludes the quality review process.

Figure 1 illustrates the ESG score creation process. The provider collects over 1,000 data points and aggregates them into exposure and management metrics. The provider publishes these metrics (corresponding to the "raw data") before the monitoring and quality review and insight from specialists. Finally, once the checks are done, the ESG ratings are published.

[Insert Figure 1 here]

The quality review process determines whether a change in raw data translates into an "MSCI ESG Research rating action" and includes multiple steps – such as data quality assurance, analytical review, ESG Ratings Methodology Committee, and ESG Assessment Committee. Due to this reviewing process, a significant amount of time – up to one year – exists between the publication of the raw data and the corresponding update in the ESG score.[5]. Therefore, it provides a unique setup where raw ESG data are updated for up to twelve months before being aggregated into the MSCI ESG score. In this regard, MSCI differs from competing ESG scores, providing a joint update of ESG scores and the underlying raw data.[6]. We work with the industry adjusted score corresponding to the final score. The

[4] "ESG Ratings Process", MSCI ESG Research LLC, April 2024

[5] "Generally, data is obtained by MSCI ESG Research on an ongoing basis. Companies are monitored by MSCI ESG Research on a systematic and ongoing basis, including daily monitoring of media and governance events. Updates to underlying data and scores by MSCI ESG Research do not in all cases lead to an analytical review of the ESG Rating. The Industry Adjusted Score and ESG Rating are only recalculated at the time of an MSCI ESG Research rating action", "ESG Ratings Process", MSCI ESG Research LLC, April 2024

[6] For example, for Refinitiv: "In most cases, reported ESG data is updated once a year in line with companies' own ESG disclosure. We refresh data more frequently in exceptional cases, usually when there is a significant change in the reporting or corporate structure during the year." London Stock Exchange Group. (n.d.). *ESG Scores*. Retrieved January 3, 2025, from https://www.lseg.com/en/data-analytics/sustainable-finance/esg-scores

final scores are widely used in the literature despite the existence of intermediary scores – such as pillar scores (Avramov et al., 2021; Pedersen et al., 2021). Table 1 gives more information about the schedule of the updates done by MSCI and four others widely used ESG providers (Berg et al., 2022; Berg et al., 2023), namely Refinitiv (ex-asset4 acquired by LSEG), Vigeo-Eiris (acquired by Moody's), S&P Trucost, and Sustainalytics. In addition to the desynchronization of the updates in scores and raw data, MSCI differs from its counterparts as it is the only provider providing monthly updates. These updates happen on average 2.49 times by issuers throughout our sample of 16 years, with updates spread uniformly across months.

[Insert Table 1 here]

The final sample requires to be covered by MSCI. Our sample consists of 3,305 companies corresponding to 235,502 firm-month observations. The financial information, including returns and market capitalization, is retrieved from the Compustat/CRSP merged database. Our period starts in January 2007, with the first scores given by MSCI, and stops in December 2022. The summary statistics for our final sample are presented in Table 2.

[Insert Table 2 here]

2.2. Fund level data: Funds characteristics and holdings

Our sample consists of US-domiciled equity funds which have an active mandate from the CRSP mutual fund database. We remove index funds from the sample. We retrieve quarterly holdings information from the CRSP mutual funds holdings database. Our final sample consists of 11,280 funds corresponding to 234,833 funds-month observations for the period 2007-2022, corresponding to the period for which MSCI ratings are available.

Table 3 presents the summary statistics for our sample of US equity funds. The funds that integrate our sample have, on average, a monthly return of 0.31%, 60.34 million dollars of assets under management, and management fees of 0.63%. They have been active for, on average six years and a half, and they receive on average 2.24 million dollars of fund flows.

[Insert Table 3 here]

3. Construction of an ESG timing strategy based on raw data updates

In this section, we exploit the lag between the raw data and ESG score updates in MSCI setting and test whether an ESG timing strategy could deliver abnormal returns. We proceed in two steps: (i) predicting ESG scores based on raw data updates and (ii) constructing a timing strategy.

3.1. Predicting ESG scores

To test whether we can predict the changes in ESG scores using raw information available prior to the announcement, we use a lasso algorithm on these raw data and reconstruct the ESG scores[7]. The parametrization is done using a five-fold cross-validation in-sample on past data. At each period, the algorithm is trained on all the available past data:

$$S_{t-1,t-2\ldots,t0,i} = f_{t-1,t-2\ldots,t0,i}\left(\Theta_{t-1,t-2\ldots,t0,i}\right) + \epsilon_{-t,i} \quad (1)$$

Where $S_{t-1,t-2\ldots,t0,i}$ is the vectors of scores[8] and $\Theta_{t-1,t-2\ldots,t0,i}$ is the matrixes of raw data published in any past period $t-1, t-2\ldots, t0$, $f(.)$ is a lasso algorithm and ϵ_{-t} is a normally distributed error term. Based on Equation (1), we train an algorithm capable of reverse engineering the score construction through a function $\hat{f}(.)$. This allows us to predict the scores at each time *t*, using the information present in the raw data:

$$\mathrm{E}(S_{t,i}|\Theta_{t,i}) = \widehat{f_t}\left(\Theta_{t,i}\right) + \epsilon_{t,i} \quad (2)$$

Our model displays an out-of-sample R-squared of 16%, which is lower than similar studies (Del Vitto et al., 2023; Aouadi & Ma, 2024). In particular, focusing on three industries (finance and insurance, manufacturing, information, and professional scientific and technical services) and three geographical regions (USA, EU, and China), Del Vitto et al. (2023) report R-squares ranging from 61 to 91%. This difference in performance, although large at first sight, can be explained by the difference in data sources. The authors use another data provider, Refinitiv, which is data-driven while MSCI relies more on qualitative and fundamental analyses from ESG analysts. Second, they based their prediction on the pillar scores, which are less processed than the global scores we used here.

Table 4 gives more information about the distribution of the actual and predicted ESG scores and about the timing of the actual and predicted upgrades and downgrades. The reconstructed scores have an overall distribution similar to the actual score – although slightly more kurtotic. We also note that 50% of the effective upgrades happen within the year following our prediction of upgrades and 75% within

[7] We use a lasso algorithm to mimic the construction process of the ESG score. This process is not fully disclosed by MSCI but includes a linear combination of the raw data which can be altered by ESG analysts. The lasso algorithm also uses a linear combination of these inputs and allows to consider the high dimensionality of the data. The parametrization is done using a five-fold cross-validation in-sample on past data.

[8] The ESG scores given by MSCI are normally distributed but bounded between 0 and 10. We apply a logit transformation on the scores and transform back the predicted score to abide by these bounds.

the two years. The time between predicted and actual downgrades is even shorter, with 50% of the downgrades happening at most ten months after the predicted downgrade and 75% at most after twenty-one months.

[Insert Table 4 here]

Table 5 shows that the predictive score is positively and significantly correlated with the actual score though a regression:

$$S_{t,i} = \alpha + \beta\widehat{S_{t,i}} + \epsilon_{t,i} \tag{3}$$

As such, β depicts the correlation between the actual score and the score which have been predicted through the raw data. This result shows that the information contained in the raw data correlates with the actual ESG scores. By looking at the raw data uniquely, we also show that we can predict updates in ESG scores. These results are also robust to the addition of financial covariates and fixed effects. Our thesis is that since the raw data can be aggregated into a signal that is related to the actual ESG score, and since the raw data include information that is not yet incorporated into the ESG score, given the time lag due to research process, it should be possible to forecast the future ESG scores from the raw data. This hypothesis is tested in the following subsection.

[Insert table 5 here]

3.2. Construction of the ESG timing strategy

Our thesis is that the predicted score conditional to the ESG raw data $E\left(S_{t,i}\middle|\theta_{t,i}\right)$ could include information not yet present in the actual score $S_{t,i}$ but is likely to be included at some time through future updates. We test this hypothesis in Table 6.

Table 6 uses a semiparametric Cox proportional hazard model (Cox, 1976). This model estimates the relationship between the probability of an event (an update in the score) at a period t and a vector of covariates X (the timing of predicted upgrades and downgrades). In this model, the hazard rate – which is then estimated by partial-likelihood function – is the following:

$$h(t) = h(0)e^{X_t'\beta} \tag{4}$$

where t is the number of months before the next update (upgrade or downgrade) in the ESG score, $h(t)$ is the hazard rate function, X_t' is a dummy equal to one when an update is predicted and a position is taken, and β is the raw coefficient from the model. The table shows that actual upgrades in the ESG score are more likely to happen following predicted upgrades, while actual downgrades are less likely to happen. In addition, after we predicted a downgrade, an actual downgrade is more likely to happen, and an actual upgrade is less likely to happen. We note a slight asymmetry between upgrades and downgrades, which are more challenging to predict from the raw data (Aouadi et Ma, 2024).

[Insert table 6 here]

We construct a long-short strategy in which we buy the stocks subject to a potential upgrade in scores according to our model and we short the stocks for which we predict a future downgrade in score[9]:

$$\text{Long if } E(S_t|\Theta_t) > E(S_{t-1}|\Theta_{t-1}) \text{ and } E(S_t > \Theta_t) > S_t \quad (5)$$
$$\text{Short if } E(S_t|\Theta_t) < E(S_{t-1}|\Theta_{t-1}) \text{ and } E(S_t > \Theta_t) < S_t$$

In addition, we consider that if the update in raw data results in a simultaneous update in the actual score, the update is unpredictable, and we do not take position. Finally, the positions are reversed either after the actual update in score happens, or after a year if the update does not materialize. Figure 2 illustrates further the strategy.

[Insert Figure 2 here]

Table 7 provides evidence of the performance of the long-short strategy. The model includes the classical Fama-French factors (market, size, value, profitability, investment) along with momentum. As such, the final six-factor model is:

$$R_t - Rf = \alpha + \beta_m\left(R_m - R_f\right)_t + \beta_s SMB_t + \beta_h HML_t + \beta_r RMW_t + \beta_c CMA_t + \beta_m Mom_t + \epsilon_t \quad (6)$$

For the equally weighted portfolio, we find that both the long and short strategies create a significant alpha across a range of factor models. The long-short strategy yields a significant monthly alpha ranging from 0.17 to 0.22%. The value-weighted long-short portfolio also yields positive, although not significant alphas ranging from 0.09 to 0.18%.

[Insert table 7 here]

Table 8 compares the outperformance of the ESG timing strategy developed in this paper to the traditional investment in response to the updates in ESG scores. We find that “front-running” the announcement of ESG scores creates an outperformance. On the other hand, we show that a strategy that consists of going long in the stocks that have been upgraded in the past and short in the stocks that have been downgraded in the past yields a non-significant alpha ranging from 0.6 to 0.9% in equally weighted portfolio and equal to 0.5% in value-weighted portfolio. These results confirm that only the "ESG timing" strategy, which consists of timing the ESG score updates, delivers abnormal returns.

[9] See Appendix 1 for more information on the timing and the construction of the strategy.

[Insert table 8 here]

4. Identification and analysis of funds which use the ESG timing strategy

4.1. Identification of the ESG timer funds

We qualify a fund as an ESG timer in quarter q if it is exposed to the ESG timing strategy defined in (5) during the quarter q. We measure this exposure via the following regression estimated at each quarter q on the daily returns within the quarter q:

$$R_{id}(Q) = \alpha_i(Q) + \beta_i(Q)LS_{id}(Q) + \beta_i^{mkt}(Rm - Rf)_d(Q) + \epsilon_{id}(Q) \text{ for } d \in [q-1; q] \quad (7)$$

Where R_{id} is the daily return of the fund i on day d, LS_{id} are the returns of the equally weighted portfolio defined through (5) and which corresponds to a strategy which goes long in the stocks which should be upgraded according to their raw data and short in the stocks which should be downgraded according to their raw data, $(Rm - Rf)_d$ are the returns of the market portfolio on day d and ϵ_{id} is a normally distributed error term. Equation (7) is estimated separately for each quarter q, using daily data within the interval corresponding to quarter q. That is, for each fund, we run the regression using daily observations $d \in [q-1; q]$. A fund is considered to be an ESG timer during quarter q if its coefficient β_i^q is positive and significant at the 10% level.

Figure 3 depicts the main features of the beta estimated though equation (7) including the distribution of the quarterly beta for our sample of 11,280 funds. The coefficients from regression (7) follows a distribution skewed to the left with an average of -0.31 and a standard deviation of 0.96. Additionally, the average beta of the ESG timer funds is 0.81. We also display the quarterly evolution of the number of funds which are identified as ESG timers. number has increased from around 250 before 2017 to 1100 after this date. In addition, we find that among the 11,280 funds in our sample, 35.1 % have been exposed at least at one quarter to the ESG timing strategy during the period 2007-2022. In addition, we find that at the end of our sample, i.e. the last quarter 2022, 13.8 % of the funds were identified as ESG timers.

[Insert Figure 3 here]

Table 9 provides summary statistics on the ESG timers compared to the rest of the sample. We find that ESG timers display on average superior quarterly return as compared to non-timers (about 0.97 % higher), have 0.15 million more under management, receive less flows – although not significantly, are on average 16.27 quarter older and have fees on average 0.01% higher than the funds which are not exposed to the ESG timing factors. The ESG timing capacity of funds also seems to be persistent with Table 11 showing that the funds which are ESG timers have been so on average 4.86 times throughout the sample. In addition, we find that a period of ESG timing is followed by another period of ESG timing in 26 % of the case while a period of non-ESG timing is followed by a period of ESG timing only 2 % of the time.

[Insert table 9 here]

Table 10 confirms the persistence of the ESG timing capacity of the funds. To do so, we perform an autoregressive model where the dependent variable is the beta estimated in equation (7):

$$\beta_t = \alpha + \lambda_1\beta_{t-1} + \lambda_1\beta_{t-1} + \lambda_2\beta_{t-2} + \lambda_3\beta_{t-3} + \lambda_4\beta_{t-4} + \epsilon_t \quad (8)$$

It shows that a fund which times ESG scores in quarters q-4, q-3, q-2, and q-1 is significantly more likely to time the ESG score again in quarter q. The persistence effect is when the timing occurs closer to the actual quarter.

[Insert Table 10 here]

4.2. Economic channel

To further investigate the channel by which investment funds time ESG scores, we perform an event study on the number of shares owned by the funds around updates and downgrades in ESG scores. In order to do that, we use an event study where the event studied is the upgrades and downgrades in ESG scores and the outcome is the number of shares bought or shorted by the funds. This allow us to identify the evolution is the number of shares owned by funds – ESG timer or not – around the ESG scores changes. The following equation is estimated:

$$Shares_{i,q} = \sum_{k\in[-4;4]} \beta_k \times D_{i,q}^k + \epsilon_{i,q} \quad (9)$$

Where $Shares_{i,q}$ is the number of shares owned by fund I during quarter q, and $D_{i,q}^k$ is a dummy equal to 1 if the observation is k periods away from the event at time t, and 0 otherwise.

Figure 4 depicts the results from the event study. Panel A takes into account the positive number of shares. We observe that the number of shares owned by the ESG timer funds increases steadily in the four quarters before an upgrade in ESG score so that the ESG timers owns on average 600,000 more shares at the moment of the upgrade as compared to one year before. The number of shares owned by the ESG timer then goes back to normal four quarters after an upgrade. As a comparison, the number of shares owned by the non-ESG timers stays constant in the two years around the upgrade in ESG score. This suggests that ESG timers tend to buy shares before the upgrades in ESG scores and to sell these shares after the upgrade materializes while other funds do not trade shares around updates in ESG scores.

In Panel B, we consider the negative number of shares corresponding to the short position. We find that the number of shares becomes more negative in the immediate quarters after the downgrade meaning that the ESG timers increase their short-selling by 4,000 shares in the quarter following the downgrade and comes back to normal one year after the downgrade. On the contrary, the number of shares which are sold short by the non-ESG timers do not change significantly around the downgrades in ESG scores. This shows that ESG timers also have a tendency to engage in short-selling around the ESG score downgrades, however, they wait until the downgrade materializes before taking the short position. This asymmetry between long position which are taken by the funds before the event and short position which are taken at the take of the event may be due to specific constraints and risks (Gargano et al., 2022) linked to short selling which may require a delay. Once again, we also display the behavior of funds which are not identified as ESG timer and show that they do not react in either way to updates in ESG scores.

[Insert Figure 4 here]

5. Concluding remarks

The rise of investment strategies taking into account sustainability considerations, such as ESG integration, has promoted the development of ESG scores as key metrics for investment. These scores, widely used by asset managers, aggregate information that is predictive of future profitability but are only released on a relatively low frequency (annually or monthly). As such, they provide a timing opportunity which is at this paper's core. We use a discrepancy between the publication of ESG disaggregated information and the final scores by one of the prominent ESG providers, MSCI, to show that it is possible to use this disaggregated information to identify the stocks that should be updated and time the score announcement. In addition, we show that some US equity funds already use this strategy.

We use a lasso algorithm and the ESG raw data to replicate the ESG scores from MSCI. As the raw data are published before the final score, this allows to estimate the scores before they are updated. We construct a strategy long in the stocks that should be upgraded and short in the stocks that should be downgraded. We show that this strategy outperforms the market and improves on the traditional post-announcement investment strategy. Using a regression analysis, we identify the funds whose returns correlate to our strategy and show that these funds are more performant than their counterparts. Finally, we validate the timing ability of the funds identified by showing that they are more likely than their counterparts to trade stocks in the months before an update in the ESG scores.

Our findings have implications for several strands of literature. We contribute to the literature on the materiality of ESG ratings by designing an investment strategy based on the information present in these ratings, which have a material effect on returns. We also provide new evidence on the existence of an ESG momentum effect by showing that it is possible to anticipate the changes in ESG scores and that this strategy yields abnormal returns. Finally, we contribute to the literature on the behavior of investment funds regarding sustainability and the performance associated with these funds by showing that some funds anticipate the ESG information present in the ESG scores and benefit from financial performance.

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TABLES AND FIGURES

Table 1: Comparison of the update schedule of the different providers

This table gives information about the update schedule of several ESG data providers. We give the average number of times each issuer has its ESG score upgraded or downgraded. Sd corresponds to the standard deviation. We also provide other frequency metrics regarding ESG scores and raw data updates.

	MSCI (2007-2023)	Refinitiv (2002-2023	Vigeo (2007-2023)	S&P (2013-2023)	Sustainalytics (2014-2023)
Average (sd) number of upgrades by issuer	2.49 (1.92)	6.14 (3.56)	3.00 (1.79)	2.72 (1.47)	4.25 (2.96)
Average (sd) number of downgrades by issuer	2.22 (1.62)	4.77 (2.82)	2.06 (1.49)	2.71 (1.54)	3.62 (2.53)
Frequency of updates	Monthly	Mostly Annual	Annual	Annual	Annual then quarterly from 2017
Month with the most updates in score	January (13%)	December (60%)	September (12%)	January (100%)	December (26%)
Simultaneity score/raw data update	No	Yes	Yes	Yes	Yes

Table 2: Construction of a sample at the stock level

This table shows the number of stocks, number of observations and summary statistics for the stocks included in the CRSP dataset and for the stocks which have been given a score by MSCI corresponding to our final sample.

	Number of stocks	Number of observations	Returns	Market Capitalization
US listed firms	10,663	1,015,289	0.91	4.99
Rated by MSCI	3,305	235,502	1.18	13.76
Not rated by MSCI	10,641	779,787	0.83	2.34
Difference between rated and not rated			*0.36**** *(9.09)*	*11.43**** *(95.57)*

Table 3: Summary statistics at the fund level
This table shows the summary statistics for the funds present in our sample including monthly returns, assets under management (size), age of the fund, the management fees and fund flows. Our sample consists of 11,280 equity active mutual funds for the period 2007-2022.

	Min	1st Quarter	Median	mean	3rd Quarter	Max
Returns (%)	-95.64	-1.86	0.69	0.31	3.20	93.96
Log Fund Size ($)	-2.30	2.43	4.25	4.10	5.94	11.89
Log Age (Months)	1.10	3.87	4.62	4.37	5.09	5.59
Fees (%)	0.00	0.38	0.68	0.63	0.87	13.47
Log Fund Flows ($)	-4.60	0.00	0.00	14.62	14.62	23.56

Table 4: Summary statistics for the prediction of the ESG score

This table shows the number of stocks, number of observations and summary statistics for the actual ESG scores, the reconstructed score (predicted scores), the number of actual upgrades and downgrades throughout our sample and the time between the time where the predicted score change and the actual update in the scores.

	ESG scores	Predicted scores	Time between predicted and actual upgrades	Time between predicted and actual downgrades
Mean	4.39	4.18	17.45	14.96
Standard deviation	2.02	2.86	16.20	14.22
Min	0.00	0.00	0.00	0.00
1st Quartile	2.86	1.73	6.00	5.00
Median	4.29	3.67	12.00	10.00
3rd quartile	5.70	6.45	24.00	21.00
Max	10.00	10.00	150.00	105.00
Number of stocks	3,317	3,317	3,317	3,317
Number of observations	236,521	236,521	236,521	236,521

Table 5: Link between the predicted and actual scores

This table presents an OLS regression where the dependent variable is the actual score S given by the provider and the independent variable is the predicted score $\hat{S}$ obtain through Equation (2). We include financial covariates (returns and market capitalization) and fixed effects for the months)

	Actual ESG score		
Predicted ESG score	0.57*** (209.04)	0.59*** (206.44)	0.63*** (209.69)
Returns		0.000 (1.04)	0.000 (0.29)
Ln(MarketCap)		-0.07*** (-21.80)	-0.04*** (-11.48)
Constant	-0.16*** (-30.14)	0.91*** (18.50)	0.02 (0.18)
R squared	0.16	0.16	0.18
Fixed effects	No	No	Yes
F-statistic	4,370***	1,475***	263.50***
Total observations	235,502	235,502	235,502

Note : * p<0.10, ** p<0.05, *** p<0.01

Table 6: Timing of the update after an investment following the strategy

This table tests the impact of a predictive update on the probability that a real update happens through a Cox model. As such, a positive β indicates that the probability of an update during period t increase after we take position in the stock.

	Timing of the update in ESG			
	Upgrade	Downgrade	Downgrade	Upgrade
Predicted Upgrade	0.12*** (20.70)	-0.07*** (-11.14)		
Predicted Downgrade			0.01** (2.55)	-0.10*** (18.05)
Number of events	41,680	55,480	55,480	41,680
Total observations	236,521	236,521	236,521	236,521

Note : * p<0.10, ** p<0.05, *** p<0.01

Table 7: Performance of the ESG timing strategy

This table shows the average excess returns and alpha from the CAPM and factor models of three portfolios following the ESG timing strategy. The long strategy corresponds to the stocks which are likely to be upgraded according to their raw data, the short leg corresponds to the stocks which are likely to be downgraded according to their raw data and the long-short is the combination of the two. The model includes the classical Fama-French factors (market, size, value, profitability, investment) along with momentum. The α are reported here with a $t-$test between parenthesis.

	Long	Short	Long-Short
Panel A: Equal-weighted returns			
Average excess return (rf)	1.18*** (2.85)	1.04** (2.33)	0.14* (1.80)
CAPM alpha	0.15*** (3.12)	-0.07* (-1.75)	0.22*** (3.16)
Three-factor (FF) alpha	0.13*** (2.88)	-0.08* (-1.82)	0.21*** (2.96)
Five-factor (FF) alpha	0.11** (2.35)	-0.10** (-2.25)	0.21*** (2.84)
Six-factor (FF+Mom) alpha	0.08* (1.82)	-0.09** (-2.01)	0.17** (2.37)
Panel B: Value-weighted returns			
Average excess return (rf)	1.43*** (4.62)	1.43*** (3.92)	0.01 (0.03)
CAPM alpha	0.05 (0.97)	-0.13 (-0.98)	0.18 (1.08)
Three-factor (FF) alpha	0.05 (0.98)	-0.15 (-1.15)	0.20 (1.22)
Five-factor (FF) alpha	0.04 (0.79)	-0.10 (-0.79)	0.14 (0.88)
Six-factor (FF+Mom) alpha	0.03 (0.52)	-0.07 (-0.52)	0.09 (0.57)

Note : * p<0.10, ** p<0.05, *** p<0.01

Table 8: Performance of the front-running and post-update investment strategy

This table shows the average excess returns and alpha from the CAPM and factor models of the portfolios following the ESG timing strategy and compare it to the traditional investment strategy. The front-running strategy goes long in the stocks which are likely to be upgraded according to their raw data, and short in the stocks which are likely to be downgraded according to their raw data. The post-update strategy goes long in the stocks which have been upgraded within the last year and short in the stocks which have been downgraded within the last year. The model includes the classical Fama-French factors (market, size, value, profitability, investment) along with momentum. The α are reported here with a $\mathrm{t-test}$ between parenthesis.

	L/S strategy before update	L/S strategy after the update
Panel A: Equal-weighted returns		
Average excess return (rf)	0.14* (1.80)	0.04 (0.49)
CAPM alpha	0.22*** (3.16)	0.09 (1.27)
Three-factor (FF) alpha	0.21*** (2.96)	0.07 (0.96)
Five-factor (FF) alpha	0.21*** (2.84)	0.07 (0.93)
Six-factor (FF+Mom) alpha	0.17** (2.37)	0.06 (0.86)
Panel B: Value-weighted returns		
Average excess return (rf)	0.01 (0.03)	0.02 (0.26)
CAPM alpha	0.18 (1.08)	0.05 (0.50)
Three-factor (FF) alpha	0.20 (1.22)	0.05 (0.44)
Five-factor (FF) alpha	0.14 (0.88)	0.06 (0.55)
Six-factor (FF+Mom) alpha	0.09 (0.57)	0.05 (0.49)

Note : * p<0.10, ** p<0.05, *** p<0.01

Table 9: Summary statistics for the ESG timer funds

This table shows the summary statistics for the funds which follow the ESG front-running strategy as defined in (7) and for the other funds. For each variable, the difference between the ESG timer and the other funds are presented along with a t-statistic between parentheses. The difference in returns and fund flows stay significant when covariates and fixed effects are included as shown in Appendix 4

	Total sample	ESG timers	non ESG timers	Difference between timers and other funds
Financial characteristics				
Returns (%)	0.34	1.28	0.31	0.97*** (15.21)
total assets ($ million)	925.39	1,073.79	920.28	153.51*** (2.72)
Age (quarter)	82.42	98.15	81.87	16.27*** (21.35)
Fees (%)	0.64	0.65	0.64	0.01** (2.35)
Flows ($ million)	-221,557	-506,583	-211,833	-294,750 (-0.61)
Timing characteristics				
Average beta	-0.31	1.15	-0.36	1.51*** (127.53)
Number of quarters being a timer	1.42	4.86	1.30	3.56*** (76.46)
Number of consecutive quarters being a timer	0.03	0.26	0.02	0.24*** (47.41)

Note : * p<0.10, ** p<0.05, *** p<0.01

Table 10:
This table displays the autoregression of the timing ability coefficient constructed through equation (7). Positive coefficients show that a fund is more likely to be an ESG timer if it has already been one in the previous periods.

	ESG timing (β_t)
ESG timing (β_{t-1})	0.37*** (166.46)
ESG timing (β_{t-2})	0.20*** (88.17)
ESG timing (β_{t-3})	0.15*** (64.45)
ESG timing (β_{t-4})	0.02*** (7.58)
Constant	-0.08*** (-41.87)
Fixed Effects	No
Adjusted R2	0.40
F-statistic	3,316***
Observations	202,627

Note : * p<0.10, ** p<0.05, *** p<0.01

Figure 1: Creation of the ESG scores by MSCI

This figure, extracted from "ESG Ratings Process", MSCI ESG Research LLC, April 2024, describes the process followed by MSCI while creating its scores.

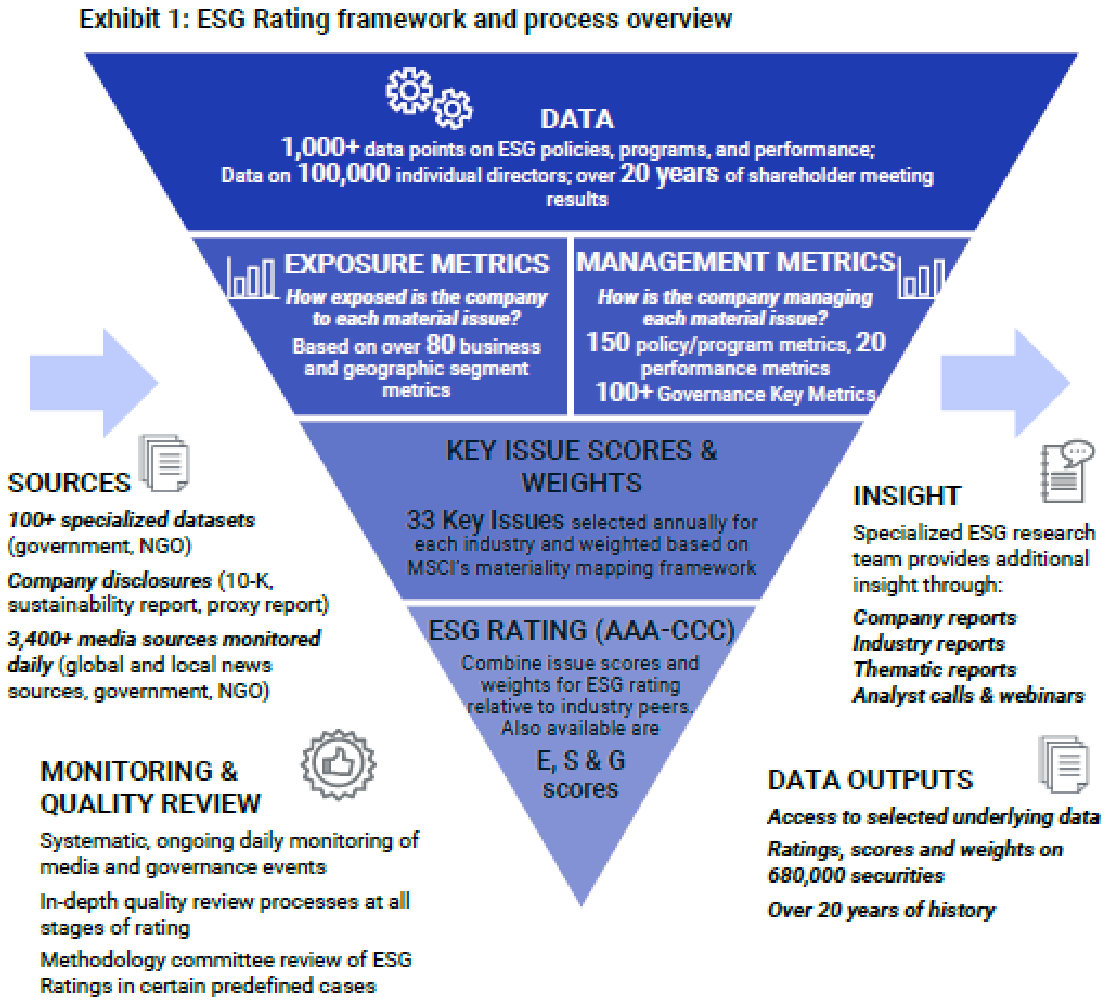


Figure 2: ESG timing strategy

This figure represents the long-short strategy defined in Equation (3) where we go long when there is an upgrade in the raw data $E(S_t|\Theta_t) > E(S_{t-1}|\Theta_{t-1})$, such that the score is underestimated $E(S_t|\Theta_t) < S_t$ and we go short when there is an downgrade in the raw data $E(S_t|\Theta_t) < E(S_{t-1}|\Theta_{t-1})$, such that the score is overestimated $E(S_t|\Theta_t) < S_t$

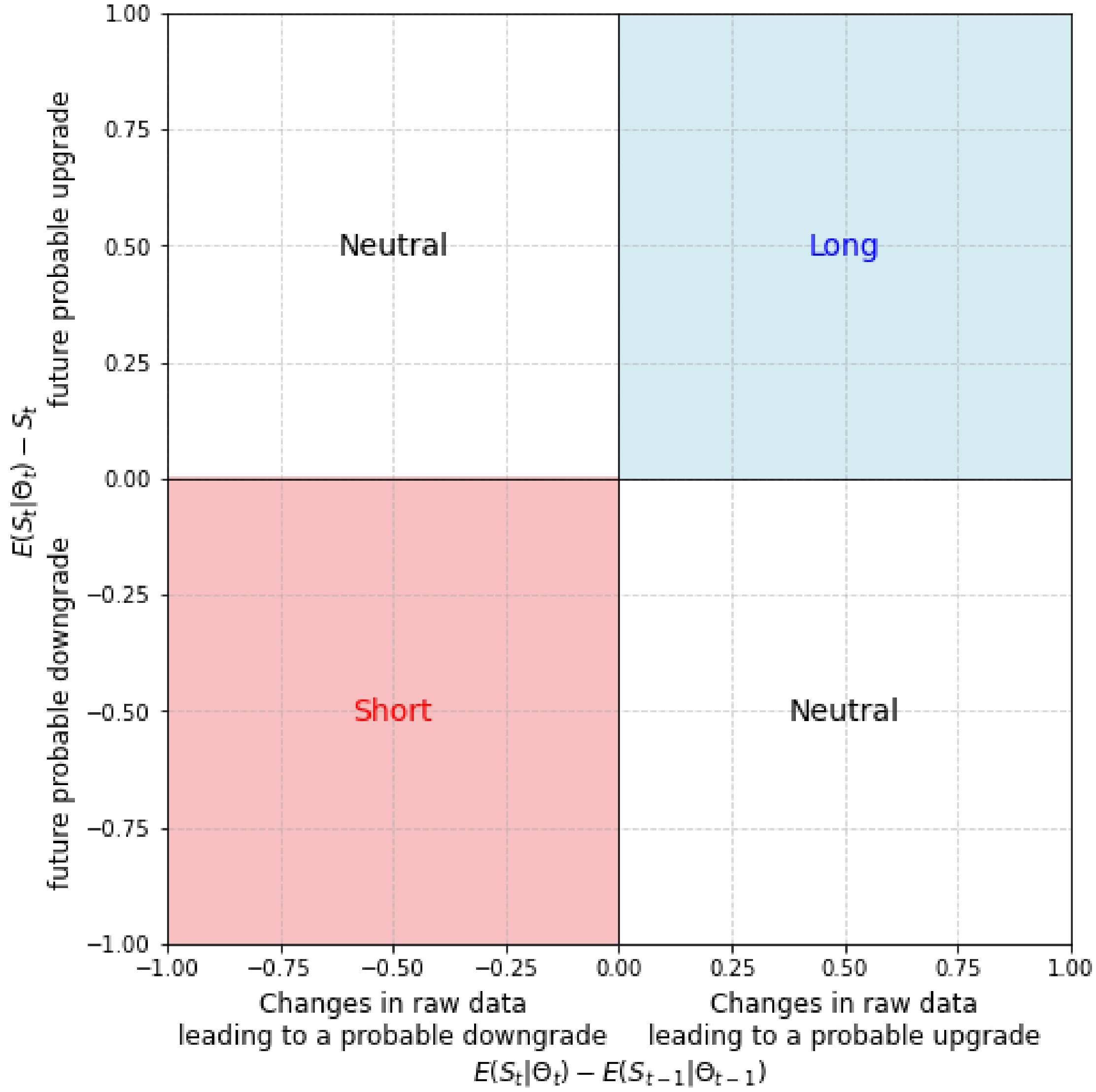
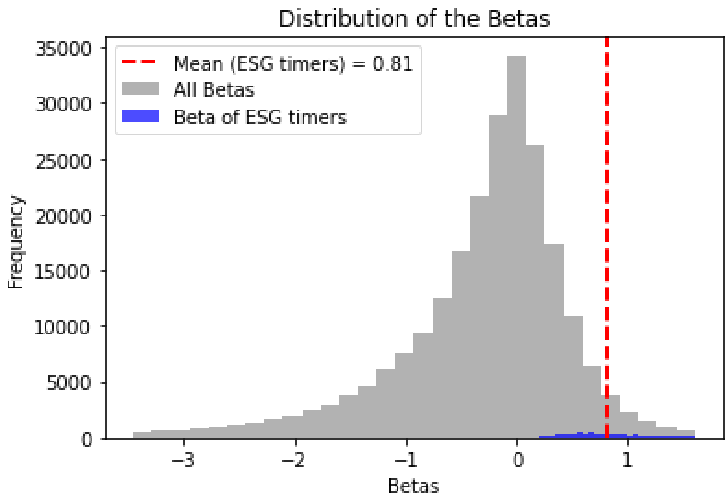


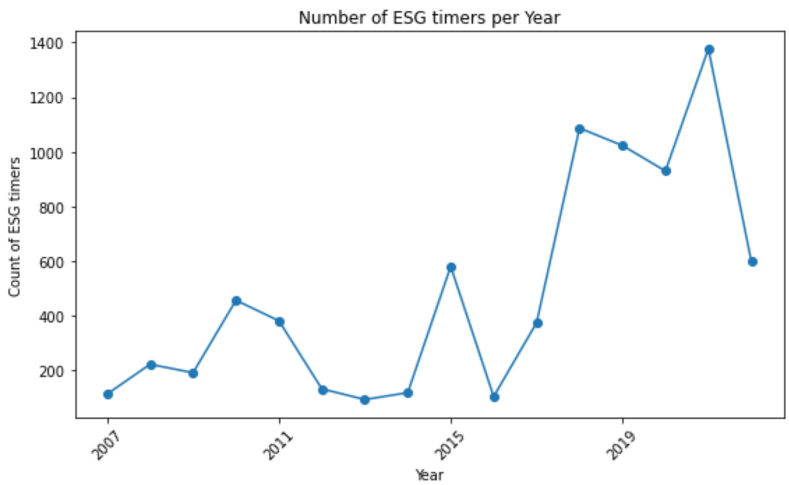
Figure 3: statistics around the betas

The first graph shows the distribution of active mutual funds' exposure to a long/short ESG momentum strategy measured by the β parameter related to Equation (7) along with thebeta of the funds identified as ESG timers. The betas have been winsorized at the 99%.

The second graph shows the evolution of the number of funds which follows a long/short ESG momentum strategy measured by the β parameter related to Equation (7).

The third graph shows the number of funds which have been ESG timers at each period or throughout the sample.





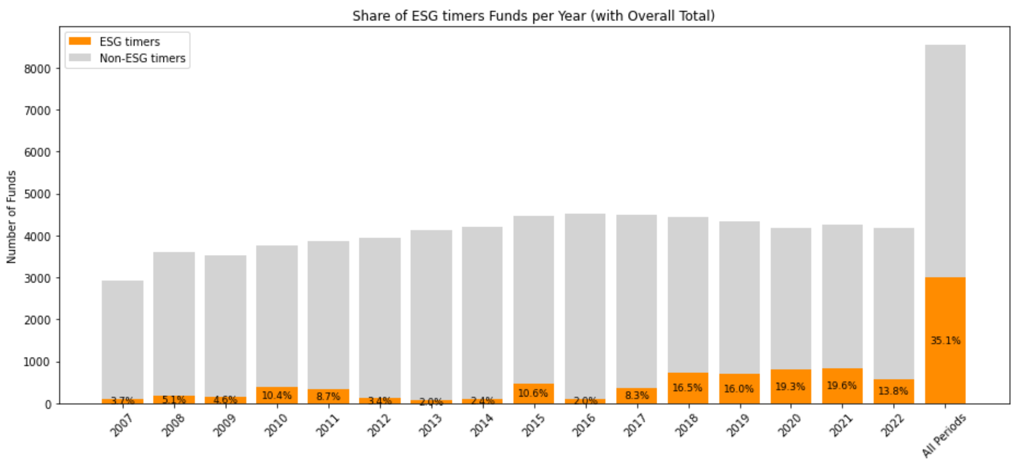
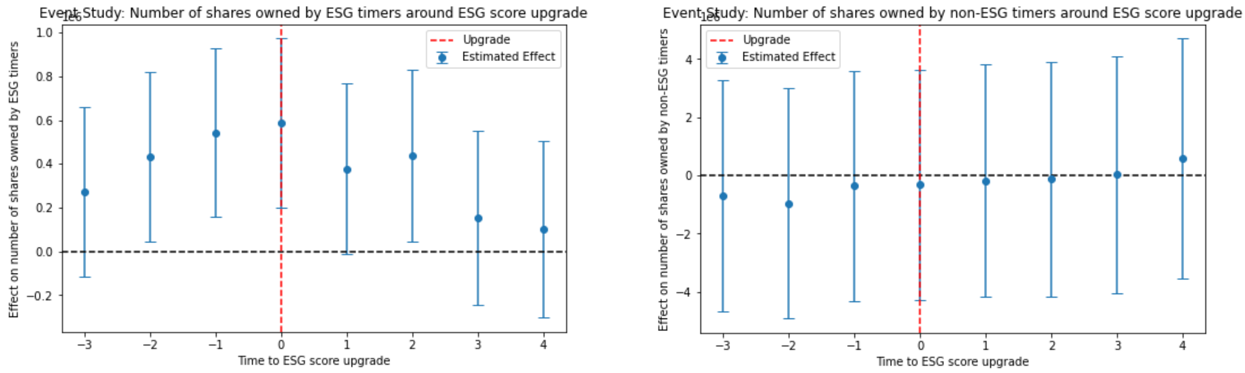
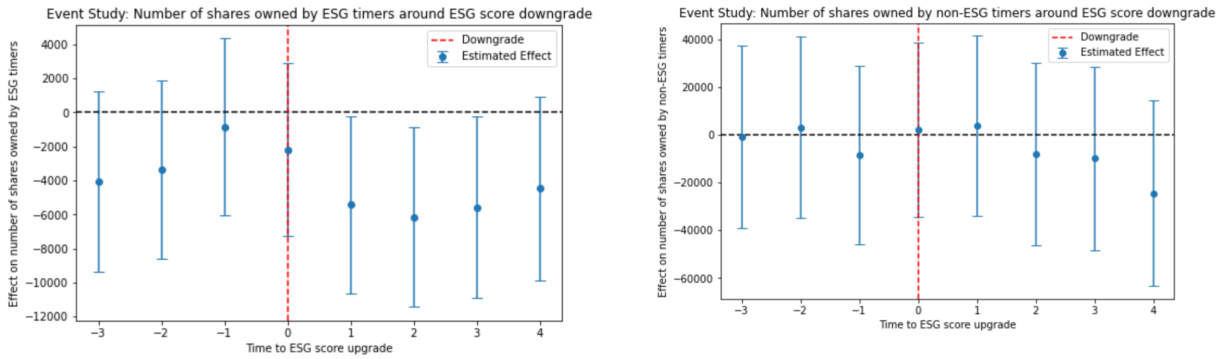


Figure 4: Number of shares owned by the funds around the ESG score changes
These graphs show the evolution of the number of shares owned by the ESG timers and by the other funds around the ESG upgrades and downgrades evaluated though an event study. Panel A considers only the positive number of shares (i.e. funds with a long position) and panel B considers only the negative number of shares (i.e. funds with a short position). The effects are given with 95% confidence intervals.

Panel A: ESG score upgrade



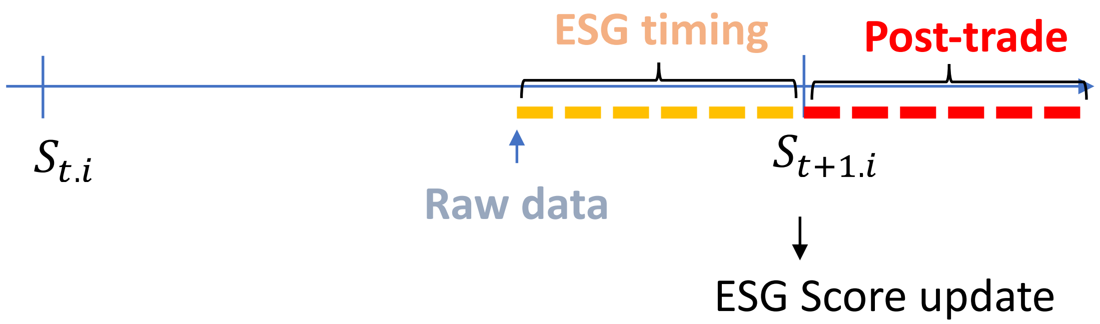
Panel B: ESG score downgrade



APPENDICES

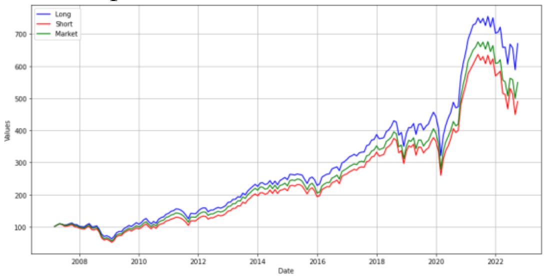
Appendix 1: Timing of the investment strategy

This graph describes the investment strategy. The period begins with the publication of the old score ($S_{t,i}$). The firm publishes a report which contains ESG information. This information is integrated by the provider which publishes ESG raw data (Θ_t) which can be used to reconstruct a predicted score ($E(S_{t+1,i}|\Theta_{t,i})$). Finally, the new ESG score (S_{t+1}) is published. The investment is done between the publication of the raw data and the publication of the score.

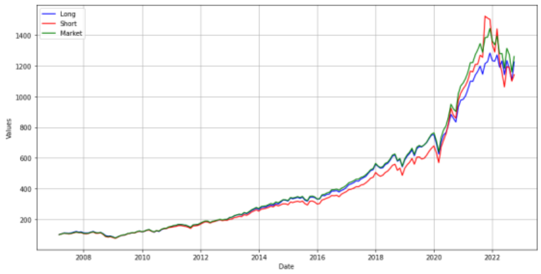


Appendix 2: Cumulated return from the long, short and long-short strategy

These two figures show the cumulative returns from three portfolios with an original investment of $100. Three strategies are presented. The green line corresponds to the market portfolio, the blue line corresponds to the long leg (stocks which are likely to be upgraded according to their raw data), and the red line corresponds to the short leg (stocks which are likely to be downgraded according to their raw data). The left figure corresponds to the equally weighted portfolio while the right figure corresponds to the portfolio weighted by the market capitalization of the stocks.



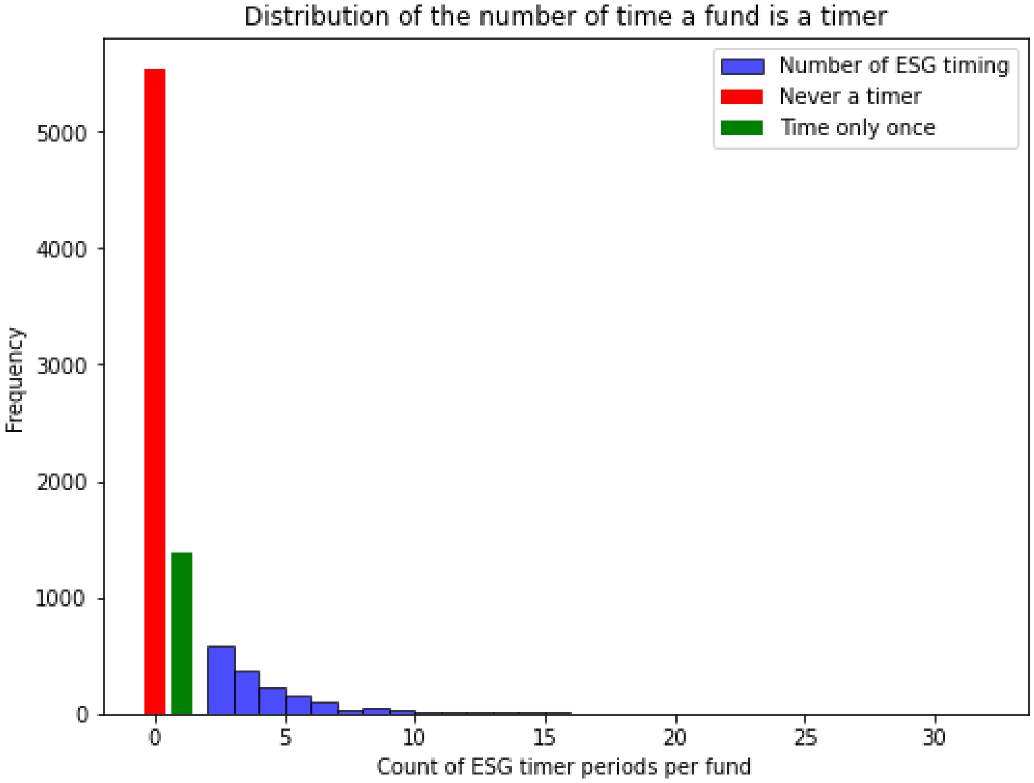
Equally-weighted



Value-weighted

Appendix 3: Number of times each fund has timed the ESG score announcement

This graph shows the number of times each fund has followed a long/short ESG momentum strategy measured by the β parameter related to Equation (7).



Appendix 4: Performance of the ESG timing funds

This table shows a regression where the dependent variable is the excess returns for Panel A and the flows to the funds in Panel B, and the independent variable is a dummy equal to one is the fund is an ESG timer.

$$R_{i,t} = \alpha + \beta ESGtimer_i + C_{i,t} + \epsilon_{i,t}$$
$$Flows_{i,t} = \alpha + \beta ESGtimer_i + C_{i,t} + \epsilon_{i,t}$$

Some covariates including the size of the fund, its age, and the fees and different sets of fixed effects are used in the regression.

Panel A: ESG timers' excess returns

	Excess returns		
ESG timer	1.02*** (15.96)	1.16*** (17.91)	0.76*** (19.77)
Asset under management	0.03*** (6.51)	0.03*** (5.26)	0.02*** (5.65)
Age	-0.12*** (-8.91)	-0.12*** (-8.60)	-0.004 (0.65)
Fees	0.11*** (3.73)	0.04 (1.16)	-0.08*** (-3.87)
Constant	0.60*** (11.19)	0.15 (1.32)	1.16*** (12.87)
Fixed Effects	No	Strategy	Strategy + Month
Adjusted R2	0.001	0.01	0.67
F-statistic	86.69***	13.31***	2,461***
Observations	234,828	234,828	234,828

Panel A: ESG timers' flows

	Fund flows		
ESG timer	0.13 (0.77)	0.38** (2.20)	0.33* (1.85)
Asset under management	0.51*** (36.61)	0.50*** (34.64)	0.48*** (33.50)
Age	-2.14*** (-54.50)	-2.00*** (-48.44)	-1.90*** (-44.10)
Fees	-0.50*** (-5.74)	0.36*** (3.54)	0.21** (2.03)
Constant	14.43*** (88.27)	12.20*** (37.90)	12.77*** (22.70)
Fixed Effects	No	Strategy	Strategy + Month
Adjusted R2	0.07	0.10	0.11
F-statistic	891.70***	42.86***	34.16***
Observations	234,828	234,828	234,828

Note : * p<0.10, ** p<0.05, *** p<0.01