Can US equity funds time ESG score updates?[1]

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Serge DAROLLES Anouck FAVERJON Marie LAMBERT

ABSTRACT

This paper examines whether delays in ESG score updates generate pricing anomalies in equity markets. Using detailed data from MSCI, which discloses ESG-related raw indicators continuously but updates final ESG scores annually, we exploit the temporal disconnect between information release and rating revision. We develop a LASSO-based model to predict future ESG score changes from raw ESG data and document that these signals contain material information prior to official rating updates. A timing strategy based on predicted upgrades and downgrades delivers a statistically significant monthly alpha of 0.13%. We show that a subset of US active funds anticipates rating changes and trades accordingly in the segment of large-cap. Large-cap stocks exhibit rapid information incorporation due to the presence of these informed arbitrageurs. Our findings highlight the role of ESG-aware investors in facilitating price discovery and reveal a persistent ESG-related mispricing in small-cap equities.

[1] Marie Lambert is affiliated with HEC Liège, Management School of the University of Liège. She holds the Deloitte Chair in Sustainable Finance at HEC Liège. Serge Darolles is affiliated with Université Paris Dauphine - PSL. Anouck Faverjon is affiliated with HEC Liège, Management School of the University of Liège and University Paris Dauphine - PSL.

Introduction

There is no doubt that environmental, social, and governance indicators constitute a set of material information for investors (among others, Edmans,2011; Gompers et al., 2003; Porter and Van der Linde,1995). To help investors process the myriads of those indicators, agencies commercialize ESG scores or ratings to capture in a single number or a letter the global and environmental, social or governance performance of companies. These ratings are generally updated at low frequency (yearly) as the raw information about firm sustainability contained in non-financial reports and other public documents takes several months to be processed by these agencies. This delay in the access to ESG rating could prevent ESG information to be priced in by investors and lead to uninformed asset allocation both on prices and ESG characteristics.

In this paper, we investigate the existence of an ESG pricing anomaly due to the temporal disconnect between the ESG rating update and the publication of the raw information measuring the sustainable firm performance on multiple dimensions. Among the major rating providers (LSEG, S&P, Sustainalytics, MSCI, Moody's), MSCI provides an interesting setting to run such an experiment as they disclose the update of constituents of the scores on a continuous basis– such as sub-scores on company performance related to carbon emission, gender diversity metrics (hereafter called the "raw data" to ESG scores as in Berg et al. 2022) – but the final scores are released once a year. The production of ESG scores is subject to a review process that assesses whether changes in raw data require a score change and takes a few months to be completed. This multi-step process allows us to disentangle the effects of the scores from the raw data on the pricing of 3,063 stocks listed over the main US exchanges and for which the ESG information is covered by MSCI over the period 2007 to 2022.

We start by examining whether it is possible to predict future updates in scores. For that, we develop a Least Absolute Shrinkage and Selection Operator (LASSO) to decompose the ESG scores and learn about the construction process of the MSCI ESG scores. We show that these signals contain material information prior to official rating updates.

Given the availability of this information and the capacity to theoretically time the update of ESG score, we continue our analysis by examining how market participants make use of the ESG-related information and in particular the raw data versus the scores. We do this by examining the capacity of US equity active investment funds to anticipate the publication of ESG ratings from the update of the raw data. Our empirical set up is grounded in the theoretical framework of Pedersen et al. (2021). We consider that some investors might be aware of the materiality of the raw data and have the capacity to anticipate and trade based on this information, ahead of changes in ESG ratings. We call them the aware investors.

To detect aware funds, we measure their return exposure to an investment strategy that develops a timing strategy on probable updates and downgrades. This strategy takes long (resp. short) positions at the time of the release of the raw data when the predicted score (using the Lasso) is above (resp. below) the current score and exited at the upgrade (resp. downgrade) or at the latest after 12 months after the release of the raw data. The equally-weighted timing strategy delivers a Jensen monthly alpha of 0.13%, statistically significant at the 1% level. Alpha is robust to the inclusion of other factors. Proof that it captures the mispricing due to non-integration of ESG related information, the strategy's alpha decays rapidly when the long and short positions of the timing strategy are initiated with some lags (days) from the raw data update. At the beginning of our sample, in January 2007, about 4% of the US active mutual funds were exposed to the timing strategy. This proportion raises to more than 10% in 2022.

To decompose the investment channel, we dig further into the shareholdings of the two types of funds. We provide evidence that ESG-aware funds buy stocks prior the realized upgrade while the funds which are unaware do not exhibit specific behavior around the upgrade. Our empirical exercise finally shows that ESG aware funds are exclusively active in the large cap segment. Large caps tend to receive more upgrades and downgrades than small caps (but are not more likely to get a rapid upgrade after an investment signal.). The strategy is therefore more liquid and less risky to implement. We moreover observe that the alpha of the timing strategy rapidly decays for large cap when the strategy is not played at the time of release of the raw data. It drops from a 0.05% monthly alpha to below zero after about 10 days. On the contrary, the alpha persists for the small cap segment. These results suggest that the ESG information for large caps is rapidly priced in contrary to the case of small caps where our results could not validate the existence of a timing strategy on their raw data and show a decreasing but persistent alpha. Our results therefore support the thesis that the presence of arbitrageurs (informed or aware investors) ensure the rapid integration of ESG raw data. These aware investors play a capital role in the markets as they ensure that sustainability information is integrated to price. This level playing field does not exist yet on the small cap companies with the consequence that significant mispricing exists for those stocks.

Building on the framework of Pedersen et al. (2021), we also consider the case of ESG lover investors. These investors are investment funds with top ESG ratings from Morningstar. We observe that ESG lovers which are also ESG aware tend to increase their number of shares before the upgrade like ESG aware funds but contrary to them, they maintain their positions thereafter. However, ESG lovers which only focus on final scores (and are not aware of the materiality of the raw data) tend to sell shares before the upgrade and buy them back at the time of the upgrade. Doing so, they act as a counterparty of aware funds. We show that the return gap between the aware lovers and their unaware counterpart is economically large and significant (a spread above 1% monthly return) – while the fund volatility is even lower for the aware lovers –.

The most direct contribution of our work is on the literature demonstrating the financial materiality of ESG scores beyond ESG-related information. Khan et al. (2016) uses the SASB materiality framework to classify the ESG scores into material and non-material information and show that only the material ESG information affect stock returns. Closely related to that, we show that the information present in the raw data is material for stock returns even before the publication of the ratings. Our paper moreover adds on Ceccarelli et al. (2023) who show that the funds which invest in the months preceding the updates in ESG ratings receive higher flows and have a higher performance demonstrating their manager skills in ESG. Our paper provides an economic channel that is consistent with their empirical results.

We also highlight the role of ESG aware investors in reaching price equilibrium (as stated in Pederson et al., 2021) in the large cap segment. However, we show the existence of a persistent ESG small cap anomaly due to the difficulty in integrating ESG information for this market capitalization. The existence of mispricing specific to small, more illiquid stock is not new. Fama and French (2008) show that the anomalies linked to net stock issues, accruals, and momentum do not hold for large stocks. Hou et al. (2019) also show that when controlling for microcaps, a significant number of published anomalies do not exist anymore. Our research indirectly contributes to this abundant literature on market anomalies, and the role of the release of information in mispricing (Bowles et al., 2024).

Our paper is structured as follows. Section 2 presents the data. Section 3 examines the impact of the temporal disconnect between the release of the raw data and the final scores on stock prices. It presents our prediction model and the pseudo-arbitrage strategy. Section 4 examines the role of investors in the processing of ESG information. Section 5 concludes.

2. Data

2.1. Corporate issuers – ESG data

We collect corporate issuer's ESG scores (normally distributed on a scale from 0 to 10) as well as their underlying raw data from MSCI. Such as in Berg et al. (2022), raw data correspond to 105 variables assessing the exposure and management of the issuers regarding issues such as carbon footprint, water consumption, human capital, corruption. MSCI ESG data are subject to potential changes every month, contrary to other providers, which proceed to annual updates: MSCI continuously collect data from annual reports, investor presentations and financial and regulatory filings to extract key metrics measuring the company exposure to environmental, social and governance factors.[2]

2.2. Stock data

The Compustat/CRSP merged database provides financial information, including returns, book to market ratio and market capitalization, on stocks traded on the US stock exchanges (New York Stock Exchange, AMEX, or NASDAQ). We retrieve the institutional ownership from the 13F filings. We consider the exchange codes 11, 12, and 14. Following Fama and French (1996), we remove[3] financial companies corresponding to sic codes 6000 to 6999. Our empirical analysis requires to be covered by MSCI. The summary statistics for our final sample are presented in Table 1.

[Insert Table 1 here]

Table 1 presents in Panel A the full sample of stocks retrieved from CRSP, i.e. 10,659 firms. Our sample drops to 3,063 firms when we require the availability of MSCI ratings. This corresponds to 233,822 firm-month observations. Our period starts in February 2007, with the first scores given by MSCI, and ends in October 2022 (189 periods). Compared to the entire CRSP dataset corresponding to the non-financial firms traded on the main stock exchanges, our sample concentrates on largest stocks (on average a market capitalization of more than $2.72 million) and stocks mostly owned by institutional investors. These are the common biases

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

[3] Following Fama and French (1996), we exclude observations with a negative price (about 0.005% of the observations).

related by the literature on ESG databases. Drempetic et al. (2020) show that larger issuers display on average a higher ESG rating. Dyck et al. (2019) show that companies with a higher institutional ownership are usually associated with higher ESG ratings.

2.3. Fund data

Our sample includes the US-domiciled equity funds that have an active mandate in the CRSP database. We exclude index funds.[4] We retrieve fund daily returns as well as quarterly holdings information from the CRSP mutual funds holdings database.

Table 2 reports summary statistics on the total CRSP equity funds dataset.

[Insert Table 2 here]

The table reports separately data on passive and active funds. CRSP datasets include 2,698 passive equity funds and 8,549 equity active funds. Our sample is larger to previous studies on US active mutual funds[5] as other studies usually apply additional filters among which a filter on the fund total net assets. In our analysis we do not exclude small funds as they could play a niche strategy. Our sample of active equity funds display smaller AUM, higher fees, higher turnover compared to passive equity funds, which is consistent with the common knowledge on the differences between these fund types.

Table 3 presents the summary statistics of the sample of 1,810 US active equity funds for which Morningstar provides a globe over the period 2018-2022. We use this sample for a sub-analysis.

[Insert Table 3 here]

Funds are sorted according to their Morningstar globes into the group of ESG lovers (Globes of 4 or 5) and non-lovers. Less than 10% receive a top ESG rating over the period. The two samples display similar statistics. Gantchev et al. (2024) display a similar sample when requiring investment funds to be rated by Morningstar.[6] Gantchev et al. (2024) reports TNA of \$2,219 million and a turnover ratio of 62% consistent with our estimates of \$2,664.78 million of TNA and 49.75% of turnover ratio.

[4] Index funds correspond to fund which "index_fund_flag" is either B (Index-based fund) or D (Pure index fund) in the Compustat Mutual Fund database.
[5] Pastor and Vorsatz (2020) use a sample of 4,292 U.S. actively managed equity mutual funds during the period 2017-2020 after excluding funds with total net assets below \$10 million. Evans et al. (2022) uses a sample of 5, 305 actively managed funds for the period 1992-2016 and only consider funds which have been managed by a single portfolio manager.
[6] They report 1,959 funds including 1,761 active funds in total during the period 2015-2017.

3. How fast is ESG-related information integrated into prices?

MSCI provides a unique setup to understand the mechanism by which ESG-related information is integrated into stock prices. The raw data underlying the construction of the ESG scores are collected on a continuous basis from external sources and published a few months to 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.[7] Figure 1 illustrates the ESG score formation process.

[Insert Figure 1 here]

The provider collects over 1,000 data points about 40 key issues such as access to commodities, corruption institution, energy efficiency, toxic emissions waste, business ethics (see Appendix B for the complete list). Under the supervision of the Methodology Committee, MSCI aggregates these data points into a key issue-level exposure and management metrics. A key issue gets a score between 1 and 10 following a non-linear combination (See Appendix C). The provider publishes these management and exposure metrics (corresponding to the "raw data") continuously throughout the year. The key issues are then derived from the management and exposure scores using the formula described in Appendix C.

The ESG rating construction process takes place after the release of the exposure and management scores and the key issues. MSCI ESG specialists initiate a quality review process to determine whether a change in raw data translates into an "MSCI ESG Research rating action".[8] This process includes multiple steps. The *Methodology committee* sets the weights used to aggregate the key issues into the pillar scores and the weighted average score. This committee meets at a low frequency, every 6 to 12 months. The *Review committee* (or the assessment committee in some very particular cases) sets the score adjusted for the industry.

Figure 2 illustrates these different steps.

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[7] 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

[8] "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

[Insert Figure 2]

As illustrated in Figure 2, management, exposure, and key issues are published first and before the weights associated with key issues are released. There exists a lag between the disclosure of the so-called raw data and the weighted average score as well as a lag between the industry-adjusted score (also called IVA score for Intangible Value Assessment) and the weighted average score. The investors mostly rely on the IVA score as well as academic studies (Chatterji et al., 2016; Pedersen et al., 2021; Berg et al., 2022).

Under the hypothesis that the average[9] investors mainly react to the update in scores rather than the raw data making up the scores, arbitrage opportunities could result from this situation. Likely updates or downgrades could be predicted at the time of the release of the raw data. Under this hypothesis, trading based on this information would deliver an abnormal return. In case the average investors rely on the raw data rather than the score, no abnormal return would be possible.

3.1. Using a lasso to predict future scores from the raw data

We use a *Least Absolute Shrinkage and Selection Operator (LASSO)* to decompose the ESG scores and learn about the construction process of the MSCI ESG scores. From MSCI methodology, we know that their scores mostly aggregate linearly the raw data but that adjustments might be performed by ESG analysts before the release of the score. The lasso allows to consider the high dimensionality of the data: the independent variables in the linear regression model are the myriads of ESG raw data, on which we add issuers' market capitalization as we know this variable impacts the scores (Drempetic et al., 2020; D'amato et al., 2021).The parameters are selected using five-fold cross-validation on historical data. We perform this analysis separately for each industry given the industry-specific weights of the key issues.

At each period *t* and for each industry *Ind*, we train an algorithm capable of reverse engineering the score construction through a function $f_{t-1,t-2...,t0,i \in Ind}(.)$ trained on all the available raw data $\Theta_{t-1,t-2...,t0,i \in Ind}$ from *t0* (initial period) to *t-1* for all stocks of the industry *Ind*.

The training algorithm reads as follows:

$$S_{t-1,t-2...,t0,i \in Ind} = f_{t-1,t-2...,t0,Ind}\left(\Theta_{t-1,t-2...,t0,i \in Ind}\right) + \epsilon_{t-1,t-2...t0,i \in Ind} \; \forall \, Ind \qquad (1)$$

[9] We talk about average investors as we will consider different types of investors in the next section of this paper.

Where $S_{t-1,t-2\ldots,t0,i,Ind}$ corresponds to the scores[10] over the period prior to time *t* for stock *i* belonging to industry *Ind*; the errors terms $\epsilon_{t-1,t-2\ldots t0,i\,\in\,Ind}$ are normally distributed.

We fit Equation (1) separately for each industry and predict the scores at each time *t,* using the information present in the raw data:

$$\mathrm{E}(S_{t,i\in Ind}|\Theta_{t,i\,\in\,Ind}) = \widehat{f_{t,Ind}}\left(\Theta_{t,i\,\in Ind}\right) \tag{2}$$

We examine the predictive power of our lasso in Table 4. We consider the following metrics.

- R^2 of the simple regression of the actual score on the prediction $S_{i,t} = \alpha + \beta\widehat{S_{i,t}} + \epsilon_{i,t}$
- Root Mean Square Error (RMSE) corresponding to $\sqrt{\frac{1}{n}\sum_{j=1}^{n}(S_{i,t} - \widehat{S_{i,t}})^2}$
- Mean Absolute Error (MAE) corresponding to $\frac{1}{n}\sum_{j=1}^{n}|S_{i,t} - \widehat{S_{i,t}}|$

As a benchmark, we report the predictive power of the simple linear combination of the key issues whose updated weights are released closer to the release of the score (and posterior to the raw data).

[Insert Table 4 here]

Our model displays an out-of-sample R-squared of 38% for the entire sample. We acknowledge that our R-squared is lower than its equivalent in similar studies (Del Vitto et al., 2023; Aouadi & Ma, 2023). Del Vitto et al. (2023) report R-squares ranging from 61 to 91% by focusing on three industries (finance and insurance, manufacturing, information, and professional scientific and technical services) and three geographical regions (USA, EU, and China), 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, and so closer to the raw data, than the global scores we used here. The table presents the performance of the lasso separately for the sample of small and big caps. We do not observe important differences in performance in the two samples. A major difference is that expectation of downgrades in the small cap segments take more time to realize.

[10] 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.

By construction, the weighted average of the key issues should better approximate the final scores (IVA). Yet, this linear combination of the key issues is not the mere replication of the score. Figure 3 displays the relationship between the MSCI weighted-average score and the final industry-adjusted scores.

[Insert Figure 3 here]

We use this approximation of the final score as a benchmark for the quality of our replication. Our R-squared and RSME is is relatively good when compared to the same indicators computed on the weighted-average score as a predictor of the IVA. The weighted-average scores computed based on the key issues display a R^2 of 61% and a RMSE of 1.36.

In addition, we perform a semiparametric Cox proportional hazard model (Cox, 1976) to model the instantaneous risk of experiencing an upgrade or downgrade ("the event") at time t, given the covariates X. The model stands as follows:

$$h(t|X_{i,t}) = h_0(t)e^{X'_{i,t}\beta} \quad (3)$$

Where $h(t|X_{i,t})$ is the function giving the instantaneous risk of the event for each time *t* given the covariates X, $h_0(t)$ is the function giving the basis instantaneous risk of the event when all covariates and equal to zero and $e^{X'_{i,t}\beta}$ is the exponential of the raw coefficients from the vector of covariates X.

Table 5 presents the results. The hazard rate for covariate X – corresponding to the exponential of betas – corresponds to the effect of the covariate on the instantaneous risk of getting the event (i.e. the upgrade or downgrade). The model is estimated using the partial-likelihood function.

[Insert Table 5 here]

In Column 1, the significant and positive coefficient on the dummy variable indicating a likely update according to the lasso estimate indicates that this increases instantaneously the risk of a realized upgrade. Firms with higher institutional ownership, higher market capitalisation and covered by more ESG rating providers are updated faster. In Column 2, we interact the upgrade signal with these cross-sectional variables. We observe that although investment signals increase the risk of an instantaneous update for small firms which tend to be updated at a lower frequency, large firms are updated faster than small cap firms independently of the investment signal (0.23-0.22).

3.2. Pseudo-arbitrage strategy

The pseudo-arbitrage strategy that exploits this lag in the updates of the industry-adjusted score is defined as follows. For a stock *i,* we define the last (L) available score as $S_{L,i}$and the last information set $\Theta_{L,i}$. We do not attach a time stamp to the score and raw data since, except at times of updates, the same values are repeated over time.

We consider the impact of the disclosure of updated raw data at month *t*, $\Theta_{t,i}$ where $\Theta_{t,i} \neq \Theta_{L,i}$ without any updates in the final scores (given the time needed for the review committee to meet and release the final score). The final score will be released a few months later, at time *t+m*. At time *t*, we use the predictive model derived from the lasso (on the total information available i.e. from time 0 to time t-1) to formulate an expected value of the future score conditional on the updated raw data $\Theta_{t,i}$, i.e. $\mathrm{E}\left(S_{t,i} \middle| \Theta_{t,i}\right)$.

If the average investors mainly react to the scores rather than the underlying public information, we would observe a potential mispricing during the period *t* to *t+m* if $\mathrm{E}\left(S_{t,i} \middle| \Theta_{t,i}\right) \neq S_{L,i}$.

We develop the following strategy to exploit this potential mispricing:

- If $\mathrm{E}\left(S_{t,i} \middle| \Theta_{t,i}\right) > S_{L,i}$, we anticipate a positive market reaction due to the update in scores and take a long position in the stock at time *t* up to *t+m*. We exit the long at the time *t+m* such that $m = \min_{\mathrm{n} \in \{1,\ldots,12\}} \{\mathrm{n}: S_{t+\mathrm{n}} > S_L\}$ or we close our positions after twelve months if there is no upgrade;
- If $\mathrm{E}\left(S_{t,i} \middle| \Theta_{t,i}\right) < S_{L,i}$, we anticipate a negative market reaction due to the update in scores and take a short position in the stock at time t up to t+m. We exit the short at the time *t+m* such that $m = \min_{\mathrm{n} \in \{1,\ldots,12\}} \{\mathrm{n}: S_{t+\mathrm{n}} < S_L\}$ or we close our positions after twelve months if there is no downgrade.

Figure 4 illustrates the strategy.

[Insert Figure 4 here]

As shown in Figure 4, several situations would lead to a neutral position or impediments to the arbitrage. First, we add a second condition for defining our long and short positions. We need the long and short signal to be confirmed by, respectively, an "improvement" or a "deterioration" of the raw data, that is a situation where the updated raw data lead to an increase or a decrease of our predicted score. Mathematically, this is translated into the following conditions: $E(S_t|\Theta_t) - E(S_{t-1}|\Theta_{t-1}) > 0$ for a long position and below zero for a short position. Not having this condition in place could lead us to take a long (short) position in an asset whose predicted score is higher (lower) than the last reported score but where the raw data deteriorate (improve). Second, our model cannot predict intra-month changes in scores and the data of MSCI does not provide the exact date of the update in raw data or score. Therefore, if the lag between the release of the raw data and the final scores is only a few days within the same month or if any update in scores due to controversies occurs, we do not take position.

Table 6 displays the performance of the long-short strategy under an equally-weighted scheme.

[Insert Table 6 here]

The table produces several metrics like the average raw return, the alpha of the the classical Fama-French model and its extensions. The factors along with the risk free are retrieved from French data library.[11] The strategy delivers significant abnormal performance under the different multi-factor models. The alternative strategy that consists of anticipating scores by simply averaging the key issues score do not generate any abnormal return. In addition, we also provide the performance of a more "traditional" post-update strategy which consists in holdings stocks during the year following upgrades and shorting them during the year following a downgrade. All alpha from this strategy – except the CAPM alpha which is marginally significant – are not significant.

Under this framework, we expect the potential gain to be maximum should the position be taken at month *t*, at the release of the raw data. From *t* to *t+m*, we expect the abnormal return to decay as additional information (such as the release of the weighting scheme of the key issues by the methodology committee) might be provided and integrated into price such. Figure 5 tests this hypothesis.

[Insert Figure here 5]

The figure displays the alpha of the strategy is it is initiated with delay, i.e. with a lag regarding time *t*, and lasts for 42 days. We observe that when the entry and exit dates are delayed or shifted, the alpha decrease from 0.11% without lag to 0.04% after 40 working days.

[11] Available at https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/

4. The role of investors regarding the integration of ESG-information

Corporate ESG ratings are derived exclusively from publicly accessible sources. All the data used in the assessment process is disclosed ex ante by the firm on their website, investor documentation or annual report. Any investor could therefore make their own assessment. The previous section shows that abnormal returns are associated with a long-short strategy that would trade on the temporal disconnect between the release of the raw data and the release of the scores.

In this section, we hypothesize that some investors, the ESG aware investors, can learn from this early disclosure while the average investor will only react at the time of the disclosure of the updated score. These aware investors would be able to replicate the timing strategy described in the previous section. We categorize the active mutual funds into the aware and non-aware groups according to their exposure to the long-short ESG strategy as described in the following sub-section.

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 Section 3.2. during the quarter q. To measure this exposure, we run the following regression estimated at each quarter q on the daily returns within the quarter q, using daily observations $d \in [q-1; q]$:

$$R_{i,d||\mathrm{d}\in\mathrm{q}} = \alpha_{i,q} + \beta_{i,q} LS_{i,d||\mathrm{d}\in\mathrm{q}} + \beta^{mkt}_{\mathrm{i,q}} (Rm - Rf)_{d||\mathrm{d}\in\mathrm{q}} + \epsilon_{i,d||\mathrm{d}\in\mathrm{q}} \text{ for } d \in [q-1; q] \quad (4)$$

Where $R_{id||\mathrm{d}\in\mathrm{q}}$ is the series of daily returns of the fund i on day d which falls within quarter q, $LS_{id||\mathrm{d}\in\mathrm{q}}$ corresponds to the equally-weighted strategy defined in Section 3.2., $(Rm - Rf)_{d||\mathrm{d}\in\mathrm{q}}$ are the returns of the market portfolio on day d and $\epsilon_{id||\mathrm{d}\in\mathrm{q}}$ designate the normally distributed error terms.

A fund is an ESG timer during quarter q if its coefficient $\beta_{i,q}$ is positive and significant at the 10% level. Figure 5 reports the joint distribution of the betas and their p-values for all funds and highlight the proportion of the betas which are positive and significant.

[Insert Figure 6 here]

Figure 6 provides the screenshots of the distributions at different points in time: at the beginning of the sample, after the introduction of the MS Globes in 2018, and at the end of the sample. We find that the number of funds defined as ESG aware increases over time. At the beginning of the sample compared to the other two time points, the distribution of the betas have a lower kurtosis. In contrast, after the introduction of the MS Globes as well as at the end of the sample, the distribution is narrower and more funds are identified as ESG aware. It might be that the introduction of the globes renders the strategy even more important for active funds who seek ESG momentum opportunities that would benefit their own ratings.

We analyze our sample of 8,549 funds and report the evolution of the proportion of funds which are identified as ESG aware[12] in Figure 7.

[Insert Figure 7 here]

The figure reports that about 58.22 % have been exposed at least at one quarter to the ESG timing strategy during the period 2007-2022. The number of ESG aware funds has increased from about 3.88% of the total sample in 2007 to 13.94% in 2022. On average, the exposition lasts for 1.36 quarters. Looking at ESG aware funds with top globes from Morningstar, so called the aware ESG lovers, the proportion is fairly constant varying from 10 to 14% of all the ESG lovers, where the ESG lover funds represent about 11% of our global sample of active mutual funds after the introduction of Globes in 2018.

4.2. Economic channel

We provide a more direct identification of the behavior of ESG aware funds versus the other types of funds by examining their trades prior an upgrade in score[13]. To do so, we perform an event study on the total number of shares held by ESG aware (and non-aware) investment funds before and after upgrade events. Our database contains the number of shares held by each individual fund for each of their holding stock i at each quarter Q.

For each score upgrade event at quarter Q of stock i, we sum the shares of stock i held by investment funds at quarter Q_i (as the upgrade date is specific to each stock i) as well as over the period $q - Q_i = \tau \ for \ \tau \in [-4; 4]$. We separate the investment funds in two groups G: for each event (upgrade) taking place at quarter Q, we qualify a fund of ESG aware or timer if the fund returns are significantly exposed to the long-short ESG timing strategy at Quarters -1 and -2 according to the Equation (4). Conditioning on two quarters allow us to reduce type I error and false positive when detecting the timers. Other funds are qualified of non ESG aware for

[12] In future updates of this paper, the significance of these proportions will be provided and robust to false discovery using the test developed by Barras et al. (2010) and described in Appendix D.
[13] The case of downgrades will be investigated in future updates of this paper.

that quarter. In total over the period, we detect 3,659 funds with an average of 1,888 funds per event.

We then estimate the following model:

$$Shares_{i,q,f} = \sum_{\substack{\tau \in [-4;4] \\ \tau \neq -1}} \beta_\tau \, 1(q - Q_i = \tau) + \varepsilon_{i,q,f} \tag{5}$$

Where $Shares_{i,q,f}$ is the total number of shares of stock i owned at time q by the funds f of the group G subject to an upgrade event taking place at time Q. β_τ is the vector of coefficients that refers to the incremental number of shares held by all funds over the event period. The reference period is set to Quarter-1. The errors are clustered at stock level and the regression includes quarter fixed effects.

Table 7 and Figure 8 present the results. In Figure 8, fund shareholdings are expressed in million shares.

[Insert Figure 8 here] [Insert Table 7 here]

Looking at Figure 8, Panel A on ESG aware funds, 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. ESG timers owns on average 740,000 more shares a quarter before the upgrade as compared to one year before the upgrade. The additional shares are then rapidly sold on the market from the date of the upgrade. Table 7 provides the coefficients from the event study. All coefficients show up as significantly below the level of shares held by the fund one quarter before the upgrade. The number of shares owned by the ESG aware funds then goes back to normal four quarters after an upgrade. As a comparison, the number of shares owned by the non-aware ESG funds stays constant and not statistically different from zero in the years surrounding the upgrade in ESG score. This suggests that ESG aware funds 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 Figure 9 (details on the regression analysis can be found in Appendix D), we present the same event study analysis separately for small and large caps.

[Insert Figure 9 here]

Figure 9 shows that the timing strategy just described for ESG aware funds are only observable in the segment of the large capitalizations. We do not observe any significant changes around the upgrade for the segment of small caps. One possible explanation is that the strategy is less risky to play in large caps – untabulated results: the L/S timing strategy on small caps deliver a monthly volatility of 0.97% compared to the one (0.66%) in large caps – and given the more frequent upgrades and downgrades for the large cap segment.

As a consequence, the entry date into the strategy for large stocks versus small caps matters even more as the performance rapidly decays over time. This is illustrated in Figure 10 that replicates Figure 5 for small and large stocks.

[Insert Figure 10 here]

This figure shows that when the strategy is delayed – both entry and exit – the alpha disappear for the Big stock (it becomes even negative after 7 days), while it persists further for the Small stocks. This fact is consistent with the idea that there is a pressure on the Big stocks due to ESG aware funds taking position, thus reducing the anomaly, while the anomaly persists on the small stocks since there are not enough arbitrageurs on this segment.

4.3. The case of ESG lovers

We finally investigate under the same empirical set up the case of funds with top ESG ratings (Globes 4 or 5 in MS Direct database). As described in Table 3, this sample represents 1,810 funds over the period 2018-2022. We categorize these funds in the Aware ESG lovers and non-Aware ESG lovers according to their exposure to the ESG timing strategy just before the upgrade. Figure 11 presents the results of the event study for the entire sample of ESG lovers, the sample of unaware funds, and aware funds. The corresponding regression table can be found in Appendix E. Fund shareholdings are expressed in millions.

[Insert Figure 11]

Figure 11, Panel C, considers the case of top ESG rated funds which are exposed to the timing strategy, that is the so-called the Aware ESG lovers. The figure repeats the previous pattern already depicted for the total sample of sample over the period 2007 to 2022 for the period preceding the upgrade. These funds gradually accumulate shares of the stocks with future upgrades. After the upgrade however, the pattern is slightly different from what we observed for the large group. ESG lovers exposed to the timing strategy maintain their investments posterior to the upgrade, which is consistent with a ESG momentum strategy performed by top ESG rated funds.

The contrast is important when looking at Panel B of Figure 11 which displays the same analysis on the subsample of ESG lovers non aware of the potential upgrades. These funds decrease the number of shares by 160,000 shares over the year before the upgrade. At and after the upgrade, we observe that on average, they tend to buy shares of the upgraded stocks. This analysis that could only be performed on a subsample of funds for which the ESG ratings are available suggest a transfer of wealth between aware funds and less sophisticated or values-driven ESG lovers.

4.4. Performance and risk of the ESG awareness

Table 8 presents return and fund statistics about the ESG aware and non-aware funds.

[Insert Table 8 here]

Panel A consider the entire sample. Aware funds tend to have more assets under management (in future version of the paper we will investigate the impact of the timing strategy on fund flows), to present higher return over the period with about the same volatility risk and display higher share turnover. Panel B consider the subsample of ESG lovers separated into the aware and unaware funds. Compared to their peers, the ESG aware & lovers display significantly higher returns and less risk (lower volatility) than the unaware counterparts. The gap is impressive as it constitutes a spread of above 1% monthly for a lower volatility. Consistent with Figure 11 Panel B and C, we also show higher volatility for the non-aware lovers and higher turnover given their active trading before and after the upgrades.

5. Conclusion

Our paper makes the point that sustainability information can remain imperfectly incorporated into prices given the general temporal disconnect between the continuous disclosure of ESG raw indicators and the low-frequency revision of final ESG ratings. We indeed document that updates in raw data command subsequent rating actions and that a LASSO-based forecasting model enables a timing strategy with economically and statistically significant abnormal performance, consistent with delayed attention to ESG information.

Fund-level evidence further supports an information-arbitrage mechanism: ESG-aware active funds accumulate positions ahead of realized upgrades, whereas non-aware funds display little systematic trading around upgrades. The effects are strongly segmented by market capitalization—large-cap stocks exhibit rapid incorporation, while small caps display persistent ESG-related mispricing—highlighting the role of informed arbitrageurs in restoring price efficiency.

These findings have several implications. For investors, the results caution against mechanically relying on low-frequency composite ESG ratings and highlight the value of monitoring underlying indicators. For financial markets, our results underscore the materiality of ESG scores and the market frictions related to lengthy review. For policymakers, while we provide evidence on the importance of disclosure of granular ESG metrics, we also show that it is not sufficient for rapid incorporation of sustainable information into prices.

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Figure 1: ESG scores production process by MSCI

This figure, extracted from "ESG Ratings Process", MSCI ESG Research LLC, April 2024, describes the process followed by MSCI for creating the ESG scores. First, Exposure and Management metrics are considered as the raw data, published first and automatically aggregated into the key issues. Second, the weights of the key issues are published after the methodology committee. Finally, the review committee releases the final score (industry adjusted ESG score).

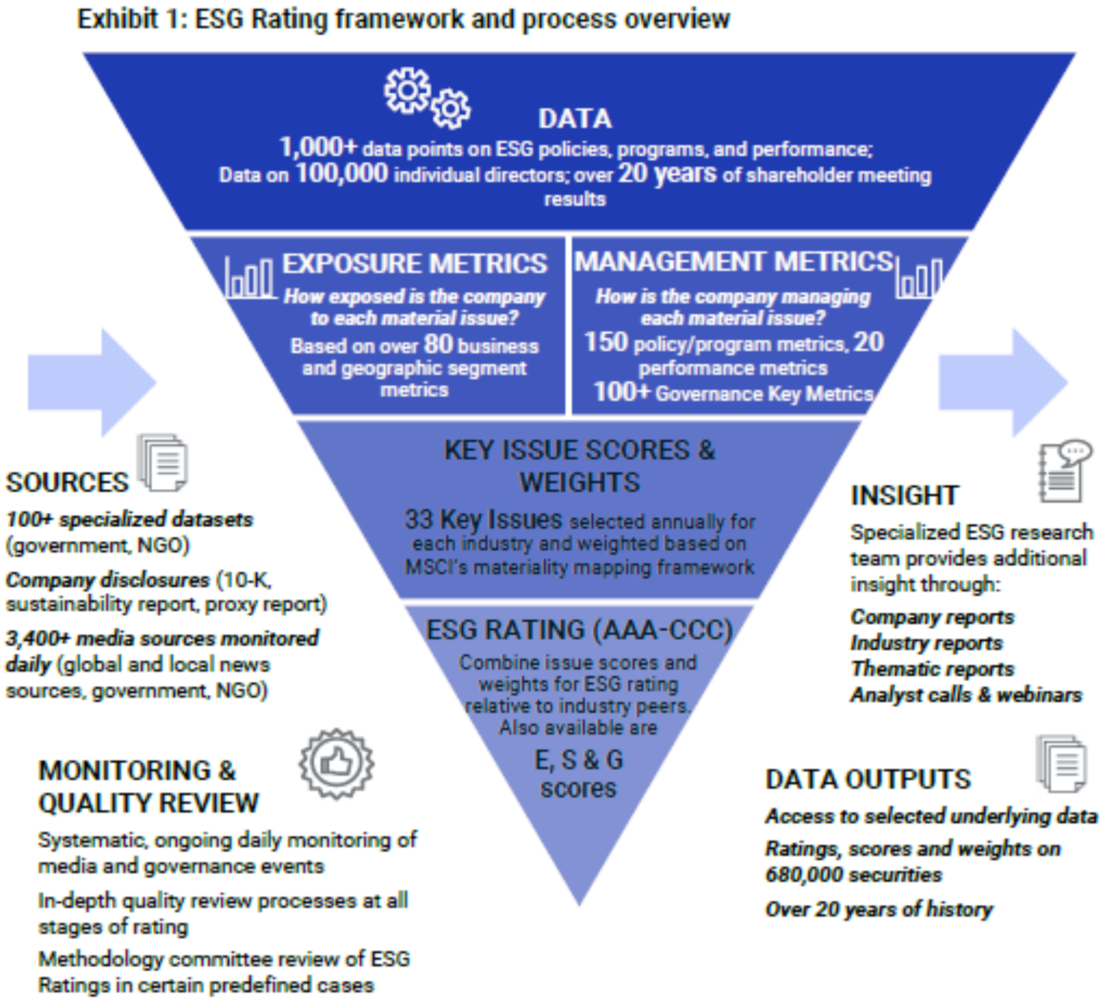


Figure 2: Construction process of MSCI IVA (industry-adjusted) scores

This figure shows the aggregation process of the raw data into final scores provided by MSCI. Raw data (RD). Raw data correspond to the exposure and management scores and are updated throughout the year. At least one of the 105 data points changes every 2 months. This change in RD might trigger a change in the weighted average score provided by MSCI through an update of the weights related to the key issues. This change is decided by the Methodology Committee that meets every 6 to 12 months. The review committee sets the industry weighting and releases the industry adjusted score based on the available average weighted score. The order of the committees is not fixed (review can happen before methodology). This means that up to one year can occur between a change in raw data and the final release of the industry-adjusted score.

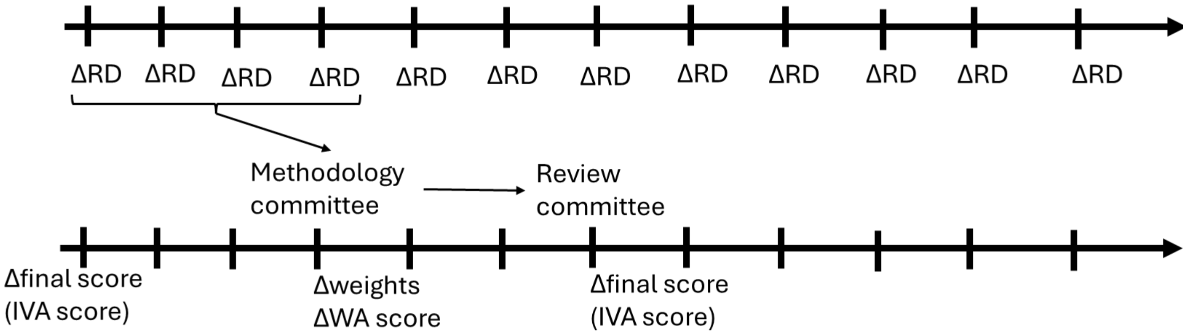


Figure 3: Relationship between underlying data and final scores

This figure shows the relation between the industry-adjusted scores (IVA score) and the weighted average of the key issues (that we called the sub-scores) when the weights are published (after the raw data publication). At the time of the release of the weighted average score, although the final score might not be released yet, it is close to a linear combination of the sub-scores. The correlation between the two is 78.4%.

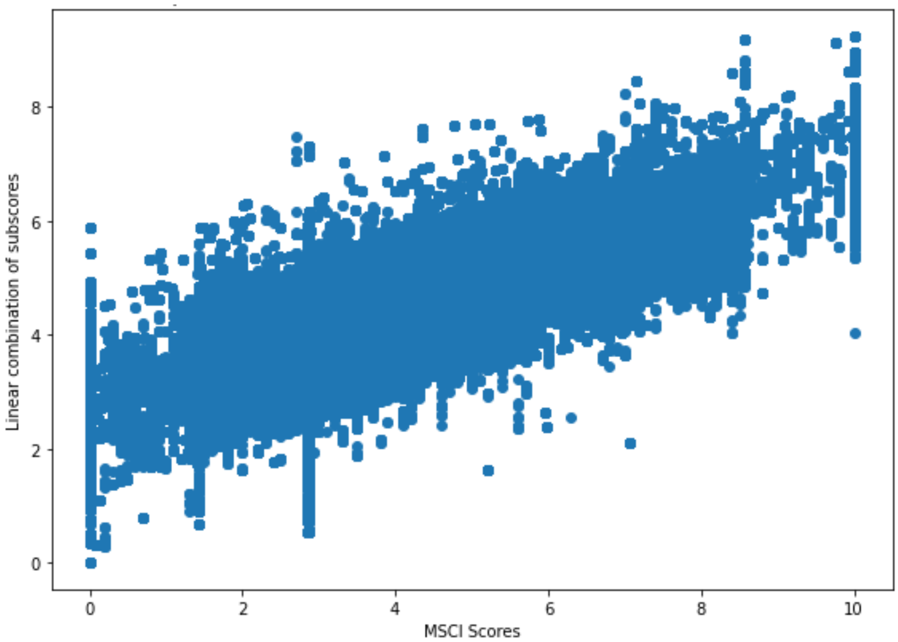


Figure 4: ESG timing strategy

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

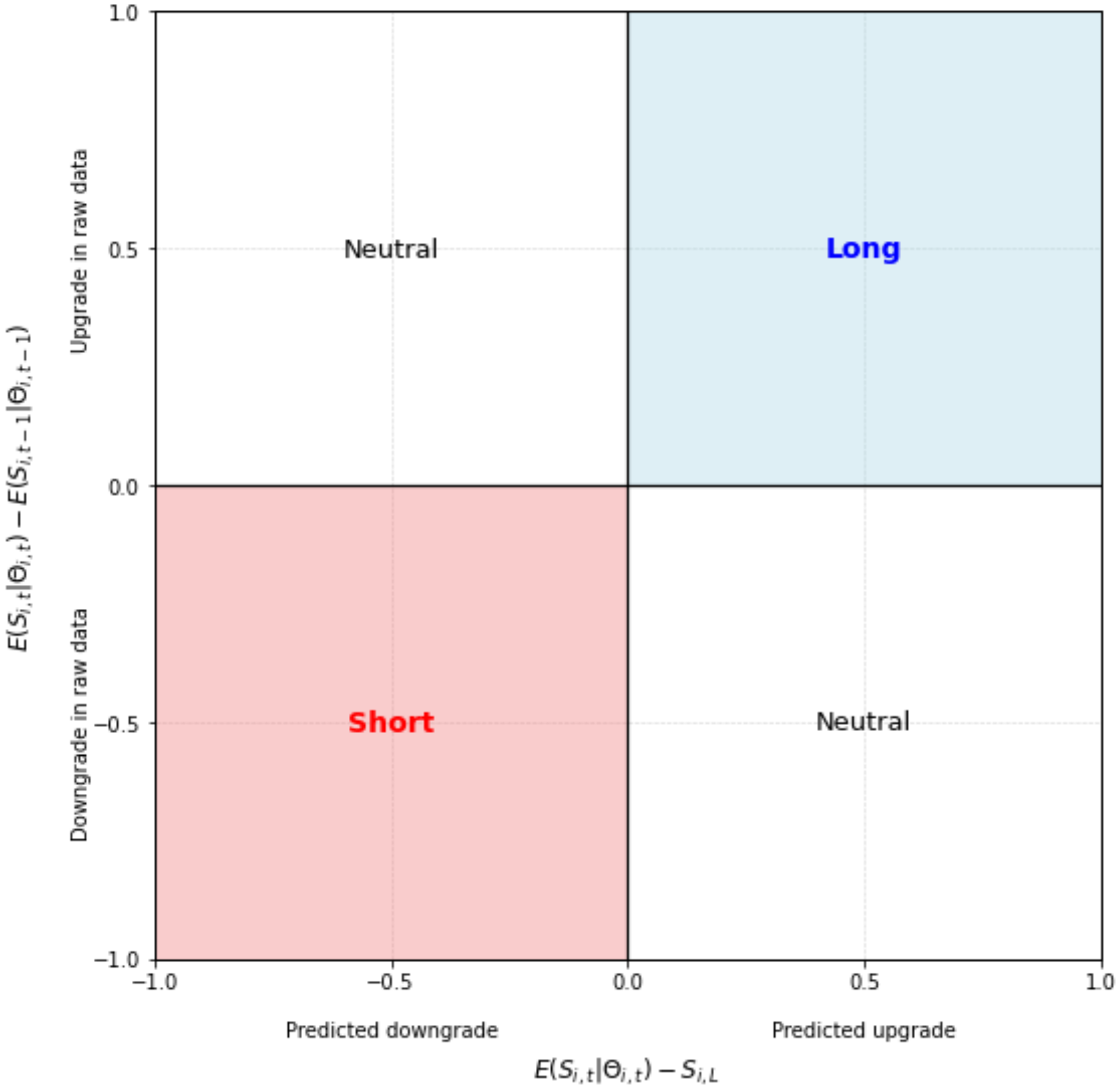


Figure 5: Alpha of the long-short timing strategy with delay in the entry and exit

This figure shows the alpha from the long-short timing strategy defined in Section 3.2. when we introduce a lag in the entry and exit dates. Lags are presented for 0 to 42 trading days.

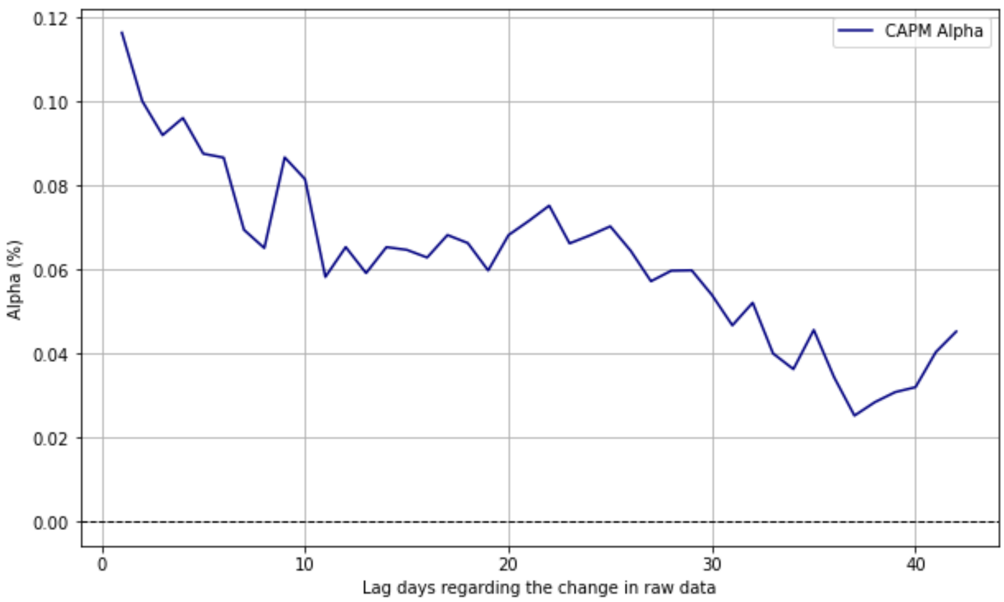
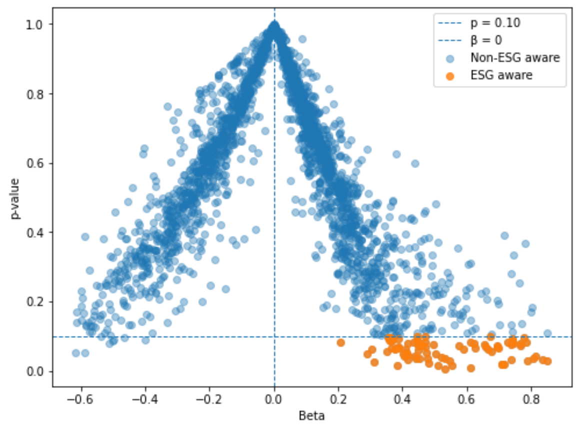


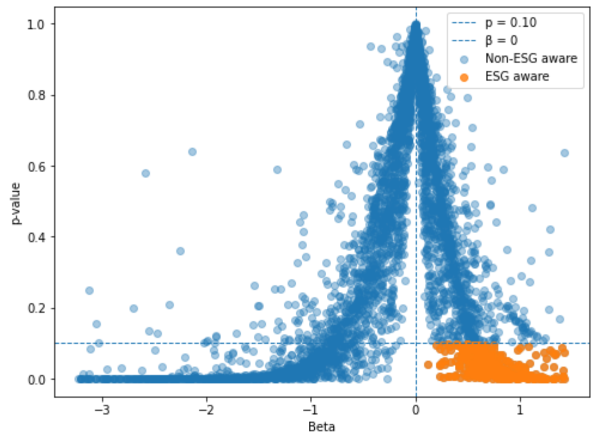
Figure 6: Classification of the ESG aware funds

This graph shows the coefficient β from Equation 4, corresponding to the exposure of the funds the long-short timing strategy and the associated p-value. Panel A presents the distributions at the beginning of the sample, Panel B presents it when the globes are introduced and panel C at the end of the sample. The ESG aware funds (in orange) meet two thresholds: (1) the p-value is below 10% and (2) the exposure coefficient is positive. The betas have been winsorized at 1%.

Panel A: Beginning of the sample (2007)



Panel B: At the time of the instroduction of Globe (2018)



Panel C: End of the sample (2022)

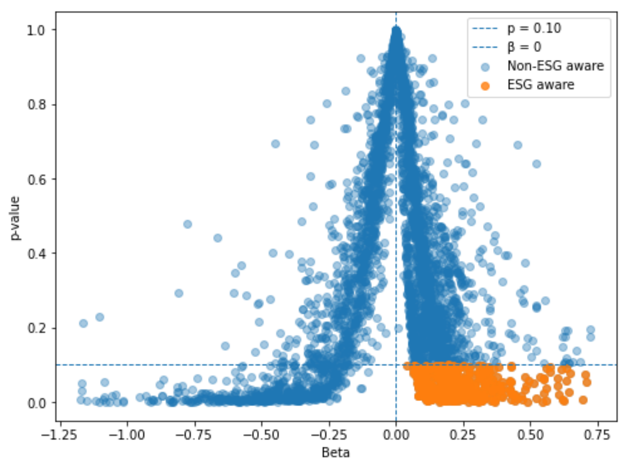


Figure 7: Distribution of ESG aware, unaware and lovers funds

The Figure shows the time evolution of the number of funds which have been qualified as ESG aware (or timers) and/or ESG lovers as well as the other (unaware) funds. ESG aware are defined as the funds which are exposed to the timing strategy at the related period. ESG lovers are defined as the funds which are attributed a high globe (globe 4 or 5). The Morningstar Globes are only available after 2018.

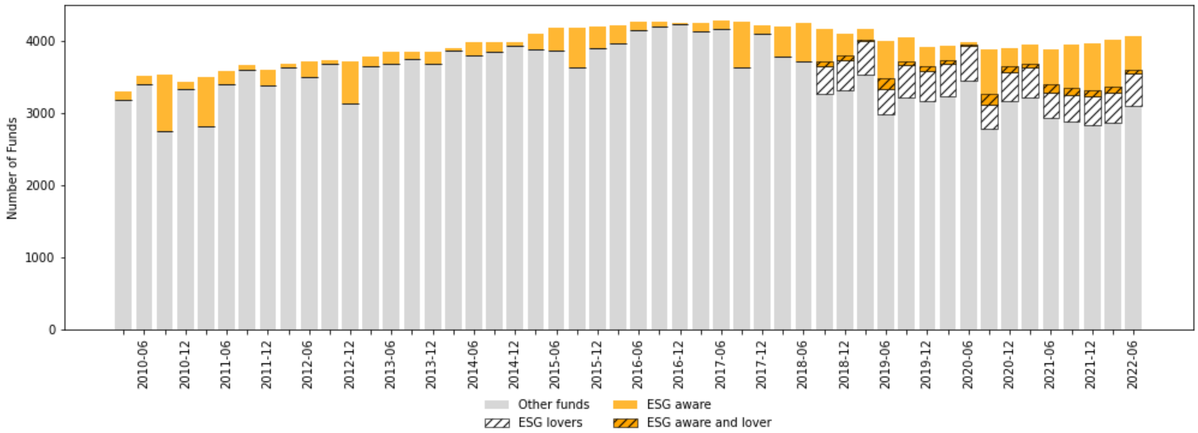


Figure 8: Event study – Fund shareholdings around ESG score upgrades

The figure shows the incremental number of shares (in millions) owned by different groups of funds (namely, the ESG aware timers and the other funds considered as ESG unaware) up to 4 quarters before and after MSCI IVA score upgrade (happening at Quarter Q). The dependent variable is the time series of the sum of the shares held by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

Panel A: ESG aware **Panel B: ESG non-aware**

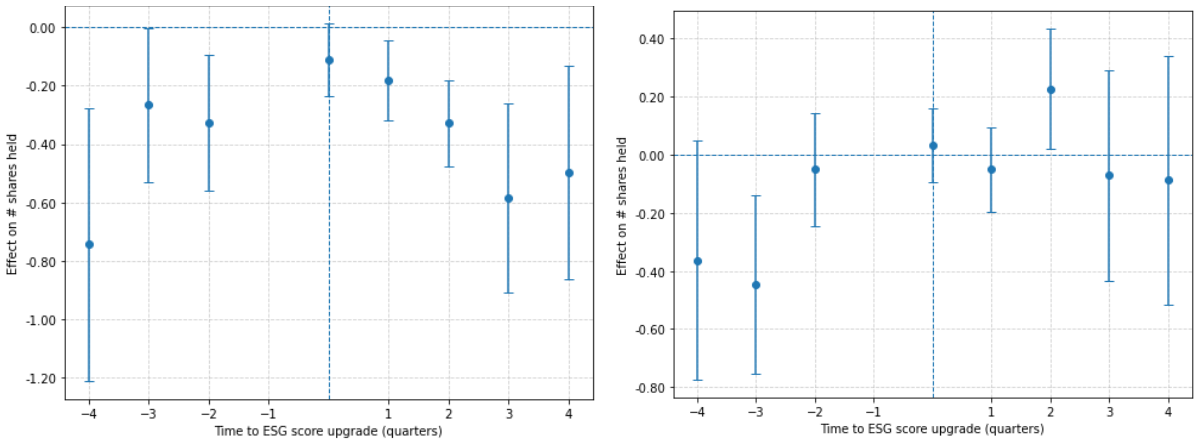
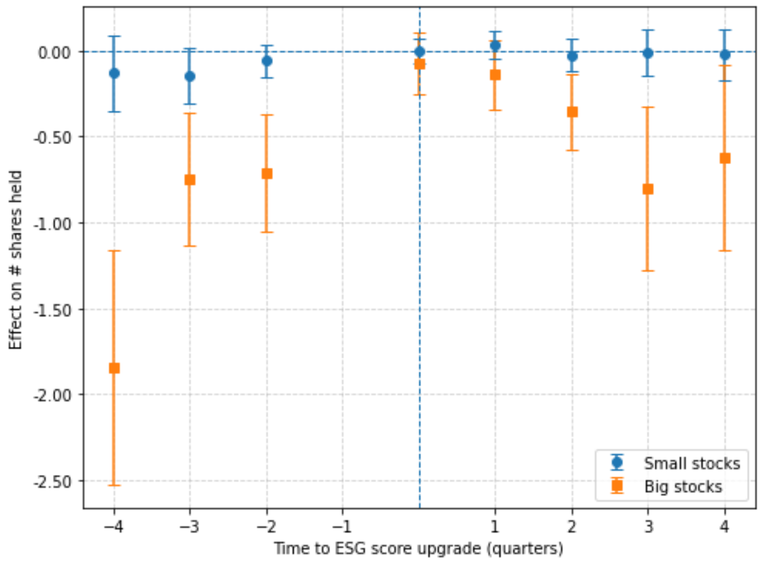


Figure 9: Event study – Fund shareholdings around ESG score upgrades for small and large caps

The figures show the incremental number of shares (in millions) of small and large caps owned by the ESG aware funds and the other funds considered as ESG unaware up to 4 quarters before and after MSCI IVA score upgrade (happening at Quarter Q). The dependent variable is the time series of the sum of the shares hold by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

Panel A: ESG aware



Panel B: ESG non-aware

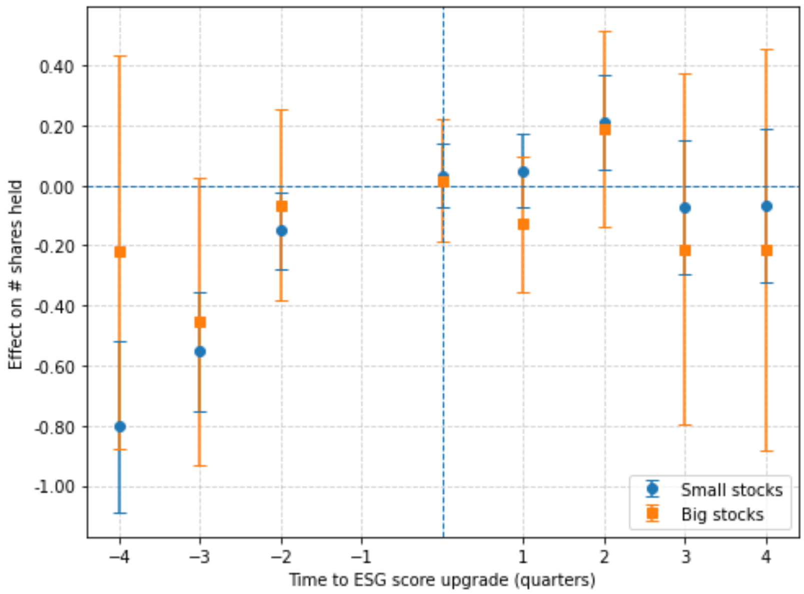


Figure 10: Alpha of the long-short timing strategy with delay in the entry and exit

This figure considers the long-short timing strategy described in Section 3.2 defined separately on small and big caps and shows the alpha from when we introduce a lag in the entry and exit dates. Lags are presented for 0 to 42 trading days.

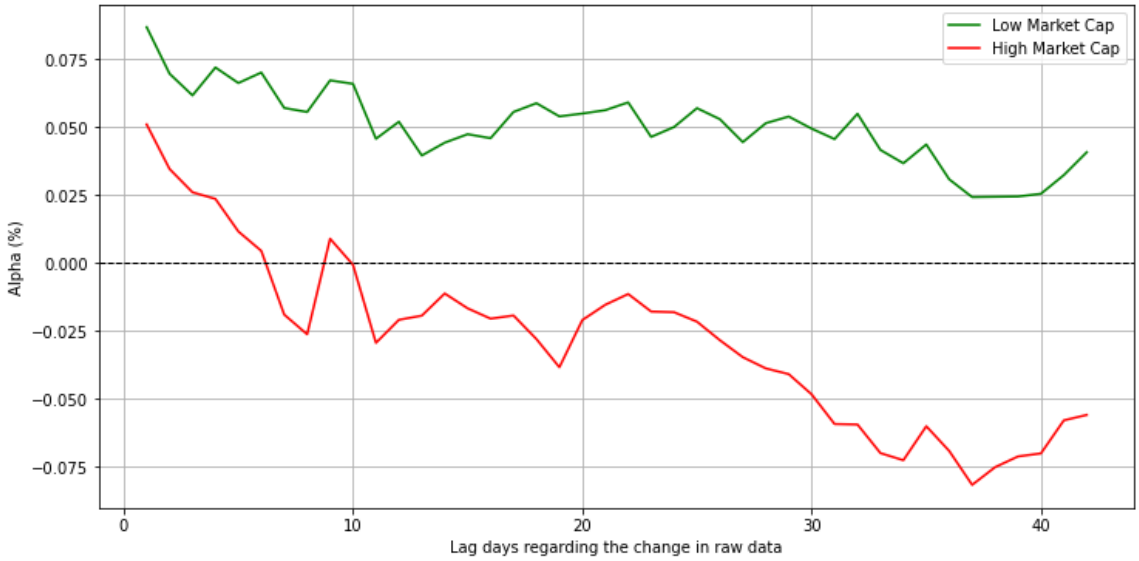
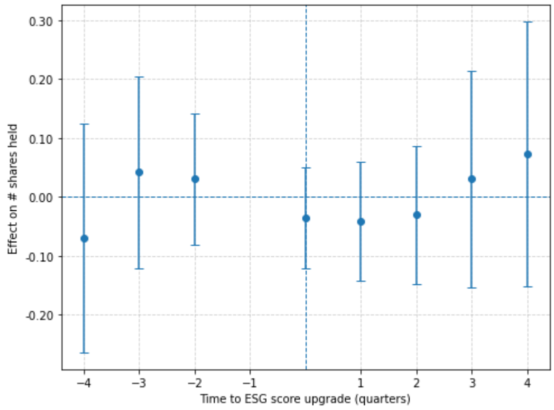


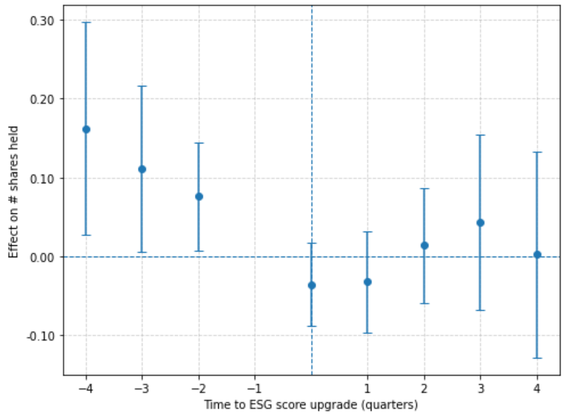
Figure 11: Event study – Fund shareholdings around ESG score upgrades for ESG lovers

The figure shows the incremental number of shares (in millions) owned by ESG lover funds (and independently for the ESG aware timers and the other funds considered as ESG unaware) up to 4 quarters before and after MSCI IVA score upgrade (happening at Quarter Q). The dependent variable is the time series of the sum of the shares held by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

Panel A: ESG lover (All)



Panel B: ESG lover non-aware



Panel C: Aware ESG lovers

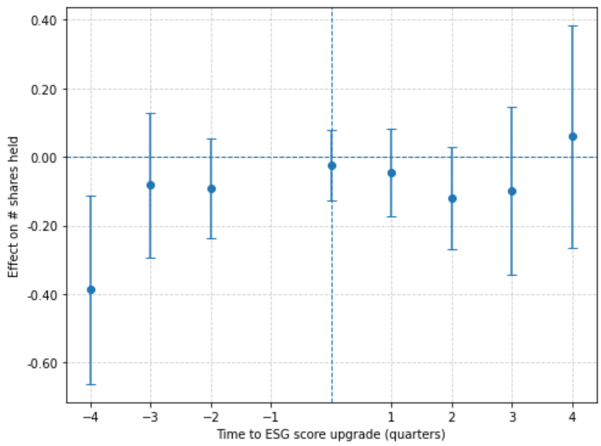


Table 1: Summary statistics - Stocks

This table displays the summary statistics for the sample of stocks from CRSP/Computstat dataset and 13F (Panel A) corresponding to stocks traded on the US stock exchanges (New York Stock Exchange, AMEX, or NASDAQ corresponding to exchange codes 11, 12, and 14). Following Fama and French (1996), we remove financial companies corresponding to sic codes 6000 to 6999. We also provide summary statistics for the subample merged with MSCI (Panel B). Our sample covers the period February 2007 to October 2022 and every variable is winsorized at the 1%.

Panel A: CRSP/Compustat data

	1^{st} percentile	1st Quarter	Median	mean	3rd Quarter	99^{th} percentile	Nb firms	Nb periods	Nb Obs
Return (%)	-0.45	-0.08	0.00	0.01	0.08	0.66	10,659	189	995,508
Market Cap (million $)	0.01	0.09	0.41	5.09	1.87	87.66	10,659	189	995,508
Book to Market ratio (%)	0.00	0.01	0.03	0.05	0.07	0.34	10,659	189	995,508
Institutional ownership (%)	0.00	6.09	50.24	47.31	81.61	112.29	10,659	189	995,508

Panel B: CRSP/Compustat data merged with MSCI

	1^{st} percentile	1st Quarter	Median	mean	3rd Quarter	99^{th} percentile	Nb firms	Nb periods	Nb Obs
Return (%)	-0.32	-0.05	0.01	0.01	0.07	0.40	3,063	189	233,822
Market Cap (million $)	0.20	0.95	2.72	13.85	8.75	198.87	3,063	189	233,822
Book to Market ratio (%)	0.00	0.02	0.03	0.04	0.05	0.19	3,063	189	233,822
Institutional ownership (%)	16.78	71.75	85.09	80.76	93.72	112.29	3,063	189	233,822

Table 2: Mutual fund database

This table displays the summary statistics for two subsamples of the CRSP mutual fund database over the period 2007 to 2022. Panel A presents the passive equity funds. Panel B presents the active equity funds. The statistics include the average monthly returns, assets under management (size), age of the fund, the management fees, and turnover (source: CRSP mutual funds). All numerical variables are winsorized at 1%. As a fund can move from the passive to the active category, the sum of the number of funds can exceed 10,753.

Panel A: CRSP passive equity mutual funds

	1st percentile	Median	mean	99th percentile	Nb periods	Nb funds	Nb Obs
Monthly return (last month of the quarter) (%)	-14.03	0.65	0.11	10.17	62	2,698	69,036
Total net assets (Million $)	0.50	145.40	2052.96	34,824	62	2,698	69,036
Age (Months)	3.00	78.00	89.64	252.00	62	2,698	69,036
Fees (%)	0.00	0.39	0.39	1.16	62	2,698	69,036
Turnover (%)	1.00	24.00	51.32	638.00	62	2,698	69,036

Panel B: CRSP active equity mutual funds

	1st percentile	Median	Mean	99th percentile	Nb period	Nb funds	Nb Obs
Monthly return (last month of the quarter) (%)	-14.03	0.69	0.34	10.17	62	8,549	234,833
Total net asset (Million $)	0.10	69.80	887.31	14,687.59	62	8,549	234,833
Age (month)	3.00	102.00	109.47	261.00	62	8,549	234,833
Fees (%)	0.00	0.68	0.63	1.59	62	8,549	234,833
Turnover (%)	1.00	50.00	77.96	635.00	62	8,549	234,833

Table 3: ESG lover and non-ESG lover database

This table displays the summary statistics for the active US equity funds with a Morningstar globe. Panel A presents statistics for the ESG lovers (i.e. the funds which a MS globe of 4 or 5) and non-ESG lover funds (other funds with a globe) over the period 2018 to 2022. The statistics are provided by CRSP mutual funds. All numerical variables are winsorized at 1%.

Panel A: ESG lover funds

	1st percentile	Median	mean	99th percentile	Nb periods	Nb funds	Nb Obs
Monthly return (last month of the quarter) (%)	-14.03	0.79	-0.36	9.12	16	157	2,215
Total net assets (Million $)	2.20	317.00	1,723.51	21,419.29	16	157	2,215
Age (Months)	6.00	219.00	175.77	267.00	16	157	2,215
Fees (%)	0.00	0.69	0.67	1.50	16	157	2,215
Turnover (%)	1.00	32.00	44.12	221.07	16	157	2,215

Panel B: Non-ESG lover funds

	1st percentile	Median	Mean	99th percentile	Nb period	Nb funds	Nb Obs
Monthly return (last month of the quarter) (%)	-14.03	0.65	-0.53	9.59	16	1,653	24,336
Total net assets (Million $)	2.00	347.35	3,079.11	50,538.07	16	1,653	24,336
Age (month)	6.00	219.00	175.65	267.00	16	1,653	24,336
Fees (%)	0.00	0.63	0.60	1.53	16	1,653	24,336
Turnover (%)	2.00	37.00	52.24	264.00	16	1,653	24,336

Table 4: Performance of the prediction models

This table presents performance indicators of two prediction models of the future IVA score. The first method is a lasso based on the raw data (management and exposure scores). The second is a linear combination of the key issues based on the weights released with a lag with regard to the raw data. The performance metrics are the R-squared of the regression of the actual score over its prediction, the Mean Absolute Error and Root Mean Square Error.

	Prediction vs. actual ESG score					
	Prediction using the lasso			Prediction using the linear combination		
	Entire sample	Big	Small	Entire sample	Big	Small
R-squared	38%	0.39%	35%	61%	61%	58%
MAE	1.52	1.52	1.45	1.09	1.10	1.01
RMSE	1.99	2.00	1.91	1.36	1.37	1.25
Average month between signal and upgrade	14.41	14.34	15.31	13.14	13.11	13.66
Average month between signal and downgrade	17.33	17.02	20.35	15.31	15.29	15.66
Total observations	233,822	116,911	116,911	233,822	116,911	116,911

Table 5: Cox model on MSCI IVA score updates

This table tests the variables that influence the instantaneous risk of an upgrade in the MSCI IVA score. The table considers the investment signal generated from the lasso algorithm, the firm size, its institutional ownership and the issuer coverage of ESG data providers. An investment signal is defined as an improvement (resp. deterioration) in raw data such that the prediction from the lasso is superior (resp. inferior) to the actual score. A positive β indicates that the variable increases the instantaneous risk of an upgrade with, while it decreases when β is negative.

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Panel A: Upgrade events

	Timing of the IVA score upgrade	
Predicted upgrade	0.12*** (19.64)	0.23*** (7.00)
Predicted upgrade × Big		-0.22*** (-8.53)
Predicted upgrade × High InstOwn		-0.005 (-0.22)
Predicted Upgrade × Nb of providers		0.04*** (8.87)
Big	0.44*** (43.51)	0.46*** (42.40)
High InstOwn	0.23*** (23.89)	0.24*** (22.16)
Nb of providers	0.12*** (69.52)	0.23*** (7.00)
Number of events	41,680	41,680
Total observations	236,521	236,521

Panel B: Downgrade events

	Timing of the IVA score downgrade	
Predicted downgrade	0.11*** (19.14)	-0.09*** (-3.01)
Predicted downgrade × Big		0.10*** (4.31)
Predicted downgrade × High InstOwn		0.04* (1.71)
Predicted downgrade × Nb of providers		0.03*** (6.49)
Big	0.36*** (33.95)	0.31*** (26.40)
High InstOwn	0.09*** (8.68)	0.08*** (7.38)
Nb of providers	-0.02*** (-10.63)	-0.03*** (-12.50)
Number of events	55,480	55,480
Total observations	236,521	236,521

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

Table 6: Performance of the ESG timing strategy using the lasso and combination of key issues

This table compares the performance of three strategies. Column (2) reports the long-short strategy exploiting the investment signal (potential upgrade or downgrade) from our lasso at the release of the raw data. Column (3) performs a similar strategy at the time of the release of the weighted-average score and the key issues weights. The strategy is based on the discrepancy between the weighted-average score and the final industry-adjusted score. Column (4) provides the performance of a strategy that consists of taking position after the score update and exiting the investment twelve months later. The model includes the classical Fama-French factors (market, size, value, profitability, investment) along with momentum. The alphas are reported with their t-stat in parenthesis.

	L/S strategy		Holding stock for 12 months after the update
	Lasso prediction	Linear combination prediction	L/S strategy post-update
Equal-weighted returns			
Average excess return	0.10** (2.57)	0.19 (1.11)	0.05 (0.94)
CAPM alpha	0.13*** (3.12)	0.04 (0.23)	0.11* (1.72)
Three-factor (FF) alpha	0.12*** (3.21)	0.09 (0.55)	0.09 (1.47)
Five-factor (FF) alpha	0.13*** (3.46)	0.09 (0.71)	0.09 (1.58)
Six-factor (FF+Mom) alpha	0.12*** (3.17)	0.11 (0.84)	0.08 (1.45)

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

Table 7: Event study – Fund shareholdings around ESG score upgrades The table shows the incremental number of shares (in millions) owned by the ESG aware funds and the other funds considered as ESG unaware up to four quarters before and after MSCI IVA score upgrade (happening at Quarter Q). The dependent variable is the time series of the sum of the shares held by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

	Total number of shares (in Millions)	
	ESG aware	ESG non-aware
Quarter -4	-0.74*** (-3.11)	0.44 (-0.28)
Quarter -3	-0.27** (-1.97)	-1.14 (-0.98)
Quarter -2	-0.33*** (-2.74)	1.17 (1.43)
Quarter 0	-0.10* (-1.73)	-0.36 (-0.67)
Quarter 1	-0.18*** (-2.60)	-1.28* (1.94)
Quarter 2	-0.33*** (-4.38)	-0.31 (-0.40)
Quarter 3	-0.58*** (-3.52)	-0.72 (-0.54)
Quarter 4	-0.50*** (-2.67)	0.47 (0.28)
ln(MarketCap)	3.12*** (8.57)	-1.83 (-1.06)
Institutional ownership	0.04*** (13.81)	0.0001*** (7.70)
Constant	-70.09*** (-10.22)	26.96*** (10.04)
Fixed effects	Quarter	Quarter
R2	0.78	0.27
F-stat	6.21***	20.50***
Observations	44,219	44,219

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

Table 8: Summary statistics for the aware and unaware funds

This table shows the average monthly returns (in %), volatility (in %), total net assets, age, fees and turnover ratio for the sample of aware and unaware funds. We provide a t-test for the difference between the two subsamples. Sample period is 2007-2022 for Panel A (Entire sample- and 2018-2022 for Panel B (Sample of ESG lovers with top MS Globes).

Panel A: Entire sample

	Entire sample	ESG aware	ESG non-aware	Difference between aware and non-aware
Monthly Returns (%)	0.34	0.78	0.30	0.48*** (13.01)
Volatility (%)	4.13	4.09	4.14	-0.04*** (-3.24)
Total net assets (Million $)	887.31	962.45	880.94	81.52** (2.44)
Age (month)	109.47	119.22	108.65	10.57*** (18.30)
Fees (%)	0.63	0.64	0.63	0.01*** (3.94)
Turnover (%)	77.96	80.05	76.57	3.49*** (4.11)

Panel B: ESG lover

	Entire sample	ESG aware	ESG non-aware	Difference between aware and non-aware
Monthly Returns (%)	-0.36	0.54	-0.52	1.06*** (6.66)
Volatility (%)	4.13	3.87	4.17	-0.31*** (-8.86)
Total net assets (Million $)	1,693.78	2,217.30	1,601.54	615*** (2.99)
Age (month)	178.80	172.73	179.87	-7.14*** (-2.72)
Fees (%)	0.69	0.63	0.70	-0.07*** (-7.43)
Turnover (%)	44.67	40.41	45.41	-5.00*** (-3.73)

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

APPENDICES

Appendix A: Non-financial report and ESG score update

This Appendix shows the timing of the release of the last ESG report/ESG filings available in Capital IQ (these reports take various names such as sustainability report, ESG report, non-financial report, …) and the first ESG rating change after this specific report

Company	Last ESG report	First update following the report
Apple	September 2024	December 2024
Nvidia	June 2024	May 2025
Microsoft	October 2024	February 2025
Amazon	December 2023	July 2024
Alphabet	July 2024	July 2024
Broadcom	October 2023	May 2024
Tesla	December 2023	August 2024
Berkshire Hathaway	July 2024	April 2025
Lilly	December 2023	September 2024
Walmart	January 2024	December 2024
JP Morgan Chase	June 2024	December 2024
Visa	July 2024	June 2025
Oracle	October 2024	December 2024
Mastercard	December 2023	October 2024
Exxon Mobil	December 2023	May 2024
Johnson & Johnson	September 2024	August 2025
Palantir	June 2024	May 2025
Bank of America	October 2024	September 2025
AbbVie	December 2023	November 2024
Netflix	December 2023	May 2024
Costco	September 2023	April 2024
Advanced Micro Devices	August 2024	May 2025
Home Depot	October 2024	November 2024
Procter and Gamble	June 2024	September 2024
Micron Technology	June 2024	February 2025
Cisco	July 2023	May 2024
Coca cola	December 2023	January 2024
Chevron	August 2024	September 2024
Wells Fargo	August 2024	August 2025
Morgan Stanley	October 2024	September 2024

Appendix B: List of raw variables

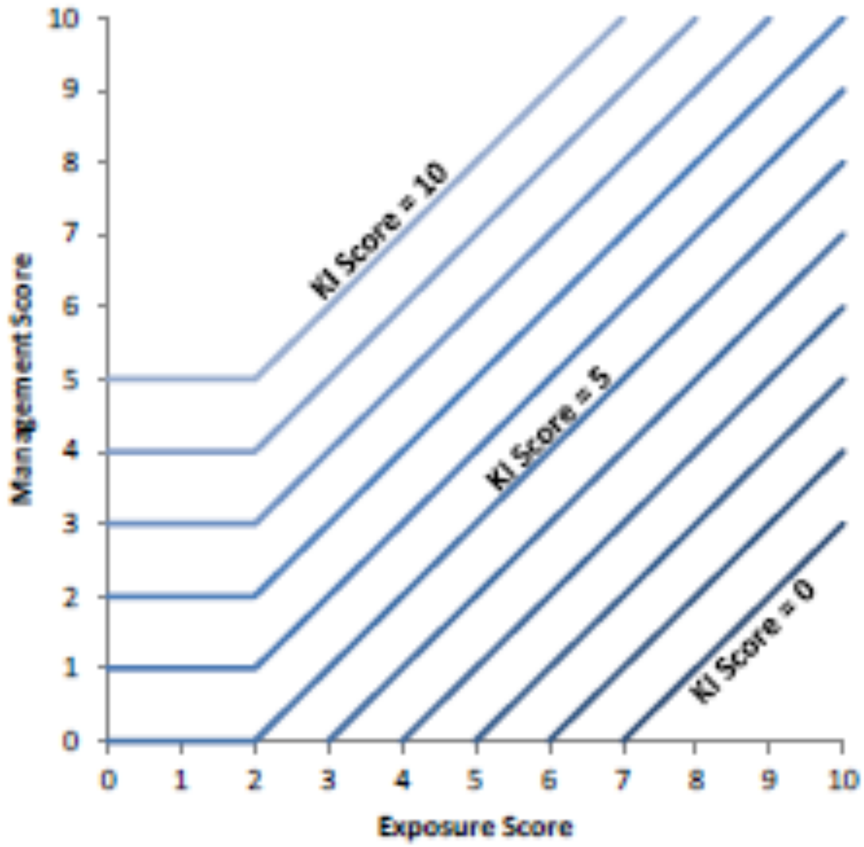
This Appendix gives the list of the variable we use for the prediction (namely the raw variables). They correspond to the exposure and management score given by MSCI

Access to communication
Access to finance
Anticompetitive practices
Biodiversity and land use
Business ethics and fraud
Carbon emissions
Chemical safety
Controversial sourcing
Corporate governance
Corruption and instability
Energy efficiency
Environmental opportunities
Environmental waste
Financial system instability
Financing environment impacts
Financial product safety
Health and safety
Human capital development
Climate change vulnerability
Insuring health and demographic risk
Labor management
Natural resources use
Opportunities in clean technology
Opportunities in green buildings
Opportunities in nutrition and health
Opportunities in renewable energy
Packaging materials and waste
Privacy data security
Product carbon footprint
Product safety and quality
Raw material sourcing
Responsible investment
Social opportunities
Stakeholder oppositions
Supply chain labor
Toxic emissions and waste
Waste management
Water stress

Appendix C: Aggregation of the exposure and management score into the key issue
This figure, retrieved from MSCI Methodology, shows the process used to transform the exposure and management score into key issues. The equation stands as follows:

$$Keyissuescore = 7 - (max(exposure, 2) - management)$$

This new score is then constrained between 0 and 10 and rounded to one decimal



Appendix D: Event study – Fund shareholdings around ESG score upgrades for small and big caps

The table shows the incremental number of shares owned by different groups of funds (namely, the ESG aware timers and the other funds considered as ESG unaware) up to 4 quarters before and after MSCI IVA score upgrade (happening at Quarter Q) and the interaction with a dummy equal to 1 for the stock with an above median market capitalization. The dependent variable is the time series of the sum of the shares hold by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

	Total number of shares	
	ESG aware	ESG non-aware
Quarter -4	-0.13 (-1.15)	-0.80*** (-5.50)
Quarter -3	-0.14* (-1.76)	-0.55*** (-5.41)
Quarter -2	-0.59 (-1.20)	-0.15** (-2.31)
Quarter 0	-0.000 (-0.02)	0.03 (0.61)
Quarter 1	0.03 (0.86)	0.05 (0.80)
Quarter 2	-0.02 (-0.53)	0.21*** (2.64)
Quarter 3	-0.01 (-0.21)	-0.07 (-0.62)
Quarter 4	-0.02 (-0.32)	-0.07 (-0.52)
Quarter -4*Big	-1.71*** (-5.05)	0.58* (1.74)
Quarter -3*Big	-0.60*** (-3.01)	0.10 (0.40)
Quarter -2*Big	-0.65*** (-3.67)	0.08 (0.49)
Quarter 0*Big	-0.08 (-0.77)	-0.02 (-0.14)
Quarter 1*Big	-0.18 (-1.47)	-0.18 (-1.38)
Quarter 2*Big	-0.33*** (-2.57)	-0.02 (-0.11)
Quarter 3*Big	-0.79*** (-3.04)	-0.14 (-0.45)
Quarter 4*Big	-0.60** (-2.07)	-0.15 (-0.41)
Big	3.82*** (8.04)	4.98*** (8.08)
Institutional ownership	0.05*** (16.67)	0.04*** (11.45)
Constant	-24.49*** (-6.57)	14.72*** (8.70)
Fixed effets	Quarter	Quarter
R2	0.76	0.66
F-stat	5.12***	13.02
Observations	44,219	44,219

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

Appendix E: Event study – Fund shareholdings around ESG score upgrades for ESG lovers

The table shows the incremental number of shares owned by ESG lover funds (and independently for the ESG aware timers and the other funds considered as ESG unaware) up to 4 quarters before and after MSCI IVA score upgrade (happening at Quarter Q). The dependent variable is the time series of the sum of the shares held by the funds which have been ESG aware in -1 and -2, i.e. have a significant loadings on the L/S strategy defined in Section 3.2. We consider only the positive number of shares (i.e. sum of long positions). We use Quarter-1 is the reference category. Errors are clustered at the stock level.

	Total number of shares (Million)		
	ESG lover	ESG lover non aware	Aware ESG lover
Quarter -4	-0.07 (-0.71)	0.16** (2.34)	-0.39*** (-2.76)
Quarter -3	0.04 (0.50)	0.11** (2.06)	-0.08 (-0.76)
Quarter -2	0.03 (0.53)	0.08** (2.18)	-0.09 (-1.25)
Quarter 0	-0.04 (-0.84)	-0.04 (-1.31)	-0.02 (-0.48)
Quarter 1	-0.04 (-0.80)	-0.03 (-1.31)	-0.04 (-0.69)
Quarter 2	-0.03 (-0.51)	0.01 (0.37)	-0.12 (-1.58)
Quarter 3	0.03 (0.32)	0.04 (0.77)	-0.10 (-0.78)
Quarter 4	0.07 (0.64)	0.002 (0.03)	0.06 (0.36)
ln(MarketCap)	0.93*** (9.17)	0.34*** (6.30)	0.86*** (7.15)
Institutional ownership	0.001*** (8.91)	0.002*** (4.29)	0.001*** (9.25)
Constant	-11.52*** (-8.40)	-3.37*** (-4.58)	-12.02*** (-6.76)
Fixed effects	Quarter	Quarter	Quarter
R2	0.62	0.26	0.61
F-stat	14.70***	12.89***	7.69***
Observations	44,219	44,219	44,219

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