

# ESG Investing and Stock Price Informativeness \*

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## Abstract

I study how ESG mutual fund holding affects firms' stock price informativeness. I utilize the change in methodology of MSCI ESG Leader Index as a quasi-exogenous shock in the level of ESG investor holdings. I show that after the treatment, stocks of firms excluded from the index are more informative about financial outcome and less informative about ESG outcome, compared with the control group. The predicting power of price for future variation in earnings increases while it decreases for CO2 emission. I show that the change in price informativeness is probably driven by traditional investors trading against ESG investors. The findings are consistent with the theory prediction in Goldstein et al. (2022).

**Keywords:** Environmental Social and Governance, Price Informativeness

**JEL classification:** G12, G14

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# 1 Introduction

Recently, the financial industry has witnessed one of the most rapidly burgeoning trends focusing on the environmental, social and governance (ESG) issues. A very significant aspect of this trend is that more and more institutional investors explicitly incorporate ESG related principles into their investment strategies. In 2020, about \$17.1 trillion assets were invested in sustainable investing assets, counting 33.2% of total managed assets in the US (GSIA, 2021). This trend of changing investor composition has the potential to fundamentally alter the equilibrium outcome of the financial market.

As suggested by Hayek (1945), one of the key fundamental functions of the financial market is to produce and aggregate information of the underlying assets traded. How informative the prices are is not only an important question for investors in the secondary market, but also has real implications by affecting firms' cost of capital and decision-making of the actively learning agents. In the traditional view of the financial market, participants all have the same pecuniary objective that focuses on the future cash flows of the assets. However, with ESG investors who care more than monetary payoff rapidly increase their participation in the market, the implications from stock prices could dramatically vary and how the informativeness of price changes needs to be investigated.

In this paper, I examine how stock price informativeness changes in response to ESG investing. To measure price informativeness of stock prices, I adapt the frame work from Bai, Philippon and Savov (2016). The measure in Bai, Philippon and Savov (2016) is a welfare-based measure developed from standard Q-theory in Hayashi (1982). They derived expressions for the forecasting power of price for future cash flow and investment, which Bond, Edmans and Goldstein (2012) refer as forecasting price efficiency (FPE) and revelatory price efficiency (RPE) respectively. I follow the modification of the measure in Kacperczyk, Sundaresan and Wang (2021) so that the measure can be estimated in the difference-in-difference setting.

It remains a challenge to identify the casual effect of ESG ownership on stock price informativeness empirically. On one hand, the proportion of ESG ownership of firms is not randomly assigned. ESG funds choose their positions in firms strategically (Friedman and Heinle, 2021; Heath et al., 2021) and they endogenously select firms with better environmental and social performance. Thus certain firm characteristics such as its production technology and greenness would affect the total ESG ownership of the firm. On the other hand, the same fundamentals could simultaneously affect how informative the stock of the firm is. For instance, there is evidence that larger stocks and stocks with higher institutional ownership are more informative (Bai, Philippon and Savov, 2016; Farboodi et al., 2022; Dávila and Parlato, 2022).

To tackle the endogeneity issue, I utilize a quasi-natural experiment that affects holdings of certain ESG funds to perform a difference-in-difference analysis. In May 2018, MSCI, one of the major ESG rating providers and the largest provider for ESG index (MSCI, 2020), changed the methodology of one of its earliest ESG indexes, the MSCI ESG Leader index. Before the change, the firms that meet the criteria for inclusion in the index consisted of all firms with rating of “B” or above. In May 2018, MSCI modified this rule and requires only firms with rating “BB” or above to be included in the ESG Leader Index. As a result of this change, "B" rated firms were excluded from the index. Consecutively, ESG funds that track MSCI ESG Leader index have to divest from those “B” rated firms. I utilize this index methodology change as a quasi-exogenous shock to firms’ ESG ownership and hence use a DID framework to identify the effect of the ESG index exclusion on stock price informativeness.

To mitigate the concern that differences in firm characteristics between the treated and control group are driving the results, I perform propensity score matching to find the best control group for DID analysis. Following the design of Kacperczyk, Sundaresan and Wang (2021) and Cao et al. (2022a), for each treated firm in the sample, I identified five closest neighbors from the control group using propensity score matching method. I show that the

matching quality is relatively high by comparing the mean difference of variables used in the matching for the treated and matched control group. In addition, I show evidence that the shock was not anticipated or enforced by related parties. Parallel trend assumptions are also verified using fully dynamic specifications of the treatment effect.

I then investigate the impact of ESG index exclusion on stock price informativeness. Based on the theory prediction of Goldstein et al. (2022), when the share of ESG investors in the market decreases, traditional investors who only care about financial outcome would trade against the ESG investors and reveal more private information they have, resulting in higher price informativeness regarding future financial outcome. When firms are excluded from an ESG index, investors who track that index would have to divest from the stocks of the excluded firms and the share of ESG investors in those stocks would decrease. Therefore, compared with the firms not affected, stock prices of firms that are excluded from the ESG index should possess more information about future financial outcomes after the ESG index exclusion.

The main empirical results support the above argument. I find that price informativeness of financial outcome becomes higher for the treated group after the ESG index exclusion. The treated group stock prices have greater power in predicting variation in future earnings (higher FPE), compared with the control group, and the effect is economically significant.

I then verify that the index exclusion reduces ESG funds' holding of the excluded firms. I find that after the index exclusion, both the total holding of all ESG funds and the total holding of all ESG index funds for the treated firms decrease compared to the control firms, indicating that ESG funds divest from the firms that were excluded from the index. The divestment from ESG funds amounts to about 33% of sample mean of total ESG holding and the ESG index funds holding reduce approximately 27%.

To further examine the reduction in ownership by ESG index funds, I investigate how the probability of a firm being included by funds that track MSCI related indexes changes.

The results show that after the index exclusion, treated firms are 30% less likely to be held by any index funds that track MSCI ESG indexes, while in the whole sample, the mean of this variable is 48%. Additionally, I check how the probability of a firm being included by funds that track MSCI ESG Leader index changes. The reduction in probability is 4.4%. Given the sample mean of 4.5%, this index exclusion basically induces all funds that track MSCI ESG Leader index to dump their holdings on the treated firms relative to the matched control firms.

Since Index exclusion could not only change the composition of the investors, but also alter the total level of institutional ownership, which in turn affects price informativeness of the treated firms relative to the controls, I then investigate how the behavior of all institutional investors changes. I find that the index exclusion did not cause significant change of total institutional ownership in the difference between treated and control group. I further check the holding of non-ESG and non-index funds and find a positive but statistically insignificant effect of the treatment, providing some evidence that traditional investors indeed trade in different direction against ESG investors, and as a result, increase the forecasting power of stock prices of treated firms on future variation in cashflow.

After that, I check whether the increase in price informativeness of the treated firms stems from change in their stock's total volatility. I find no evidence that the difference of total volatility between treated and control group is driving the results. I further verify that if traditional investors are trading more actively on the treated stocks relative to the control group. I find that the treated firms' stocks become more liquid compared with the matched control group after the treatment. However, the differences in turnover and volume between the treated and control group do not change. In addition, I inspect another measure of price informativeness used extensively in previous literature, non-synchronicity, and find that after the ESG index exclusion, the stock price of excluded firms become more informative.

In the robustness section, I also include a relatively less formal test using the MSCI ESG

Leader Index exclusion shock as an instrument variable (IV) for the percentage of ESG fund holdings within all mutual fund holdings and check whether lower (higher) ESG investor share increases (decreases) stock prices' predicting power of future variation in earnings. The IV results using the whole sample confirm that increase in ESG investing reduce stock price informativeness regarding financial outcome. I additionally verify that in the whole sample, relative to the control group, the treated group's ESG investor share decreases and total institutional share remains unchanged after the ESG index exclusion.

So far the paper focuses on forecasting price efficiency (FPE) of stock prices. To shed some light on revelatory price efficiency (RPE), I follow [Bai, Philippon and Savov \(2016\)](#) and use the same modification spirit of [Kacperczyk, Sundaresan and Wang \(2021\)](#). I replace earnings by investments and estimate the same regression. The results suggest that ESG index exclusion does not improve the predicting power of price on future variation in investments.

Now let's look at the other side of the story. How does the price informativeness regarding ESG outcome change after the ESG index exclusion? When firms are excluded from an ESG index, ESG investors divest from the stocks of the excluded firms and the market share of ESG investors in those stock markets decreases. Therefore, compared with the firms not affected, stock prices of firms that are excluded from the ESG index should possess less information about future ESG outcomes after the ESG index exclusion, as predicted in [Goldstein et al. \(2022\)](#). In the context of this paper, the predictive power of stock price on future variation in ESG outcome should decrease for the treated versus the control group.

To investigate this question, I use the most quantifiable ESG outcome of a firm, its annual CO2 emission from Trucost. The Greenhouse Gas Protocol classifies emission into three categories, Scope 1, 2 and 3. I mainly focused on Scope 1 and Scope 1 plus 2 emissions since Scope 1 and Scope 2 emissions are more systematically reported and accurately estimated ([Bolton and Kacperczyk, 2021](#)).

A notable issue has to be addressed, however. Although there is evidence (e.g. [Bolton](#)

and Kacperczyk (2021)) that investors care about carbon risk resulting from firms' emission, whether price should positively or negatively predict future variation in emission is unclear. In an ESG investor dominating market, it is plausible that stocks of firms which produce more emission in the future are punished by these ESG investors now and consequently price would negatively predict future emissions. However in the current situation where traditional investors still take up a much larger fraction of the market, the relationship is uncertain. Hence, I perform baseline regression tests on the relationship between current price and future emissions. The results unanimously show that stock prices are positively predicting future variation in emission. Therefore if ESG index exclusion reduce price informativeness regarding ESG outcome, the price of treated group should become less informative about ESG outcome relative to the control group and the coefficient of interest should be negative.

The empirical results are in line with above predictions. I find that price informativeness of ESG outcome is lower for the treated group after the ESG index exclusion. The treated group stock prices have weaker power in predicting variation in future emissions, compared with the control group. The effect is economically large, ranging from 18% to 30%.

In summary, I find evidence to support the prediction in Goldstein et al. (2022) that with less (more) ESG investors in the market, stock price becomes more (less) informative about financial outcome and less (more) informative about ESG outcome.

## Related Literature

This study contributes to at least following three streams of literature. First, this paper contributes to the fast-growing literature on how ESG investing affects outcome of financial markets. Goldstein et al. (2022) studied how ESG investors may affect information aggregation by prices using a rational expectation equilibrium (REE) model, which is the theory motivation of this paper. Their model involves green and traditional investors with different preferences over financial and ESG outcomes. The traditional investor cares only about the financial outcome, namely cash flow, while the green investors care about both outcomes.

This difference in preference induces the two types of investors to trade against each other. Consequently, they argued that increase in fraction of green investors may reduce price informativeness about financial output, increase informativeness about ESG output and raise cost of capital. There are a lot of discussion on the effect of ESG investing on cost of capital, both from the theory (e.g. [Pástor, Stambaugh and Taylor \(2021\)](#); [Hart and Zingales \(2017\)](#); [Broccardo, Hart and Zingales \(2022\)](#)), and empirical sides ([Hong and Kacperczyk \(2009\)](#); [Chava \(2014\)](#); [Bolton and Kacperczyk \(2021\)](#); [Derwall et al. \(2005\)](#); [Pástor, Stambaugh and Taylor \(2022\)](#)). The empirical evidence on the effect of ESG investor on cost of capital is mixed, and probably small according to [Berk and van Binsbergen \(2022\)](#).

More closely related to the topic of this paper, [Cao et al. \(2022b\)](#) showed that socially responsible institutions are likely to focus more on ESG information and less on signals of financial value, and this may affect stock return patterns. [Lu \(2022\)](#) studied how ESG information transparency affect management active learning from stock prices and show that greater ESG transparency could hurt real efficiency by restraining managerial learning and driving firms away from shareholder value maximizing. [Ng and Rezaee \(2020\)](#) showed that better ESG performance of firms is associated with higher stock price informativeness, and this effect is larger among those who have higher sustainability disclosure. [Grewal, Hauptmann and Serafeim \(2021\)](#) found that firms voluntarily disclosing more SASB-identified sustainability information exhibit greater price informativeness, while the disclosure of non-SASB information does not relate to informativeness. These two papers use non-synchronicity as primary measure of stock price informativeness. This study contributes by bringing ESG investors' share in firms' equity into the discussion and provides casual evidence.

Second, this paper is related to the literature on information production by financial markets. As classified by [Bond, Edmans and Goldstein \(2012\)](#), the informativeness of financial markets are mainly assessed in two ways, its ability to predict future financial outcomes (FPE) and guide future real decision-making (RPE). To evaluate the former empirically, following the address of [ROLL \(1988\)](#), a lot of studies focused on utilizing the  $R^2$  resulting



from CAPM style regression to measure stock price informativeness.  $1 - R^2$  is referred as non-synchronicity of stock and higher the non-synchronicity, higher the stock price informativeness. Examples of early studies exploiting this measure include [Morck, Yeung and Yu \(2000\)](#), [Durnev, Morck and Yeung \(2004\)](#), [Chen, Goldstein and Jiang \(2007\)](#), etc. However this measure is subject to the critique that it lacks a structural interpretation ([Hou, Peng and Xiong \(2013\)](#)).

[Bai, Philippon and Savov \(2016\)](#) proposed a welfare-based measure. They started from standard Q-theory in [Hayashi \(1982\)](#) and derived the forecasting power of price for future cash flows and investments, which is the measure used in this paper. This measure is also extensively used in literature. [Farboodi et al. \(2022\)](#) used this measure to study how increase in supply of data affect informativeness of stock price. [Carpenter, Lu and Whitelaw \(2021\)](#) used this measure to evaluate value of China’s stock market. [Kacperczyk, Sundaresan and Wang \(2021\)](#) utilized this measure to investigate whether foreign investors increase price efficiency of domestic stock market. [Cao et al. \(2022a\)](#) used the same measure to show how option volume affects stock price informativeness. [Dávila and Parlatore \(2022\)](#) also propose another measure of stock price informativeness from regression of changes in asset prices on changes in asset payoffs. [Bond, Edmans and Goldstein \(2012\)](#) provided a summary on the RPE side of price informativeness. This study contributes by examining how ESG investors affect stock price informativeness using the same measure.

Third, this paper is also relevant to the literature on the relationship between institutional investors and price efficiency. [Campbell, Ramadorai and Schwartz \(2009\)](#) showed that institutions engage in aggressive trading to take advantage of mispricing during earnings announcements. Meanwhile, [Boehmer and Kelley \(2009\)](#) observed a positive correlation between institutional shareholdings and the relative information efficiency of prices. However, [Stein \(2009\)](#) documents that the rise in institutional ownership could have detrimental effects on price efficiency. More importantly, [Farboodi et al. \(2022\)](#) and [Dávila and Parlatore \(2022\)](#) both found that stocks of firms held more by institutional investors are more informative

about future financial outcome. This paper contributes by examining how ESG fund as a special type of institutional investor affects stock price informativeness.

A closely related contemporaneous paper to this one is [Yang et al. \(2023\)](#), where they find higher level of socially responsible institutional ownership results in a lower level of informativeness of current returns on future earnings.

The remaining parts of the paper are structured as follows. Section 2 introduces the data. Section 3 shows the empirical design. Section 4 presents the results and provides some discussion. Section 5 concludes and discusses potential future extensions.

## 2 Data

### 2.1 MSCI Ratings

MSCI is one of the major ESG rating providers for firms around the world and the largest provider for ESG index ([MSCI, 2020](#)). Using rich data on firm’s ESG related outcomes, MSCI measures firms’ exposure to ESG risks and how well they manage those risks relative to peers. MSCI then produce letter grade ratings at firm level, which includes “CCC”, “B”, “BB”, “BBB”, “A”, “AA” and “AAA”, from the worst to the best.

MSCI provides its ratings through the database MSCI ESG Direct<sup>1</sup>. It contains individual reports for all firms that MSCI ESG team rated. Examples of the MSCI ESG rating report are included in appendix. The current rating and rating history are reported in the figure located at the top-right of the first page of the document. I manually collect all the ratings for US-incorporated firms contained in MSCI ESG Direct. My goal is to identify MSCI ESG ratings for these firms in May 2018 when the methodology change of MSCI ESG Leader Index happened.

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<sup>1</sup>I thank Siyi Song for kindly sharing this data.

When extracting ESG ratings from MSCI ESG Direct, I encounter an issue that I have to compromise with. Firms are rated by MSCI once a year or more frequently, but the report contains only the five most recent ratings. Since I extract the reports in March 2023 and some firms were rated multiple times within a year, I cannot find exact May 2018 ratings for the firms that were rated five or more times after May 2018. This issue may harm my results if the firms that were rated five or more times after May 2018 are not randomly selected, and the unobserved reason is correlated with factors that could affect firms' stock price informativeness. To partially mitigate the concern, I include all the firms whose earliest observable rating is before Jan 2019. I use their rating in May 2018 or the most recent prior rating as the firms' May 2018 rating if such rating is observable in their report. For the firms with earliest rating between June 2018 and December 2018, I use the rating closest to May 2018 as their May 2018 rating. All other firms are excluded from my sample.

I then merge the rating data from MCSI to CRSP-Compustat merged database based on ticker and firm name. Out of the total around 2,800 reports I extract from MSCI ESG Direct, I successfully matched 1,612 firms that have identified rating in May 2018 and CRSP-Compustat fundamental information. This results in a smaller sample size for this paper compared with [Lakkis \(2022\)](#), in which 1,800 firms are matched with CRSP-Compustat.

## 2.2 Price Informativeness

In this paper, the main measure for price informativeness is a modified version of the measure derived in [Bai, Philippon and Savov \(2016\)](#), the predicted variation of future cash flow from current market prices. The measure in [Bai, Philippon and Savov \(2016\)](#) is a welfare-based measure. They started from standard Q-theory in [Hayashi \(1982\)](#) and derived the forecasting power of price for future cash flows and investments, which [Bond, Edmans and Goldstein \(2012\)](#) refer as forecasting price efficiency (FPE) and revelatory price efficiency

(RPE) respectively. They empirically estimated FPE and RPE by the following specification:

$$E_{i,t+h}/A_{i,t} = \alpha + \beta_{1,h} \log(M/A)_{i,t} + \beta_{2,h} E_{i,t}/A_{i,t} + \xi_{i,t} + \epsilon_{i,t+h} \quad (1)$$

where  $i$ ,  $t$  and  $h$  represents firm, year and the number of years after  $t$  respectively;  $E_{i,t+h}/A_{i,t}$  is firm  $i$ 's EBIT  $h$  years after  $t$  divided by total assets of year  $t$ ;  $\log(M/A)_{i,t}$  is log of year  $t$  ratio between firm  $i$ 's market cap and total assets;  $\xi_{i,t}$  are sector indicators;  $\epsilon_{i,t+h}$  is the error term.  $\beta_{1,h}$  times the standard deviation of  $\log(M/A)$  is the FPE. RPE is estimated similarly but with future investments (including R&D expense and CAPEX) instead of future earnings.

Bai, Philippon and Savov (2016) empirically estimated one price informativeness measure for each cross-section of firms and studied the time series of the estimated results. The cross-sectional nature of this measure makes it implausible to be implemented in a DID setting with panel data. If I go through the same procedure, trying to estimate the cross-section price informativeness for each time period, I will only get one observation for the treated and control group respectively each year. The final test on the treatment effect would only contain a handful of observations with no statistical power. Therefore, I adopt the approach used in Kacperczyk, Sundaresan and Wang (2021), in which they provide an implementable version of Bai, Philippon and Savov (2016) to estimate treatment effect of a shock. Details regarding the estimation procedure are provided in the empirical strategy section.

The measure of price informativeness regarding ESG information is estimated using the same empirical method but replacing future earnings with future emission data collected from Trucost. In this manner, I am estimating the forecasting power of price for future emission. Details on data from Trucost are provided below.

## 2.3 Emission Data

I obtain firm level emission data from Trucost<sup>2</sup>. The Greenhouse Gas Protocol classifies emission into three categories. Scope 1 emissions refer to direct emissions from establishments owned or controlled by the company, including all emissions from fossil fuel used in production over the course of one year. Scope 2 emissions are generated from purchased heat, steam, and electricity consumed by the company. Meanwhile, Scope 3 emissions result from the company’s operations and products, but originate from sources outside of its ownership or control. These include emissions from the production of purchased materials, product use, waste disposal, and outsourced activities. Bolton and Kacperczyk (2021) stated that Scope 1 and Scope 2 emissions are more systematically reported and accurately estimated. Thus I mainly focused on Scope 1 and Scope 1 plus 2 emissions. I then merge the data to CRSP-Compustat merged using gvkey.

## 2.4 Mutual Fund Holding

I use the mutual fund holding database from CRSP to compute institutional holdings. To comply with regulations set by the Securities and Exchange Commission (SEC), mutual funds in the United States must disclose their holdings quarterly using N-Q and N-CSR forms. I maintain records of the latest report date’s holdings for each fund in any given year. Additionally, I gather information on whether each fund in the sample is an index fund. The institutional holdings are linked by CRSP portno at fund portfolio level and permno/permco at firm level.

The next step is to identify ESG funds. I use the same definition by Raghunandan and Rajgopal (2022), where they define ESG funds based on the list of ESG funds published by Morningstar in 2020<sup>3</sup>. Morningstar Sustainable Funds Landscape provide a list of self-

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<sup>2</sup>I thank Yiming Zhang for kindly sharing this data.

<sup>3</sup>I thank Aneesh Raghunandan for kindly sharing this data.

identified ESG funds mainly based on the fund’s prospectuses, fund reports and websites. Using the data kindly shared by [Raghunandan and Rajgopal \(2022\)](#), 311 ESG funds are identified, out of which 7 track MSCI ESG Leader Index and 14 track other ESG indexes by MSCI.

I calculate the combined total of the shares held by all mutual funds for each firm in the sample. Then, I divide it by the firm’s total number of outstanding shares from CRSP to determine the percentage of outstanding equity held by mutual funds. In addition, I determine the portion of a firm’s equity held by index funds, ESG funds, ESG index funds, non-index non-ESG funds, as well as ESG funds that are benchmarked against MSCI ESG Leaders index or other MSCI ESG index using similar procedure. I then merge all the holdings to CRSP-Compustat merged database using permno/permco.

## 2.5 Firm and Stock Characteristics

I obtain firm characteristics directly from CRSP-Compustat merged database. Specifically, I obtained firms’ assets, leverage, sales, tangibility, cash, R&D, CAPEX, market value and EBIT from Compustat. I obtain corresponding stocks’ return, total volatility, illiquidity, illiquidity volatility, turnover and trade volume from CRSP. Detailed variable definition is provided in appendix.

## 2.6 Summary Statistics

The final sample contains 1,612 unique firms over the period from 2015 to 2021. Among them, 399 were rated as “B” by MSCI in May 2018, which is the treated group for this study. In the control group, 11 were rated as “AAA”, 77 were rated as “AA”, 222 were rated as “A”, 398 were rated as “BBB”, 473 were rated as “BB”, 32 were rated as “CCC”. The summary statistics and the differences in mean between the treated and control group are reported in Table 1. On average, the market capitalization of a firm in sample is around 12 billion, with

ROA about 5%. The average firm holds 15% cash and 20% tangible assets. The average stock has weekly volatility of 5% and average daily turnover of 0.9%.

To take a closer look at the ownership structure of companies within the sample, I report the proportion of a company’s stock that is owned by mutual funds. The average total mutual fund holding in the sample is approximately 33.5%. Index funds constitute a major part of institutional investors, amounting to 17.4% of shares. ESG funds, which have seen rapid growth in recent years, hold on average around 0.5% of shares for companies within the sample, while the non-ESG non-index funds hold about 16% of the firms. With respect to holdings of MSCI ESG related funds, on average, 48% of firms are held by funds that track MSCI ESG indexes, and about 4.5% are held by funds that track MSCI ESG Leader indexes.

Next, I check the difference between the mean of variables between treated and control group. From the table, most of the variables included are different between the treated and control group, and only tangibility, cash holding and investment do not significantly differ between the two groups. This difference in firm characteristics highlights the importance of finding a matched sample, which will be discussed further in the next section.

## 3 Empirical strategy

### 3.1 DID Design

Identifying the casual effect of ESG ownership on stock’s price informativeness is challenging empirically. On one hand, ESG funds choose their positions in a firm strategically. According to [Heath et al. \(2021\)](#), ESG funds select firms with better environmental and social performance. Thus certain firm characteristics such as its production technology and greenness would affect the total ESG ownership of the firm. On the other hand, the fundamentals could also affect how informative the stock of the firm is at the same time. For

instance, there is evidence that larger stocks and stocks with higher institutional ownership are more informative (Bai, Philippon and Savov, 2016; Farboodi et al., 2022; Dávila and Parlatore, 2022). To tackle the endogeneity issue, I utilize a quasi-natural experiment that affects holdings of certain ESG funds to perform a difference-in-difference analysis. In the remaining part of this section, I describe the shock I use and the identifying assumptions needed.

### 3.1.1 MSCI ESG Leader Index

MSCI is one of the major ESG rating providers for firms around the world and the largest provider for ESG index (MSCI, 2020). Using rich data on firm’s ESG related outcomes, MSCI measures firms’ exposure to ESG risks and how well they manage those risks relative to peers and produce letter grade ratings at firm level. Based on the ratings, MSCI also construct indexes for institutional investors to use as benchmarks. For example, iShares by BlackRock provides several index funds that track MSCI indexes.

In May 2018, MSCI changed the methodology of one of its earliest ESG indexes, the MSCI ESG Leader index, which was first established in 2001. Preceding the change, the firms that meet the criteria for inclusion in the index consisted of all firms with rating of “B” or above (namely B, BB, BBB, A, AA and AAA). In May 2018, MSCI modified this rule and requires only firms with rating “BB” or above to be included in the ESG Leader Index. As a result of this change, "B" rated firms were excluded from the index. Consecutively, ESG funds that track MSCI ESG Leader index are likely to divest from those “B” rated firms. I utilize this index methodology change as a quasi-exogenous shock to firms’ ESG ownership. To be more specific, after the change, firms that were rated as “B” by MSCI are excluded from the index, and therefore, index funds that originally invested in those firms were forced to exit their positions. However, firms with MSCI ESG ratings different from “B” would not experience such shock in their ESG investor ownership. Hence, I use a



difference-in-difference framework to identify the effect of the ESG index exclusion on stock price informativeness. The “B” firms naturally serve as the treated group and the rest would be the control group.

### 3.1.2 Matching Treated and Control

The cons of using all other firms as the control group is that they may differ a lot from the treated firms and the estimated treatment effect actually results from these differences. To mitigate such concern, I perform propensity score matching to find the best control group for DID analysis. Following the design of [Kacperczyk, Sundaresan and Wang \(2021\)](#) and [Cao et al. \(2022a\)](#), for each treated firm in the sample, I identified five closest neighbors from the control group using propensity score matching method. The matching, with replacement, is based on the three-year average of the following variables prior to the treatment:  $\log(M/A)$ ,  $E/A$ , *Size*, *Leverage*, *Sales*, *Tangibility*, *Cash*, *ESG Holding* and *ESG Index Holding*. The quality of matching is shown in Table 2. The averages of the variables used to match are listed for the treated and control group and a t-test of sample mean difference is presented for each variable. From the table, all the variables used in the matching process are statistically similar between the treated and control group. The smallest p-value comes from the result of size, which is 0.19, but the difference in magnitude is negligible, where treated group average is 7.693 and control group average is 7.757. All other p-values are larger than 0.40, suggesting that the matching quality is high. However, there would still be concerns about whether the evolution of the outcome variable would be similar. More discussion on the parallel trend assumption is provided in the next section. Robustness tests on different matching and number of closest neighbors used are provided at the end of the paper.

### 3.1.3 Identifying Assumptions

The first identifying assumption needed is that the index exclusion decision made by MSCI is truly exogenous to the DID specification error term. In another word, the decision that “B” rated firms to be excluded from MSCI ESG Leader Index cannot be associated with factors that affect stock price informativeness. This assumption would fail if the exclusion decision were anticipated or enforced by the firms or investors affected by the exclusion. According to [Lakkis \(2022\)](#), there is no mention in the press of MSCI’s decision to change the methodology of MSCI ESG Leader index before 2018 based on LexisNexis search. [Lakkis \(2022\)](#) also states that although MSCI approaches its institutional investor clients to get input for the construction of indexes, there is no evidence that its eligibility criteria is affected by those clients. Hence, it would be safe to argue, at least in the context of price informativeness, the exogeneity of the shock is valid.

Second, empirically, a valid DID design must satisfy the parallel trend assumption. The assumption requires that absent the treatment, the outcome variable of the treated and control group will evolve similarly. So far, by the propensity score matching process discussed above, I identify control groups that have similar observable characteristics as the treated group prior to the treatment. More importantly, however, the treated and control group should have parallel trend of the outcome variable of interest. In the context of this paper, it would be best to observe that evolution of price informativeness measure of both the treated and the matched control group are parallel. To provide evidence on this, I conduct several tests with fully dynamic specifications and plot the difference of price informativeness measure between the treated and matched control group over periods of three years prior to and after the shock. The figures are reported in the result section. The estimated results show no statistical evidence that before the shock, there is difference in price informativeness measure between the treated and matched control group.

### 3.2 Empirical Specification

The main empirical specification follows [Kacperczyk, Sundaresan and Wang \(2021\)](#), in which they slightly modified the expression in [Bai, Philippon and Savov \(2016\)](#). The focus of this specification is to investigate the contribution of the index exclusion to price informativeness, not the level of price informativeness measure of the individual stock or the stock market as a whole. In particular, the regression model is presented below:

$$\begin{aligned}
 E_{i,t+h}/A_{i,t} = & \alpha + \beta_{1,h} \log(M/A)_{i,t} \times Treat_i \times Post_t + \beta_{2,h} \log(M/A)_{i,t} \times Treat_i + \\
 & \beta_{3,h} \log(M/A)_{i,t} \times Post_t + \beta_{4,h} \log(M/A)_{i,t} + \beta_{5,h} Treat_i \times Post_t + \beta_{6,h} X_{i,t} \quad (2) \\
 & + \beta_{7,h} \log(M/A)_{i,t} \times X_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t+h}
 \end{aligned}$$

where  $i$ ,  $t$  and  $h$  represents firm, year and the number of years after  $t$  respectively;  $Treat_i$  is a dummy that equals one if a firm is rated as “B” at in May 2018 and zero otherwise;  $Post_t$  is a dummy that equals one for 2018 and years after, and zero otherwise;  $E_{i,t+h}/A_{i,t}$  is firm  $i$ ’s EBIT  $h$  years after  $t$  divided by total assets of year  $t$ ,  $\log(M/A)_{i,t}$  is log of year  $t$  ratio between firm  $i$ ’s market cap and total assets,  $X$  includes  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ ,  $\gamma_i$  and  $\lambda_t$  are firms fixed effects and year fixed effects respectively;  $\epsilon_{i,t+h}$  is the error term, which is double clustered at both firm and year level to account for possible dependence along those two dimensions. The coefficient of interest is  $\beta_{1,h}$ , which captures the difference in price informativeness around the treatment of the treated relative to the control group.

The regression model used to verify parallel trend assumption is similar to the above specification, but with  $Post_t$  split into year dummies. The year prior to treatment (2017) is

set as the base level and therefore omitted from the regression. The estimated model is:

$$\begin{aligned}
E_{i,t+h}/A_{i,t} = & \alpha + \sum_{k=-3; k \neq -1}^3 \beta_{1,h,k} \log(M/A)_{i,t} \times Treat_i \times 1_{\{t-2018=k\}} \\
& + \beta_{2,h} \log(M/A)_{i,t} \times Treat_i + \sum_{k=-3; k \neq -1}^3 \beta_{3,h,k} \log(M/A)_{i,t} \times 1_{\{t-2018=k\}} \\
& + \beta_{4,h} \log(M/A)_{i,t} + \sum_{k=-3; k \neq -1}^3 \beta_{3,h,k} \beta_{5,h,k} Treat_i \times 1_{\{t-2018=k\}} \\
& + \beta_{6,h} X_{i,t} + \beta_{7,h} \log(M/A)_{i,t} \times X_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,t+h}
\end{aligned} \tag{3}$$

The series of  $\beta_{1,h,k}$  is plotted in Figure 1.

The results related to price informativeness of ESG outcome use similar specification as in equation 2 and 3. The difference is on the left-hand-side, where I replace future earnings over assets with natural log of future Scope 1 and Scope 1 plus 2 emissions over assets. Parallel trend assumption for price informativeness of ESG outcome is verified in Figure 3 and 4.

## 4 Results

### 4.1 Price Informativeness of Financial Output

#### 4.1.1 Results on Price Informativeness

In this section, I examine the impact of ESG index exclusion on stock price informativeness. Based on the theory prediction of Goldstein et al. (2022), when the share of ESG investor in the market decreases, price would be more informative to traditional investors who only care about financial outcome. When firms are excluded from an ESG index, investors that track that index would have to divest from the stocks of the excluded firms and the market share of ESG investors in those stock markets would decrease. Therefore,

compared with the firms not affected, stock prices of firms that are excluded from the ESG index should possess more information about future financial outcomes after the ESG index exclusion. Specifically, in the context of this paper, prices of the treated firms' stock should possess more predicted power for future variation in cashflow relative to the control group. Using the empirical specification in equation 2, the coefficient of interest is  $\beta_{1,h}$ , which captures the change in price informativeness around the treatment of the treated relative to the control group, should be positive.

I report the result of estimating equation 2 using the one-to-five matched sample in Table 3. The quality of matching pre-treatment is shown in Table 2. Figure 1 provides evidence on the parallel trend assumption using estimated result of the dynamic model, plotting the difference of price informativeness between the treated and control group before and after the treatment. The numerical results are omitted.

Figure 1 shows that prior to the treatment, the coefficient of interest  $\beta_{1,h,k}$  is not statistically significant different from zero, suggesting that there is no statistically significant difference for price informativeness measure between the treated and the control group, which verifies the parallel trend assumption. However, after the treatment,  $\beta_{1,h,k}$  becomes positive and significant and retains its level for several years, showing that after the treatment, the price informativeness measure of treated group is larger relative to the control group.

More formally, in Table 3, the coefficient of interest  $\beta_{1,h}$  is consistently positive and significant across all specifications. The dependent variables are future 1, 2 and 3 years' earnings scaled by current assets for column (1) and (2), (3) and (4), and (5) and (6) respectively. In column (1), (3) and (5), I include the interaction term between the control variables and  $\log(M/A)_{i,t}$ , while in the other columns I omit them. The positive and significant coefficients on  $\log(M/A) * Treat * Post$  suggest that, after the treatment, the treated group stock price have greater power in predicting variation in future earnings, compared with the control group. This indicates that stock prices of firms that are excluded from the MSCI ESG

Leader Index are more informative about future financial outcome than the prices of firms that are not affected. This effect is also economically large.

#### 4.1.2 Results on Institutional Holding

Next I examine the effect of ESG index exclusion on firms' ownership structure. This exercise serves two primary purposes. First, I aim to verify that after being excluded by the MSCI ESG Leader Index, the excluded firms do experience divestment from related funds that track the index and ESG funds holding in general also decreases. Second, if the divestment from ESG funds happens, how the total institutional ownership changes. Particularly, since stocks with more institutional ownership tend to be more informative, as suggested by [Bai, Philippon and Savov \(2016\)](#); [Farboodi et al. \(2022\)](#); [Dávila and Parlatore \(2022\)](#), change in total institutional ownership could harm my results.

I report the estimated results on ESG funds related Holdings in Table 4. I regress different holding percentage points on  $Treat * Post$  and natural log of firm market capitalization, controlling for firm and year fixed effects. In column (1) the dependent variable is all ESG funds holding. The coefficient estimate on  $Treat * Post$  is negative and significant at 10% level, suggesting that after the index exclusion, the total holding of ESG funds for the treated firms decreases more than the control firms, indicating ESG funds divest from the firms that were excluded from the index. Compared with the mean of treated and matched control group prior to the treatment, the divestment from ESG funds amount to about 33% of total ESG holding. In column (2) I use ESG index fund holding as the dependent variable. The coefficient on  $Treat * Post$  is also negative and significant, and the magnitude is approximately 27%, which is comparable to the total divestment of ESG funds. I also plot the dynamic difference of total ESG ownership between the treated and control group in Figure 2. Prior to the treatment, the difference between treated and control group is not statistically significant, which provides evidence supporting the parallel trend assumption.

After the treatment, the ESG holding for the treated group is significantly smaller than that for the matched control group.

To further examine the reduction in ownership by ESG index funds, I investigate how the probability of a firm being included by funds that track MSCI related indexes changes. In column (3) of Table 4, the dependent variable is a dummy variable that equals one if the firm’s stock is held by any index fund which tracks one of the MSCI ESG indexes, and zero otherwise. The coefficient estimate of  $Treat * Post$  is negative and significant at 1% level, and the magnitude is also large at -30%. This implies that after the index exclusion, treated firms are 30% less likely to be held by any index funds that track MSCI ESG indexes. In the original sample, the mean of this variable is 48%, suggesting that the exclusion has a relatively large effect on index funds that track MSCI ESG indexes.

In addition, I check how the probability of a firm being included by funds that track MSCI ESG Leader index changes. In column (4), the dependent variable now equals one if the firm’s stock is held by any index funds which track MSCI ESG Leader Index, and zero otherwise. The resulting coefficient is negative and significant at 5% level. Compared with the sample mean of 4.5%, this -4.4% coefficient suggests that this index exclusion basically induces all funds that track MSCI ESG Leader index to dump their holdings on the treated firms relative to the matched control firms.

To sum up, the exclusion of “B” rated firms from MSCI ESG Leader index results in a significant reduction in ESG ownership of these firms, compared to the unaffected ones. Then, I investigate how the behavior of all institutional investors changes. Index exclusion could not only change the composition of the investors, but also alter the total level of institutional ownership, which in turn affects price informativeness of the treated firms relative to the controls.

Table 5 reports the results on change in institutional investor holding comparing treated and matched control group. In column (1), the dependent variable is the total holding of all

mutual funds. The coefficient of  $Treat * Post$  is not significant. This suggests that the index exclusion did not cause significant change of total institutional ownership in the difference between treated and control group. In column (2), I investigate all index fund holding and the coefficient of interest is also insignificant at 10% level. These results suggests that the total institutional holding difference remains unchanged between the treated and control group and help alleviate concerns that the change in price informativeness is because of change in total institutional holding.

I further checked the holding of non-ESG and non-index funds in column (3). Although the resulting coefficient of  $Treat * Post$  is still insignificant, it is interesting to see that this coefficient is positive while the coefficient on index funds are negative. Since the ESG investors are statistically significantly reducing their holding on the treated firms relative to the control, the above results provide some evidence that traditional investors indeed trade in different direction against ESG investors, and as a result, increase the forecasting power of stock prices of treated firms on future variation in cashflow.

#### 4.1.3 Results on Other Stock Characteristics and RPE

It could be that after the treatment, the treated firms' stock becomes less volatile and hence contain more precise information on future earnings and results in the positive and significant coefficient I find in Table 3. To mitigate concern on this issue, I examine whether the total volatility difference between treated and control changed after the index exclusion shock. In column (1) of Table 6, I show results of regressing firms' weekly return volatility on  $Treat * Post$  and several fixed effects. Given the insignificant coefficient of  $Treat * Post$ , I find no evidence that the difference of total volatility between treated and control group is driving the results.

To further verify that traditional investors are trading more actively on the treated stocks relative to the control, I looked at how illiquidity, illiquidity volatility, turnover and trade



volume of these stocks change after the shock. I report the results in column (2) to (5) of Table 6. The coefficients of  $Treat * Post$  in column (2) and (3) are negative and significant at 5% and 10% respectively. Thus the treated firms' stocks becomes more liquid compared with the matched control group after the treatment. However, the coefficients in column (4) and (5) are not statistically significant, indicating that the difference in turnover and volume between the treated and control group do not change after the index exclusion. Further evidence on the trading activity channel is still needed.

I also check another measure of price informativeness used extensively in previous literature, non-synchronicity. I follow the literature and measure stock non-synchronicity using log transformed  $1 - R^2$ . Specifically, non-synchronicity is calculated as  $\ln[(1 - R^2)/R^2]$ , where  $R^2$  is from the regression regressing weekly individual stock return on the market return and industry return. I exclude all yearly observation with less than 26 weekly return observations following Cao et al. (2022a). In Table 7 I report the results regressing non-synchronicity on  $Treat * Post$ , different sets of controls and fixed effects. The coefficients of  $Treat * Post$  are positive and significant at 10% level across different specifications, which supports that after the ESG index exclusion, the stock prices of excluded firms become more informative.

So far the paper focuses on forecasting price efficiency (FPE) of stock prices. Would the change in the ownership structure resulting from the index exclusion also affect revelatory price efficiency (RPE)? To answer this question empirically, I follow Bai, Philippon and Savov (2016) and use the same modification spirit of Kacperczyk, Sundaresan and Wang (2021). I replace earnings on the left-hand side of equation 2 by investments and estimate this regression. I use the sum of R&D cost and CAPEX as proxy for investments. The results are shown in Table 8. The layout of this table is similar to the main results presented in Table 3, with 1-, 2- and 3-year future investment adjusted by total assets as the dependent variables. However, none of the coefficients of  $\log(M/A) * Treat * Post$  is significant, though all of them are positive. The results suggest that ESG index exclusion does not significantly improve the predicting power of price on future variation in investment.

To summarize, in this section, I show that the exclusion by MSCI ESG Leader Index reduces ESG investor ownership and increases the stock price informativeness of treated firms in terms of FPE. In the next section, I am going to show how predicting power of stock price on future variation in ESG outcome changes after the index exclusion.

## 4.2 Price Informativeness of ESG Output

When firms are excluded from an ESG index, ESG investors divest from the stocks of the excluded firms and the market share of ESG investors in those stock markets decreases. Therefore, compared with the firms not affected, stock prices of firms that are excluded from the ESG index should possess less information about future ESG outcomes after the ESG index exclusion, as predicted in [Goldstein et al. \(2022\)](#). In this section, I use the most quantifiable ESG outcome of a firm, its annual CO2 emission, to study whether the above prediction is valid.

As introduced in Section 2.3, the Greenhouse Gas Protocol classifies emission into three categories, Scope 1, 2 and 3. I mainly focused on Scope 1 and Scope 1 plus 2 emissions since Scope 1 and Scope 2 emissions are more systematically reported and accurately estimated, as [Bolton and Kacperczyk \(2021\)](#) suggested in their work.

Similarly to the previous section on price informativeness of financial outcome, I report the results of estimating equation 2 using the one-to-five matched sample in Table 9 and Table 10 for Scope 1 plus 2 and Scope 1 emission respectively. Figure 3 and Figure 4 provide evidence on the parallel trend assumption using estimated result of the dynamic model, plotting the difference of price informativeness between the treated and control group before and after the treatment. The numerical results are omitted.

Before going into the details of the results, a notable issue needs to be addressed. Although there is evidence that investors care about carbon risk resulting from firms' emission (e.g. [Bolton and Kacperczyk \(2021\)](#)), whether price should positively or negatively

predict future variation in emission is unclear. If ESG investor is dominating the stock market, it is plausible that stocks of firms which produce more emissions in the future could be punished by these ESG investors now and consequently price would negatively predict future emission. However in the current situation where traditional investors still take up a larger fraction of the market, the relationship is uncertain and remains an empirical question. Thus I include a baseline regression where I regress future emission on current price to examine on average, which direction is empirically shown in the data. In column (3) and (6) of Table 9 and Table 10, I report this base line results using 1- and 2-year future emission on the left-hand side respectively. The coefficients of  $\log(M/A)$  are all positive and significant. Thus the baseline implication is that in the current market condition, stock prices are still positively predicting future variation in emission. Therefore if ESG index exclusion reduce price informativeness regarding ESG outcome, the coefficient of interest  $\beta_{1,h}$  should be negative.

First let's look at if the parallel trend assumption is satisfied. Figure 3 and Figure 4 show that prior to the treatment, the coefficient of interest  $\beta_{1,h,k}$  is not statistically significant different from zero, suggesting that there is no statistically significant difference for price's predicting power of future variation in emission between the treated and the control group, which verifies the parallel trend assumption. After the treatment,  $\beta_{1,h,k}$  gradually becomes negative and significant, showing that after the treatment, the price of treated group becomes less informative about ESG outcome relative to the control group.

More formally, in Table 9, the coefficient of interest  $\beta_{1,h}$  is consistently positive and significant across all specifications. The dependent variables are log of future 1- and 2-year Scope 1 plus 2 emissions scaled by current assets for column (1) and (2), and (4) and (5) respectively. In column (2), and (5), I include the industry-by-year fixed effect since emission pattern is highly heterogeneous across industries. The negative and significant coefficients on  $\log(M/A) * Treat * Post$  suggest that, after the treatment, the treated group stock price have weaker power in predicting variation in emission, compared with the control group.

This indicates that stock prices of firms that are excluded from the MSCI ESG Leader Index are less informative about future ESG outcome than the prices of firms that are not affected. This effect is also economically large, ranging from 18% to 30%. Table 10 where Scope 1 emission is used shows similar results.

Overall, results from previous two sections support the prediction in Goldstein et al. (2022) that with less (more) ESG investors in the market, stock price becomes more (less) informative about financial outcome and less (more) informative about ESG outcome.

## 4.3 Robustness

### 4.3.1 IV Approach in Full Sample

In this section, I provide some further evidence on how ESG ownership of a firm affects its stock's price informativeness regarding financial outcome. The DID setting requires the treated and control group to be similar before the treatment so that parallel trend assumption holds and the identification is robust. Here I perform a relatively less formal test using the MSCI ESG Leader Index Exclusion shock as an instrument variable (IV) for the percentage of ESG fund holdings within all mutual fund holdings ( $ESG/Ins$ ) and check whether lower (higher) ESG investor share increases (decreases) stock price's predicting power of future variation in earnings.

First, I perform similar tests on the change in institutional holdings difference between treated and control group using the whole sample, which conceivably serves as an informal test on the inclusion condition of IV. In table 11, I report the results on ESG fund holdings and find similar results as in Section 4.1.2. Compared with the control group, after being excluded by the index, the treated group is held less by all ESG funds and ESG index funds. They are also less likely to be held by funds that track MSCI ESG related indexes or MSCI ESG Leader index. Notably, the coefficient on  $Treat * Post$  is -9.85% in column (4), which

is larger than the 4.5% sample mean of the dependent variable. This results from the linear probability model used. Next, I show how difference in total institutional holding between the treated and control group changes as a result of the shock. Since total institutional holding affects stock price informativeness, this test could help alleviate some concern on the exclusion restriction of IV. The results are shown in Table 12. Not surprisingly, this table show similar results as in Section 4.1.2, that the coefficient on  $Treat * Post$  is statistically insignificant, implying that the difference of total institutional ownership between the treated and control group remains unchanged after the treatment.

In Table 13, I show the results using the index exclusion as an instrument variable for the percentage of ESG fund holdings within all mutual fund holding and the effect of  $ESG/Ins$  on price's predicting power of future variation in earnings. In column (3) I perform the first stage regressing  $ESG/Ins$  on  $Treat * Post$ , controls and fixed effects and generate predicted value as  $\widehat{ESG/Ins}$ . I then use  $\widehat{ESG/Ins}$  interact with  $\log(M/A)$  and perform the second stage regression. Results are shown in column (1) and (2). The coefficient on the interaction term is negative and significant, suggesting that with a higher share of ESG investor in the investor pool, price's predicting power of future variation in earnings decreases. This informal IV analysis further confirms the results I find that increase in ESG investor holding reduces stock price informativeness regarding financial output.

#### 4.3.2 Other Robustness tests

In this section, I perform several additional tests to verify my results. First, I add fixed effects of the May 2018 MSCI ESG rating into equation 2 and presents the results in Table 14. The coefficients of  $\log(M/A) * Treat * Post$  are still positive and significant, and the magnitude remains similar. Second, I include industry-by-year fixed effect. Results are shown in Table 15. In column (5) the coefficient of  $\log(M/A) * Treat * Post$  becomes insignificant but the coefficient is still comparable to the main results. The coefficients of

interest in all other columns remain positive and significant. Third, I use different numbers of matched neighbors, ranging from 1-to-1 to 1-to-4, to perform the tests. I include the results in Table 16. The coefficients of interest are still positive, although the significance level for the first three reduced to 10% level. The size of the coefficient, however, remains at the same magnitude. Forth, I matched another sample using only one-year prior (2017) characteristics and presents the results in Table 17. The resulting coefficients are all positive and significant.

## 5 Conclusion

In this paper, I investigate how stock price informativeness changes in response to ESG investing. To measure price informativeness of stock prices, I adapt the frame work from Bai, Philippon and Savov (2016). I also utilize the shock that MSCI ESG Leader Index excluded "B" rated firms in May 2018 as a quasi-natural experiment to help establish casual relationship. I find that after the index exclusion, compared with the control group, the treated firms' stock price informativeness regarding financial outcome increases while informativeness regarding ESG outcome decreases. I verify that ESG funds holding of the treated firms decreases while the total institutional holdings remain unchanged. This shed light on the potential channel of the effect that traditional investor trade against ESG investors and reveal more their private information through trading.

This study contributes to the rapid growing literature assessing how ESG investing affect the outcome of financial markets. It also provides evidence that ESG investor may distort the function of the stock market by reducing price informativeness of financial outcome. Future improvement of the paper would include more robust evidence on the mechanism behind.

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**Table 1: Summary Statistics-Full Sample**

VARIABLES	N	mean	sd	25%	50%	75%	Treated	Control	diff
<i>E/A</i>	12,291	0.0532	0.119	0.0215	0.0561	0.103	0.044	0.056	-0.013***
<i>log(M/A)</i>	12,293	-0.164	1.127	-0.850	-0.0956	0.603	-0.289	-0.124	-0.165***
<i>Size</i>	12,293	8.222	1.580	7.137	8.122	9.171	7.947	8.312	-0.364***
<i>Leverage</i>	12,267	0.624	0.249	0.458	0.625	0.810	0.598	0.632	-0.034***
<i>Tangibility</i>	12,896	0.194	0.236	0.0155	0.0977	0.274	0.188	0.196	-0.008
<i>Sale</i>	12,198	7.339	1.588	6.304	7.290	8.358	6.817	7.510	-0.693***
<i>Cash</i>	12,293	0.150	0.190	0.0259	0.0730	0.189	0.146	0.151	-0.004
<i>Investment</i>	12,896	0.0423	0.0787	0	0	0.0550	0.041	0.043	-0.002
<i>Institutional Holding</i>	10,927	33.48	11.93	25.98	34.64	41.78	31.263	34.206	-2.942***
<i>Index Fund Holding</i>	10,927	17.38	7.489	12.24	17.13	22.37	16.941	17.519	-0.578***
<i>nonESG nonIndex Fund Holding</i>	10,927	15.96	8.694	9.661	15.39	21.24	14.240	16.531	-2.292***
<i>ESG Holding</i>	10,927	0.529	0.979	0.00330	0.0454	0.555	0.287	0.609	-0.323***
<i>ESG Index Holding</i>	10,927	0.392	0.765	0	0.0160	0.0874	0.204	0.454	-0.250***
<i>MSCI Index = 1</i>	10,927	0.481	0.500	0	0	1	0.230	0.563	-0.334***
<i>MSCI ESG Leader Index = 1</i>	10,927	0.0448	0.207	0	0	0	0.003	0.059	-0.056***
<i>log(EM1/A)</i>	8,329	1.489	2.799	-0.0493	1.975	3.315	1.221	1.576	-0.355***
<i>log(EM12/A)</i>	8,337	2.573	2.443	1.575	2.990	4.151	2.361	2.642	-0.281***
<i>log(M)</i>	12,293	8.060	1.387	7.053	7.900	8.866	7.661	8.190	-0.529***
<i>Volatility</i>	12,226	5.207	3.018	3.331	4.448	6.243	5.339	5.164	0.175**
<i>Illiquidity</i>	12,291	0.389	0.165	0.002	0.008	0.026	0.062	0.031	0.031***
<i>IlliqVol</i>	12,290	4.713	29.02	0.21	0.719	2.382	8.015	3.635	4.380***
<i>Turnover</i>	12,291	0.954	1.136	0.512	0.737	1.101	0.882	0.978	-0.095***
<i>Volume</i>	12,291	389.1	1,006	58.15	143.4	364.5	339.345	405.368	-66.023**

*Note:* This table reports the summary statistics of the whole sample with identified May 2018 MSCI ESG rating and matched financial information from Compustat. The sample contains 1,612 firms in total, 399 firms are treated and the rest are in the control group, covering the sample period from 2015 to 2021. The "Treated" and "Control" column reports mean value of variables within each group respectively. In the "diff" column, t-tests on the difference between the treated and control group are performed. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 2: Pre-treatment Comparison**

	Treatment Group	Control Group	t-test(p-value)
<i>log(M/A)</i>	-0.209	-0.229	0.57
<i>E/A</i>	0.043	0.044	0.89
<i>Size</i>	7.693	7.757	0.19
<i>Leverage</i>	0.584	0.590	0.50
<i>Tangibility</i>	0.181	0.187	0.49
<i>Sales</i>	6.582	6.627	0.42
<i>Cash</i>	0.152	0.150	0.68
<i>ESG Holding</i>	0.241	0.242	0.95
<i>ESG Index Holding</i>	0.151	0.155	0.77

*Note:* This table reports the comparison of mean of variables used in the propensity score matching process prior the treatment between treated group and matched control group of the matched sample. Each observation in the Treated group is matched with five closest neighbors. The "Treated Group" and "Control Group" column reports mean value of variables within each group respectively. The last column reports the t-stat and corresponding p-value. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 3: ESG Index Exclusion and FPE**

	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1}/A_t$		$E_{t+2}/A_t$		$E_{t+3}/A_t$	
$\log(M/A) * Treat * Post$	0.0085** (0.0028)	0.0088** (0.0030)	0.0123* (0.0053)	0.0118* (0.0053)	0.0143* (0.0065)	0.0133* (0.0060)
$\log(M/A) * Treat$	-0.0025 (0.0066)	-0.0043 (0.0060)	-0.0053 (0.0084)	-0.0074 (0.0079)	-0.0019 (0.0102)	-0.0015 (0.0122)
$\log(M/A)t * Post$	-0.0074* (0.0035)	-0.0053* (0.0025)	-0.0098 (0.0055)	-0.0053 (0.0056)	-0.0025 (0.0054)	0.0000 (0.0050)
$\log(M/A)$	0.0190 (0.0164)	0.0278*** (0.0076)	-0.0330 (0.0412)	0.0180 (0.0134)	-0.0516* (0.0228)	-0.0082 (0.0130)
$Treat * Post$	0.0101** (0.0040)	0.0106** (0.0041)	0.0137* (0.0067)	0.0142* (0.0071)	0.0140 (0.0088)	0.0135 (0.0093)
$E/A$	0.3378** (0.1409)	0.3483** (0.1412)	0.0220 (0.1742)	0.0324 (0.1846)	0.2374 (0.1332)	0.2534 (0.1367)
$Size$	-0.0165** (0.0066)	-0.0182** (0.0064)	-0.0343* (0.0140)	-0.0395** (0.0151)	-0.0602*** (0.0082)	-0.0639*** (0.0077)
$Leverage$	0.1013*** (0.0284)	0.0720** (0.0206)	0.0917 (0.0499)	0.0733 (0.0439)	0.0473 (0.0554)	0.0610 (0.0480)
$Tangibility$	-0.0264 (0.0376)	-0.0243 (0.0375)	0.0060 (0.0584)	0.0104 (0.0481)	0.0537 (0.0510)	0.0676 (0.0340)
$Sale$	0.0082 (0.0093)	0.0113 (0.0099)	0.0127 (0.0116)	0.0201 (0.0142)	0.0217 (0.0180)	0.0272 (0.0172)
$Cash$	0.0014 (0.0128)	-0.0020 (0.0154)	0.0084 (0.0357)	0.0252 (0.0351)	-0.0214 (0.0649)	0.0069 (0.0635)
$\log(M/A) * Size$	-0.0002 (0.0038)		0.0011 (0.0041)		0.0013 (0.0093)	
$\log(M/A) * Leverage$	-0.0650** (0.0274)		-0.0483 (0.0336)		0.0216 (0.0314)	
$\log(M/A) * Tangibility$	-0.0058 (0.0352)		-0.0617 (0.0332)		-0.1012 (0.0612)	
$\log(M/A) * Sale$	0.0085* (0.0038)		0.0131* (0.0066)		0.0061 (0.0076)	
$\log(M/A) * Cash$	-0.0170 (0.0282)		0.0217 (0.0237)		0.0418 (0.0255)	
$Constant$	0.0541 (0.0322)	0.0701* (0.0335)	0.1819** (0.0699)	0.1826** (0.0702)	0.3435** (0.0983)	0.3137** (0.0824)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
$N$	15549	15549	13231	13231	10879	10879
$R^2$	0.855	0.851	0.820	0.815	0.820	0.817

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE using equation 2. The sample is the propensity score matched sample. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 4: ESG Index Exclusion and ESG Fund Holding-Matched Sample**

	(1) <i>ESG Holding</i>	(2) <i>ESG Index Holding</i>	(3) <i>MSCI Index = 1</i>	(4) <i>MSCI ESG Leader Index = 1</i>
<i>Treat * Post</i>	-0.0790* (0.0352)	-0.0399* (0.0178)	-0.3017*** (0.0423)	-0.0439** (0.0151)
<i>log(M)</i>	0.1149*** (0.0248)	0.0745*** (0.0190)	0.1914*** (0.0125)	0.0089 (0.0050)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	16000	16000	15999	15999
<i>R</i> <sup>2</sup>	0.720	0.836	0.673	0.386

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on ESG fund holding. The sample is the propensity score matched sample. The dependent variables are ESG funds holding measured using different standards. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 5: ESG Index Exclusion and Institutional Holding-Matched Sample**

	(1) <i>Institutional Holding</i>	(2) <i>Index Fund Holding</i>	(3) <i>nonESG nonIndex Fund Holding</i>
<i>Treat * Post</i>	0.0445 (0.5008)	-0.2051 (0.3086)	0.2865 (0.3520)
<i>log(M)</i>	3.5504*** (0.4365)	0.3474 (0.2800)	3.1646*** (0.2607)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
<i>N</i>	15999	15999	15999
<i>R</i> <sup>2</sup>	0.793	0.861	0.742

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on mutual fund holding. The sample is the propensity score matched sample. The dependent variables are mutual funds holding measured using different standards. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 6: ESG Index Exclusion and Stock Characteristics**

	(1) <i>Volatility</i>	(2) <i>Illiquidity</i>	(3) <i>IlliqVol</i>	(4) <i>Turnover</i>	(5) <i>Volume</i>
<i>Treat * Post</i>	0.0279 (0.0843)	-0.0492** (0.0200)	-0.2972* (0.1365)	0.0208 (0.0375)	-2.0197 (20.5676)
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry by Year FE	Yes	Yes	Yes	Yes	Yes
<i>N</i>	15217	15285	15285	15285	15285
<i>R</i> <sup>2</sup>	0.820	0.521	0.547	0.792	0.905

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on stock characteristics. The sample is the propensity score matched sample. The dependent variables are volatility, illiquidity, illiquidity volatility, turnover and volume. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.



**Table 7: ESG Index Exclusion and Stock non-Synchronicity**

	(1) <i>NSYNC</i>	(2) <i>NSYNC</i>	(3) <i>NSYNC</i>
<i>Treat * Post</i>	0.1103* (0.0463)	0.1064* (0.0455)	0.1118* (0.0474)
Controls	Yes	No	Yes
Stock Controls	No	Yes	Yes
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
<i>N</i>	15909	15978	15909
<i>R</i> <sup>2</sup>	0.595	0.599	0.600

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on stock non-synchronicity. Controls include *E/A*, *Size*, *Leverage*, *Sales*, *Tangibility* and *Cash*, all at year *t*. Stock controls include *log(M)*, *Volatility*, *Illiquidity*, all at year *t*. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 8: ESG Index Exclusion and RPE**

	(1)	(2)	(3)	(4)	(5)	(6)
	$INV_{t+1}/A_t$		$INV_{t+2}/A_t$		$INV_{t+3}/A_t$	
$\log(M/A) * Treat * Post$	0.0046 (0.0049)	0.0047 (0.0052)	0.0049 (0.0053)	0.0050 (0.0056)	0.0008 (0.0038)	0.0025 (0.0038)
$\log(M/A) * Treat$	-0.0085 (0.0069)	-0.0082 (0.0079)	-0.0054 (0.0036)	-0.0053 (0.0035)	0.0112* (0.0051)	0.0080 (0.0056)
$\log(M/A) * Post$	-0.0082* (0.0034)	-0.0104* (0.0045)	-0.0091* (0.0039)	-0.0099* (0.0047)	-0.0101 (0.0054)	-0.0097 (0.0066)
$\log(M/A)$	0.0478 (0.0332)	0.0126 (0.0099)	0.0373 (0.0368)	-0.0013 (0.0020)	0.0608 (0.0498)	-0.0006 (0.0078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\log(M/A) * Controls$	Yes	No	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
$N$	15978	15978	13687	13687	11395	11395
$R^2$	0.779	0.778	0.793	0.792	0.789	0.783

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on RPE using equation 2. The sample is the propensity score matched sample. The dependent variables are future investments scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 9: ESG Index Exclusion and FPE of Scope 1 and 2 Emission**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(EM12_{t+1}/A_t)$			$\log(EM12_{t+2}/A_t)$		
$\log(M/A) * Treat * Post$	-0.0395*	-0.0363*		-0.0600*	-0.0602*	
	(0.0186)	(0.0177)		(0.0247)	(0.0242)	
$\log(M/A) * Treat$	0.0866	0.0993		0.1433*	0.1348*	
	(0.0700)	(0.0665)		(0.0563)	(0.0563)	
$\log(M/A) * Post$	-0.0090	-0.0339		0.0153	-0.0018	
	(0.0210)	(0.0234)		(0.0235)	(0.0261)	
$\log(M/A)$	0.1605**	0.1936**	0.1632**	0.2155***	0.2620***	0.2460***
	(0.0508)	(0.0566)	(0.0431)	(0.0433)	(0.0423)	(0.0337)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry by Year FE	No	Yes	No	No	Yes	No
$N$	9835	9832	9835	7619	7616	7619
$R^2$	0.985	0.986	0.985	0.987	0.987	0.987

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE of Scope 1 plus 2 emission using equation 2. The sample is the propensity score matched sample. The dependent variables are log of future Scope 1 plus 2 emission scaled by current assets. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 10: ESG Index Exclusion and FPE of Scope 1 Emission**

	(1)	(2)	(3)	(4)	(5)	(6)
	$\log(EM1_{t+1}/A_t)$		$\log(EM1_{t+2}/A_t)$			
$\log(M/A) * Treat * Post$	-0.0494*	-0.0444*		-0.0628*	-0.0625*	
	(0.0196)	(0.0179)		(0.0255)	(0.0249)	
$\log(M/A) * Treat$	0.1241*	0.1355*		0.1527*	0.1469*	
	(0.0592)	(0.0590)		(0.0649)	(0.0628)	
$\log(M/A) * Post$	-0.0109	-0.0397		0.0136	-0.0030	
	(0.0201)	(0.0272)		(0.0241)	(0.0313)	
$\log(M/A)$	0.1463*	0.1899**	0.1525**	0.2093**	0.2629***	0.2401***
	(0.0627)	(0.0707)	(0.0520)	(0.0457)	(0.0483)	(0.0348)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry by Year FE	No	Yes	No	No	Yes	No
$N$	9829	9826	9829	7613	7610	7613
$R^2$	0.983	0.983	0.983	0.984	0.985	0.984

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE of Scope 1 emission using equation 2. The sample is the propensity score matched sample. The dependent variables are log of future Scope 1 emission scaled by current assets. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 11: ESG Index Exclusion and ESG Fund Holding-Full Sample**

	(1) <i>ESG Holding</i>	(2) <i>ESG Index Holding</i>	(3) <i>MSCI Index = 1</i>	(4) <i>MSCI ESG Leader Index = 1</i>
<i>Treat * Post</i>	-0.1180** (0.0403)	-0.0994** (0.0325)	-0.2486*** (0.0393)	-0.0985** (0.0321)
<i>log(M)</i>	0.1652*** (0.0317)	0.1142*** (0.0242)	0.1743*** (0.0103)	0.0142* (0.0065)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
<i>N</i>	10921	10921	10921	10921
<i>R</i> <sup>2</sup>	0.774	0.856	0.687	0.427

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on ESG fund holding. The sample is the full sample. The dependent variables are ESG funds holding measured using different standards. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 12: ESG Index Exclusion and Institutional Holding-Full Sample**

	(1) <i>Institutional Holding</i>	(2) <i>Index Fund Holding</i>
<i>Treat * Post</i>	0.1135 (0.4191)	0.0884 (0.2525)
<i>log(M)</i>	3.0782*** (0.4009)	0.2497 (0.2315)
Firm FE	Yes	Yes
Year FE	Yes	Yes
<i>N</i>	10921	10921
<i>R</i> <sup>2</sup>	0.819	0.867

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on mutual fund holding. The sample is the full sample. The dependent variables are mutual funds holding measured using different standards. Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 13: ESG Index Exclusion and FPE-IV Approach**

	(1) $E_{t+1}/A_t$	(2) $E_{t+3}/A_t$	(3) $ESG/Ins$
$\log(M/A) * \widehat{ESG/Ins}$	-4.2632** (1.2622)	-7.2569** (2.2541)	
$\log(M/A)$	-0.0582* (0.0274)	-0.2313*** (0.0316)	
$\widehat{ESG/Ins}$	-3.9942** (1.4702)	-5.0104 (3.0624)	
$Treat * Post$			-0.0028* (0.0013)
Controls	Yes	Yes	Yes
$\log(M/A)*Controls$	Yes	Yes	No
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
$N$	9713	6732	9932
$R^2$	0.832	0.796	0.777

*Note:* This table reports regression results of using MSCI ESG Leader index exclusion as a instrument variable. The sample is the full sample. Column (3) report results of the first stage regression. Column (1) and (2) use predicted value of  $\widehat{ESG/Ins}$  from first stage regression. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 14: Robustness: ESG Index Exclusion and FPE-ESG Rating**

	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1}/A_t$		$E_{t+2}/A_t$		$E_{t+3}/A_t$	
$\log(M/A) * Treat * Post$	0.0085** (0.0028)	0.0088** (0.0030)	0.0123* (0.0053)	0.0118* (0.0053)	0.0143* (0.0065)	0.0133* (0.0060)
$\log(M/A) * Treat$	-0.0025 (0.0066)	-0.0043 (0.0060)	-0.0053 (0.0084)	-0.0074 (0.0079)	-0.0019 (0.0102)	-0.0015 (0.0122)
$\log(M/A) * Post$	-0.0074* (0.0035)	-0.0053* (0.0025)	-0.0098 (0.0055)	-0.0053 (0.0056)	-0.0025 (0.0054)	0.0000 (0.0050)
$\log(M/A)$	0.0190 (0.0164)	0.0278*** (0.0076)	-0.0330 (0.0412)	0.0180 (0.0134)	-0.0516* (0.0228)	-0.0082 (0.0130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\log(M/A) * Controls$	Yes	No	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
$N$	15549	15549	13231	13231	10879	10879
$R^2$	0.855	0.851	0.820	0.815	0.820	0.817

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE using equation 2, with 2018 MSCI ESG rating fixed effect. The sample is the propensity score matched sample. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.



**Table 15: Robustness: ESG Index Exclusion and FPE-Industry**

	(1)	(2)	(3)	(4)	(5)	(6)
	$E_{t+1}/A_t$		$E_{t+2}/A_t$		$E_{t+3}/A_t$	
$\log(M/A) * Treat * Post$	0.0077** (0.0028)	0.0077** (0.0029)	0.0118* (0.0052)	0.0109* (0.0051)	0.0142 (0.0067)	0.0129* (0.0060)
$\log(M/A) * Treat$	-0.0008 (0.0072)	-0.0021 (0.0058)	-0.0063 (0.0084)	-0.0070 (0.0087)	-0.0057 (0.0087)	-0.0047 (0.0072)
$\log(M/A) * Post$	-0.0047 (0.0029)	-0.0040 (0.0024)	-0.0086 (0.0047)	-0.0057 (0.0051)	-0.0067 (0.0036)	-0.0046 (0.0034)
$\log(M/A)$	0.0313* (0.0150)	0.0264*** (0.0062)	-0.0302 (0.0409)	0.0188 (0.0109)	-0.0523 (0.0274)	0.0068 (0.0082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
$\log(M/A) * Controls$	Yes	No	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry by Year FE	Yes	Yes	Yes	Yes	Yes	Yes
$N$	15543	15543	13225	13225	10879	10879
$R^2$	0.875	0.872	0.846	0.844	0.845	0.845

*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE using equation 2, with industry-by-year fixed effect. Industry is defined as 2 digits NAICS code. The sample is the propensity score matched sample. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 16: Robustness: ESG Index Exclusion and FPE-Matching Neighbors**

	(1)	(2)	(3)	(4)
	$E_{t+1}/A_t$			
	1-1	1-2	1-3	1-4
$\log(M/A) * Treat * Post$	0.0051* (0.0026)	0.0069* (0.0030)	0.0062* (0.0028)	0.0077** (0.0029)
$\log(M/A) * Treat$	-0.0010 (0.0082)	-0.0067 (0.0071)	-0.0037 (0.0076)	-0.0033 (0.0068)
$\log(M/A) * Post$	-0.0025 (0.0035)	-0.0056 (0.0041)	-0.0054 (0.0036)	-0.0070 (0.0037)
$\log(M/A)$	0.0379 (0.0229)	0.0215 (0.0178)	0.0311 (0.0170)	0.0208 (0.0164)
Controls	Yes	Yes	Yes	Yes
$\log(M/A)*Controls$	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
$N$	5163	7775	10382	12959
$R^2$	0.848	0.843	0.849	0.854

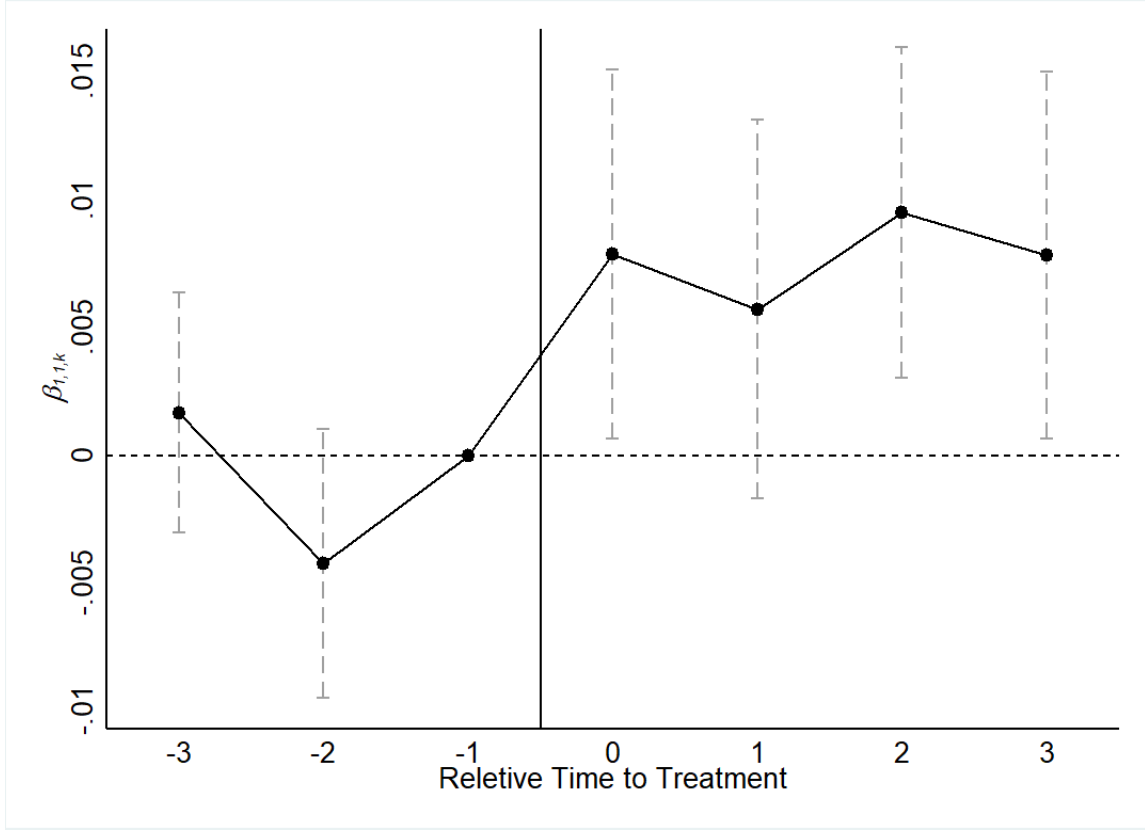
*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE using equation 2. The sample is the propensity score matched sample with 1, 2, 3 and 4 nearest neighbor for each treated firm. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

**Table 17: Robustness: ESG Index Exclusion and FPE-Matching One-Year Prior**

	(1)	(2)	(3)	(4)
	$E_{t+1}/A_t$		$E_{t+3}/A_t$	
$\log(M/A) * Treat * Post$	0.0098** (0.0029)	0.0097** (0.0032)	0.0174* (0.0075)	0.0167* (0.0076)
$\log(M/A) * Treat$	-0.0058 (0.0067)	-0.0055 (0.0053)	-0.0009 (0.0147)	-0.0003 (0.0147)
$\log(M/A) * Post$	-0.0059* (0.0031)	-0.0042 (0.0032)	-0.0033 (0.0051)	-0.0012 (0.0042)
$\log(M/A)$	0.0059 (0.0218)	0.0216*** (0.0049)	-0.0649 (0.0448)	-0.0092 (0.0102)
Controls	Yes	Yes	Yes	Yes
$\log(M/A) * Controls$	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
$N$	14178	14178	9906	9906
$R^2$	0.874	0.872	0.826	0.822

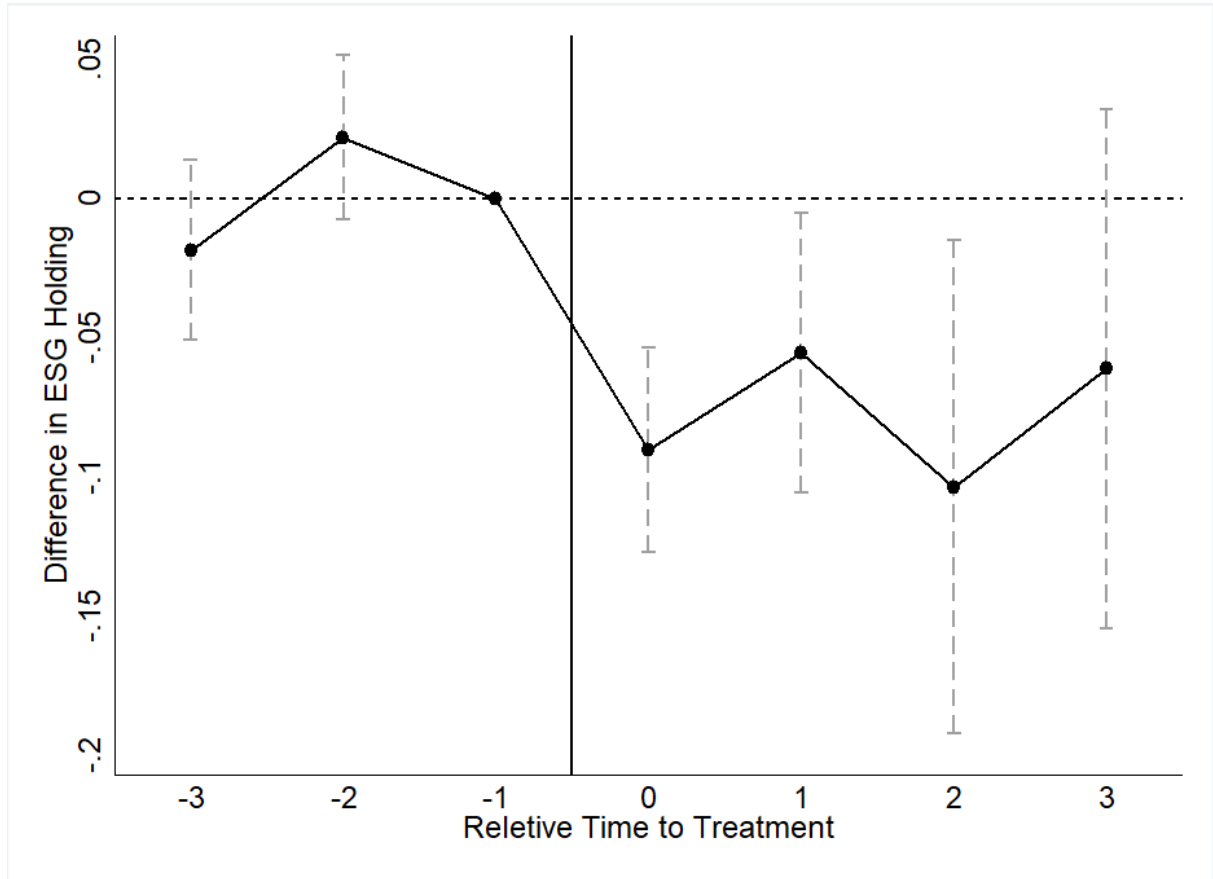
*Note:* This table reports regression results of MSCI ESG Leader index exclusion on FPE using equation 2. The sample is the propensity score matched sample using variables from 2017. The dependent variables are future earnings scaled by current assets. Controls include  $E/A$ ,  $Size$ ,  $Leverage$ ,  $Sales$ ,  $Tangibility$  and  $Cash$ , all at year  $t$ . Standard errors are clustered at firm and year level. \*, \*\*, and \*\*\* corresponds to statistically significant at 10%, 5% and 1% respectively. Variable definitions are provided in Appendix.

Figure 1: ESG Index Exclusion and FPE-Dynamic Effect



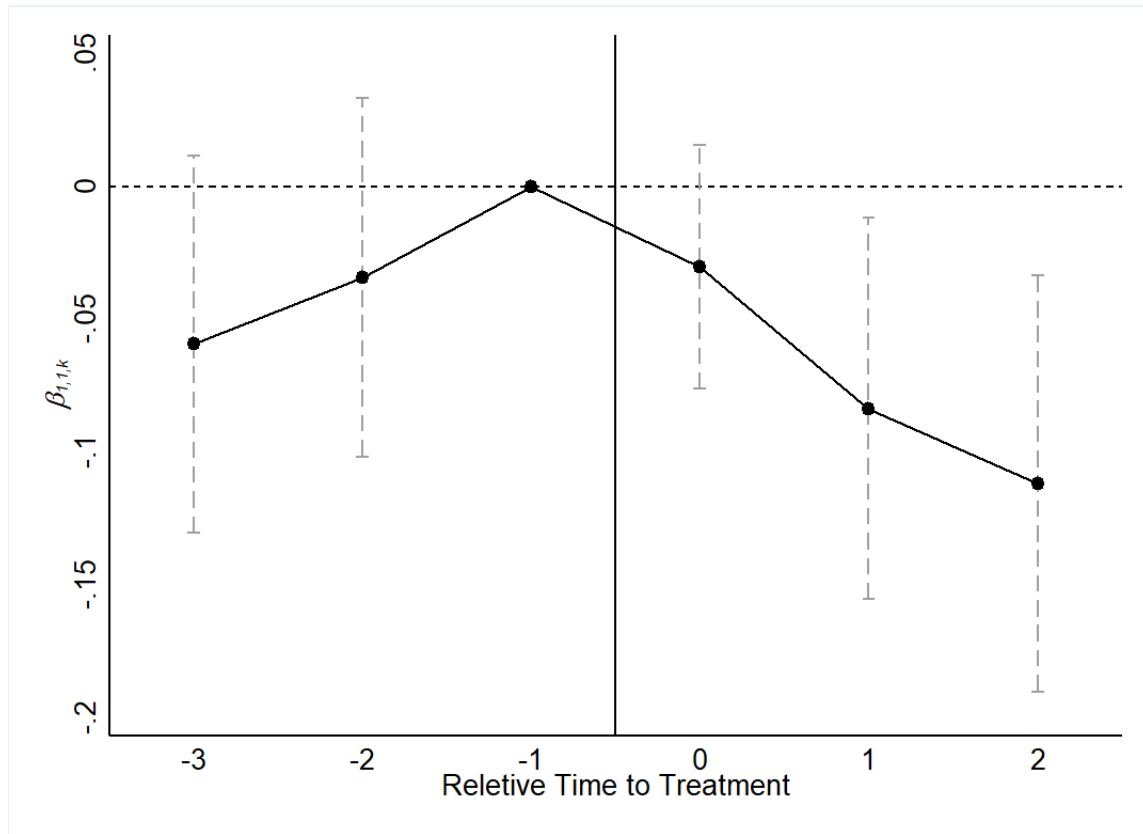
*Note:* This figure show the regression results of MSCI ESG Leader index exclusion on FPE using equation 3. The coefficient of interest  $\beta_{1,h,k}$  is plotted against time relative to the treatment. the coefficient of one-year prior the treatment is omitted and set as the base level. The sample is the propensity score matched sample. The dependent variables are future earnings scaled by current assets. Controls include *E/A*, *Size*, *Leverage*, *Sales*, *Tangibility* and *Cash*, all at year  $t$ . Standard errors are clustered at firm and year level. 95% confidence interval of the point estimates are included.

Figure 2: ESG Index Exclusion and ESG Holding-Dynamic Effect



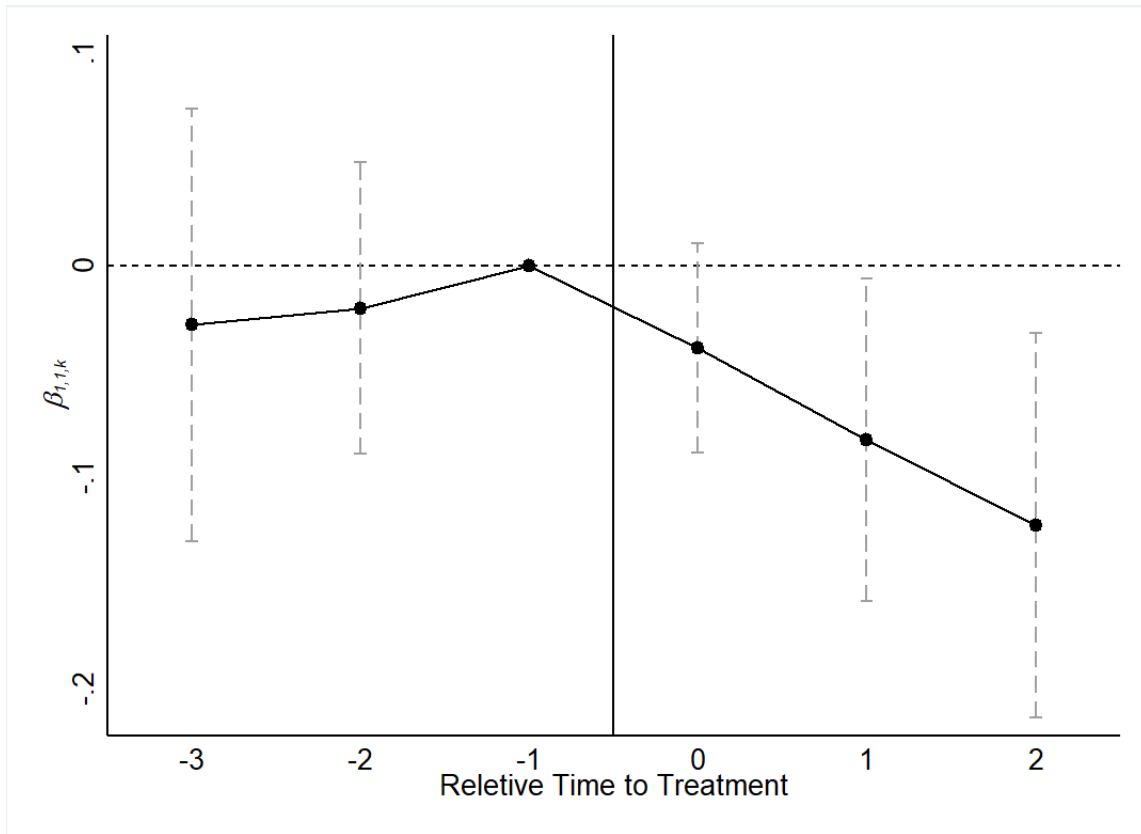
*Note:* This figure show the regression results of MSCI ESG Leader index exclusion on ESG holding. The coefficient of interest  $\beta_{1,k}$  is plotted against time relative to the treatment. the coefficient of one-year prior the treatment is omitted and set as the base level. The sample is the propensity score matched sample. The dependent variables are future earnings scaled by current assets. Standard errors are clustered at firm and year level. 95% confidence interval of the point estimates are included.

**Figure 3: ESG Index Exclusion and FPE of Scope 1 and 2 emission-Dynamic Effect**



*Note:* This figure show the regression results of MSCI ESG Leader index exclusion on FPE of Scope 1 and 2 emission using equation 3. The coefficient of interest  $\beta_{1,h,k}$  is plotted against time relative to the treatment. the coefficient of one-year prior the treatment is omitted and set as the base level. The sample is the propensity score matched sample. The dependent variables are log of future emission scaled by current assets. Standard errors are clustered at firm and year level. 95% confidence interval of the point estimates are included.

**Figure 4: ESG Index Exclusion and FPE of Scope 1 and 2 emission-Dynamic Effect**



*Note:* This figure show the regression results of MSCI ESG Leader index exclusion on FPE of Scope 1 emission using equation 3. The coefficient of interest  $\beta_{1,h,k}$  is plotted against time relative to the treatment, the coefficient of one-year prior the treatment is omitted and set as the base level. The sample is the propensity score matched sample. The dependent variables are log of future emission scaled by current assets. Standard errors are clustered at firm and year level. 95% confidence interval of the point estimates are included.

# APPENDIX

## A Figure and Table

Figure A1: Example of MSCI ESG Report-APPLE INC.

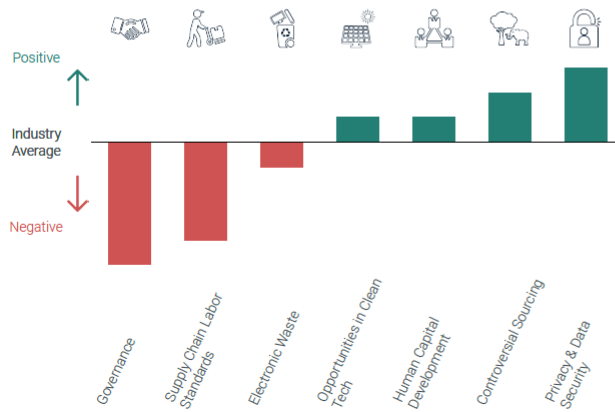
### APPLE INC. (AAPL)

Technology Hardware, Storage & Peripherals | US

Supply chain-related labor controversies weigh down otherwise strong ESG practices

#### Score attribution by key issue

This chart highlights the company's positioning relative to the industry average for each Key Issue that contributed to its ESG Rating as of February 22, 2023.



Note: Source: MSCI ESG Direct

### MSCI ESG RATINGS

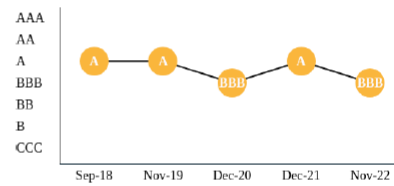


CCC B BB **BBB** A AA AAA

RATING ACTION DATE: November 11, 2022

LAST REPORT UPDATE: February 22, 2023

#### ESG Rating history



ESG Rating history shows five most recent rating actions

#### ESG Rating distribution

Universe: MSCI ACWI Index constituents, Technology Hardware, Storage & Peripherals, n=46

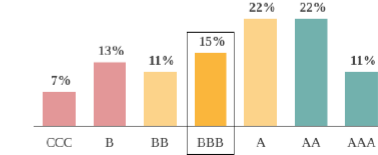
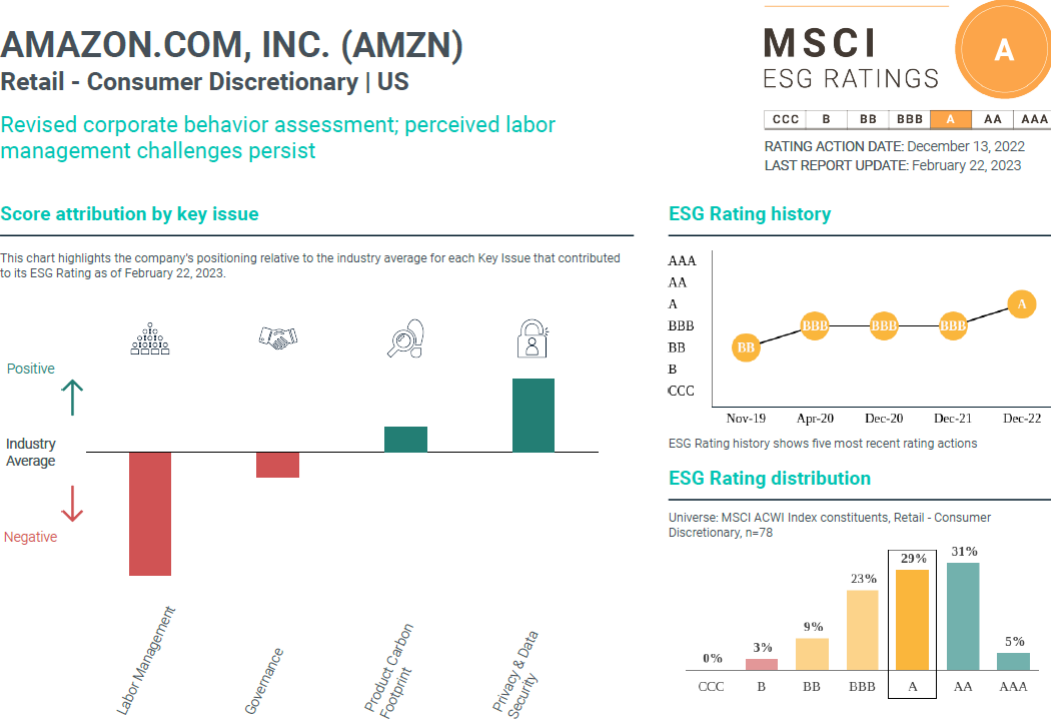




Figure A2: Example of MSCI ESG Report-AMAZON.COM INC.



**Table A1: Variable Definition**

VARIABLES	Definition
$E/A$	EBIT/total assets
$\log(M/A)$	$\ln(\text{market value of equity} / \text{total assets})$
$Size$	$\ln(\text{total assets})$
$Leverage$	total liabilities/total assets
$Tangibility$	property, plants and equipment/total assets
$Sale$	$\ln(\text{sales})$
$Cash$	cash and cash equivalent/total assets
$Investment$	$(R\&D \text{ expenses} + CAPEX)/\text{total assets}$
$Institutional Holding$	100*sum of all mutual fund holdings for a specific firm from the last reported holding in a year
$Index Fund Holding$	100*sum of all index mutual fund holdings for a specific firm from the last reported holding in a year
$nonESG nonIndex Fund Holding$	100*sum of all non-ESG non-index mutual fund holdings for a specific firm from the last reported holding in a year
$ESG Holding$	100*sum of all ESG mutual fund holdings for a specific firm from the last reported holding in a year
$ESG Index Holding$	100*sum of all ESG index mutual fund holdings for a specific firm from the last reported holding in a year
$MSCI Index = 1$	dummy variable equals one if this year, the firm is hold by any mutul fund that tracks MSCI ESG indexes
$MSCI ESG Leader Index = 1$	dummy variable equals one if this year, the firm is hold by any mutul fund that tracks MSCI ESG Leader indexes
$\log(EM1/A)$	$\ln(\text{Scope 1 emmision} / \text{total assets})$
$\log(EM12/A)$	$\ln(\text{Scope 1 and 2 emmision} / \text{total assets})$
$\log(M)$	$\ln(\text{market value of equity})$
$Volatility$	weekly return volatility evaluated for whole calendar year
$Illiquidity$	100*daily average of Amihud illiquidity ratio for whole calendar year
$IlliqVol$	100*daily volatility of Amihud illiquidity ratio for whole calendar year
$Tunrover$	daily average of volume/total share out standing, for whole calendar year
$Volume$	total daily volume for whole calendar year