The Power of ESG Labels*

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Abstract

This paper examines how firms' ESG ratings impact their cost of capital through affecting the investment strategies and portfolio decisions of ESG institutional investors. Using a regression discontinuity design, I find that, all else being equal, high-ESG firms with better ESG labels attract more ownership by ESG institutional investors than similar high-ESG firms with worse ESG labels. Conversely, among low-ESG firms, those with worse ESG labels have higher ownership by ESG institutional investors than similar low-ESG firms with better ESG labels. In both cases, higher ownership by ESG institutional investors lowers the firms' perception of their cost of capital, though it does not affect their implied cost of capital. I argue that this opposite behavior of ESG institutional investors reflects distinct responsible investment strategies that they pursue.

Keywords: Socially responsible investing, ESG ratings, Cost of capital, Institutional investors

JEL Classification: G11, G23, G32

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1 Introduction

Socially responsible investing (SRI) has become a prominent trend in capital markets, with a growing number of institutional investors incorporating firms' Environmental, Social, and Governance (ESG) performance into their portfolio decisions (PRI, 2024). However, evaluating firms' ESG performance poses substantial challenges, leading to the rise of third-party ESG rating agencies. Recent studies suggest that institutional investors rely on these ESG ratings in addition to their own ESG evaluations when making financial decisions (Glück et al., 2021; Raghunandan and Rajgopal, 2022; Berg et al., 2024; Rzeźnik et al., 2024). Consequently, these ratings can affect the portfolio decisions of socially responsible investors and, through this demand channel, change the firms' cost of capital (Pástor et al., 2021).[1] By shifting their portfolio allocations toward responsible assets, investors can lower the equilibrium cost of capital for these firms, thereby encouraging firms to adopt more responsible behaviors. (Heinkel et al., 2001; Hong and Kacperczyk, 2009).

In this paper, I explore the effect of firms' ESG ratings on their cost of capital. Using a quasi-experimental design, I provide robust empirical evidence on how ESG ratings influence firms' perception of their cost of capital (perceived cost of capital) by affecting the SRI strategies and portfolio decisions of socially responsible institutional investors.[2] Notably, my findings reveal that these investors' strategies and the consequent effect on the firms' cost of capital critically depend on whether the firms' ESG performance is high or low, demonstrating how these investors value not only high levels of ESG performance, but also potential for ESG improvements, mainly for financial reasons.

Despite the growing importance of ESG ratings, their impact on firms' cost of capital remains unclear for several reasons. First, there is an ongoing theoretical debate about the potential effect of firms' ESG performance on their cost of capital. While Pástor et al. (2021) demonstrate that, in equilibrium, firms with better ESG performance generally experience lower expected returns due to higher demand from socially responsible investors, other studies (Berk and Van Binsbergen, 2023; Pedersen et al., 2021; Goldstein et al., 2024) suggest that this relationship depends on various factors, such as the proportion of socially responsible capital in the market, leaving the ex-ante effect on cost of capital uncertain. Moreover, these models typically assume that socially responsible investors prefer high-ESG firms and therefore tilt their portfolios toward these firms through negative screening (exclusion of socially controversial assets from their investment universe) and ESG integra-

[1] A large body of literature has explored the effect of shareholder demand and ownership on a firm's cost of capital; see, for example, Merton et al. (1987); Gompers and Metrick (2001); Ferreira and Matos (2008). This literature finds that increased (decreased) demand from institutional investors raises (lowers) stock prices, which consequently lowers (increases) expected returns, effectively reducing (increasing) the cost of capital for firms.

[2] The perceived cost of capital is the estimated discount rate that the managers of the firms, after making certain adjustments, use in making their investment decisions. The perceived cost of capital is usually disclosed to investors during corporate conference calls (Gormsen and Huber, 2024).

tion (considering ESG criteria into investment decisions) strategies. However, as reported by GSIA (2022), while these practices were the most popular SRI strategies until 2020, they were surpassed by corporate engagement strategy in 2022. Through engagement strategy (Dimson et al., 2015, 2023), socially responsible investors increase their ownership in low-ESG firms with potential for ESG improvement, which can lower the cost of capital for these firms. By valuing the ESG improvement instead of high ESG performance, this scenario adds another dimension to the main assumption of prominent SRI theoretical models.[3] Finally, estimating the cost of capital based on the limited historical data is challenging and often unreliable, as it requires long time-series of financial data that are typically unavailable to researchers (Eskildsen et al., 2024).

These challenges have resulted in conflicting and mixed empirical findings in the literature. Some studies report that high-ESG firms have a lower cost of capital compared to low-ESG firms (Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023; Gormsen et al., 2023), while others find the opposite (Pástor et al., 2022; Zhang, 2023) or no significant differences at all (Aswani et al., 2024). To address these challenges, in this paper I employ a novel empirical approach that allows me to examine the causal effect of ESG ratings on firms' ownership by ESG institutional investors (those that take into account ESG considerations while making financial decisions) and consequently, firms' perceived cost of capital.[4] Furthermore, I investigate the motivations that drive ESG institutional investors' strategies based on firms' ESG performance.

The primary empirical challenge in identifying these effects lies in disentangling the impact of ESG ratings from other firm characteristics, such as financial performance, which are likely correlated with ESG ratings, institutional ownership, and cost of capital. To address this issue, I employ a regression discontinuity (RD) design focused on the two MSCI ESG score cutoffs that categorize firms into three groups with distinct ESG labels—i.e., *"Leader," "Average,"* and *"Laggard."*[5] The quasi-random assignment of firms to these ESG labels in a small neighborhood around each of the two cutoffs allows me to identify the causal effect of ESG labels on firms' ownership by ESG institutional investors and their perceived cost of capital, isolated from confounding firm characteristics. A key

[3] Hirschman (1970) introduced the concepts of "exit" and "voice" in the context of corporate governance as channels through which stakeholders can put pressure on firms to achieve certain outcomes. More recently, this terminology has been applied by Edmans (2009) and Edmans (2014) in the general case of corporate governance, and by Broccardo et al. (2022) in the case of corporate social responsibility. Here, the engagement channel is similar to the "voice" strategy, where investors actively engage with firms to improve ESG practices. The negative screening and ESG integration channels resemble the "exit" strategy but in reverse: instead of divesting due to poor ESG performance, investors select high-ESG firms, reallocating capital toward companies already meeting desired ESG standards without engaging to prompt further change. This approach involves favoring high-ESG firms while reducing exposure to low-ESG ones.

[4] Like Gormsen et al. (2023), by using this measure instead of data-driven proxies of expected returns, I can directly investigate the impact of ESG performance on how firms estimate their cost of capital.

[5] Berg et al. (2024) also utilize MSCI ESG scores to examine the economic impact of ESG ratings. They first show that among five major ESG ratings, only MSCI ESG can explain the holdings of US funds with an ESG mandate. Their approach employs a panel event study to assess the effects of upgrades and downgrades in MSCI ESG *letter ratings* ("CCC," "B," "BB," etc.) on firm outcomes. In contrast, I apply an RD design at the specific MSCI cutoffs where ESG *labels* shift, allowing for a robust analysis of investor behavior and ownership changes at these thresholds.

advantage of this approach is that by focusing on cutoffs at both ends of the ESG spectrum, I can investigate and compare the impact of investors' strategies on the cost of capital for firms with both high and low ESG performance, separately, but within the same setting. My sample comprises U.S. publicly traded firms with MSCI ESG scores from 2011 to 2019.

I show that ESG institutional investors respond differently to firms' ESG labels depending on the firms' ESG performance.[6] In particular, I find that everything else being equal, among high-ESG firms (firms at the top of ESG spectrum with high MSCI ESG scores), those with better ESG labels (i.e., *"Leader"*) in year t, have disproportionately higher ESG institutional ownership and lower perceived cost of capital in year $t+1$ compared to similar high-ESG firms with worse ESG labels (i.e., *"Average"*). Conversely, among low-ESG firms (firms at the bottom of ESG spectrum with low MSCI ESG scores), those with worse ESG labels (i.e., *"Laggard"*) in year t, attract disproportionately more ESG institutional ownership and have lower perceived cost of capital in year $t+1$ compared to similar low-ESG firms with better ESG labels (i.e., *"Average"*).[7] The higher ownership of ESG institutional investors in high-ESG firms with better ESG labels and low-ESG firms with worse ESG labels suggest that these investors may pursue different SRI strategies at the two ends of ESG spectrum—i.e., ESG integration strategy for the former group of firms and engagement strategy for the latter.

To determine whether these investment preferences are driven by non-financial motives, I compare the realized returns of these two groups of firms with their respective control groups. Specifically, I compare *"Leader"* high-ESG firms to similar high-ESG firms that have *"Average"* labels, and *"Laggard"* low-ESG firms to similar low-ESG firms with *"Average"* labels. In both cases, I find that the former groups—those with higher ownership by ESG institutional investors—yield lower realized returns compared to the latter groups. This analysis supports the argument that short-term financial motives do not drive the distinct investment strategies of ESG institutional investors toward these firms.

Moreover, my findings indicate that at both ends of the ESG spectrum, higher ownership by ESG institutional investors is the reason that lowers the firms' perceived cost of capital. In a fuzzy RD design, I use assignment to different ESG labels as an instrumental variable (IV) for ESG institutional ownership in a small neighborhood around each cutoff to isolate the effect of ESG institutional ownership on the firms' perceived cost of capital from other firm characteristics. I show that managers of

[6]In Section 2.2, I use three different ways to define ESG institutional investors: those in the top quantile of institutional investors based on their value-weighted average of the portfolio firms' MSCI ESG scores, those that explicitly commit to incorporating ESG criteria in their decision-making by signing into PRI (Principles for Responsible Investment), and those that have ESG-related terms in their names. My results are similar for all definitions.

[7]By disproportionately, I mean while the underlying numerical ESG scores change continuously across the cutoffs, there is a discontinuity (jump) in the ownership by ESG institutional investors and the perceived cost of capital between the firms that are below and above these cutoffs. In RD framework, the statistical significance of this discontinuity indicates the causal effect of the treatment (being assigned different ESG labels) on the outcome variable (ESG institutional ownership and the perceived cost of capital).

the firms with higher ownership by ESG institutional investors, whether high-ESG firms with better ESG labels or low-ESG firms with worse ESG labels, *perceive* that their firms will have a lower cost of capital due to the higher ownership by ESG institutional investors. However, consistent with Berk and Van Binsbergen (2023), I find no evidence that higher ownership by ESG institutional investors reduces the firms' implied (forward-looking) cost of capital.

Furthermore, I investigate the potential reasons behind the opposite behavior of ESG institutional investors toward high- versus low-ESG firms. Gollier and Pouget (2022) show that in the presence of socially responsible (SR) investors, activist investors can increase their financial returns by adopting pro-social objectives and committing to a long-term investment horizon. The activists' strategy involves acquiring a firm that is not socially responsible, transforming it into a responsible entity, and then selling a portion of it back to the market. Consistently, I find that ESG institutional investors have both long-term monetary and non-monetary incentives to follow engagement strategy and increase holdings in low-ESG firms labeled as "*Laggard*" relative to similar firms with "*Average*" labels. Regarding the monetary incentives, in a panel event study, I show that when high-ESG firms upgrade from "*Average*" to "*Leader*" label, they yield negative Buy-and-Hold Returns (BHRs).[8] Consistently, after the upgrade, there is no significant change in their ESG institutional ownership. When high-ESG firms downgrade from "*Leader*" to "*Average*" label, there is no significant abnormal BHRs, and again, no significant change in their ESG institutional ownership. However, when low-ESG firms upgrade from "*Laggard*" to "*Average*" label, they generate positive BHRs and their ESG institutional ownership starts increasing. Conversely, when they downgrade from "*Average*" to "*Laggard*" label, they yield negative BHRs and their ESG institutional ownership starts decreasing. This analysis underscores the role ESG labels play in shaping investors' monetary incentives in increasing their holdings in low-ESG firms with worse ESG labels, with the aim of gaining positive abnormal returns when their ESG labels upgrade.

Finally, I find that ESG institutional ownership has a stronger positive impact on the ESG performance improvement of the firms with lower prior ESG scores, and as the firm's prior ESG score increases, the marginal effect of ESG institutional ownership on further ESG improvements decreases. These results imply that for low-ESG firms with weaker labels, ESG institutional investors are driven by an *engagement* strategy, actively working to enhance these firms' ESG performance. Considering the investors' monetary incentives at this cutoff, this strategy aligns with the findings of Dyck et

[8] Note that In the RD setting, I compared the outcome variables of firms one year after their assignment to the treatment versus control groups, allowing for a cross-sectional assessment of the effects of ESG labels. By contrast, in the panel event study analysis, I examine the time series changes in firms' outcome variables following upgrades or downgrades in their ESG labels. The former approach is more empirically robust, as it allows me to compare the outcome variables for similar firms with different ESG labels. Furthermore, while the RD design uses annual intervals, the panel event study operates on a more granular time scale, with monthly intervals for BHR and quarterly intervals for institutional ownership.

al. (2019), which demonstrate that investors improve firms' environmental and social (E&S) performance following financial incentives tied to E&S enhancements, allowing ESG investors to expect abnormal positive returns as these firms' ESG ratings improve. In contrast, ESG investors are motivated by an *ESG integration* strategy for high-ESG firms with stronger labels, investing in these firms to meet ESG mandates or attract increased flows from responsible investors (Hartzmark and Sussman, 2019). Therefore, ESG institutional investors' strategy changes according to a firm's ESG performance, reflecting the motivations that drive SRI practices.

In the RD setting of this paper, the disproportionately higher attention that institutional investors give to firms with "*Leader*" or "*Laggard*" ESG labels, despite having very close ESG scores to firms labeled "*Average*," can be interpreted through the lens of category thinking (Ellis and Masatlioglu, 2022) and salience theory (Bordalo et al., 2012, 2013b,a). These models suggest that extreme categorizations draw disproportionate attention and influence decision-making more strongly, as investors may focus on these labels as signals that stand out, amplifying their importance in portfolio decisions. Recent empirical findings in SRI suggest that salient categorization and ESG labels, such as Morningstar's sustainability ratings, play a significant role in directing retail investor demand towards or away from mutual funds with salient labels Ammann et al. (2019); Ceccarelli et al. (2024); Hartzmark and Sussman (2019). While these studies focus on how labels and categorizations influence retail investors' decisions, I document a similar mechanism affecting institutional investors' decisions, showing that firms' ESG labels can drive demand among institutional managers by shaping their portfolio decisions.

This paper contributes to the growing literature that studies the effect of firms' ESG performance on their ownership by ESG institutional investors and their cost of capital. A large body of empirical literature has focused on studying the effect of ESG performance on the firms' cost of capital, with mixed and sometimes contradictory results. While some of these studies have found that high-ESG firms have lower cost of capital compared to low-ESG firms (Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023; Gormsen et al., 2023; Eskildsen et al., 2024), others have found the opposite results (Pástor et al., 2022; Zhang, 2023). Yet others have found no significant difference whatsoever (Berk and Van Binsbergen, 2023; Aswani et al., 2024). I contribute to this literature by demonstrating that the impact of ESG performance on perceived cost of capital is different for firms with high and low ESG ratings. This contradictory effect may partially explain why scholars have struggled to find a consistent effect of ESG performance on the firms' cost of capital. Moreover, my findings show that socially responsible investors value not only firms' high ESG performance, but also the change in their ESG performance. Some prominent models of SRI have focused on the former (Heinkel et al., 2001; Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022; Goldstein et al., 2024), while others are increasingly taking into account the latter (Gollier and Pouget, 2022; Gupta et al., 2022; Broccardo et al., 2022). By showing the opposite impact of these preferences on the firms' cost of capital based on their ESG performance, my findings underscore the need to consider both types of ESG investor preferences while developing models, to study this interaction in a single framework.

Moreover, I contribute to the literature that studies how the firms' ESG performance affects the portfolio decisions of ESG institutional investors (Starks, 2023). In a survey of institutional investors about climate risk perception, Krueger et al. (2020) find that ESG funds consider the firms' ESG performance when making financial decisions. They also find that many of the investors, especially larger ESG investors, prefer engagement strategy to negative screening and ESG integration. However, they do so mostly because of financial and risk management reasons, and not with the aim of improving the ESG performance of their portfolio firms. Heath et al. (2023) find that self-labeled ESG institutional investors do select firms with better E&S performance; however, inconsistent with their claimed impact, they do not improve the E&S performance of their portfolio firms. Gantchev et al. (2024) find that self-labeled ESG funds try to improve the overall ESG performance of their portfolio holdings only through trading, and not engaging with them, and only if it helps them perform better financially. According to Raghunandan and Rajgopal (2022), there is no evidence that ESG funds' portfolio firms have better ESG performance than other funds' portfolio firms. They also find that ESG funds hold high-ESG firms to be able to charge higher management fees. Similarly, Kim and Yoon (2023) find that PRI funds have a higher aggregate revenue from capital inflows but no improvement in the underlying fund level ESG score. Finally, Berg et al. (2024) show that ESG funds increase their holdings in firms that experience an upgrade in their MSCI ESG ratings and decrease their holdings in firms that experience a downgrade, mainly to comply with ESG mandates. My results contribute to this literature by demonstrating that ESG institutional investors pay attention to the MSCI ESG ratings while making their portfolio decisions, although in more complicated manners than already explored. I show that firms' ownership by ESG institutional investors depends on their underlying ESG scores. In particular, I provide empirically robust evidence that ESG institutional investors have higher ownership in high-ESG firms with stronger ESG labels and low-ESG firms with weaker ESG labels, reflecting their preferred strategies.

An important contribution of this paper is to bridge these two research areas. Related theories (Pástor et al., 2021; Pedersen et al., 2021; Goldstein et al., 2024) explain how heterogeneous demands, resulting from different ESG preferences of socially responsible investors versus traditional ones, have implications for the firms' cost of capital. Recently, van der Beck (2023) shows that increased demand, resulting from higher flows into ESG funds, generates a significant price impact that explains the recent abnormally high *realized* returns from sustainable investing. I demonstrate that there is a similar effect of sustainable investing on the firms' *expected* returns and thus, on their perceived cost of capital. I find that increased ownership by ESG institutional investors decreases the perceived cost of capital for the target firms without necessarily affecting their implied cost of capital. Interestingly, this effect is similar for high- and low-ESG firms.

Finally, this paper contributes to the recent literature that investigates the effects of ESG ratings on firms and investors. Recent studies have suggested that institutional investors rely on the ESG ratings besides (or sometimes, instead of) performing their own ESG evaluations (Raghunandan and Rajgopal, 2022). According to Rzeźnik et al. (2024), a decline in ESG ratings resulting from an exogenous change in rating methodology generates a positive abnormal monthly return. However, they attribute this effect to the reliance of retail investors, and not mutual funds, on ESG ratings. Glück et al. (2021) show that while downgrades in MSCI environmental and social scores are followed by negative abnormal returns, upgrades in the MSCI environmental and governance scores lead to lower downside and systematic risks, respectively. Amel-Zadeh et al. (2023) provide evidence that sustainability ratings significantly impact asset allocation decisions among wealthy European retail investors. More recently, Berg et al. (2024) show that among five major ESG ratings, only MSCI ratings can explain the holdings of US mutual funds with an ESG mandate. They find that downgrades in the MSCI ESG letter ratings reduce the ownership by ESG mutual funds, while upgrades increase it. Moreover, they document a negative abnormal return following ESG rating downgrades.[9] I contribute to this literature by providing empirically robust evidence that MSCI ESG ratings do affect the financial decisions of ESG institutional investors. Moreover, I explore the intricate dynamics of this relationship and its impact on the firms' perceived cost of capital.

2 Data & Variables

2.1 MSCI ESG Rating Methodology

In this study, I use MSCI's ESG ratings to examine the effect of ESG ratings on firms' ESG ownership and cost of capital. MSCI's ESG ratings is one of the most widely used in the market.[10] Furthermore, Berg et al. (2024) find that MSCI's ESG rating is the only ESG rating that can explain the portfolio holdings of U.S. mutual funds with an ESG mandate. This rating assesses a firm's ability to manage financially significant ESG risks and opportunities. In calculating the ESG rating, MSCI considers the materiality of ESG risks and the firm's capacity to manage those risks (MSCI, 2023).

Each firm is evaluated based on two to seven environmental and social "Key Issues," selected from a total of 33 issues based on the firm's industry and market factors (*Key Issue Exposure Score*). The firm's ability to manage its aggregate ESG risks and opportunities is then assessed by evaluating

[9] As mentioned before, while Berg et al. (2024) focus on MSCI ESG *letter* rating upgrades and downgrades, I focus on MSCI ESG *labels*. This can explain the partial differences between my findings and theirs.

[10] The top three ESG data providers—MSCI, ISS ESG, and Sustainalytics—collectively account for approximately 60% of the ESG ratings market, as reported by https://www.opimas.com/research/742/detail/

Table 1: The MSCI method of mapping the Final Industry-Adjusted Company ESG Scores to ESG Letter Ratings and ESG Labels

This table shows how MSCI maps the final industry-adjusted company ESG scores to ESG letter ratings and ESG labels (MSCI, 2023). The 0-10 numerical score is divided into seven equal parts, and each part is assigned an ESG letter rating, changing from CCC to AAA. Moreover, at the ESG score of 2.857, where the letter rating changes from B to BB, the ESG label changes from Laggard to Average; at the ESG score of 7.143, where the ESG letter rating changes from A to AA, the ESG label changes from Average to Leader. (Note that the overlap in the score ranges is because of the rounding.)

Final Industry-Adjusted Company ESG Score	ESG Letter Rating	ESG Label
8.571 - 10.000	AAA	Leader
7.143 - 8.571	AA	Leader
5.714 - 7.143	A	Average
4.286 - 5.714	BBB	Average
2.857 - 4.286	BB	Average
1.429 - 2.857	B	Laggard
0.000 - 1.429	CCC	Laggard

its governance structure, policies and targets, quantitative performance measures, and relevant controversies (*Key Issue Management Score*). Firms receive a 0-10 score for each selected environmental and social Key Issue (*Key Issue Score*). Additionally, all firms are assessed on the governance pillar, receiving a 0-10 score in this area as well (*Governance Pillar Score*). A Weighted Average Key Issue Score (*WAKIS*) is then calculated for each firm, combining the *Key Issue Score* and the *Governance Pillar Score*. Finally, the *WAKIS* is normalized relative to the ESG ratings of other firms within the same industry to produce the *Industry-Adjusted Company Score*, which ranges from 0 to 10.

Finally, the *Industry-Adjusted Company Score* is divided into seven equal categories, with each firm receiving an ESG letter rating ranging from "CCC" (lowest) to "AAA" (highest) (see Table 1). In addition, MSCI assigns ESG labels based on the firm's ESG score: firms with scores above 7.143 are labeled "Leader," those with scores between 2.857 and 7.143 are labeled "Average," and firms with scores below 2.857 are labeled "Laggard."[11] These letter ratings, along with other tools for assessing the climate risks and opportunities a firm faces, are publicly available on MSCI's website.[12]

For the purposes of this study, it is crucial to note that MSCI's ESG rating process relies exclusively on publicly available information, such as company financial and sustainability disclosures, specialized government and academic data sets, and media searches. MSCI explicitly states on its website that it does not send surveys, conduct interviews with firms, or accept any non-publicly available data provided by firms. As a result, firms cannot manipulate their assigned ESG ratings.

I use MSCI ESG ratings as a measure of firms' ESG performance for several reasons. First, MSCI is one of the largest and most widely recognized providers of ESG ratings, utilized by both academics and practitioners. Second, MSCI relies solely on publicly available data to evaluate firms, ensuring that firms cannot manipulate their ratings. Finally, MSCI provides an underlying ESG numerical

[11] For more details, see https://www.msci.com/esg-and-climate-methodologies.

[12] https://www.msci.com/our-solutions/esg-investing/esg-ratings-climate-search-tool

score that changes continuously and an ESG label that changes discontinuously at arbitrarily chosen cutoffs. These features make MSCI's ESG rating system particularly suitable for the Regression Discontinuity design employed in this study.

I combine the MSCI ESG ratings dataset with institutional ownership data from the Thomson Reuters Institutional Holdings (13F) database and firms' fundamental information from Compustat. Additionally, I use data on firms' perceived cost of capital and discount rates from Gormsen and Huber (2024), and analyst forecasts from the Thomson Reuters IBES database. Consistent with standard financial research practices, I exclude companies in the finance sector (SIC Industry Codes 6000 to 6999) and winsorize all variables at the 1st and 99th percentiles to mitigate the influence of outliers. The final sample comprises 13,268 unique firm-year observations from 2011 to 2019, covering 3,186 distinct firms listed on the U.S. stock market.

2.2 Outcome Variables

2.2.1 Firms' Ownership by Institutional Investors

I calculate ownership by all institutional investors, *Ins_Ownership*, as the percentage of a firm's shares owned by any type of institutional investor reported in the Thomson Reuters Institutional Holdings (13F) database.

To calculate ownership by ESG institutional investors, it is first necessary to define these investors. The literature typically employs two methods. The first identifies ESG institutional investors as those explicitly committed to incorporating ESG criteria in their decision-making. For instance, studies such as Raghunandan and Rajgopal (2022), Heath et al. (2023), Michaely et al. (2024), Berg et al. (2022), and Gantchev et al. (2024) classify ESG mutual funds by screening their names and their strategies for keywords related to ESG, such as "SRI," "social," "ESG," "green," and similar terms. Similarly, Gibson Brandon et al. (2022) and Liang et al. (2022) define ESG institutional investors as those who have signed the Principles for Responsible Investment (PRI), thereby publicly committing to incorporating ESG issues into their investment processes. However, as noted by Dumitrescu et al. (2022), 29% of self-labeled ESG funds engage in "greenwashing," meaning they do not consistently adhere to their stated ESG commitments.

The second approach, used by Cao et al. (2023), Hwang et al. (2022), and Dasgupta et al. (2023), calculates each investor's ESG score as the value-weighted ESG score of its portfolio holdings. This method has the advantage of identifying investors who actively practice socially responsible investing (SRI), even if they do not explicitly advertise or publicly declare it. However, one drawback is that firms' ESG scores often correlate with their financial performance, which means this measure may capture the financial preferences of investors rather than their ESG focus.

In this study, I use the second approach as the primary method to identify ESG institutional investors and report my findings accordingly. At the end of each quarter, I calculate the value-weighted average ESG score of each fund's portfolio firms. I then compute the yearly ESG score for each investor by averaging these quarterly ESG scores. Investors are then divided into five quantiles annually, and those in the top quantile are classified as ESG institutional investors. For each firm, I calculate the total shares owned by ESG institutional investors annually to derive the *ESG_Ownership* variable.

As explained in Section 3.2.2, the drawback of this method—namely, the potential correlation between firms' ESG scores and financial performance—is not relevant in the empirical setting of this study. Nevertheless, I will demonstrate that my results remain qualitatively unchanged when using the first approach, which identifies ESG investors through their explicit commitment to ESG strategies.

2.2.2 Firms' Perceived Cost of Capital and Actual Discount rate

According to the standard economic view, firms should invest in any project that offers expected returns above a certain threshold—i.e., the firm's discount rate, or required rate of return. In equilibrium, this discount rate is equivalent to the firm's cost of capital. However, estimating the discount rate is a complex and non-trivial task. As a result, many firms rely on financial markets to estimate their cost of capital, based on observed asset prices and interest rates. Gormsen and Huber (2024) refer to this estimate as the firm's perceived cost of capital, explaining that firms adjust this figure by incorporating factors such as beliefs about value creation, risks, and financial constraints when determining the final discount rate used for investment decisions. Consequently, a firm's actual discount rate, which serves as the threshold for investment decisions, often differs from its perceived cost of capital.

Gormsen and Huber (2024) measure firms' perceived cost of capital and their discount rates by analyzing corporate conference call transcripts, during which managers discuss their firms' operations and sometimes disclose their estimates of these rates. By collecting and examining the transcripts, Gormsen and Huber (2024) have compiled a dataset of perceived cost of capital and discount rates for approximately 2,500 firms across 20 countries between 2002 and 2021.[13] I use this dataset to construct the *Perceived_CoC* and *Discount_Rate* variables for this study.

[13] Publicly available at: https://costofcapital.org/

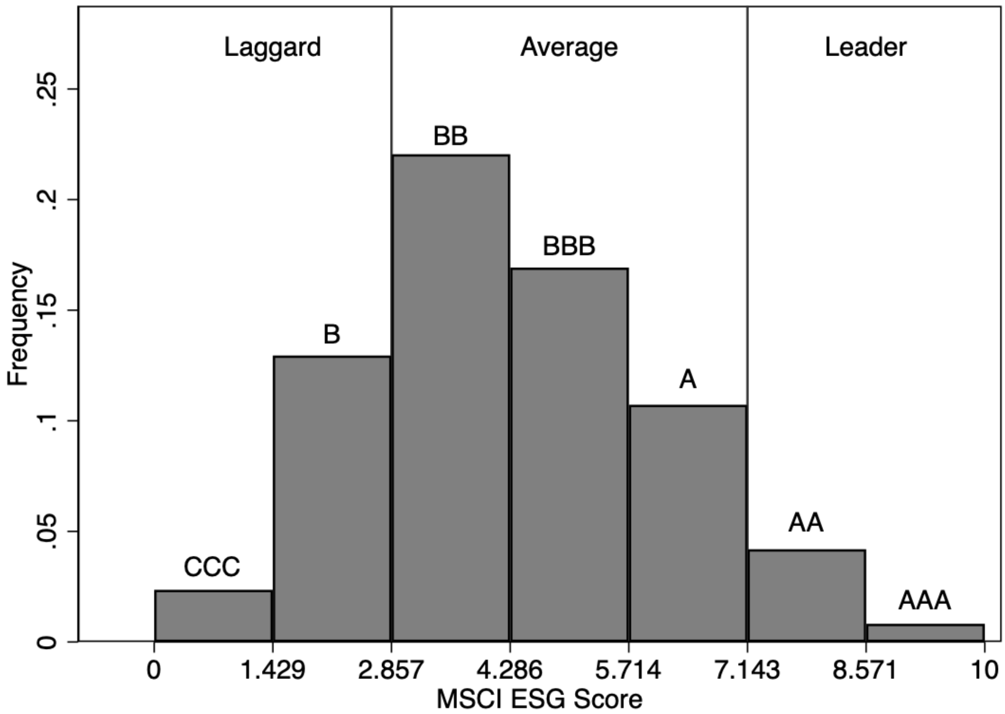

Figure 1: Histogram of MSCI ESG scores across firms. The graph shows the frequency distribution of firms' MSCI ESG scores, categorized into ESG letter ratings (on top of each bar) and ESG labels (on top of the chart). The majority of firms are concentrated in the middle of the distribution, with scores corresponding to the "Average" ESG label (BB, BBB, and A ratings). Firms in the "Laggard" category (CCC, B) and "Leader" category (AA, AAA) are less frequent. The vertical lines indicate the thresholds for transitioning between the "Laggard," "Average," and "Leader" ESG label categories.

2.2.3 Firms' Implied Cost of Capital

Measuring firms' expected returns is notoriously challenging, and the literature has proposed numerous proxies to estimate them. Lee et al. (2021) assess the relative performance of various measures and conclude that, in general, implied cost of capital (ICC) metrics perform best in time series analysis. In this study, I focus on this class of expected return proxies. Specifically, I calculate three ICC proxies for each firm-year observation. The first two proxies are based on the dividend discount model (Ohlson and Juettner-Nauroth, 2005; Easton, 2004), which equates a stock's price with the sum of its discounted future dividends. The third proxy is derived from the residual income model (Gebhardt et al., 2001; Claus and Thomas, 2001). I follow the methodology described in Appendix A.1 of Eskildsen et al. (2024) to calculate these measures.

2.3 Data Description and Summary Statistics

Figure 1 shows how the firm year observations are distributed in each ESG letter rating and each ESG label categories in the whole sample. Figure 2 illustrates the distribution of firm-year observations based on their MSCI ESG labels over the sample period. The figure reveals that the majority

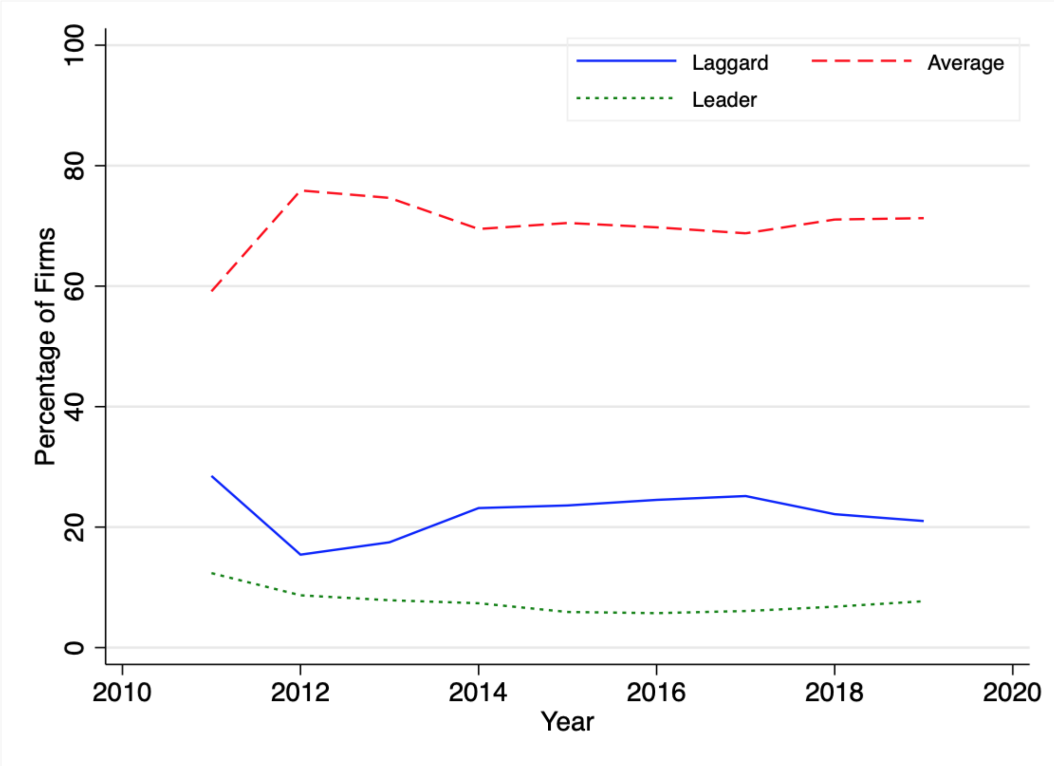

Figure 2: Percentage of firms in each MSCI ESG label category (Laggard, Average, Leader) from 2010 to 2019. The graph shows that a majority of firms fall within the "Average" ESG label, maintaining a stable percentage over time. Firms labeled as "Laggard" exhibit a slight increase in the early years, while "Leader" firms remain a small fraction throughout the period. The data highlights the persistent distribution of firms across ESG categories during the sample period.

of firm-year observations fall in the "Average" category, indicating that most firms are positioned in the middle of the ESG distribution. This pattern suggests that firms are unlikely to manipulate their ESG ratings, as manipulation would likely result in a disproportionate number of firms achieving a "Leader" label. Furthermore, the distribution of observations has remained relatively stable throughout the sample period, with more than 60% of firms consistently categorized as "Average" each year. Figure 3 displays how MSCI ESG labels are distributed in each Fama-French 12 industry groups. While some industries, like Energy and Chemicals, have a higher percentage of "Laggard" labels, in general a high percentage of firms are assigned the "Average" label. Table 2 provides summary statistics for the variables used in this study, disaggregated by MSCI ESG label. Detailed descriptions of how these variables are calculated can be found in Appendix A.1.

3 Firms' ESG Labels, Institutional Ownership and Cost of Capital

Recent empirical literature has demonstrated that institutional investors increasingly incorporate firms' ESG performance into their portfolio decisions mainly to attract flows from investors who may have both monetary (e.g., mitigating future regulatory risks) and non-monetary motives (e.g., gaining non-financial utility) to invest responsibly (Hartzmark and Sussman, 2019; Gantchev et al., 2024; Raghu-

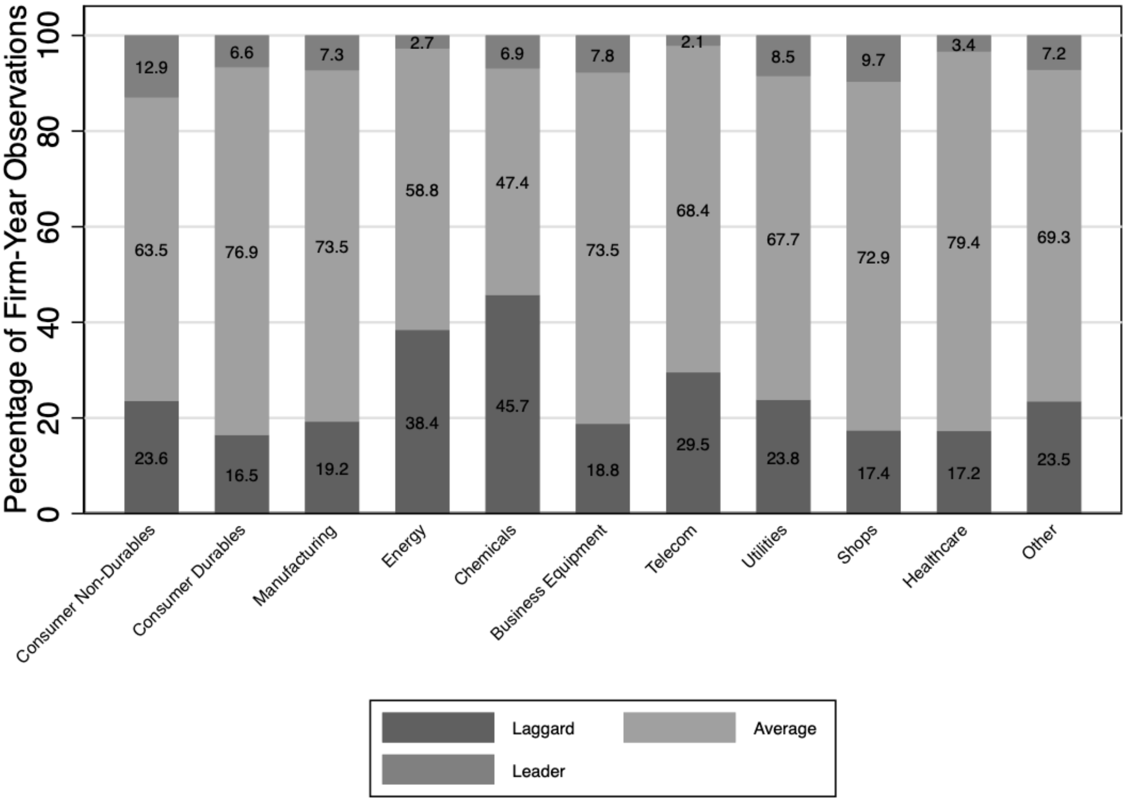

Figure 3: Distribution of firm-year observations by MSCI ESG labels (Laggard, Average, and Leader) across industries. The chart illustrates the percentage breakdown of each ESG label within each Fama-French 12 industries. For example, industries like Energy and Chemicals have a notably higher proportion of "Laggard" firms, whereas industries like Consumer Durables and Business Equipment have a larger share of "Average" firms.

nandan and Rajgopal, 2022). As institutional investors seek to attract flows from socially responsible clients, they rely heavily on ESG ratings to inform their investment choices. MSCI, as one of the largest ESG rating providers, can affect the investment decisions of institutional investors. In this section, I first analyze the effect of firms' MSCI ESG ratings on their ownership by institutional investor.

Additionally, I examine how ESG ratings influence firms' cost of capital. Prior theoretical literature (Pástor et al., 2021) suggests that investors with ESG preferences are willing to pay a premium for firms based on their ESG performance, leading to lower expected returns and thus a reduced cost of capital for these firms. Accordingly, MSCI ESG ratings may influence firms' cost of capital by altering institutional investors' demand for firms based on their ESG performance.

Figure 4 illustrates the relationship between MSCI ESG ratings, firms' average perceived cost of capital, and their average ownership by ESG institutional investors. The perceived cost of capital initially increases, suggesting that among firms with low ESG ratings, those with slightly worse ESG scores face lower perceived costs of capital. However, among firms with high ESG ratings, those

Table 2: Summary Statistics

This table shows the summary statistics for the firm-level characteristics (yearly observations) used in this study. Panel A reports the summary statistics for firms with the MSCI ESG Label of "Laggard," while Panel B and Panel C report the statistics for firms with MSCI ESG Labels of "Average," and "Leader," respectively. Panel D shows the statistics for all the firms. In Appendix A.1, I describe how I calculate these variables.

	Mean	SD	Min	p25	p50	p75	Max	N
Panel A - Firms with "Laggard" MSCI ESG Label								
Dividend/1y Lagged Assets	.017	.028	0	0	.0054	.022	.17	2,387
CAPEX/1y Lagged Assets	.059	.059	.00078	.02	.04	.073	.29	2,390
Leverage	.85	3	-15	.11	.56	1.2	16	2,890
Return on Assets	.055	.15	-.67	.03	.07	.12	.34	2,895
Market to Book Ratio	1.6	1.6	.12	.58	1.1	2	9.2	2,893
ESG_Ownership	.54	.2	.038	.43	.58	.68	.95	2,551
Perceived_CoC	9.4	.96	7.3	8.8	9.4	10	12	2,404
Panel B - Firms with "Average" MSCI ESG Label								
Dividend/1y Lagged Assets	.016	.027	0	0	.0025	.022	.17	7,529
CAPEX/1y Lagged Assets	.049	.049	.00078	.017	.033	.063	.29	7,539
Leverage	.79	2.9	-15	.06	.49	1.1	16	9,376
Return on Assets	.049	.16	-.67	.034	.074	.12	.34	9,423
Market to Book Ratio	1.8	1.7	.12	.7	1.2	2.2	9.2	9,401
ESG_Ownership	.59	.19	.038	.49	.63	.73	.95	8,029
Perceived_CoC	9.5	1	7.3	8.8	9.5	10	12	8,046
Panel C - Firms with "Leader" MSCI ESG Label								
Dividend/1y Lagged Assets	.025	.03	0	0	.018	.038	.17	782
CAPEX/1y Lagged Assets	.043	.037	.0013	.02	.034	.054	.29	782
Leverage	.91	3	-15	.2	.58	1.3	16	944
Return on Assets	.098	.088	-.58	.053	.097	.15	.34	947
Market to Book Ratio	1.8	1.6	.12	.75	1.3	2.2	9.2	940
ESG_Ownership	.65	.17	.038	.57	.67	.76	.95	763
Perceived_CoC	9.1	.96	7.3	8.4	9.1	9.7	12	855
Panel D - All Firms								
Dividend/1y Lagged Assets	.017	.028	0	0	.005	.023	.17	10,698
CAPEX/1y Lagged Assets	.051	.051	.00078	.018	.035	.065	.29	10,711
Leverage	.81	2.9	-15	.078	.51	1.1	16	13,210
Return on Assets	.054	.15	-.67	.035	.075	.12	.34	13,265
Market to Book Ratio	1.8	1.7	.12	.67	1.2	2.2	9.2	13,234
ESG_Ownership	.59	.2	.038	.48	.62	.72	.95	11,343
Perceived_CoC	9.5	1	7.3	8.8	9.5	10	12	11,305

with better ESG scores tend to benefit from a reduced perceived cost of capital.

On the other hand, ESG institutional ownership shows the opposite pattern. It first decreases, suggesting that among firms with low ESG scores, ESG institutional investors are less inclined to hold ownership in firms with slightly better ESG scores. However, ownership then starts to increase significantly, with high-ESG firms attracting more ESG institutional investors. This reflects how investors might allocate capital to firms with better ESG performance, thus showing increased demand for higher-rated ESG firms.

This divergence in trends highlights the complex dynamics in how ESG ratings affect firms' cost of capital and ESG institutional ownership, with investors favoring worse ESG scores among low-ESG firms and better ESG scores among high-ESG firms, while perceived cost of capital drops for these two groups of firms as well.

Investigating whether these mechanisms are results of ESG scores is challenging, primarily due

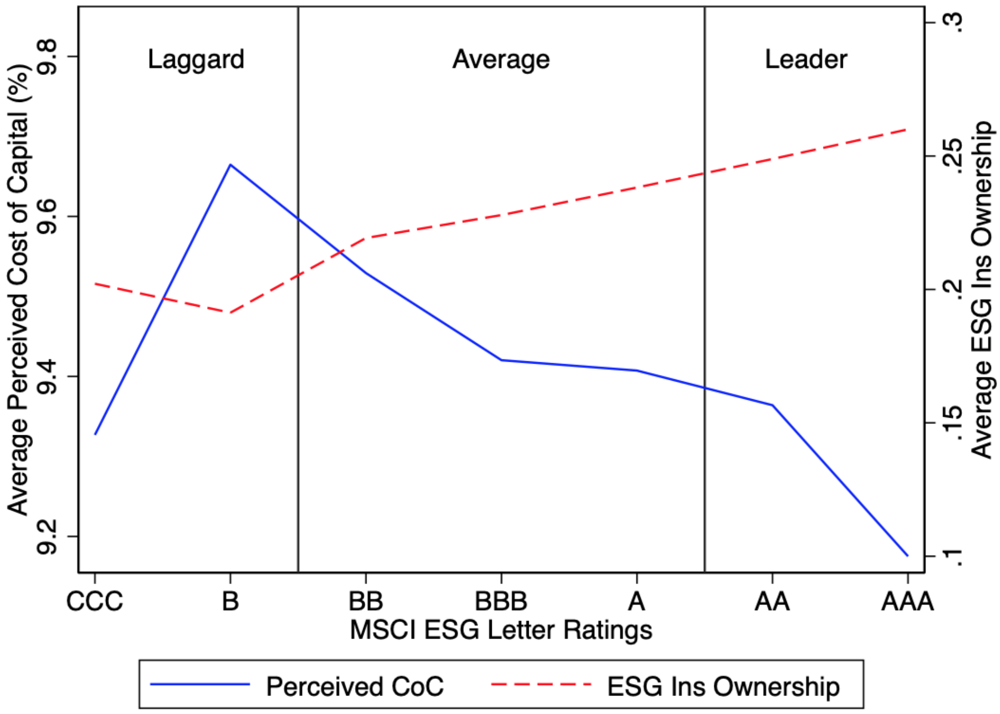

Figure 4: Relationship between MSCI ESG scores, perceived cost of capital, and ESG institutional ownership. This figure illustrates a nuanced relationship between MSCI ESG scores and two key variables: the average perceived cost of capital (CoC) and average ESG institutional ownership. The solid line represents the average perceived CoC, while the dashed line indicates the average ESG institutional ownership.

to the difficulty in disentangling the effect of ESG ratings from other firm characteristics, such as financial performance, that can influence ESG ratings, institutional ownership, and cost of capital. For instance, firms with stronger financial performance tend to engage in more socially responsible activities (Hong et al., 2012), which can improve their ESG ratings. At the same time, superior financial performance tends to attract institutional investors and reduce firms' cost of capital.

To address these endogeneity concerns, I employ a regression discontinuity (RD) design based on MSCI's rating methodology. By focusing on firms near the cutoffs where ESG scores are converted into distinct ESG labels, I isolate the causal impact of firms' ESG ratings on institutional ownership and cost of capital. The findings reveal that high-ESG firms with better ESG labels attract more ESG institutional ownership and have a lower perceived cost of capital, while low-ESG firms with worse ESG labels also experience increased ESG ownership and reduced perceived cost of capital. In Section 4, I explore whether institutional ownership by ESG investors causally affects the cost of capital, and in Section 5, I investigate the possible motivations behind ESG investors' opposing behavior at the two cutoffs.

3.1 Methodology: *Sharp* Regression Discontinuity Design

To estimate the causal effect of MSCI ESG ratings on institutional ownership and cost of capital, I employ a Regression Discontinuity (RD) design. The assignment variable in this context is the firms' numerical ESG score in year t, while the outcome variables, as described in Section 2.2, are measured in year $t+1$. Two cutoffs are defined in this study. The first occurs at the MSCI ESG score of 7.143. Firms that are above this cutoff are labeled "Leader," while firms that are below it are labeled "Average" (henceforth, the "Top-Cutoff"). The second occurs at the ESG score of 2.857. Firms that are above this cutoff are labeled "Average," while firms that are below it are labeled "Laggard" (henceforth, the "Bottom-Cutoff"). The regression analysis is conducted separately at these cutoffs to isolate the effects of ESG ratings on the outcome variables at different points along the ESG rating spectrum.[14]

Firm-year observations above each cutoff are designated as "treated," while those below the cutoff are classified as "control" observations.[15] Since MSCI has determined these cutoffs arbitrarily, and firms cannot precisely manipulate their ESG scores to influence their label assignment, the treatment assignment near the cutoffs can be viewed as random. This quasi-randomness allows for causal inference: any observed differences in outcome variables between treated and control firms in year $t+1$ can be attributed to their ESG label in year t.

Because all firms above the Top-Cutoff are labeled "Leader" and all firms below it are labeled "Average" (with analogous compliance at the Bottom-Cutoff), I implement a Sharp RD design.[16] I employ a continuity-based RD framework, fitting local polynomial regressions on each side of the cutoff to estimate the treatment effect. The treatment effect is defined as the difference in the intercepts of the two polynomials at the cutoff. This approach follows the established framework for RD analysis (Cattaneo et al., 2019). I limit the analysis to firms whose ESG scores lie within a bandwidth h of the cutoff, i.e., between $c-h$ and $c+h$, where c represents the cutoff point, and $h(>0)$ is the chosen bandwidth. The local regression model is specified as follows:

$$Y_{it+1} = \alpha + \tau T_{it} + f_b^p(X_{it} - c) + T_{it} f_a^p(X_{it} - c) + \varepsilon_{it}, \tag{1}$$

where Y_{it+1} represents the outcome variable for firm i in year $t+1$, and X_{it} is the numerical ESG score (the assignment variable) for firm i in year t. The treatment status, denoted by T_{it} is a binary variable equal to 1 if firm i's ESG score lies above the cutoff in year t, and 0 otherwise. The functions f_b^p

[14] In this design, I compare the outcome variables for year $t+1$ between firms above and below the cutoff in year t. In Section 5, I focus on analyzing the effect of firms jumping across cutoffs.

[15] This assignment is arbitrary, and the labels of treated and control groups could be reversed without altering the analysis.

[16] In Section 4, I extend the analysis using a *fuzzy* RD design.

and f_a^p represent polynomials of order p, fitted separately below and above the cutoff, respectively, and c is the cutoff value (7.143 for the Top-Cutoff and 2.857 for the Bottom-Cutoff). The coefficient τ captures the difference in the intercepts of the two fitted polynomials at the cutoff, thus providing an estimate of the causal effect of ESG labels on the outcome variables. Given the quasi-random assignment of firms around the cutoffs, no additional control variables are required in the model. [17]

RD analysis results can be sensitive to the choice of bandwidth, polynomial order, and the kernel function used to weight observations. To ensure robustness, I apply various combinations of these settings for each outcome variable, including polynomials of both first and second order, and both triangular and uniform kernel functions. To avoid arbitrary bandwidth selection, I use the MSE-optimal bandwidth for estimating coefficients and the CE-optimal bandwidth for constructing bias-corrected confidence intervals, as recommended by Cattaneo et al. (2019). This approach provides valid point estimates and robust bias-corrected confidence intervals. For further discussion on these settings, see Appendix A.2. In Section 6, I assess the robustness of the results by testing alternative bandwidths around the MSE-optimal value.

3.2 Results

3.2.1 Validation Test

A critical assumption of the RD identification strategy is that observations just above and below the cutoff are as good as randomly assigned with respect to other characteristics. This assumption would be violated if firms could precisely manipulate their ESG scores to influence their treatment status. In this section, I present evidence that there is no pre-existing difference in observable characteristics between the treated and control firms. Therefore, the likelihood that firms systematically manipulate their ESG scores around the cutoff is highly improbable.

To test this, I replace Y_{it+1} with Y_{it} in the regression specified in Equation (1) and estimate it using a range of observable characteristics as outcome variables. If no significant discontinuities exist at the cutoff between the treated and control firms, it suggests that there is no pre-existing differences between the two groups. The results of this analysis, shown in Table 3, confirm that there are no systematic differences in observable characteristics near the cutoffs. Additionally, MSCI relies solely on publicly available information in its rating process. Furthermore, MSCI's numerical ESG scores are industry-adjusted. It means that firms cannot decide what their final ESG scores would be because while they can affect their own ESG indicators, they have no control over the scores of their peers within the same industry, against which their final ESG score are normalized.

[17]The empirical analysis was conducted using the RD Packages developed by Calonico et al. (2014) and Calonico et al. (2017), available at https://rdpackages.github.io/.

Table 3: RD validity test for lack of systematic differences between treated and control firms prior to the treatment

This table shows the results of the RD validity test for the lack of pre-existing differences in observable characteristics between the treated and control observations prior to the treatment. As this table shows, at both cutoffs, there are no significant pre-existing differences in the observable characteristics between the treated and control firms *prior* to the treatment. Therefore, there is no evidence to reject the assumption that the distribution of observations around the cutoffs is as good as random. This implies the validity of the RD regression analysis. I estimate Equation (1) after replacing Y_{it+1} with Y_{it}, where Y_{it} is the outcome variable for the firm i in the year t. The first column of the table shows the different firm characteristics as the outcome variable. The coefficients τ for the estimation at the Top-Cutoff are reported in Column (1) and at the Bottom-Cutoff in Column (2). I follow the recommendations of Cattaneo et al. (2019) to use the MSE-optimal bandwidth for point estimation of the treatment effect, and CE-optimal bandwidth to estimate robust bias corrected standard errors to calculate t-statistics. The t-statistics are reported in parentheses. Note that the optimal bandwidth, and thus, the effective number of observations that enter into the equation, are different when different outcome variables are used. I have used triangular kernel and polynomials of order 2 to estimate the results. (*, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.)

	Top-Cutoff (Leader - Average)			Bottom-Cutoff (Average - Laggard)		
	bw = 0.6	bw = 0.7	bw = 0.8	bw = 0.6	bw = 0.7	bw = 0.8
Dividend/1yLaggedAssets	-0.005 (-0.454)	-0.003 (-0.352)	0.000 (0.022)	0.001 (0.086)	0.002 (0.290)	0.005 (0.766)
CAPEX/1y Lagged Assets	0.006 (0.305)	0.014 (0.860)	0.012 (0.785)	0.009 (0.331)	0.015 (0.803)	0.022 (1.529)
Leverage	0.236 (0.209)	-0.479 (-0.544)	-0.299 (-0.419)	0.714 (0.724)	0.051 (0.066)	-0.085 (-0.136)
Return on Assets	0.009 (0.029)	0.006 (0.357)	-0.002 (0.524)	0.065 (-0.854)	0.052 (1.097)	0.036* (1.926)
Market to Book Ratio	-0.080 (-0.686)	-0.082 (-0.371)	-0.014 (-0.424)	-0.090 (0.534)	0.053 (-0.547)	0.141 (-0.497)
Total Assets	7770.437 (0.093)	7727.405 (0.730)	5538.127 (1.506)	-17963.738 (-0.483)	-17495.989 (-1.072)	-16806.605 (-1.377)

In conclusion, there is no evidence to suggest that firms can precisely manipulate their ESG ratings around the cutoffs. As a result, any observed effect of treatment status on the outcome variables is not driven by systematic differences between treated and control firms, supporting the validity of interpreting these results as the causal effect of ESG ratings on the outcome variables.

3.2.2 ESG Labels and the Firms' Ownership by ESG Institutional Investors

In this section, I analyze Equation (1) by using *Ins_Ownership* and *ESG_Ownership* as the outcome variables to estimate the differences in ownership by all institutional investors and by ESG institutional investors between treated and control groups, separately for the Top- and Bottom-Cutoffs.

The results for *Ins_Ownership* at the Top-Cutoff (Panel A of Table 4) indicate that firms with better ESG labels exhibit marginally higher institutional ownership in the year following treatment. However, these results are only marginally significant across some of the specifications. At the Bottom-Cutoff (Panel B of Table 4), there are no statistically significant differences in ownership

Table 4: The difference in ownership by all institutional investors between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *Ins_Ownership* for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have slightly higher ownership by ESG institutional investors compared to control observations. At the Bottom-Cutoff, however, there are no significant differences between the institutional ownership of treated and control firms. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.737	(2) bw = 1.240	(3) bw = 0.519	(4) bw = 0.700
Treatment Dummy	0.053* (1.659)	0.062* (1.665)	0.041 (1.441)	0.055 (1.140)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[835 289]	[1319 489]	[649 234]	[835 289]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 1.098	(2) bw = 1.368	(3) bw = 0.633	(4) bw = 0.934
Treatment Dummy	0.002 (0.356)	0.010 (0.274)	0.016 (0.897)	0.021 (0.503)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1209 2690]	[1573 3343]	[725 1998]	[1093 2531]

by institutional investors between treated and control firms. These findings suggest that, overall, institutional investors do not consistently prioritize MSCI ESG labels when making portfolio decisions, indicating limited responsiveness to these labels as a standalone factor.

Next, I analyze the impact of MSCI ESG labels on firm ownership by ESG institutional investors (*ESG_Ownership*). The results of the RD analysis at the Top-Cutoff, shown in Panel A of Table 5, indicate that treated firms—those with better ESG labels—experience significantly higher ownership by ESG institutional investors in the year following treatment. Notably, these treated and control firms are similar in all observable characteristics before the treatment, as confirmed by the validity tests in Section 3.2.1. The only difference between these groups is the ESG label assignment, which is based on predetermined cutoffs by MSCI and lacks an economic rationale. Therefore, these findings suggest that ESG labels play a crucial role in shaping the portfolio decisions of ESG institutional investors.

Interestingly, while ESG institutional investors exhibit a preference for firms with better ESG

Table 5: The difference in ownership by ESG institutional investors between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *ESG_Ownership* for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have higher ownership by ESG institutional investors compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have lower ownership by ESG institutional investors compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.560	(2) bw = 0.926	(3) bw = 0.666	(4) bw = 0.675
Treatment Dummy	0.060*** (2.529)	0.064** (2.273)	0.029* (1.691)	0.086*** (2.502)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[649 234]	[1024 358]	[722 270]	[722 270]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 0.510	(2) bw = 0.954	(3) bw = 0.809	(4) bw = 0.577
Treatment Dummy	-0.060*** (-3.238)	-0.063*** (-3.090)	-0.047*** (-3.840)	-0.074** (-2.479)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[636 1836]	[1093 2531]	[945 2297]	[636 1836]

labels at the Top-Cutoff—where firms generally have strong ESG performance—the pattern reverses at the Bottom-Cutoff. As shown in Panel B of Table 5, firms with worse ESG labels at the Bottom-Cutoff attract higher ownership by ESG institutional investors than those with better labels. This suggests that ESG institutional investors tend to favor firms with weaker ESG labels at the lower end of the performance spectrum. Figure 5 illustrates this contrasting behavior at the two cutoffs. In Section 5, I explore potential explanations for this counterintuitive result.

A potential concern with these results is that they may be influenced by the method used to define ESG institutional investors. In this study, ESG institutional investors are identified based on the higher weighted average ESG scores of their portfolio holdings. Given that firms with stronger financial performance often have higher ESG scores, it is possible that the analysis is capturing ESG investors' preference for financially better-performing firms. However, it is crucial to emphasize that the firms being compared in this analysis are similar in all aspects except for their MSCI ESG labels. This makes it unlikely that the observed differences in ESG ownership are driven by differences in

(a) Bottom-Cutoff **(b)** Top-Cutoff

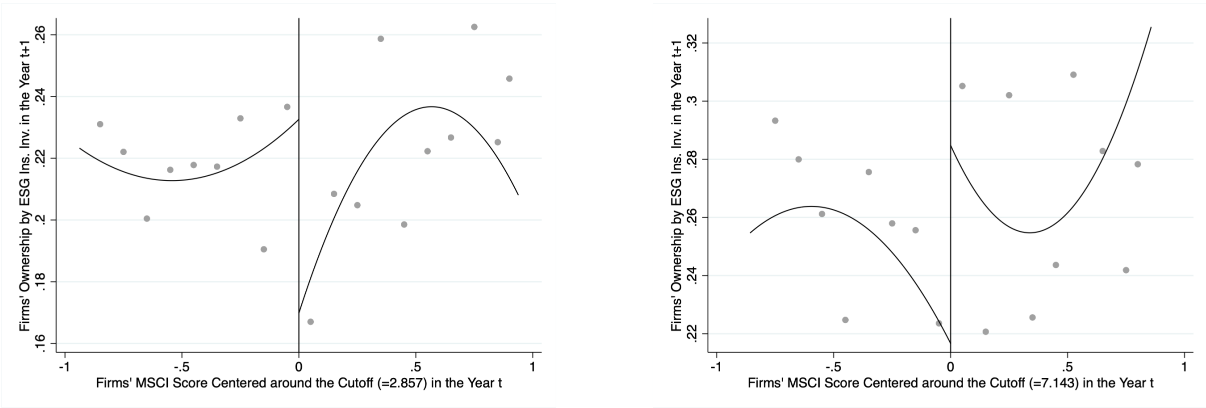

Figure 5: Firms' ownership by ESG institutional investors around the cutoffs. This figure shows the results of Equation (1) where the outcome variable (Y_{it+1}) is *ESG_Ownership* for the firm i in the year $t+1$. Panel **a** shows the results for the Bottom-Cutoff, and Panel **b** show the results for the Top-Cutoff. These figures show that observations above the Bottom-Cutoff have lower ownership by ESG institutional investors compared to observations below this cutoff. At the Top-Cutoff, however, the results are reversed. In all the panels, triangular kernel functions and polynomials of order 2 have been used (corresponding to Column 2 of Table 5). Dots in graphs show the average ownership by ESG institutional investors of the observations in each bin.

financial performance. If financial performance were the primary factor, we would expect a uniform increase in ESG ownership across the cutoff, rather than the observed discontinuity at the ESG score where the ESG label changes. Thus, the differences in ESG ownership are attributable to the firms' ESG labels rather than their underlying financial performance.

To further validate the robustness of these findings, I apply two alternative definitions of ESG institutional investors—those who have signed the Principles for Responsible Investment (PRI), and those that have terms related to SRI in their names.[18] As shown in Table A.1, the results remain consistent for both cutoffs under the first alternative definition. Under the second alternative definition, however, the results remain consistent only at the Top-Cutoff (Table A.2).[19] These results confirm that the observed differences in ESG ownership are indeed driven by the ESG labels and not by the method used to classify ESG institutional investors.

In summary, there is no evidence to suggest that institutional investors, in general, differentiate between firms based on their MSCI ESG labels when making investment decisions. However, the results clearly indicate that ESG institutional investors do take MSCI ESG labels into account in their financial decision-making. Specifically, among firms with high ESG performance, those with better ESG labels attract higher ownership from ESG institutional investors. In contrast, for firms

[18]Following Michaely et al. (2024), I use the following terms: sustain (excluding "sustainable dividend", "sustainable growth", and "sustainable momentum"), social (excluding "social media"), esg, pax, responsib, clean, impact, sri, environm, green, catholic, parnassus, aquina, women, alternative energy, equality, wind energy, fossil, low carbon, amana, eco or ecolog, epiphany, solar, climate, better world, energy solutions, gender, and just.

[19]The lack of significance at the Bottom-Cutoff may be due to the small number of institutional investors in my sample with the SRI terms in their names, or that such investors prefer to focus on the firms with high ESG scores.

Table 6: The difference in perceived cost of capital between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *Perceived_CoC* for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have lower perceived cost of capital compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have higher perceived cost of capital compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.578	(2) bw = 0.782	(3) bw = 0.335	(4) bw = 0.642
Treatment Dummy	-0.341**	-0.477***	-0.432***	-0.560***
	(-2.514)	(-2.677)	(-2.840)	(-2.859)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[601 231]	[782 290]	[406 155]	[672 269]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 0.962	(2) bw = 0.966	(3) bw = 0.416	(4) bw = 0.652
Treatment Dummy	0.561***	0.624***	0.542***	0.574***
	(5.154)	(3.762)	(3.655)	(2.836)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1010 2327]	[1010 2327]	[466 1572]	[677 1829]

with low ESG performance, those with worse ESG labels see higher ownership by ESG institutional investors. This highlights the nuanced role that ESG labels play in shaping the portfolio decisions of ESG institutional investors, depending on the firm's overall ESG performance.

3.2.3 ESG Labels and the Firms' Cost of Capital

In this section, I analyze the differences in various measures of cost of capital between treated and control firms at the two cutoffs, separately. I begin by focusing on the perceived cost of capital. As shown in Table 6, at the Top-Cutoff, treated firms—those with better ESG labels—exhibit a lower perceived cost of capital compared to control firms (Panel A). In contrast, at the Bottom-Cutoff (Panel B), the relationship is reversed, with control firms (those with worse ESG labels) having a lower perceived cost of capital than treated firms. These results suggest that the impact of ESG labels on perceived cost of capital is contingent on the firm's underlying ESG performance, mirroring the pattern observed in ESG institutional ownership in Section 3.2.2. This opposite behavior is visually represented in Figure 6.

(a) Bottom-Cutoff **(b)** Top-Cutoff

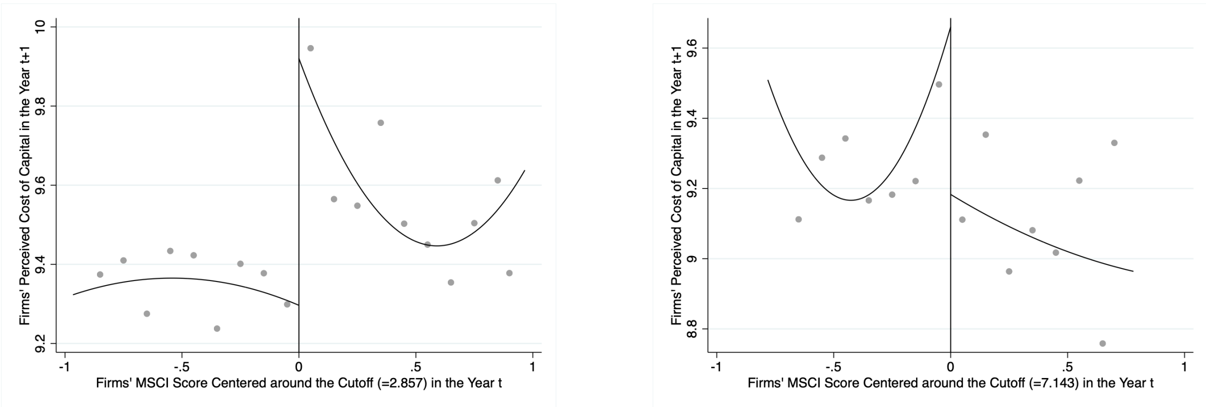

Figure 6: Firms' perceived cost of capital around the cutoffs. This figure shows the results of Equation (1) where the outcome variable (Y_{it+1}) is *Perceived_CoC* for the firm i in the year $t+1$. Panel **a** shows the results for the Bottom-Cutoff, and Panel **b** shows the results for the Top-Cutoff. These figures show that observations above the Bottom-Cutoff have higher perceived cost of capital compared to observations below this cutoff. At the Top-Cutoff, however, the results are reversed. In all the panels, triangular kernel functions and polynomials of order 2 have been used (corresponding to Column 2 of Table 6). Dots in graphs show the average perceived cost of capital of the observations in each bin.

Next, I examine the discount rates used by firms in their investment decisions, as well as their implied cost of capital. As shown in Panel A of Table A.3, at the Top-Cutoff, there is no significant difference in the discount rates between treated and control firms. This indicates that the lower perceived cost of capital observed for treated firms at this cutoff is not reflected in the actual discount rates they apply when making investment decisions.

At the Bottom-Cutoff, however, firms with better ESG labels exhibit both higher perceived cost of capital and higher actual discount rates compared to control firms. This suggests a stronger alignment between perceived cost of capital and discount rate for low-ESG firms. Nevertheless, at both cutoffs, there is no significant difference in the implied cost of capital between treated and control firms, as shown in Table A.4.

3.2.4 ESG Labels and the Firms' Realized Returns

An important question is whether the contrasting strategies of ESG institutional investors toward similar firms with different ESG labels at the two ends of ESG spectrum are driven solely by financial motives or also involve non-financial considerations. To investigate this, I analyze the differences in realized returns between treated and control firms at both cutoffs separately. Higher demand from ESG institutional investors would elevate the prices of high-ESG firms with better ESG labels compared to similar high-ESG firms with worse ESG labels, thereby lowering their realized returns. The same would happen to low-ESG firms with worse ESG labels compared to similar low-ESG firms with better ESG labels. In this scenario, ESG institutional investors, at least in the short term, earn

Table 7: The difference in realized returns between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *RealizedRetuen* for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have lower realized returns compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have lower realized returns compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.568	(2) bw = 0.916	(3) bw = 0.507	(4) bw = 0.791
Treatment Dummy	-0.103**	-0.139**	-0.064	-0.163**
	(-2.111)	(-2.389)	(-1.375)	(-2.424)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[679 248]	[1066 380]	[679 248]	[870 309]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 1.138	(2) bw = 1.184	(3) bw = 0.592	(4) bw = 1.029
Treatment Dummy	0.096***	0.105***	0.072*	0.111**
	(3.280)	(2.320)	(1.940)	(2.571)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1352 2960]	[1352 2960]	[661 1868]	[1247 2754]

lower return by disproportionately investing in the former groups of firms. If this argument holds, then the distinct SRI investment strategies of ESG institutional investors around the two cutoffs are not solely driven by their short-term financial motives.

Consistent with this argument, the results in Panel A of Table 7 show that at the Top-Cutoff, treated firms—those with better ESG labels—exhibit lower realized returns compared to control firms. Conversely, at the Bottom-Cutoff (Panel B of Table 7), the relationship is reversed; control firms—those with worse ESG labels—have lower realized returns. This evidence supports the notion that ESG institutional investors have non-financial preferences influencing their distinct investment strategies toward these firms.

4 ESG Institutional Ownership and Firms' Perceived Cost of Capital

Thus far, my analysis has demonstrated that ESG labels influence both the ownership of firms by ESG institutional investors and their perceived cost of capital in a similar manner around the two cutoffs. At both cutoffs, increased ownership by ESG institutional investors is associated with a lower perceived cost of capital. This observation aligns with the findings of Pástor et al. (2021), who argue that higher demand from ESG investors drives down the expected returns of the target firms.

In this section, I further investigate whether there is a causal link between these two variables. Specifically, I aim to demonstrate how higher (or lower) ownership by ESG institutional investors leads to a corresponding reduction (or increase) in a firm's perceived cost of capital. By establishing this causal relationship, I provide a deeper understanding of the mechanisms through which ESG institutional ownership influences firms' financial outcomes.

Up to this point, I have employed a Sharp RD design, as all firm-year observations above the Top-Cutoff (Bottom-Cutoff) are assigned the "Leader" ("Average") ESG labels, and those below the Top-Cutoff (Bottom-Cutoff) are assigned the "Average" ("Laggard") ESG labels. In this section, I present the results of a Fuzzy RD design. The rationale for this approach is that ESG institutional investors do not necessarily increase their holdings in all firms above the Top-Cutoff or below the Bottom-Cutoff. ESG institutional investors may selectively invest based on additional criteria, meaning that being above the Top-Cutoff or below the Bottom-Cutoff only partially increases the likelihood of higher ownership by ESG institutional investors, rather than guaranteeing it.

My hypothesis is that increased ESG institutional ownership drives up firm prices for those firms above the Top-Cutoff and below the Bottom-Cutoff, which in turn lowers their perceived cost of capital. Thus, the reduction in perceived cost of capital is expected to be significant only for firms that actually receive the treatment (i.e., those that experience increased ownership by ESG institutional investors), rather than for all firms above the Top-Cutoff or below the Bottom-Cutoff. This distinction leads to the consideration of two related variables: the first is the treatment assignment variable, T_{it}, which indicates whether a firm is assigned to the treated or control group based on its ESG label; the second is the treatment-receiving variable, which is the actual ownership by ESG institutional investors.

In the Fuzzy RD design, I focus on estimating the causal effect of receiving the treatment—higher ownership by ESG institutional investors—on the perceived cost of capital. This approach is analogous to an Instrumental Variable (IV) strategy, where the treatment assignment serves as an instrument for receiving the treatment. Thus, using a two-stage least-squares (2SLS) framework, I estimate the effect of receiving the treatment on the outcome variable through the following regressions:

$$D_{it+1} = \alpha + \tau T_{it} + f_b^p(X_{it} - c) + T_{it} f_a^p(X_{it} - c) + \varepsilon_{it}, \tag{2}$$

and,

Table 8: Ownership by ESG institutional investors and the perceived cost of capital: Fuzzy RD

This table shows the regression coefficient λ in Equation (3) under different settings, where the outcome variable (Y_{it+1}) is *Perceived_CoC* for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. D_{it+1} is *ESG_Ownership* and T_{it} is the treatment assignment dummy. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At both cutoffs, higher ownership by ESG institutional investors reduces the perceived cost of capital. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.842	(2) bw = 1.025	(3) bw = 0.447	(4) bw = 0.469
Treatment Dummy	-6.328	-6.457**	-5.017**	-7.368**
	(-1.288)	(-2.037)	(-2.072)	(-2.174)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[828 301]	[1016 367]	[461 186]	[461 186]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 1.155	(2) bw = 1.048	(3) bw = 0.291	(4) bw = 0.556
Treatment Dummy	-10.378***	-8.826***	-5.831***	-6.510**
	(-4.117)	(-2.769)	(-2.716)	(-2.187)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1167 2592]	[1078 2410]	[232 1134]	[569 1665]

$$Y_{it+1} = \beta + \lambda \widehat{D}_{it+1} + g_b^p(X_{it} - c) + \widehat{D}_{it+1} g_a^p(X_{it} - c) + \nu_{it}. \tag{3}$$

In this setting, the coefficient λ captures the causal effect of the treatment-receiving for units close to the cutoff (Cattaneo et al., 2023). Here, D_{it+1} represents ownership by ESG institutional investors, and Y_{it+1} is the perceived cost of capital. As in Equation (1), T_{it} is the treatment assignment dummy, which serves as the IV for D_{it+1}. This is because T_{it} is the only factor that can cause changes in ESG institutional ownership in a small neighborhood around the cutoffs, and in this local neighborhood, it affects the perceived cost of capital exclusively through this channel.

The results of the fuzzy RD analysis are presented in Table 8. These findings indicate that the effect of higher ownership by ESG institutional investors on the perceived cost of capital is more pronounced for firms that actually receive the treatment. Since the only source of variation in the firms' ESG institutional ownership around the cutoff is the difference in their ESG labels, we can conclude that the difference in ESG institutional ownership is the driving mechanism behind the observed differences in perceived cost of capital at both cutoffs.

5 Different Return Expectations and Investor Strategies Around ESG Label Cutoffs

The results from Section 3 and Section 4 provide key insights into the relationship between firms' MSCI ESG ratings, their ownership by ESG institutional investors, and their perceived cost of capital. The analysis shows that, all else being equal, ESG labels influence the ownership of firms by ESG institutional investors, which subsequently impacts their perceived cost of capital. Interestingly, this relationship varies depending on the firm's underlying ESG ratings. Among firms with high ESG ratings, those with better ESG labels attract higher ownership by ESG institutional investors, while among firms with low ESG ratings, those with worse ESG labels experience higher ownership by ESG institutional investors. In both cases, I find that increased ownership by ESG institutional investors reduces the perceived cost of capital, even though the implied cost of capital remains unaffected.

These findings suggest that ESG institutional investors consider ESG labels when making financial decisions. At first glance, this behavior might seem surprising given the reputation of institutional investors as sophisticated market participants. However, firms compared in this analysis are otherwise identical except for their ESG labels. Additionally, as recent studies highlight, evaluating the ESG performance of firms is challenging even for institutional investors, leading many of them to rely on third-party ESG ratings for decision-making (Raghunandan and Rajgopal, 2022; Berg et al., 2024). Thus, when presented with two otherwise comparable investment options, ESG institutional investors tend to favor the one with an ESG label that better aligns with their preferences.

This raises an important question: why do ESG institutional investors exhibit different preferences for firms with high versus low ESG ratings? Specifically, why do ESG investors favor firms with better ESG labels near the Top-Cutoff but prefer those with worse labels near the Bottom-Cutoff? To address this question, I propose two potential explanations consistent with Gollier and Pouget (2022). The first is a monetary explanation, based on the findings of a panel event study, which suggests that ESG institutional investors may be responding to potential financial gains. The second explanation is non-monetary, rooted in the different socially responsible investing (SRI) strategies employed by ESG investors—namely, the use of engagement versus ESG integration strategies.

5.1 Methodology: Panel Event Study

Up to this point, I have employed an RD framework to identify the effect of ESG ratings in year t on outcome variables in year $t+1$. In this approach, I compared the outcomes of two groups of firms that were similar in all aspects except for their ESG labels in the previous year. In this section, I shift the methodological focus to examine the impact of ESG label upgrades and downgrades on the outcome variables. Specifically, I investigate how an upgrade or downgrade across the two cutoffs affects firms' ownership by ESG institutional investors and their buy-and-hold returns (BHR). This analysis aims to achieve two objectives: first, to further confirm that ESG institutional investors factor ESG ratings into their portfolio decisions, and second, to provide evidence explaining the contrasting behavior of ESG institutional investors at the two cutoffs. In particular, I demonstrate that ESG institutional investors derive financial returns by investing in firms with worse ESG labels around the Bottom-Cutoff.

To estimate these effects, I utilize a panel event study model (Schmidheiny and Siegloch, 2019; Clarke and Tapia-Schythe, 2021; Freyaldenhoven et al., 2021), which allows for a dynamic treatment effect estimation akin to a general staggered difference-in-difference design. This model enables me to estimate the treatment effect for any period before and after the event, comparing firms that experience an ESG label upgrade or downgrade with those that do not. The underlying assumption is that, absent the event, treated firms would behave similarly to control firms. I validate this assumption by testing for pre-treatment effects in periods before the event. Additionally, I incorporate firm and time fixed effects into the model. This methodology is closely aligned with the approach of Berg et al. (2024), with the key difference being that while their study examines changes in ESG *letter ratings*, I focus on changes in ESG *labels*.

To estimate the impact of ESG label upgrades and downgrades, I follow the framework proposed by Schmidheiny and Siegloch (2019). I define two event dummy variables for upgrades (u_{it}) and downgrades (d_{it}), where u_{it} and d_{it} equal 1 if firm i experiences an upgrade or downgrade, respectively, in quarter t, and 0 otherwise. I then assess the effect of ESG label upgrades and downgrades on BHR for various holding periods (τ), following the analytical methodology outlined in Berg et al. (2024). I estimate the treatment effect on BHR using distinct models for each holding period of τ months:

$$BHR_{\tau,it} = \sum_{j=-\tau}^{j=\tau} \beta_{j\tau} b_{it}^{j} + \sum_{j=-\tau}^{j=\tau} \lambda_{j\tau} c_{it}^{j} + \mu_{i\tau} + \theta_{t\tau} + X_{it}^{'} \psi_{\tau} + \varepsilon_{it\tau}. \quad (4)$$

In this specification, X_{it} represents a vector of control variables, including leverage, size, book-to-market ratio, and profitability (defined in Appendix A.1). Variables $\mu_{i\tau}$ and $\theta_{t\tau}$ denote firm and time fixed effects, respectively, and $\varepsilon_{it\tau}$ is the error term. Standard errors are clustered at both the firm and month levels to account for potential correlations within these dimensions. The terms b_{it}^{j} and c_{it}^{j} correspond to $u_{i,t-j}$ and $d_{i,t-j}$, indicating upgrades and downgrades for firm i in quarter $t-j$. The variables of interest, $b_{it}^{j=0}$ and $c_{it}^{j=0}$, indicate whether an upgrade or downgrade occurred for firm i in month t. By controlling for all other $b_{it}^{j\neq 0}$ and $c_{it}^{j\neq 0}$ variables, the coefficients $\beta_{j\tau}$ and $\lambda_{j\tau}$ estimate the abnormal BHR for a holding period of τ months after the event, relative to BHRs for observations that are at least τ months away from an event (Berg et al., 2024).

In the next step, I estimate the impact of MSCI ESG label upgrades and downgrades on firms' ownership by ESG institutional investors (*ESG_Ownership*), observed at quarterly intervals $t = \underline{t}, ..., \bar{t}$, using the following specification:

$$Y_{it} = \sum_{j=\underline{j}}^{\bar{j}} \beta_j b_{it}^j + \sum_{j=\underline{j}}^{\bar{j}} \lambda_j c_{it}^j + \mu_i + \theta_t + \varepsilon_{it}. \tag{5}$$

In this specification, Y_{it} represents quarterly ownership by ESG institutional investors, while μ_i and θ_t denote firm and time fixed effects, respectively, and ε_{it} is the error term. The objective is to estimate the dynamic effect of the treatment over the effect window, which spans from $\underline{j} < 0$ quarters prior to the event to $\bar{j} > 0$ quarters following the event. The variables b_{it}^j (for upgrades) and c_{it}^j (for downgrades) represent the leads and lags for label changes, indicating whether firm i at quarter t is j periods away from a label change.

For periods that exceed $\underline{j}$ quarters before or $\bar{j}$ quarters after an event, the variables b_{it}^j and c_{it}^j are binned, and they are defined as:

$$c_{it}^j = \begin{cases} \sum_{s=t-\underline{j}}^{\bar{t}-\underline{j}-1} d_{is} & \text{if } j = \underline{j} \\ d_{i,t-j} & \text{if } \underline{j} < j < \bar{j} \\ \sum_{s=\underline{t}-\bar{j}+1}^{t-\bar{j}} d_{is} & \text{if } j = \bar{j}, \end{cases} \tag{6}$$

and,

$$b_{it}^j = \begin{cases} \sum_{s=t-\underline{j}}^{\bar{t}-\underline{j}-1} u_{is} & \text{if } j = \underline{j} \\ u_{i,t-j} & \text{if } \underline{j} < j < \bar{j} \\ \sum_{s=\underline{t}-\bar{j}+1}^{t-\bar{j}} u_{is} & \text{if } j = \bar{j}. \end{cases} \tag{7}$$

I exclude $\beta_{j=-1}$ and $\lambda_{j=-1}$ from the model, allowing the coefficients of interest, $\beta_{j=0}$ to $\beta_{j=\bar{j}}$ and $\lambda_{j=0}$ to $\lambda_{j=\bar{j}}$, to estimate the effect of label upgrades and downgrades on *ESG_Ownership* within $\bar{j}$ quarters following the event, relative to its level one period prior to the event. Additionally, the coefficients $\beta_{j=\underline{j}}$ to $\beta_{j=-2}$ and $\lambda_{j=\underline{j}}$ to $\lambda_{j=-2}$ allow for testing of parallel trends between treated and control units in the periods leading up to the events, ensuring that any post-event differences can be attributed to the treatment rather than pre-existing trends.

5.2 Different Return Expectations Based on ESG Performance

One possible explanation for the higher ESG ownership of firms with worse ESG labels at the Bottom-Cutoff is the potential for monetary gains, as investors may anticipate financial returns from investing in these undervalued firms. To test this hypothesis, I examine the effect of MSCI ESG label upgrades and downgrades on firms' BHRs at both cutoffs by estimating the treatment effect in Equation (4). If firms with worse ESG labels present higher return prospects for ESG institutional investors, this should manifest in positive BHRs for these firms. Figure 7 supports this argument. It shows that firms experiencing an upgrade across the Bottom-Cutoff yield positive BHRs (Panel **c**), while firms undergoing a downgrade yield negative BHRs (Panel **a**). Conversely, both upgrades and downgrades across the Top-Cutoff result in negative BHRs (Panels **b** and **d**).

These findings suggest that firms with worse ESG labels near the Bottom-Cutoff may offer higher financial opportunities, potentially due to being undervalued by other investors. ESG institutional investors may anticipate positive abnormal returns from holding these firms, especially if they expect to influence future improvements in ESG practices through engagement, which is probable due to their proximity to the cutoff. Conversely, firms around the Top-Cutoff are less likely to be viewed as growth opportunities by ESG investors due to their already strong ESG performance. Instead, ESG investors may invest in these firms to maintain alignment with their ESG mandates, receiving stable (or even marginally negative) returns rather than potential financial outperformance.

To further support this explanation, I estimate the effect of MSCI ESG label upgrades and downgrades on *ESG_Ownership* using Equation (5). The results of the event study confirm that ESG institutional investors monitor MSCI ESG labels. As shown in Figure 8, when a firm upgrades across the Bottom-Cutoff, its ownership by ESG institutional investors increases. Conversely, when a firm downgrades across this cutoff, its ownership by ESG institutional investors declines. This pattern of responsiveness to label changes is observed only at the Bottom-Cutoff, not at the Top-Cutoff.[20]

On one hand, ESG institutional investors tend to increase their ownership in firms following an upgrade across the Bottom-Cutoff. This suggests that label upgrades across this cutoff act as a positive signal to ESG investors, encouraging them to initiate or expand their positions in these firms. On the other hand, firms that experience an upgrade across the Bottom-Cutoff also exhibit positive BHRs, indicating that the market perceives the upgrade as a favorable event. This may signal improvements in the firm's ESG practices or financial performance, ultimately leading to higher stock prices over time. The positive signal from label upgrades appears to drive increased ESG ownership, which in turn contributes to the boost in BHRs.

[20]The lack of sensitivity to label changes for firms with high ESG performance contrasts with the findings of Berg et al. (2024). However, their study focuses on jumps across MSCI ESG letter ratings, while my analysis centers on jumps across MSCI labels.

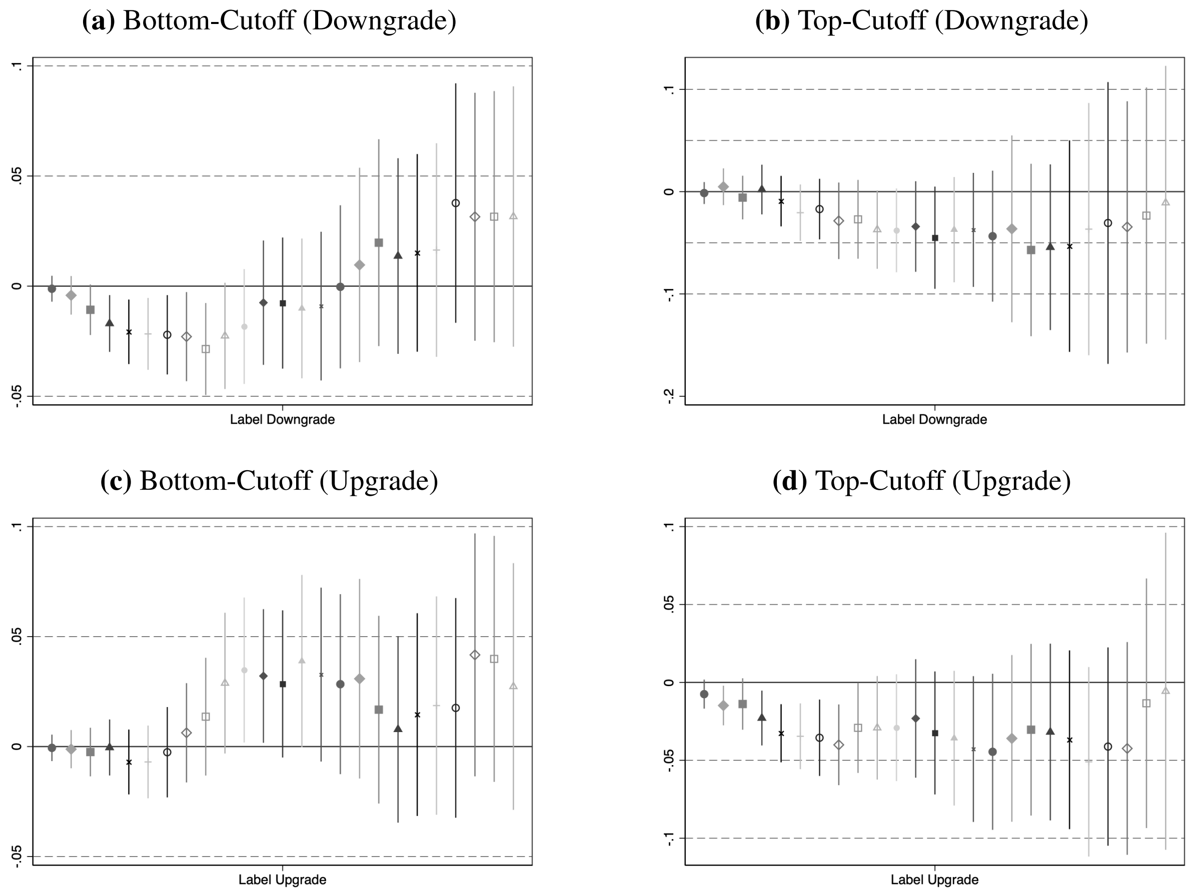

Figure 7: Firms' BHRs after the jumps across the cutoffs. This figure shows the estimations of the treatment effect from several panel event studies based on Equation (5), with 0 to 24 months holding periods (90% confidence intervals are indicated). The events are upgrades or downgrades across the two cutoffs. Panels **a** and **c** show the results of labels downgrades and upgrades, respectively, across the Bottom-Cutoff. Panels **b** and **d** show the results of labels downgrades and upgrades, respectively, across the Top-Cutoff. Firms yield positive BHRs after experiencing an upgrade across the Bottom-Cutoff. Other jumps across the cutoffs are associated with negative BHRs.

To provide further evidence, I run a panel data regression of BHRs over various holding periods on the firms' ownership by ESG institutional investors and its interaction with MSCI ESG label upgrades across the two cutoffs. The results indicate that, in general, higher ownership by ESG institutional investors is associated with negative BHRs. However, the coefficient of the interaction term between ESG ownership and label upgrades at the Bottom-Cutoff is significantly positive (Table 9).[21] These findings suggest that when firms upgrade across the Bottom-Cutoff, higher ESG institutional ownership becomes positively associated with BHRs, reinforcing the notion that label upgrades at this cutoff act as a positive market signal. Interestingly, I do not find similar results for upgrades across the Top-Cutoff (Table 10).

In summary, this section shows that ESG institutional investors respond to upgrades across the Bottom-Cutoff by increasing their ownership, which, in turn, enhances BHRs. This supports the

[21] As shown in Table A.5, the results remain directionally consistent but lose significance when defining ESG institutional investors using PRI signatories.

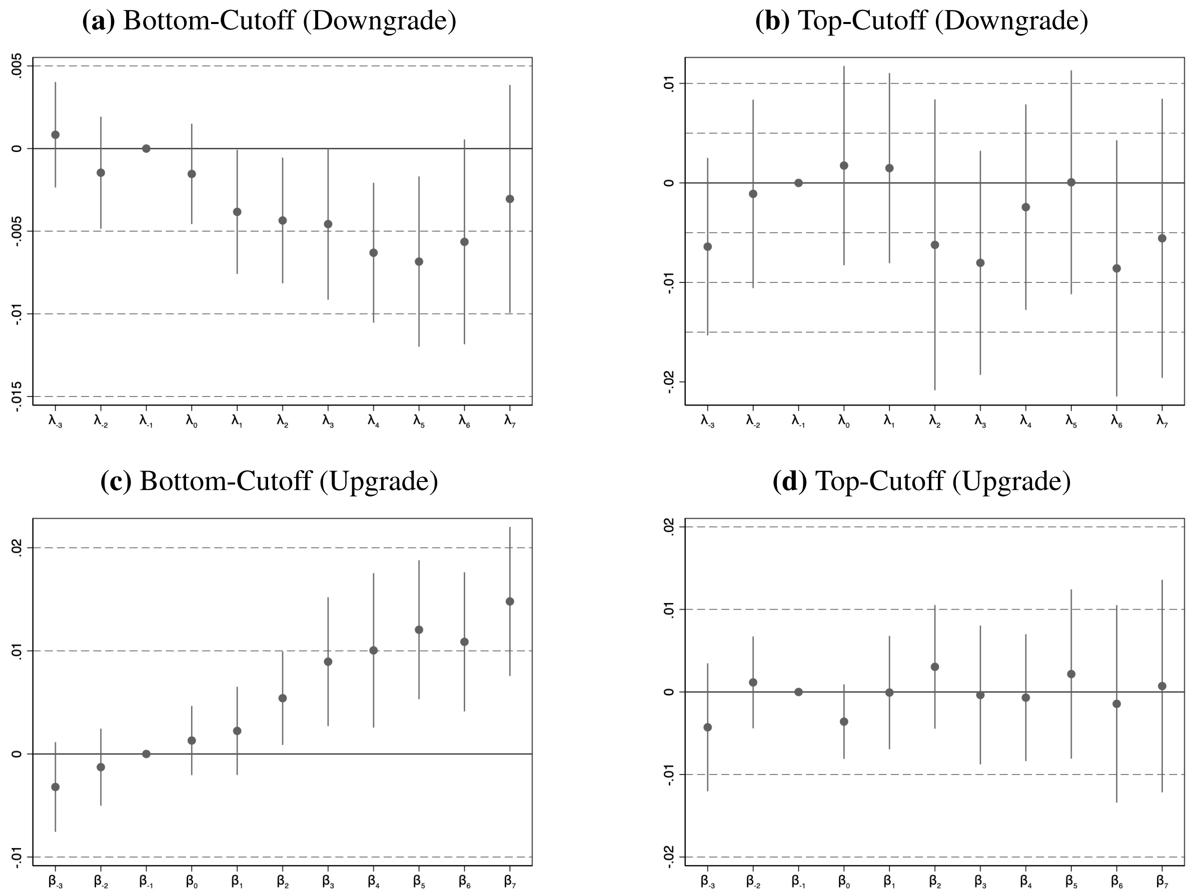

Figure 8: Firms' change in ownership by ESG institutional investors pre- and post- jumps across the cutoffs. This figure shows the estimations of the treatment leads and lags (β_j's and γ_j's) in Equation (5), from three quarters before (pre-event parallel trends are observable) to seven quarters after the events (90% confidence intervals are indicated). The coefficients are normalized based on the coefficient from 1 quarter before the event (β_{-1} and γ_{-1}). The events are upgrades or downgrades across the two cutoffs. Panels **a** and **c** show the results of labels downgrades and upgrades, respectively, across the Bottom-Cutoff. Panels **b** and **d** show the results of labels downgrades and upgrades, respectively, across the Top-Cutoff. ESG institutional investors reduce their ownership in firms that downgrade across the Bottom-Cutoff and increase their ownership in firms that upgrade across the Bottom-Cutoff. There are no evidence that they act similarly for the Top-Cutoff.

earlier findings in Section 3.2.2, indicating that ESG institutional investors maintain higher ownership in firms with worse MSCI ESG labels around the Bottom-Cutoff because they anticipate financial gains. These gains, however, are absent around the Top-Cutoff, where ESG institutional investors, as expected, hold more ownership in firms with better MSCI ESG labels.

5.3 Different SRI Strategies: Engagement versus ESG Integration

Academic literature suggests that shareholders can exert influence on their portfolio firms through two distinct strategies: exit and voice (Edmans, 2009, 2014). Shareholders can either employ exit strategy by selling their shares, which can signal disapproval and influence the stock price, or employ voice strategy by directly engaging with management to improve firm performance. A similar classification

Table 9: Panel Data Regression of BHR on the Ownership by ESG Institutional Investors and Upgrades across the Bottom-Cutoff

This table shows the results of a panel regression where the dependent variables are BHRs with different holding periods (between 3 and 24 months). Independent variables are $ESG\_Ownership$ (Section 2.2), $Bottom-Cutoff$ (a dummy variable that equals 1 in periods where the firm upgrades across the Bottom-Cutoff), and the interaction of these two. Control variables are defined in Appendix A.1. Standard errors are clustered at the firm and quarter levels. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

	(1) 3-month BHR	(2) 6-month BHR	(3) 9-month BHR	(4) 12-month BHR	(5) 15-month BHR	(6) 18-month BHR	(7) 21-month BHR	(8) 24-month BHR
$ESG\_Ownership$	-0.123**	-0.169**	-0.232**	-0.313***	-0.404***	-0.490***	-0.520***	-0.520***
	(-2.57)	(-2.22)	(-2.56)	(-2.96)	(-3.51)	(-3.85)	(-4.01)	(-3.99)
$Bottom-Cutoff$	0.0150	-0.0542	-0.0437	-0.0400	-0.0790	-0.0936	-0.132**	-0.0171
	(0.49)	(-1.51)	(-0.98)	(-0.87)	(-1.19)	(-1.44)	(-2.26)	(-0.25)
$ESG\_Ownership \times Bottom-Cutoff$	**-0.0183**	**0.233***	**0.345****	**0.344****	**0.476***	**0.483****	**0.422****	**0.121**
	(-0.18)	**(1.70)**	**(2.15)**	**(2.06)**	**(1.90)**	**(2.35)**	**(2.09)**	**(0.51)**
$Leverage$	0.0266	0.0302	0.0732	0.103	0.135*	0.152*	0.136	0.126
	(1.20)	(0.88)	(1.56)	(1.48)	(1.70)	(1.85)	(1.69)	(1.55)
$Size$	0.00206	-0.109***	-0.216***	-0.310***	-0.392***	-0.476***	-0.537***	-0.594***
	(0.21)	(-6.18)	(-8.50)	(-10.53)	(-11.61)	(-12.17)	(-13.26)	(-14.08)
$Book\,to\,Market\,Ratio$	-0.0244***	-0.0229	-0.0104	0.0106	0.0314	0.0500	0.0687	0.0840**
	(-3.22)	(-1.51)	(-0.49)	(0.37)	(0.96)	(1.44)	(1.69)	(2.38)
$Profitability$	0.176***	0.347***	0.377***	0.351***	0.308**	0.248**	0.242**	0.153
	(4.48)	(4.30)	(4.12)	(3.78)	(2.61)	(2.20)	(2.05)	(1.31)
$Constant$	0.0613	0.842***	1.575***	2.230***	2.794***	3.372***	3.801***	4.189***
	(0.90)	(7.08)	(9.57)	(11.68)	(12.43)	(13.01)	(14.26)	(14.98)
Observations	120715	120104	119307	118429	117605	116765	115891	115052
Time- & Firm- FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

has been used in the context of socially responsible investing strategies (Broccardo et al., 2022). In this context, under the exit strategy, investors divest from firms with poor ESG performance, thereby increasing the demand for high-ESG firms, raising their stock prices, and reducing their cost of capital (Heinkel et al., 2001; Pástor et al., 2021; Edmans et al., 2022). This divestment motivates low-ESG firms to improve their ESG practices in order to remain competitive. In contrast, the voice strategy involves actively engaging with firms to influence their ESG performance (Dimson et al., 2015). Investors use tools such as voting rights or direct engagement with management to push for changes that improve ESG performance. Both strategies reflect distinct ways in which ESG institutional investors impact firms' behavior.

I argue that ESG institutional investors employ the engagement strategy around the Bottom-Cutoff, where they engage with low-ESG firms in an effort to improve both ESG performance and financial returns. By investing in these firms, ESG investors aim to create long-term value through engagement. Conversely, around the Top-Cutoff, ESG investors pursue an ESG integration strategy. In

Table 10: Panel Data Regression of BHR on the Ownership by ESG Institutional Investors and Upgrades across the Top-Cutoff

This table shows the results of a panel regression where the dependent variables are BHRs with different holding periods (between 3 and 24 months). Independent variables are $ESG\_Ownership$ (Section 2.2), $Top-Cutoff$ (a dummy variable that equals 1 in periods where the firm upgrades across the Top-Cutoff), and the interaction of these two. Control variables are defined in Appendix A.1. Standard errors are clustered at the firm and quarter levels. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

	(1) 3-month BHR	(2) 6-month BHR	(3) 9-month BHR	(4) 12-month BHR	(5) 15-month BHR	(6) 18-month BHR	(7) 21-month BHR	(8) 24-month BHR
$ESG\_Ownership$	-0.123**	-0.169**	-0.232**	-0.313***	-0.403***	-0.490***	-0.519***	-0.520***
	(-2.57)	(-2.22)	(-2.56)	(-2.96)	(-3.51)	(-3.85)	(-4.01)	(-3.99)
$Top-Cutoff$	-0.0591	-0.0629	-0.0139	0.0487	-0.0504	-0.0570	0.0354	-0.109
	(-0.47)	(-0.63)	(-0.14)	(0.33)	(-0.38)	(-0.40)	(0.17)	(-0.52)
$ESG\_Ownership\times$ Top-Cutoff	0.170	0.267	0.260	0.0835	0.464	0.325	0.0377	0.545
	(0.50)	(0.88)	(0.77)	(0.19)	(1.18)	(0.83)	(0.07)	(0.96)
$Leverage$	0.0267	0.0302	0.0733	0.103	0.135*	0.152*	0.136	0.126
	(1.20)	(0.88)	(1.57)	(1.48)	(1.70)	(1.85)	(1.68)	(1.55)
$Size$	0.00206	-0.109***	-0.216***	-0.310***	-0.392***	-0.476***	-0.537***	-0.594***
	(0.21)	(-6.18)	(-8.50)	(-10.53)	(-11.61)	(-12.18)	(-13.26)	(-14.08)
$Book\,to\,Market\,Ratio$	-0.0244***	-0.0229	-0.0104	0.0106	0.0314	0.0500	0.0687	0.0840**
	(-3.22)	(-1.51)	(-0.49)	(0.37)	(0.96)	(1.44)	(1.69)	(2.38)
$Profitability$	0.176***	0.347***	0.377***	0.351***	0.308**	0.248**	0.241**	0.153
	(4.48)	(4.30)	(4.12)	(3.78)	(2.61)	(2.20)	(2.05)	(1.31)
$Constant$	0.0613	0.842***	1.575***	2.230***	2.794***	3.372***	3.801***	4.189***
	(0.90)	(7.08)	(9.57)	(11.68)	(12.43)	(13.01)	(14.26)	(14.98)
Observations	120715	120104	119307	118429	117605	116765	115891	115052
Time- & Firm- FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

this scenario, investors allocate capital to high-ESG firms to comply with ESG mandates or to attract inflows from responsible investors. This involves divesting from low-ESG firms to align with their ESG objectives, resembling the exit strategy. This dual behavior reflects a nuanced approach to SRI, with ESG investors engaging with low-ESG firms for ESG improvement while favoring high-ESG firms for compliance or inflows.

To pursue their respective strategies at each cutoff, ESG institutional investors must identify firms that align with their distinct objectives. When presented with two otherwise similar firms, ESG institutional investors would choose the firm whose ESG label better fits their strategy. At the Top-Cutoff, investors are likely to favor firms with better ESG labels as part of an ESG integration strategy, selecting firms that already meet high ESG standards to align their portfolios with their ESG mandates or to attract inflows. In contrast, at the Bottom-Cutoff, investors may focus on firms with worse ESG labels, viewing these firms as opportunities for engagement, where it can lead to substantial improvements in ESG performance. This differentiation enables investors to either divest from or engage with firms based on how well the firms' ESG labels align with their goals of improving ESG outcomes or adhering to ESG standards. Thus, ESG labels act as signals that help investors allocate capital in accordance with their strategic preferences.

To test whether these non-monetary incentives influence institutional investors' behavior differently across the two cutoffs, I regress firms' MSCI ESG numerical scores on their lagged ESG institutional ownership, lagged MSCI ESG scores, and the interaction between the two. The hypothesis is that if ESG investors target low-ESG firms to improve their performance, higher ESG ownership should have a stronger effect on future ESG scores for firms with lower current ESG scores. The interaction term between lagged ESG ownership and the lagged ESG score captures this relationship. I expect a negative coefficient for this term, indicating that as a firm's lagged ESG score increases, the effect of ESG ownership on improving its ESG performance diminishes. A significantly negative coefficient would support the hypothesis that ESG investors focus on low-ESG firms to enhance their ESG scores.

The results in Table 11 confirm that the coefficient of the interaction term is significantly negative across different lagged periods.[22] The negative interaction term implies that ESG ownership has a stronger positive impact on firms with lower previous ESG scores, and as the firm's prior ESG score increases, the marginal effect of ESG ownership on further improvements decreases. This finding aligns with the engagement strategy, where ESG investors actively engage with low-ESG firms to improve their performance. These firms, having more issues to address, present more potential for positive change, making them prime targets for investor engagement.

6 Robustness

A key feature of the RD framework is that treatment assignment is based on an observable characteristic of the units. If units cannot precisely manipulate this characteristic, the treatment assignment is essentially random, allowing the effect of the treatment on the outcome variable to be isolated from other unit characteristics. As a result, RD analysis yields results comparable to those of a randomized assignment strategy. In Section 3.2.1, I demonstrate that the treated and control firms in this study are similar across observable characteristics. Moreover, given the complexity of the MSCI ESG rating methodology, it is highly unlikely that firms can manipulate their ratings to ensure placement in the treatment group.

In this section, I conduct additional tests to further validate the robustness of my empirical results. First, I re-estimate the results of Equation (1) for various outcome variables using different bandwidths around the optimal one to assess the sensitivity of the findings to bandwidth selection.

[22] As shown in Table A.6, these results are robust when using PRI signatories to define ESG institutional investors.

Table 11: Panel Data Regression of MSCI ESG Scores on the Lagged Ownership by ESG Institutional Investors and Lagged MSCI ESG Score

This table shows the results of a panel regression where the dependent variable is *MSCI ESG Score*. Independent variables are *ESG_Ownership* (Section 2.2), *MSCI ESG Scores* with different lags (2 quarters to 8 quarters), and the interaction of these two. Control variables are defined in Appendix A.1. Standard errors are clustered at the firm and quarter levels. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

	(1) *MSCI* ESG Score	(2) *MSCI* ESG Score	(3) *MSCI* ESG Score	(4) *MSCI* ESG Score
2q Lagged ESG_Ownership	0.350^{*} (2.03)			
2q Lagged ESG Score	0.769^{***} (30.23)			
2q Lagged ESG_Ownership × *2q Lagged ESG Score*	**-0.0513** **(-1.62)**			
4q Lagged ESG_Ownership		0.645^{**} (2.67)		
4q Lagged ESG Score		0.524^{***} (11.78)		
4q Lagged ESG_Ownership × *4q Lagged ESG Score*		**-0.0944*** **(-2.05)**		
6q Lagged ESG_Ownership			0.837^{***} (3.07)	
6q Lagged ESG Score			0.360^{***} (6.92)	
6q Lagged ESG_Ownership × *6q Lagged ESG Score*			**-0.126**** **(-2.46)**	
8q Lagged ESG_Ownership				0.751^{***} (2.98)
8q Lagged ESG Score				0.186^{***} (3.82)
8q Lagged ESG_Ownership × *8q Lagged ESG Score*				**-0.107**** **(-2.38)**
Leverage	0.0519 (1.18)	0.0675 (0.77)	0.125 (0.99)	0.171 (1.11)
Size	0.00167 (0.20)	0.00909 (0.52)	0.0269 (1.17)	0.0385 (1.45)
Book to Market Ratio	-0.000753 (-0.16)	0.00100 (0.10)	0.00501 (0.38)	0.00340 (0.22)
Profitability	-0.0109 (-0.20)	-0.0241 (-0.23)	-0.0905 (-0.67)	-0.171 (-1.40)
Constant	0.943^{***} (7.26)	1.915^{***} (8.04)	2.463^{***} (8.15)	3.116^{***} (9.70)
Observations	25807	22462	19200	16278
Time- & Firm- FEs	Yes	Yes	Yes	Yes

Table 12: Sensitivity of Results to the choice of different bandwidth

This table shows the sensitivity of results in Section 3 to the choice of different bandwidths. Each column reports the regression coefficient τ from Equation (1) for different outcome variables, choosing four different bandwidths around the MSE-optimal bandwidth, which is shown at the top of the corresponding column. Note that the MSE-optimal bandwidth is a function of outcome variable, among other factors; therefore, the optimal bandwidth and the four test bandwidths around it are different for each outcome variable. For saving space, I have only presented the result of using triangular kernel and polynomials of order 2. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively

	Top-Cutoff (Leader - Average)		Bottom-Cutoff (Average - Laggard)	
	(1)	(2)	(3)	(4)
Arbitrary Bandwidth	*ESG_Ownership*	*Perceived_CoC*	*ESG_Ownership*	*Perceived_CoC*
	bw = 0.926	bw = 0.782	bw = 0.954	bw = 0.966
0.6		-0.683***		
		(-3.033)		
0.7		-0.617***		
		(-3.063)		
0.8	0.079**	-0.466***	-0.064***	0.646***
	(2.545)	(-2.641)	(-2.866)	(3.570)
0.9	0.065**	-0.438***	-0.062***	0.638***
	(2.234)	(-2.663)	(-2.921)	(3.677)
1.0	0.064**		-0.063***	0.621***
	(2.310)		(-3.139)	(3.772)
1.1	0.063**		-0.061***	0.609***
	(2.398)		(-3.126)	(3.830)
Kernel	Triangular	Triangular	Triangular	Triangular
Polynomial Order	2	2	2	2

Next, I conduct a placebo test by applying the analysis to arbitrarily chosen cutoffs. If the observed effect is indeed due to the treatment, we should not observe similar effects when using these placebo cutoffs.

6.1 Sensitivity of Results to the Choice of Bandwidth

Table 12 presents the results of analyzing Equation (1) for various outcome variables using different bandwidths around the MSE-optimal bandwidth. I have restricted the analysis to four bandwidths close to the MSE-optimal bandwidth to minimize bias and variance in the estimation of the regression coefficients. It is important to note that the MSE-optimal bandwidth depends on the outcome variable and other factors, meaning that both the optimal bandwidth and the four test bandwidths vary for each outcome variable. The results reported here are based on a triangular kernel and second-order polynomials to fit the data above and below the cutoff. The findings indicate that, across nearly all settings, the results from Section 3 are robust to different bandwidth choices and remain statistically significant.

Table 13: Sensitivity of Results to the placebo cutoffs

This table shows the results of using placebo cutoffs, instead of Top- and Bottom- cutoffs. Each column reports the analysis of regression Equation (1) for the outcome variables. Each row represents an arbitrarily chosen cutoff. t-statistics are shown in parentheses. In almost all settings, the results are not statistically significant, implying that the detected effects in Section **??** have been due to the treatment, which is not present in other cutoffs. (*, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.)

Arbitrary Cutoff	(1) *ESG_Ownership*	(2) *Perceived_CoC*
7.8	-0.110*	-0.658
	(-1.860)	(-1.615)
6.5	-0.024	-0.244
	(-1.470)	(-1.214)
5.0	-0.015	-0.080
	(-1.095)	(-0.416)
3.6	0.042**	0.417**
	(2.271)	(2.308)
Kernel	Triangular	Triangular
Polynomial Order	2	2

6.2 Placebo Cutoffs

Table 13 reports the regression coefficients from Equation (1) for various outcome variables using different arbitrary cutoffs. The analysis is conducted with a triangular kernel and second-order polynomials to fit the data on either side of the cutoffs. The lack of statistically significant results across these placebo cutoffs reinforces the conclusion that the effects identified in Section 3.2.2 and 3.2.3 are attributable to the treatment—namely, the sudden change in ESG labels at the designated cutoffs. These findings further validate that the detected effects are not due to random fluctuations but rather the specific ESG label changes.

7 Conclusion

This paper explores the impact of MSCI ESG labels on the firms' ownership by ESG institutional investors and their perceived cost of capital. Specifically, I examine how differences in ESG labels affect high-ESG and low-ESG firms differently, providing insights into the SRI strategies. Using a Regression Discontinuity (RD) design, I isolate the causal effect of ESG labels by leveraging the quasi-random assignment of firms around the two cutoffs where MSCI numerical ESG scores are converted into distinct labels. The findings reveal that high-ESG firms with better labels attract higher ESG institutional ownership, leading to a reduced perceived cost of capital. Surprisingly, low-ESG firms with worse labels also experience increased ESG ownership and a similar reduction in perceived cost of capital. I examine ESG investors' incentives for this opposite behavior around the two cutoffs.

The results suggest that ESG institutional investors pursue distinct strategies across the two cutoffs. At the Top-Cutoff, investors follow an ESG integration strategy by tilting their portfolios toward high-ESG firms. Conversely, at the Bottom-Cutoff, ESG investors adopt an engagement strategy, targeting low-ESG firms with the potential for significant improvement, even if they have worse labels. This highlights a duality in investor behavior, where ESG ownership is not solely linked to better sustainability practices but also to engagement with firms that have room for ESG performance improvement.

This paper contributes to the SRI literature by demonstrating how ESG institutional investors react to MSCI ESG labels in nuanced ways, rewarding high-ESG firms with better ESG labels while investing in low-ESG firms with worse ESG labels. This behavior challenges the common perception that ESG investors prioritize firms with better sustainability performance. It also shows how higher ESG ownership translates into a lower perceived cost of capital, reflecting investors' monetary and non-monetary motivations. Future studies should examine the precise mechanisms driving investors' behavior, especially the reasoning behind ESG investors' preference for low-ESG firms with worse ESG labels. Additionally, the distinction between perceived and implied cost of capital could benefit from further empirical validation to fully capture its implications for firm financial decisions.

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A Appendix

A.1 Variables

This is how I calculate statistics variables:

$Dividend/1y\,Lagged\,Assets$: Total dividends (item *dvt* in Compustat) divided by the firm's 1-year lagged total assets (item *at* in Compustat)

$CAPEX/1y\,Lagged\,Assets$: Capital Expenditures (item *capx* in Compustat) divided by the firm's 1-year lagged total assets (item *at* in Compustat)

$Leverage$: Sum of total long-term debt (item $dltt$ in Compustat) and debt in current liabilities (item dlc in Compustat) divided by stockholders equity (item *seq* in Compustat)

$Return\,on\,Assets$: Operating income after depreciation (item $oiadp$ in Compustat) divided by the firm's total assets (item *at* in Compustat)

$Market\,to\,Book\,Ratio$: Market value item *mkvalt* in Compustat) divided by the firm's total assets (item *at* in Compustat)

A.2 Regression Discontinuity

In a RD design, treatment status is assigned to units whose assignment variables exceed a known cutoff point. If units cannot precisely manipulate the assignment variable, then the variation in the treatment status in a small enough neighbourhood around the cutoff is as good as random, as though generated from a randomized experiment. Therefore, the causal effect of treatment on the outcome variables can be identified because the units that are above the cutoff (treated units) and those that are below the cutoff (control units) are, on average, similar in every aspect, except for their treatment status (Imbens and Lemieux, 2008; Lee and Lemieux, 2010; Cattaneo and Titiunik, 2022).

As an example, consider two firms with very similar ESG scores. One has an ESG score of 7.2 and the other has an ESG score of 7.1. These two firms have very similar ESG performance according to MSCI ESG rating methodology. However, the former is assigned an ESG label of "Leader" (and thus, treated status), because its ESG score exceeds the Top-Cutoff point of 7.143; the latter is assigned an ESG label of "Average" (and thus, control status) because its ESG score falls below this cutoff. Since the firms cannot precisely manipulate (or decide) what their ESG scores would be, it can be argued that the assignment of these two firms to the treated or control group is as though from a random experiment. Therefore, any observed differences between their outcome variables in the year $t+1$ are a causal effect of their treatment status, i.e., their ESG labels, in the yerar t.

Several issues arise in estimating the regression Equation (1). The first issue is the functional form of the polynomials f_b^p and f_a^p, which can affect the treatment effect estimator τ. While using higher orders generally improves the accuracy of estimation, it also increases the variability of the treatment effect estimator and may lead to overfitting of the data near the cutoff. Therefore, I report the results of the analysis using only linear and quadratic polynomials and ignore polynomials of higher order.

The second issue is the bandwidth around the cutoff that is used to estimate the treatment effect. Choosing a small bandwidth tends to reduce the misspecification error in approximating the polynomial to fit the data below and above the cutoff. However, by using a small bandwidth, fewer observations will be used in the estimation and thus, the variances of the estimated coefficients increase. Therefore, there is a trade-off between bias and variance in choosing the appropriate bandwidth. In this regard, since the results of the analysis can be sensitive to the choice of the bandwidth, using a data-driven approach to choose the optimal bandwidth prevents arbitrary decisions. The most popular data-driven approach optimizes the aforementioned bias-variance trade-off by minimizing the Mean Square Error (MSE) of the local polynomial estimator (Imbens and Kalyanaraman, 2012; Cattaneo et al., 2020). While MSE-optimal bandwidth is appropriate for estimation purposes, Calonico et al. (2016) and Calonico et al. (2018) show that it is not necessarily optimal for constructing confidence intervals for inference purposes. Instead, they recommend using a different, smaller bandwidth that minimizes the Coverage Error (CE) probability to make the inferences. It is important to note that both MSE- and CE-optimal bandwidths are sensitive to the total sample size, the order of the polynomials used for estimation, kernel function, variables, and several other factors. Therefore, to be consistent and avoid using arbitrary bandwidths, I report the results of the empirical analysis using MSE-optimal bandwidth for estimating the coefficients and CE-optimal bandwidth for constructing the confidence intervals. This approach would result in both a valid point estimation of the coefficient, and a valid robust bias-corrected confidence interval (Cattaneo et al., 2019). In Section 6 I check the robustness of my results by choosing different bandwidths around the MSE-optimal one.

The third issue is the choice of the kernel function that is used to assign (possibly different) weights to each observation around the cutoff, based on the distance between the observation's assignment variable and the cutoff. The intuition behind using different weights is that observations that are closer to the cutoff can be more important in estimating the coefficients compared to farther observations, and thus, the triangular kernel that assigns higher weights to closer observations may be more appropriate. Once again, to be consistent in reporting the results and avoid subjective decisions in this regard, I report the results of the empirical analysis using both a triangular kernel and a uniform one.

Table A.1: The difference in ownership by PRI institutional investors between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *ESG_Ownership* for the firm i in the year $t+1$. I have used an alternative approach to define ESG institutional investors as those that have signed into PRI. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have higher ownership by ESG institutional investors compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have lower ownership by ESG institutional investors compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.470	(2) bw = 0.776	(3) bw = 0.598	(4) bw = 0.566
Treatment Dummy	0.039***	0.048***	0.007	0.073***
	(2.751)	(2.796)	(0.849)	(3.439)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[524 202]	[835 289]	[649 234]	[649 234]

Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 0.503	(2) bw = 1.275	(3) bw = 0.733	(4) bw = 0.563
Treatment Dummy	-0.064***	-0.062***	-0.057***	-0.065***
	(-5.575)	(-6.662)	(-7.293)	(-4.051)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[636 1836]	[1445 3164]	[870 2118]	[636 1836]

Table A.2: The difference in ownership by institutional investors with SRI-related terms in their names between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is *ESG_Ownership* for the firm i in the year $t+1$. I have used an alternative approach to define ESG institutional investors as those that have terms related to SRI in their names. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, treated firm-year observations have higher ownership by ESG institutional investors compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have lower ownership by ESG institutional investors compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 1.271	(2) bw = 1.051	(3) bw = 0.746	(4) bw = 0.830
Treatment Dummy	0.001 (1.286)	0.002** (2.192)	0.001 (1.592)	0.002** (20214)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1319 489]	[1119 398]	[835 289]	[920 325]

Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 1.280	(2) bw = 1.145	(3) bw = 0.934	(4) bw = 0.899
Treatment Dummy	-0.000 (0.238)	0.000 (-0.001)	0.000 (0.416)	0.000 (-0.124)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[1445 3164]	[1309 2893]	[1093 2531]	[945 2297]

Table A.3: The difference in discount rate between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is $discount_rate$ for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At the Top-Cutoff, there is no significant difference in the discount rate between the treated firm-year observations compared to control observations. At the Bottom-Cutoff, however, treated firm-year observations have higher discount rates compared to control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 0.894	(2) bw = 1.121	(3) bw = 0.964	(4) bw = 0.719
Treatment Dummy	-0.446 (-0.678)	-0.275 (-0.144)	-0.486 (-0.929)	-0.120 (0.190)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[539 209]	[703 286]	[603 229]	[489 187]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 0.643	(2) bw = 1.153	(3) bw = 0.394	(4) bw = 0.630
Treatment Dummy	1.141*** (3.562)	1.347*** (3.823)	1.250*** (3.197)	1.408** (2.368)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[382 879]	[641 1292]	[200 638]	[382 879]

Table A.4: The difference in implied cost of capital between treated and control firms

This table shows the regression coefficient τ (the intercept of the fitted polynomials above the cutoff minus the intercept of the fitted polynomial below the cutoff) in Equation (1) under different settings, where the outcome variable (Y_{it+1}) is implied cost of capital for the firm i in the year $t+1$. The assignment variable (X_{it}) is the MSCI ESG score for the firm i in the year t. t-statistics are shown in parentheses. Panel A reports the results for the Top-Cutoff, and Panel B reports the results for the Bottom-Cutoff. At both cutoffs, there is no evidence that there is any significant difference among the implied cost of capital between treated and control observations. In all columns, MSE-optimal bandwidths (bw) have been used to estimate the coefficients, and CE-optimal bandwidths have been used to estimate the standard errors, which are clustered at the firm level. Columns (1) and (2) report the results using triangular kernel functions, while columns (3) and (4) report the results using uniform kernel functions. Column (1) and (3) use polynomials of order 1 to fit the data, while columns (2) and (4) use polynomials of order 2. The last row in each panel reports the effective number of observations below and above the cutoff that enter the estimation. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

Panel A: Top-Cutoff (Leader - Average)				
	(1) bw = 1.260	(2) bw = 1.559	(3) bw = 0.695	(4) bw = 0.753
Treatment Dummy	0.013 (1.180)	0.021 (1.082)	0.017 (1.231)	0.023 (0.581)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[691 318]	[805 389]	[380 177]	[444 186]
Panel B: Bottom-Cutoff (Average - Laggard)				
	(1) bw = 1.209	(2) bw = 1.306	(3) bw = 0.461	(4) bw = 0.745
Treatment Dummy	0.003 (0.915)	0.005 (1.377)	0.006 (1.198)	0.014 (1.613)
Kernel	Triangular	Triangular	Uniform	Uniform
Polynomial Order	1	2	1	2
No. Obs. [below above]	[591 1376]	[635 1466]	[210 710]	[361 889]

Table A.5: Panel Data Regression of BHR on the Ownership by (PRI) ESG Institutional Investors and Upgrades across the Bottom-Cutoff

This table shows the results of a panel regression where the dependent variables are BHRs with different holding periods (between 3 and 24 months). Independent variables are *ESG_Ownership* by PRI signatories (Section 2.2), $Bottom-Cutoff$ (a dummy variable that equals 1 in periods where the firm upgrades across the Bottom-Cutoff), and the interaction of these two. Control variables are defined in Appendix A.1. Standard errors are clustered at the firm and quarter levels. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

	(1) 3-month BHR	(2) 6-month BHR	(3) 9-month BHR	(4) 12-month BHR	(5) 15-month BHR	(6) 18-month BHR	(7) 21-month BHR	(8) 24-month BHR
ESG_Ownership	-0.222***	-0.275**	-0.321**	-0.406***	-0.497***	-0.612***	-0.650***	-0.625***
	(-3.40)	(-2.64)	(-2.64)	(-2.77)	(-2.95)	(-3.13)	(-3.19)	(-3.17)
$Bottom-Cutoff$	0.00864	-0.00858	-0.0181	0.00563	-0.0698	-0.110	-0.151	-0.0447
	(0.22)	(-0.18)	(-0.22)	(0.08)	(-1.01)	(-1.01)	(-1.54)	(-0.37)
ESG_Ownership× Bottom-Cutoff	0.0119	0.0367	0.325	0.195	0.618	0.794	0.724	0.347
	(0.06)	(0.13)	(0.75)	(0.50)	(1.55)	(1.45)	(1.40)	(0.55)
Leverage	0.0275	0.0311	0.0739	0.103	0.135*	0.153*	0.136	0.126
	(1.24)	(0.90)	(1.58)	(1.49)	(1.71)	(1.86)	(1.69)	(1.55)
Size	0.00251	-0.109***	-0.217***	-0.313***	-0.395***	-0.480***	-0.542***	-0.599***
	(0.25)	(-6.01)	(-8.28)	(-10.29)	(-11.34)	(-12.00)	(-13.06)	(-13.88)
Book to Market Ratio	-0.0240***	-0.0226	-0.0103	0.0107	0.0317	0.0505	0.0692*	0.0844**
	(-3.16)	(-1.50)	(-0.49)	(0.38)	(0.97)	(1.46)	(1.71)	(2.40)
Profitability	0.178***	0.349***	0.380***	0.356***	0.314**	0.255**	0.249**	0.160
	(4.50)	(4.31)	(4.14)	(3.82)	(2.66)	(2.27)	(2.13)	(1.38)
Constant	0.0631	0.847***	1.585***	2.243***	2.810***	3.391***	3.821***	4.210***
	(0.92)	(6.99)	(9.43)	(11.51)	(12.26)	(12.88)	(14.13)	(14.86)
Observations	120715	120104	119307	118429	117605	116765	115891	115052
Time- & Firm- FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.6: Panel Data Regression of MSCI ESG Scores on the Lagged Ownership by (PRI) ESG Institutional Investors and Lagged MSCI ESG Score

This table shows the results of a panel regression where the dependent variable is *MSCI ESG Score*. Independent variables are *ESG_Ownership* by PRI signatories (Section 2.2), *MSCI ESG Scores* with different lags (2 quarters to 8 quarters), and the interaction of these two. Control variables are defined in Appendix A.1. Standard errors are clustered at the firm and quarter levels. t-statistics are shown in parentheses. (*, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.)

	(1) *MSCI* ESG Score	(2) *MSCI* ESG Score	(3) *MSCI* ESG Score	(4) *MSCI* ESG Score
2q Lagged ESG_Ownership	0.972***			
	(3.21)			
2q Lagged ESG Score	0.791***			
	(32.70)			
2q Lagged ESG_Ownership × *2q Lagged ESG Score*	-0.199***			
	(-3.49)			
4q Lagged ESG_Ownership		1.784***		
		(3.41)		
4q Lagged ESG Score		0.565***		
		(13.41)		
4q Lagged ESG_Ownership × *4q Lagged ESG Score*		-0.371***		
		(-3.83)		
6q Lagged ESG_Ownership			2.419***	
			(3.60)	
6q Lagged ESG Score			0.416***	
			(8.29)	
6q Lagged ESG_Ownership × *6q Lagged ESG Score*			-0.511***	
			(-4.18)	
8q Lagged ESG_Ownership				2.496***
				(3.09)
8q Lagged ESG Score				0.253***
				(4.96)
8q Lagged ESG_Ownership × *8q Lagged ESG Score*				-0.556***
				(-3.94)
Leverage	0.0478	0.0598	0.117	0.172
	(1.10)	(0.70)	(0.96)	(1.16)
Size	0.00242	0.00844	0.0258	0.0385
	(0.29)	(0.48)	(1.13)	(1.47)
Book to Market Ratio	-0.00155	0.000128	0.00531	0.00482
	(-0.32)	(0.01)	(0.40)	(0.30)
Profitability	-0.0150	-0.0355	-0.110	-0.192
	(-0.27)	(-0.34)	(-0.82)	(-1.58)
Constant	0.855***	1.767***	2.257***	2.868***
	(6.85)	(7.84)	(7.82)	(9.12)
Observations	25807	22462	19200	16278
Time- & Firm- FEs	Yes	Yes	Yes	Yes