HOW DOES ESG INFORMATION AFFECT STOCKS' COST OF CAPITAL?

A Thesis

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Master of Science in Applied Economics and Management

by

Ho Yin Chien

August 2023

ABSTRACT

I examine the causal effect of Environment, Social, and Governance (ESG) information on the cost of capital of U.S. stocks using a quasi-natural experiment. Exploiting the discontinuity in the mapping mechanism of a ESG score to a ESG rating, I conduct Regression Discontinuity Design tests around each ESG score threshold, comparing the ex-ante cost of capital of stocks with similar ESG scores but distinct ESG ratings. I find that a negative change in ESG rating has a positive impact on the cost of capital of stocks on the highest-rating ESG stocks. The effect reversed for the lowest-rating ESG stocks. The finding is broadly coherent with the argument in the existing literature that high ESG stocks have lower expected returns, and further suggests a hump-shape relationship between ESG information and stock ex-ante cost of capital.

BIOGRAPHICAL SKETCH

Ho Yin Chien (or Vic Chien) is currently both a Master's student and a first-year Ph.D. student at the Charles H. Dyson School of Applied Economics and Management at Cornell University. His area of concentration is Finance. He received his bachelor's degree in Economics and Finance from the University of Hong Kong in 2018, and a masters' degree in Applied Economics and Management from the Dyson school in 2021. He has two years of industry experience in equity valuation.

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1. Introduction

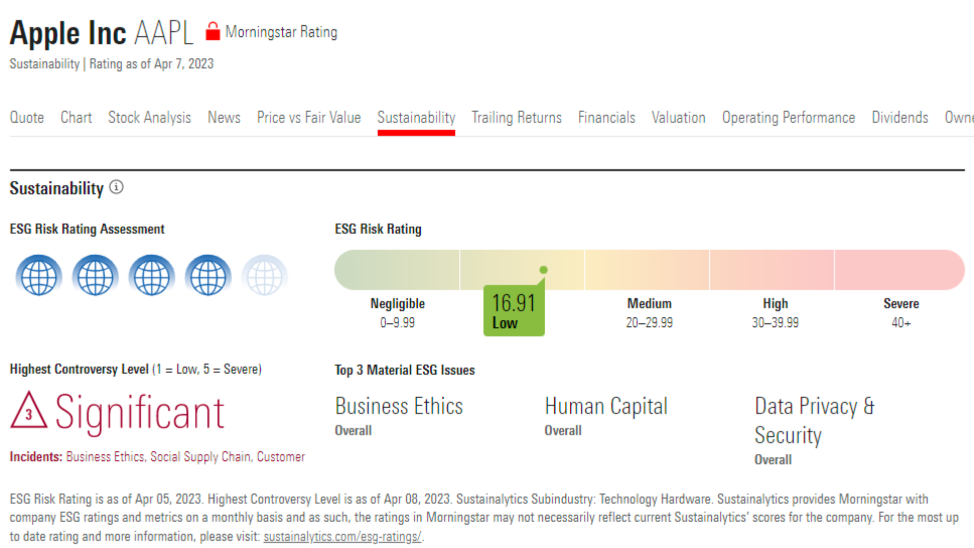
1.1 ESG Investing

ESG investing has been a popular trend in the investment industry in the past decade. Investment institutes are increasingly incorporating ESG assets into their portfolio. According to the Global Sustainability Investment Alliance (2021), investment funds in the U.S. alone invested about $17 trillion in 2020 with ESG considerations. Higher returns, second only to brand and reputation, has been one of the primary motivations for ESG investing. According to Paribas (2022), 45% of respondents expect that ESG investing would improve long-term returns, and 60% of them expect their ESG portfolio would outperform in 5 years. The effect of ESG performance on the financial performance of firms can be explained through multiple channels. Some believe that firms "do well by doing good". In other words, corporate sustainability strategies and investment in ESG assets have a real cash flow impact on firms, and firm valuations reflect such an impact. In this view, it naturally follows that ESG information is only a factor amongst many others that predicts corporate profitability and risks. Some believe that investors' perceptions and preferences for green firms intrinsically change the equilibrium outcome of the equity market, thus impacting the firm valuation without necessarily requiring a change in fundamentals. In other words, ESG information in the market is a determinant of the cost of equity capital by investor interactions at the equilibrium. In this paper, I will focus on the latter mechanism and show that controlling for actual firm ESG performance, ESG information alone can induce changes in the cost of equity capital.

1.2 ESG Ratings

ESG ratings are one of the most broadly adopted sources of ESG information in the financial market. Analogous to credit ratings, ESG ratings are published and regularly updated by rating agencies, but are designed to measure the degree to which firms comply with ESG standards. It has been shown that investors rely on ESG ratings to make investment decisions (Hartzmark and Sussman 2019). The influential ESG ratings include the Morningstar Sustainalytics (formerly Sustainalytics) ESG Risk Rating, the MSCI ESG Rating, the Bloomberg ESG Scores, the Refinitiv ESG Score. Amongst the aforementioned rating agencies, Morningstar Sustainalytics releases both an ESG score, which is a numerical score that captures precisely the ESG performance of firms, and an ESG rating, which is categorical and reflects broadly the ESG performance of a firm in a lower granularity. Figure 1 presents an example of the information displayed on the Morningstar website. The ESG score and rating are freely accessible for all investors in real time.

Figure 1: Example of ESG information on the Morningstar Website



This figure presents an example of the ESG information shown on the Morningstar website (https://www.morningstar.com/stocks/xnas/aapl/sustainability).

The Morningstar Sustainalytics ESG Risk Rating Category (the "ESG risk rating" or "ESG rating" henceforth) is a simple function of the Morningstar Sustainalytics ESG Risk Rating Score (the "ESG risk score" or "ESG score" henceforth). Depending on which particular interval the ESG score of an individual firm is in, that firm receives a corresponding ESG risk rating. It thus follows that firms with very similar ESG scores can have different ESG risk ratings if they are on different sides of a score "threshold" (or "breakpoint").

Table 1: Mapping between ESG score and ESG rating

Sustainalytics ESG Risk Score	Sustainalytics ESG Risk Rating Assessment	Sustainalytics ESG Risk Rating
0-9.99	🌐 🌐 🌐 🌐 🌐	Negligible
10-19.99	🌐 🌐 🌐 🌐	Low
20-29.99	🌐 🌐 🌐	Medium
30-39.99	🌐 🌐	High
>40	🌐	Severe

This table presents the five Sustainalytics ESG Risk Rating categories and the corresponding assessments (globe ratings) and range of the Sustainalytics ESG Risk Score.

Table 1 shows the mechanism under which the ESG score is transformed into the ESG rating. The ESG rating jumps discontinuously at the four ESG score breakpoints (i.e. 10, 20, 30, 40). It follows that comparisons between firms with close ESG scores but distinct ESG ratings would yield an estimate of the treatment effect of being assigned a different ESG rating while controlling for actual ESG performance. This constitutes a setup for a Regression Discontinuity Design.

In this paper, I first conduct a correlational analysis between the cost of capital and ESG information with Ordinary Least Square regressions, and then use the aforementioned discontinuity to establish a casual inference. The methodology is detailed in section 3.

1.3 Regression Discontinuity Design

1.3.1 Introduction

Regression Discontinuity Design (RDD) is regarded as one of the most credible quasi-experimental methods in economics in the past two decades. Since the publication of the

Thistlewaite and Campbell (1960) paper, economists have applied the method to a variety of settings to establish causal inferences. The design applies to data-generating processes under which treatments are assigned to units according to whether an observed unit-specific running variable (also known as an “assignment” or a “forcing” variable) exceeds a predetermined threshold. Conceptually, identification is driven by the idea that even if unobservables confound the relationship between the running and outcome variables, observations just above and below the threshold should be “good comparisons” with each other, for the running variable is essentially kept constant. Thistlewaite and Campbell (1960) first proposed this method to study the effect of academic awards on future educational outcomes. In their study, students received awards if and only if their exam scores were above a cutoff point. An endogeneity concern for the simple OLS model arises from the fact that confounders like wealth and intelligence affect both the educational outcome and the probability of receiving an award. However, by focusing on students with scores almost equal to the threshold, this bias diminishes.

The standard RDD estimator is the difference between the two estimates of the expected outcome variable conditional on the running variable being the threshold value, each estimated only using observations on one side of the cutoff:

$$\hat{\tau} = E[Y(1) - Y(0)|X = c] = \lim_{x \to c^+} E[Y|X = x] - \lim_{x \to c^-} E[Y|X = x],$$

where $\hat{\tau}$ is the treatment effect estimator, $Y(1), Y(0)$ indicates the outcome variable with and without treatment, respectively, X indicates the running variable, and c indicates the threshold. In practice, the two estimations are often performed in one regression. The RDD estimator is consistent in yielding the local average treatment effect under appropriate regularity conditions (Hahn, Todd & Van der Klaauw, 2001; Lee, 2008).

1.3.1 Non-parametric RDD

While RDD could be in theory parametric, the standard practice in the empirical RDD literature involves non-parametric estimations, particularly local polynomial regressions (Cattaneo et. al, 2016). Researchers often use a local linear polynomial to approximate the functional form of the regression equation in the narrow sample region, and then conduct weighted linear least squares estimation by applying weights to observations based on a uniform or triangular kernel function (Calonico, Cattaneo, and Titiunik, 2014; Calonico et al., 2019). The estimator can be expressed as:

$$\hat{\tau} : \widehat{Y_i} = \hat{\alpha} + \hat{\tau}T_i + \widehat{\beta^-}(1 - T_i)X_i + \widehat{\beta^+}T_iX_i + \widehat{\boldsymbol{\delta}}\boldsymbol{Z}',$$

where $\hat{\tau}$ is the treatment effect estimator, $\widehat{Y_i}$ is the outcome variable, T_i is the treatment indicator, X_i is the running variable, $\boldsymbol{Z}'$ is the vector of covariates, $\hat{\alpha}$ is the intercept, $\widehat{\beta^-}$ and $\widehat{\beta^+}$ are the slope coefficients of the running variable on the left and right of the threshold respectively, and $\widehat{\boldsymbol{\delta}}$ is the vector of covariates coefficients. This configuration incorporates covariates according to Calonico, Cattaneo, and Titiunik (2014), which showed that this setup requires the weakest regularity conditions to achieve consistency. A local polynomial regression is used in the main setup for this paper.

1.3.1 Multi-cutoff RDD

The locality of the RDD estimates (i.e. the estimated treatment effect being conditional on the running variables approximately equating the threshold value) naturally limits the generality of the result. To uncover the treatment effect conditional on a set of running variable values, one may consider a cumulative multi-cutoff RDD (Cattaneo et. al, 2016), which applies to settings with multiple fixed cutoff values, and different treatments assigned between different cutoffs. Each treatment effect can be independently identified under this setup. The estimation procedure is essentially the same as running multiple standard RDDs across the set of cutoffs, but with the selected sample region for each regression constrained inside the interval formed by two adjacent cutoffs (Cattaneo et. al, 2016). A multi-cutoff RDD is used in the main setup for this paper.

1.4 Identification strategy and Main Result

I use a cumulative multi-cutoff sharp RDD to examine the effect of ESG risk rating changes on the ex-ante cost of equity capital. Specifically, I focus on stocks with a ESG score near each of the four score thresholds and perform an RDD test around each threshold using the ESG score as a running variable, examining the effect of the difference in the ESG Risk Rating on the cost of capital of stocks. As the comparison is between stocks with similar ESG scores, the ESG performance of firms and any fundamental impact it causes is controlled for, effectively isolating the effect of only ESG information on the equity market outcome. Conducting RDD tests around the four score thresholds allows the identification of the potentially heterogeneous effect of ESG risk rating along the axis of ESG performance (i.e. A rating downgrade from "Negligible" to "Low" may have a different cost of capital impact than a rating change from "High" to "Severe").

I find that a positive ESG risk rating change increases the cost of capital for low ESG stocks, and decreases the cost of capital for high ESG stocks. The magnitude of this effect is significant, being approximately 3.95 to 4.50 percentage points for high ESG stocks, and -1.78 to -2.19 percentage points for low ESG stocks, depending on the regression specification.

2. Literature Review

The ESG asset pricing literature has risen in popularity since the early 2000s. A strand of literature examines the correlation between firm profitability and ESG performance, and provides evidence that firms "do well by doing good". In other words, firm Corporate Social Responsibility (CSR) strategies are profit-maximizing (Mc Williams and Siegel 2001). Studies have shown that firms adopt CSR as a product differentiation strategy (Bagnoli and Watts 2003; Siegel and Vitaliano 2007).

Following this rationale, Luo and Bhattacharya (2009); Albuquerque, Koskinen, and Zhang (2019) developed equilibrium models and found evidence that high CSR firms have higher customer loyalty and more pricing power. Hong and Kacperczyk (2009) argue "sin" firms face higher litigation risks. There is also a strand of literature on green firms having lower climate risks (Ilhan, Zacharias, and Vilkov 2021; Seltzer, Starks, and Zhu 2022).

Another body of literature focuses on the effect of ESG information on investor perceptions and preferences, which in equilibrium affects firm value. This literature investigates the value effect of ESG information through the channel of the cost of capital instead of profitability. Early empirical work consists of mainly correlational studies that documented a negative relationship between firm ESG performance and cost of capital (Sharfman and Fernando 2008; Goss and Roberts 2011; El Ghoul et al. 2011). Hong and Kacperczyk (2009) famously showed that stocks in "sin" industries have higher returns, a phenomenon possibly driven by social norms on markets. Bolton and Kacpercyzk (2021) provided similar evidence on high carbon-emitting firms. Baker et al. (2019) found that green bonds have a lower yield and trade at a premium compared to traditional bonds. These studies suggest that a non-pecuniary motive may be at play in equilibrium, causing green assets to trade at a premium (or "greenium"). Theory work that attempts to incorporate such motive has a long-standing history. Fama and French (2007) showed that heterogeneity in investor tastes affects equilibrium asset prices. Heinkel, Kraus, and Zechner (2001) constructed a model in which a portion of investors only hold ESG stocks. These stocks have a lower cost of capital in equilibrium due to a more diverse investor base and consequential higher risk sharing. Pedersen, Fitzgibbons, and Pomorski (2021) built a model and predicted that with the presence of ESG-motivated investors, the price of ESG assets will be lower in equilibrium due to investor preference even if ESG information has no predicting power over the fundamental. Pastor, Stambaugh, and Taylor (2021) constructed an ESG factor, and showed that although green stocks have lower expected returns, a positive shock to the ESG factor (e.g. increase in environmental awareness) causes increases in realized green returns.

This paper adds to the empirical evidence by showing that stocks with similar fundamentals but higher ESG risk ratings have different costs of capital, and such a difference is significant. Moreover, except for Hong and Kacperczyk (2009), most studies did not differentiate the effect of ESG information on stocks at different ESG levels, and Hong and Kacperczyk (2009) only focused on low ESG stocks. This paper is the first to provide causal evidence that such an effect varies largely along the ESG score axis.

Finally, most closely related to this paper is the work by Goldstein et al. (2022), who developed a noisy rational expectation (RE) model in which traditional investors and ESG investors seek information from the stock prices. In their model, if trading is dominated by traditional investors, prices convey mainly information about financial returns. This further increases trading responsiveness by traditional investors, forming a positive feedback loop. The opposite holds true when ESG investors dominate trading, which means there are multiple equilibria. The model predicts that for stocks that are either dominated by traditional or ESG investors, prices are more informative for the dominant group of investors, and thus the equilibrium cost of capital is low, as the cost of capital represents information risk in RE models (Easley and O'Hara 2004). For stocks with comparable amounts of ESG and traditional investors, information risk is high for both groups, and so is the cost of capital. The result of this paper supports this prediction. By using ESG risk rating as a proxy for the size of ESG investor base, I show that the sign of the effect of positive ESG information on the equilibrium cost of capital changes from positive (i.e. positive ESG information causes increases in the cost of capital) at the lower end of the ESG spectrum to negative at the higher end.

3. Methodology

3.1 Ordinary Least Square Regression

For the first set of results, I conducted Ordinary Least Square (OLS) regressions using the cost of capital as the dependent variable. I regressed the cost of capital on the ESG risk score and ESG risk rating dummies, controlling for size, book-to-market ratio, beta, and leverage. A square term for the ESG score is included to account for possible non-linearity of the effect as suggested by Goldstein et al. (2022). Year and industry fixed effects are added. The regression formula is as follows:

$$CoC_{i,t} = \alpha + \beta_1 S_{i,t} + \beta_2 {S_{i,t}}^2 + \sum_{k=1}^{4} \gamma_k rating_{k,i,t} + \boldsymbol{\delta Z}_{i,t} + \varepsilon_t + \eta_j + \epsilon_{i,t},$$

where i, t, j are the firm, month, and industry indexer, CoC denotes Cost of Capital, S is the ESG score, and $\boldsymbol{Z}$ represents control variables, $rating$ is the indicator of the observation having an ESG risk rating category k, ε and η are year and industry fixed effects.

It is to be noted that OLS results are correlational and could fail to establish causal inference between ICC and ESG information due to a few endogeneity issues. First, reverse causality could arise from the fact that companies with better financial performance have more resources to invest in green assets and improve ESG conditions. An exogenous variation in ESG information is required to establish the direction of causation. Second, potential confounding factors such as management quality and public relations strategies of firms could be positively correlated with both financial and ESG performances, biasing the estimates. Such confounders are unquantifiable and cannot be controlled for. Amongst them, the most significant and obvious is risk. The ESG score and rating are risk measures that are designed to inform investment decisions, and by construction correlates with the risk level of stocks. Standard asset pricing theory predicts that a high ESG score or rating (high ESG risk) would be associated with a higher ICC, if investors price risks correctly. This masks the effect of ESG information on ICC. An RDD addresses both aforementioned issues by creating an almost-random assignment of treatment.

3.2 Regression Discontinuity Design

The main regression setup is a multi-cutoff cumulative sharp RDD. Following the common approach in the RDD literature, the treatment effect estimator for the *k*-th threshold is obtained by conducting a local weighted least square regression of the cost of capital on the treatment indicator (whether the score exceeds the *k*-th threshold), the running variable (the ESG score), and the covariates, using only stock-month observations with ESG score in a pre-determined bandwidth around the threshold. Polynomials of order 2 are used to approximate the regression functions in the neighborhoods. Weights are assigned to observations based on a triangular kernel function, as is commonly done in the RDD literature (Calonico, Cattaneo, and Titiunik, 2014). Covariates and fixed effects are added according to the method proposed by Calonico et al. (2019). The sample bandwidth around each threshold is selected according to the method by Calonico, Cattaneo, and Titiunik (2014). Bias-corrected estimates and Z-statistics based on the heteroskedasticity-robust nearest-neighbor estimators were used (Calonico, Cattaneo, and Titiunik 2014). The treatment effect estimator for the *k*-th threshold can be represented by:

$$\widehat{\tau_k} : \widehat{CoC_{\iota,t}} = \widehat{\alpha_k} + \widehat{\tau_k} T_{i,t} + \widehat{\beta_k^-}(1 - T_{i,t})S_{i,t} + \widehat{\beta_k^+} T_{i,t} S_{i,t} + \widehat{\beta_{k,2}^-}(1 - T_{i,t}){S_{i,t}}^2 + \widehat{\beta_{k,2}^-}(1 - T_{i,t}){S_{i,t}}^2 + \widehat{\boldsymbol{\delta}}\boldsymbol{Z}'$$

where i and t denote stock and month, $CoC_{i,t}$ is the cost of capital, $T_{i,t}$ is the treatment indicator (i.e. $1[S_{i,t} \geq c_k]$), $S_{i,t}$ is the ESG score, c_k is the kth ESG score threshold, and $\boldsymbol{Z}$ is the vector of control variables. $\widehat{\beta_k^-}$ and $\widehat{\beta_k^+}$ are, respectively, the coefficient of the running variable on the right and left of the threshold, $\widehat{\beta_{k,2}^-}$ and $\widehat{\beta_{k,2}^+}$ are the coefficients for the squared running variables, and $\widehat{\tau_k}$ is the parameter of interest, the estimated treatment effect of ESG risk rating increment.

This design addresses the aforementioned endogeneity issues as comparisons are made between observations with similar ESG scores. Any potential confounders, including risks, that correlate with

ESG score is hence kept constant in the comparison. Furthermore, whether an observation within the threshold neighborhood receives the treatment is almost random. Such an assignment mechanism establishes the direction of causality.

4. Variables And Sample

4.1 Implied Cost of Capital

Empirical studies have increasingly used the Implied Cost of Capital (ICC), defined as the return rate implied by the infinite horizon dividend discount model for share price, as a cost of capital measure (Chen, Chen, and Wei 2009; Ghoul et al. 2011; Hail and Leuz 2009; Chava 2014). Compared to traditional expected returns measures like earnings-to-price (E/P) and dividend yield (D/P), ICC controls for earnings growth rates and dividend yield. The ex-ante nature of ICC makes it free from the noises in realized returns. Paster, Sinha, and Swaminathan (2008) showed that if stocks' conditional expected returns follow an AR(1) time series, the ICC and the conditional expected returns are perfectly correlated, providing theoretical evidence for the effectiveness of ICC as an expected returns proxy. Finally, Pastor, Stambaugh, and Taylor (2022) showed that the realized returns of green stocks were systematically higher than the expected returns in recent years due to the increase in environmental awareness, making realized return a poor proxy for the cost of capital. I use ICC as the measure of implied cost of capital in this paper.

4.1.1 Definition

Implied Cost of Capital (ICC) is defined as the value of expected return r_e that solves the infinite horizon dividend discount model for stock price:

$$P_t = \sum_{k=1}^{\infty} \frac{E_t(D_{t+k})}{(1+r_e)^k} ,$$

where t indicates year, P_t is the stock price, and $E_t(D_{t+k})$ is the expected dividend at year $t+k$

forecasted in year t. As observed in the formulation, ICC captures the market expectation of stock return implied by the stock price P_t and dividend forecast $E_t(D_{t+k})$, incorporating information regarding future growth and dividend yield.

4.1.2 Empirical Construction

Empirically, I construct ICC following Pastor, Sinha, and Swaminathan (2008), Lee, Ng, and Swaminathan (2009), and Li, Ng, and Swaminathan (2013), by estimating an empirically tractable finite horizon dividend discount model in the following form:

$$P_t = \sum_{k=1}^{T} \frac{FE_{t+k} \times DP_{t+k}}{(1+r_e)^k} + \frac{FE_{t+T+1}}{r_e(1+r_e)^T},$$

where t indicates year, P_t is the stock price, FE_{t+k} is the forecast earnings in year $t+k$, DP_{t+k} is the forecast dividend payout ratio for year $t+k$, and T is the horizon of the forecasts. The first term represents the discounted value of the dividend stream in the forecast period and the second term represents the terminal value. The forecast horizon T is set to 15 years in this paper. Price and stock data, financial statement data, and analyst forecasts are from the Center for Research in Security Prices (CRSP), Compustat North America, and Thompson Institutional Broker Earnings Services (I/B/E/S), respectively.

4.1.2.1 Earnings Forecast

I construct the earnings forecasts in three steps. First, I calculate FE_1, the forecast earning exactly one year forward from the month of observation (year $t+1$). I/B/E/S contains analyst earnings forecasts timed at the end of fiscal years. As the stock price data is in a monthly frequency, the forecast earnings at the next fiscal year end, FY_1, is timed at 1 to 12 months ahead of the time of the observation. I take a linear interpolation of the median forecast earnings at the two most recent fiscal year ends, FY_1 and FY_2, to construct FE_1. Specifically,

$$FE_1 = w \times FY_1 + (1 - w) \times FY_2 \ ,$$

where w is the number of months between the time of the observation and the next fiscal year end divided by 12. Implicit in this construction is the assumption that the forecast earnings grow linearly from the next fiscal year end. I then calculate the forecast earnings at year $t + 2$, FE_2, by applying the growth rate implied by $FY_1$and FY_2:

$$FE_2 = FE_1 \times \frac{FY_2}{FY_1} \ .$$

I assume that the implied dividend growth rate $g_2 = FY_2/FY_1 - 1$, over the forecast period, revert exponentially to the long-term steady-state growth rate g, which is proxied by the long-run nominal gross domestic product (GDP) growth rate. Specifically, for years $t + 3$ to $t + T + 1$, the forecast dividends are computed as:

$$g_{t+k} = g_{t+k-1} \times \exp[\frac{\ln\left(\frac{g}{g_2}\right)}{T}],$$

$$FE_{t+k} = FE_{t+k-1} \times (1 + g_{t+k}).$$

4.1.2.2 Dividend Payout Ratio Forecast

I assume that DP_{t+1}, the dividend payout ratio at year $t + 1$, approximated by dividing the most recent actual dividends by the earnings in the same period, linearly revert to the steady-state value DP. Specifically, for years $t + 2$ to $t + T$, the dividend payout ratio is calculated as:

$$DP_{t+k} = DP_{t+k-1} + \frac{(DP - DP_{t+1})}{T} \ .$$

The steady-state value DP is obtained from the sustainable growth rate formula:

$$ROI \times (1 - DP) = g \ ,$$

where ROI indicates steady-state return on new investments, and g is the steady-state earnings growth rate aforementioned. This formula states that in the steady-state, competition reduces return on new investments to the cost of equity. Therefore by equating ROI and r_e, I obtain $DP = g/r_e$.

4.2 ESG Risk Score and ESG Risk Rating

I obtain the ESG score and the ESG rating from Morningstar Sustainalytics. The ESG score is designed to quantify the unmanaged ESG risks that a stock is exposed to, and to provide a universal risk measure comparable across industries and subindustries. The data covers more than 13,000 US stocks, 42 industry groups and 138 subindustries. Each stock is assessed based on the material ESG issues it faces and the strategies it adopts to manage the corresponding risks. The result is represented by a numerical score, typically rounded to 2 decimal places, ranging from 0 to 100, with more than 95% of stocks scoring below 40. A higher score indicates a higher ESG risk (i.e. worse ESG performance).

The ESG rating is a categorical variable that classifies stocks into 5 risk categories: Negligible, Low, Medium, High, and Severe. Negligible indicates the lowest ESG risk and hence best ESG performance. Starting from September 2019, Morningstar adopted the current mechanism, under which the rating is completely determined by the score through a simple mapping: a score in the interval [0,10) translates into a rating of "Negligible", a score in the interval [10,20) translates into a rating of "Low", a score in the interval [20,30) translates into a rating of "Medium", a score in the interval [30,40] translates into a rating of "High", a score higher than 40 translates into a rating of "Severe".

4.3 Control Variables

Under the standard assumptions, identifications of RDDs do not rely on the inclusion of covariates. Including covariates with the appropriate methods can, however, increase the power of inference in finite sample (Imbens & Lemieux, 2008; Calonico et al. 2019). Prior studies indicate that ICC is affected by size (logarithm of month-end market capitalization), book-to-market ratio, market model beta, and financial leverage (ratio of total debt to market capitalization) (Dhaliwal, Heitzman, and Li 2006; Chen, Chen, and Wei 2009; Chava 2014). I followed Bali, Engle, and Murray (2016) in calculating the size and book-to-market ratio, using price and share data from CRSP and financial statement data from Compustat North America. Financial leverage is calculated with the same approach for the book-to-market ratio due to their similar natures. Market model beta is extracted from the Beta Suit of the Wharton Research Database Service (WRDS). I additionally controlled for year fixed effects and industry fixed effects according to Fama and French (1997) 48 industries.

4.4 Sample and Descriptive Statistics

The full sample consists of observations from September 2019 to March 2022, covering 2,913 stocks in all Fama and French (1997) 48 industries.

Table 2 contains the descriptive statistics for the regression variables. Table 3 contains the mean and median of the regression variable categorized by the ESG rating. The covariates are approximately balanced for the 5 ESG rating categories. Table 4 contains the correlation coefficients for the regression variables. The lower-left part of the table provides the Pearson coefficients and the upper-right part provides the Spearman coefficients. None of the pairs of variables has a correlation coefficient higher than 0.5. Note that the descriptive statistics are computed using the entire sample before restricting to the window around each threshold.

Table 2: Descriptive Statistics

	Mean	Min	Q1	Median	Q3	Max	S.D.
ICC	0.11	0.00	0.07	0.09	0.12	1.29	0.07
Size	11.43	2.13	9.66	11.32	13.07	21.11	2.45
Book-to-Market	0.59	0.00	0.26	0.47	0.77	20.58	0.58
Beta	1.21	-8.96	0.80	1.14	1.53	7.00	0.64
Leverage	0.43	0.00	0.04	0.18	0.44	110.06	1.42
ESG score	27.98	5.20	20.74	27.40	33.98	69.88	9.65

Table 3: Descriptive Statistics by Morningstar Sustainalytics ESG Risk Rating

Mean	Negligible	Low	Medium	High	Severe
ICC	13.94	11.06	11.11	11.22	13.20
Size	11.52	12.21	11.82	10.82	10.21
Book-to-market	0.54	0.55	0.56	0.66	0.79
Beta	1.45	1.24	1.23	1.24	1.36
Leverage	0.60	0.48	0.47	0.56	0.62
ESG score	8.65	16.14	25.14	34.13	46.06
Median	Negligible	Low	Medium	High	Severe
ICC	10.32	8.49	8.50	8.33	9.17
Size	11.15	12.32	11.68	10.67	10.26
Book-to-Market	0.47	0.35	0.42	0.60	0.60
Beta	1.34	1.14	1.19	1.16	1.21
Leverage	0.14	0.17	0.20	0.21	0.30
ESG score	8.89	16.45	25.25	33.81	44.40
N	389	11402	19129	15434	5461

Table 4: Pearson (lower-left) and Spearman Correlation Coefficients (upper-right)

	ICC	Size	Book-to-Market	Beta	Leverage	ESG score
ICC	1.00	-0.17	0.20	0.29	0.18	0.03
Size	-0.18	1.00	-0.28	-0.16	0.07	-0.28
Book-to-Market	0.19	-0.25	1.00	0.07	0.44	0.19
Beta	0.27	-0.17	0.14	1.00	0.11	0.02
Leverage	0.15	-0.09	0.45	0.14	1.00	0.07
ESG score	0.06	-0.28	0.13	0.07	0.04	1.00

5. Empirical Results

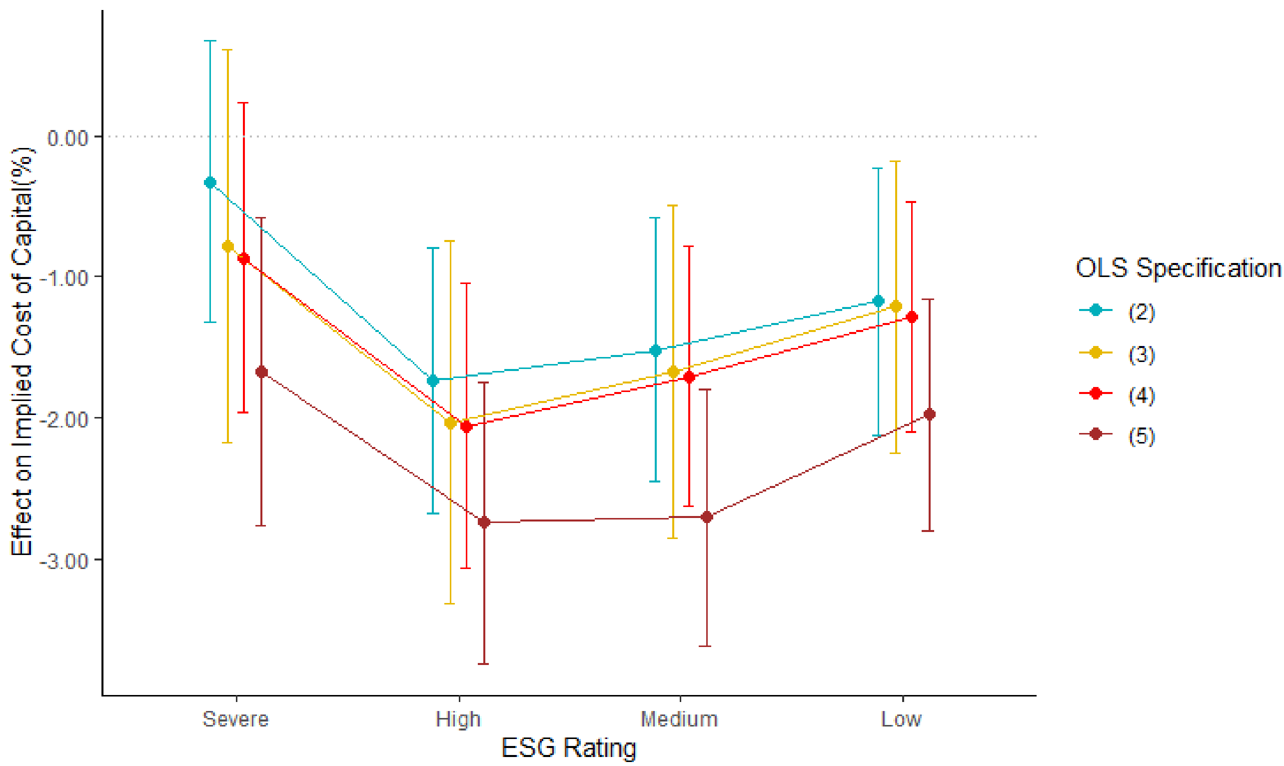
Table 5 presents the results of the OLS regressions. The dependent variable (ICC) is in percentage form. In column (1), I regress Implied Cost of Capital on the ESG score, with a square term, and control variables without adding fixed effects. The coefficients of the ESG score and the square term are -0.145 and 0.003 respectively, both significant at 0.1% level, indicating a convex effect of the score on ICC. Coefficients on the control variables are significant at all levels for all specifications, with the same signs as in the literature (El Ghoul et al. 2011). In column (2), I regress ICC on indicators of ESG risk ratings instead of scores, with the “Negligible” rating category as the benchmark. The coefficients of the ESG risk rating indicators from “Severe” to “Low” are, respectively, -0.327, 1-.732, -1.519, and -1.174, with the coefficients for “High”, “Medium”, and “Low” being 0.1%, 1%, and 5% significant. In column (3), the ESG risk score and rating indicators are both included. The effect of the score disappeared after including the ratings indicators. Coefficients of the indicators of “High” and “Medium” categories are -2.031 and -1.668, both significant at the 1% level, the rating of “Low” has a coefficient of -1.211 significant at 5% level. In column (4), year fixed effects are added. The magnitudes of coefficients on ESG risk ratings are approximately unchanged, but are more statistically significant. In column (5), both year and industry fixed effects are added. The coefficients on the ESG score and square term are 0.075 and -0.002, significant at the 5% and 1% level respectively, decreasing both in magnitude and significance compared to the result in column (1). Coefficients of the indicators from “Severe” to “Low” are -1.671, -2.745, -2.707, and -1.975 respectively, all significant at the 0.1% level except for that of “Severe”, which is 1% significant. Figure 2 presents the coefficients of the ESG risk ratings with the 95% confidence interval under difference specifications, using the “Negligible” category as the benchmark.

Table 5: Effect of ESG Rating on Implied Cost of Capital (OLS)

	(1)	(2)	(3)	(4)	(5)
ESG Score	-0.145***		0.010	-0.000	0.075*
	(-5.968)		(0.218)	(-0.012)	(2.058)
ESG Score^2	0.003***		0.000	0.000	-0.002**
	(6.080)		(0.151)	(0.359)	(-3.084)
Size	-0.395***	-0.403***	-0.396***	-0.374***	-0.469***
	(-20.011)	(-20.892)	(-20.037)	(-20.288)	(-24.523)
Book-to-Market	1.082***	1.093***	1.104***	1.164***	0.869***
	(7.166)	(7.425)	(7.271)	(12.973)	(9.126)
Beta	3.707***	3.698***	3.728***	3.788***	3.295***
	(40.342)	(41.163)	(40.331)	(50.949)	(39.864)
Leverage	0.910***	0.902***	0.890***	0.938***	0.950***
	(10.037)	(10.176)	(9.857)	(17.185)	(17.386)
<u>ESG rating</u>					
Severe		-0.327	-0.781	-0.865	-1.671**
		(-0.643)	(-1.096)	(-1.539)	(-3.010)
High		-1.732***	-2.031**	-2.057***	-2.745***
		(-3.607)	(-3.103)	(-3.993)	(-5.363)
Medium		-1.519**	-1.668**	-1.706***	-2.707***
		(-3.178)	(-2.769)	(-3.639)	(-5.799)
Low		-1.174*	-1.211*	-1.282**	-1.975***
		(-2.439)	(-2.295)	(-3.078)	(-4.710)
Intercept	12.435***	12.078***	11.828***	11.686***	13.900***
	(25.596)	(21.033)	(17.395)	(19.937)	(22.820)
Year Fixed Effect				X	X
Industry Fixed Effect					X
N	34363	34363	34363	34363	34363

This table presents the result of the OLS regressions of Implied Cost of Capital on ESG Score, ESG Rating, size, book-to-market ratio, beta, leverage ratio, year fixed effect, and industry fixed effect. *t*-statistics is presented in the bracket. ***,**,* indicates, respectively, a 0.1%, 1%, and 5% level of statistical significance.

Figure 2: OLS Coefficients of ESG Risk Ratings



This graph presents the correlational effect of ESG rating categories on the implied cost of capital of stocks compared to the baseline category of "Negligible". The regression specifications and results are presented in in Table 5. Error bars represent the 95% confidence interval with respect to the *t*-statistics.

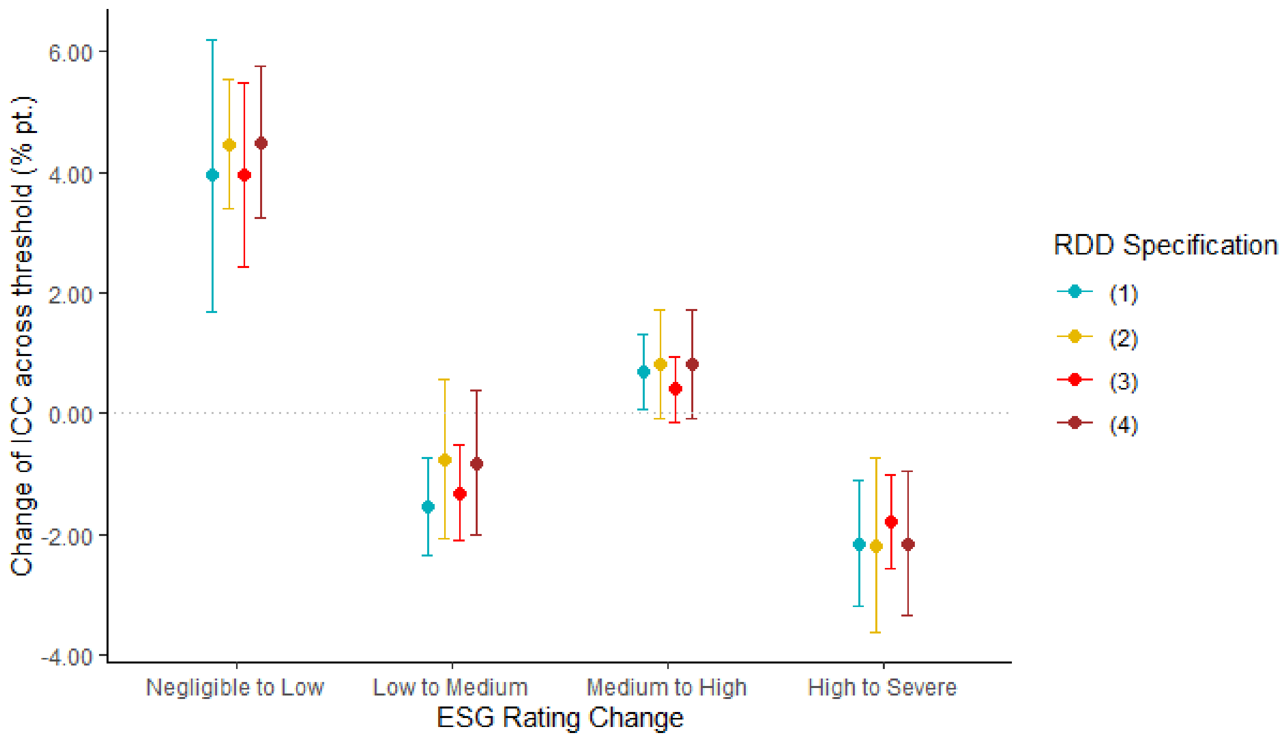
Table 6 presents the main results of the regression discontinuity tests. The coefficients indicate the estimated local average treatment effects of rating changes on the implied cost of capital at ESG score thresholds in the unit of percentage points. Coefficients in the same column are obtained by conducting RDD around different ESG score thresholds using the same regression specification. Covariates and fixed effects, including size, book-to-market ratio, market model beta, financial leverage, year fixed effects, and industry fixed effects are included in all specifications. In the first column, the estimates without error clustering are, in the order of "Negligible to Low", "Low to Medium", "Medium to High", and "High to Severe", 3.952, -1.555, 0.692, and -2.154 pp, all significant at the 0.1% level except for "Medium to High". This indicates that an ESG rating change from "Negligible" to "Low", all else equal, induces an increase in the implied cost of capital by 3.952 pp. Interpretations of other coefficients are analogous. In column (2), errors were clustered by industry. Only the effects at the two extremes, "Negligible to Low" and "High to Severe" are significant, the signs and magnitudes of which are similar to the column (1) specification. In column (3), errors were clustered by year. The coefficients of "Negligible to Low" and "High to Severe" are significant at the 0.1% level, and "Low to Medium" at the 1% level. The coefficients are similar to that obtained in columns (1). For column (4), a year-by-industry two-way cluster robust error is used. Similar to column (2), only the coefficients for the rating changes of "Negligible to Low" and "High to Severe" are significant, both at 0.1%, with the size of 4.495 pp and -2.159 pp. Figure 3 presents the effects of the ESG risk ratings changes with the 95% confidence intervals.

Table 6: Effect of ESG Rating Changes on Implied Cost of Capital (Regression Discontinuity Tests)

	(1)	(2)	(3)	(4)
Negligible to Low	3.952***	4.466***	3.970***	4.495***
	(3.43)	(8.18)	(5.12)	(6.99)
Low to Medium	-1.555***	-0.763	-1.315**	-0.818
	(-3.76)	(-1.13)	(-3.25)	(-1.33)
Medium to High	0.692*	0.813	0.407	0.808
	(2.21)	(1.75)	(1.47)	(1.76)
High to Severe	-2.154***	-2.188**	-1.781***	-2.159***
	(-4.11)	(-2.97)	(-4.49)	(-3.54)
Control Variables/ Fixed Effects	X	X	X	X
Error Clustering	None	Industry	Year	Industry-Year
Total No. of Left Obs.	15430	17268	14038	17058
Total No. of Right Obs.	11850	13597	11321	13431

This table presents the result of regression discontinuity tests of Implied Cost of Capital around ESG score thresholds. The estimates are bias-corrected estimates proposed by Calonico, Cattaneo, and Titiunik (2014). Sample bandwidths are chosen according to Calonico, Cattaneo, and Titiunik (2014) and Calonico et al. (2019). Columns (4) to (6) include the covariates of size, book-to-market ratio, market model beta, financial leverage, year fixed effects, and industry fixed effects by the method described in Calonico et al. (2019). Z-statistics based on the heteroskedasticity-robust nearest-neighbor estimators (Calonico, Cattaneo, and Titiunik 2014) were presented in the brackets. ***,**,* indicates, respectively, a 0.1%, 1%, and 5% level of statistical significance.

Figure 3: Effect of ESG Risk Rating Changes on Implied Cost of Capital (RDD)



This graph presents the effect of change in ESG rating categories on the implied cost of capital of stocks. The regression specifications and results are presented in in Table 6. Error bars represent the 95% confidence interval with respect to the *t*-statistics.

6. Discussion

6.1 OLS regression

I identify a negative correlation between the ESG ratings and the cost of capital for low ESG firms. This is consistent with the evidence in the literature that lower ESG firms have higher expected returns (Sharfman and Fernando 2008; Goss and Roberts 2011; El Ghoul et al. 2011). This result can be explained by the higher risks that low ESG firms bear, including litigation risks and climate risks (Hong and Kacperczyk, 2009; Ilhan, Zacharias, and Vilkov 2021; Seltzer, Starks, and Zhu 2022), and risks that the ESG risk score measures, for instance, risks in occupational health, data privacy, and product governance. This echoes the result of Chava (2014) who found that investors require significantly higher returns for stocks excluded from environmental screens.

Additionally, I show that the highest ESG performing firms have the highest ICC. The effect is economically significant and robust to all specifications. This presents contrasting evidence to the majority of the empirical ESG literature, which assumes that the correlation of ESG performance with expected returns is homogeneous. The phenomenon could be induced by correlations between high ESG performance and firm profitability that are not fully captured by the control variables. Examining the exact mechanism behind such correlation could be an interesting subject of future research.

6.2 RDD

I identify a strong positive cost of capital effect of ESG rating changes from “Negligible” to “Low”, and a strong negative effect from “High” to “Severe”, under all regression specifications. Rating changes from “Low” to “Medium” and “Medium” to “High” caused effects of smaller that is not robust to variations in specifications. This finding presents new evidence both in terms of the causality and the non-monotonicity of the effect of ESG information, as the contemporary literature is focused on correlation studies and mostly assumed a monotonic effect. The negative sign of the effect of rating increment at the higher end of the ESG risk spectrum indicates that the identified treatment effects are not purely caused by differences in investors’ perceived risk. If the changes in cost of capital induced by rating changes are driven solely by investor perception that stocks with higher ESG risk ratings as riskier, the treatment effect would be positive across all thresholds. Instead, this result is coherent with the hypothesis that investors’ intrinsic preferences for ESG play a role in determining the equilibrium cost of capital. The hump-shaped relationship between ESG rating and cost of capital fits the prediction of (Goldstein et al., 2022)’s model, whereby a low ESG rating attracts a more traditional investor base, hence increasing price informativeness and reducing the cost of capital.

It is worth noting that strong effects are found only when ESG rating changes from Negligible, the highest ESG rating category, to Low, the second highest, and from High, the second lowest category, to Severe, the highest. This result is similar to that of Hartzmark and Sussman (2019) in that the fund flow effect of ESG rating difference on mutual funds is only significant for the most extreme fund ESG rating categories. This phenomenon is consistent with prior evidence that investors tend to focus on discrete instead of continuous measures, and they place the highest emphasis on extreme outcomes (Hartzmark and B. 2015; Feenberg et al. 2017). It also highlights the significance of salience for investment decisions (Bordalo, Gennaio, and Andrew 2012; Bordalo, Gennaio, and Andrew 2013).

6.3 Further Research

In this paper, I identified the non-monotonic effect of ESG information on the cost of equity capital. It would be interesting to further examine the mechanism that induces the non-monotonicity. A viable candidate is Goldstein et al. (2022)'s hypothesis, which states that price informativeness drives this equilibrium phenomenon. To directly test this hypothesis, future researchers could construct measures of price informativeness such as PIN (Easley et al., 2002) and VPIN (Easley et al., 2012), and employ exogenous changes in ESG ratings to estimate the causation between ESG ratings and price informativeness. If such a causal effect is significant, in other words, ESG rating is a relevant instrument, then a second stage regression of cost of capital on the price informativeness would yield the same prediction as that of this paper.

7. Conclusion

This paper examines the causal impact of ESG information on stocks' ex-ante cost of capital. Implementing RDD around the ESG score thresholds, I found that ceteris paribus, a drop in ESG rating from the highest to the second highest category increases the ICC of stocks for 3.95 to 4.50 pp, while a rating change from the second lowest category to the lowest decreases the ICC of stocks for 1.78 to 2.19 pp. This finding provides indirect evidence to the theory that investor base homogeneity affects the equilibrium cost of capital through price informativeness.

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