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ESG Scores and Secondary Equity Offerings: A Case of Secondary Equity Offering in the US

Master Thesis

by

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MSc in Business with Major Sustainable Finance

Supervisor: Roberto Tubaldi

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ABSTRACT

The relationship between environmental, social, and governance (ESG) scores and secondary equity offerings (SEO) has received limited attention in the literature. This thesis explores this topic using a sample of US-listed firms and applies various econometric methods. We find that ESG scores are inconsistent measures for a firm's performance in the event of an SEO and that they do not affect the market reaction. Additionally, we find that CO2 emissions have a negative impact on the abnormal returns of firms issuing secondary equity and that firms with high ESG scores are less likely to issue equity to raise capital and more likely to use the proceeds for dividend payments. We conclude that ESG scores are unreliable predictors of SEO performance, and find evidence for the probability of issuing equity and allocation of proceeds.

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Contents

Table 1: Table of Abbreviations

Abbreviation	Description
ESG	Environmental, Social, and Governance
SEO	Seasoned Equity Offering
IPO	Initial Public Offering
CAR	Cumulative Abnormal Return
MM	Adjusted Market Model
FF	Fama French French Model
FFM	Fama French + Momentum Model
(x,y)	Event window: x=days before announcement, y=days after announcment
IV	Instrumental Variable
2SLS	Two-stage Least Square

1 Introduction

As the world faces the challenge of achieving net zero emissions by 2050, sustainability is becoming an increasingly important factor to consider in finance. This thesis aims to advance the existing knowledge on this topic by exploring how the market reacts to secondary equity offerings by companies with different levels of Environmental, Social, and Governance (ESG). This thesis is motivated by the growing demand for ESG research and a response to the global challenge of achieving net zero emissions by 2050 (n.d.), as stipulated by the Paris Agreement. As a company grows, it may need external funding to pursue new opportunities to grow. Secondary equity offerings are important corporate events as they represent a repeatable avenue for external funding for companies to pursue growth opportunities. While IPOs are typically considered a one-off event through a company´s lifecycle, there is an unlimited and flexible mechanism for capital-raising potential in secondary equity offerings. Our thesis will further explore how ESG scores relate to the allocation of the obtained equity proceeds as well as estimating the probability of issuing a secondary equity offering for firms holding different levels of ESG scores.

By shedding light on the relationship between ESG ratings and secondary equity offerings, this research can inform and improve the decision-making process of investors, as well as encourage companies to adopt better sustainability practices. Moreover, the literature advocates that investors increasingly take carbon risk into consideration in their investment decisions and view climate risk as having important financial implications for their portfolios(Bolton and M. Kacperczyk, 2021a,Krueger, Sautner, and Starks, 2020). In addition, we also analyze the relationship between alternative variables to ESG ratings, such as CO2 emissions, climate-risk exposure, and Carbon Intensity.

Research on the ESG topic is extensive and continuously expanding, specifically with an emphasis on the correlation between ESG scores and financial performance. Our aim is to gain a deeper understanding of how ESG affect companies' stock price fluctuations and those who invest in them. However, the knowledge of the economic effects of ESG criteria remains fragmented due to the lack of generalization(Friede, Busch, and Bassen, 2015). Early literature mainly focused on the link between corporate social responsibility (CSR) and firm value. CSR measurements lack quantifiable data due to multifaceted and complex numerical indicators for comparison and validation, as opposed to ESG measurements which are validated through specific metrics to enhance the level of transparency (Ho, 2021).

The first part of our thesis builds upon the work of Dutordoir, Strong, and Sun (2018), who examined the relationship between corporate social responsibility (CSR) and secondary equity offerings. Our analysis begins by augmenting their methodology using ESG scores instead. However, our approach does not yield the same results. To gain a more comprehensive view of the relationship between ESG and financial performance we then refine the model, but without observing significant results. Our approach indicates that there is no significant relationship between ESG ratings and abnormal returns around secondary equity offerings. Introducing alternative variables to ESG ratings to reflect climate exposure in our analysis, we were able to demonstrate a negative relationship between CO2 emissions and cumulative abnormal returns in the event of a secondary equity offering. This suggests that investors exhibit rational behavior and opt to refrain from purchasing shares in companies with higher levels of CO2 emissions following a secondary equity offering.

Furthermore, our analysis reveals that firms with high ESG scores have a lower probability of issuing equity to raise capital for company purposes. This suggests that firms with higher ESG ratings may not have the same need for external capital raising as firms with lower ESG ratings. Finally, we employ a difference-in-differences method to examine the use of equity proceeds one fiscal year preceding and one fiscal year following the offering. Our findings indicate that firms with high ESG scores significantly allocate their capital toward paying out dividends.

Our thesis is structured as follows: Section 2 reviews the relevant literature on ESG ratings and the implications of ESG scores. Section 3 describes the reasoning and development of the hypothesis. Section 4 provides a comprehensive overview of the sample data used throughout the analysis, as well as a detailed explanation of the empirical analysis methodology applied. Section 5 presents the main findings and insights derived from the research, and discusses the implications of the results. Section 6 offers a conclusion of the thesis and directions for future research.

2 Literature review

Early literature argued that allocating valuable corporate resources towards sustainable practices is a misallocation of a company‘s profitable opportunities. Corporate responsibility lies in acting toward shareholders’ interests, specifically in terms of maximizing shareholder profits. Conversely, early literature acknowledged the inability to outright condemn social responsibility (Friedman, 2007). Investors‘ preferences for holding assets with higher ESG scores affect asset prices as they derive utility from sustainable investments(Pástor, Stambaugh, and Taylor, 2021). Consequently, ESG-conscious investors are willing to accept sub-optimal financial performance of their investments if it contributes to the advancement of social objectives associated with them (Renneboog, Ter Horst, and C. Zhang, 2008).

Dutordoir, Strong, and Sun (2018) examines the relationship between corporate social responsibility (CSR) and stock price reactions to secondary equity offering announcements. In this thesis, numerous control variables are employed in the same manner as a proxy to predict variations in CAR while accounting for the influence of other factors. CSR scores are not standardized and rely on self-regulated practices which can result in a lack of accountability and transparency in the reporting process. In comparison, ESG scores offer a more comprehensive approach to sustainability measurement. We intend to utilize ESG scores in our study, recognizing their advantages over CSR scores(Ho, 2021, Dutordoir, Strong, and Sun, 2018), primarily examine a sample of U.S-listed companies spanning from 2004 to 2013. In order to expand the scope of the research and include more recent years, we extend the period from 2004 to 2022. They found a negative association between CSR and stock price reactions to SEO announcements showing that higher CSR issuers yield a lower post-SEO stock price performance than issuers with lower CSR Dutordoir, Strong, and Sun, 2018. Furthermore, they used a single-factor market model to explain CAR, through its dependency on the market index returns. In order to enhance the comprehensiveness of the research, we incorporate Fama-French multi-factor models by integrating size and value factors to elucidate the impacts on CAR. An event window of (0,1) days would capture some but not all the effects resulting from the informational impact of the SEO. Conversely, a more extended window would more accurately encompass all the relevant effects on the CAR. As opposed to the analysis done by Dutordoir, Strong, and Sun (2018), we improved the accuracy of our analysis by using industry-clustered standard errors to control for unobserved heterogeneity and correlation.

Since ESG is a multidimensional concept, it is challenging to condense all its aspects into one score, making it difficult for investors to use ESG as a decision-making tool. ESG ratings have been highly debated as the divergence of the different rating agencies sends mixed signals when measuring ESG performance. There is a significant disagreement of 56% among different rating agencies on how they measure ESG performance(Berg, Kölbel, and Rigobon, 2022). To some extent, it lowers the credibility and informativeness of an ESG rating, and the divergence makes it difficult for investors to interpret and act on investment decisions based solely on ESG data. The lack of transparency is a big issue as investing in higher ESG-rated stocks does not provide the correct information, which makes it more challenging to price ESG risks correctly. More disclosure usually associates with reduced disagreement due to lower information asymmetry. However, greater disclosure leads to greater disagreement because it increases the likelihood of ESG ratings being assigned different metrics to evaluate sustainability performance on the same issues(Christensen, Serafeim, and Sikochi, 2021). Additionally, they find that firms characterized by a higher level of ESG disagreement are less inclined to seek external funding and rely more on internal financing. This raises the question of whether higher ESG-scored companies or lower ESG-scored companies are in more need of external financing arises (Figure.1). The potential impact on our results arises from the possibility that biased outcomes occur if only companies already exhibiting a high level of sustainability or a low level of sustainability are included.

Furthermore, regarding investor sentiment, prior research discusses three different types of risks related to climate change and their importance of them in investment decisions(Krueger, Sautner, and Starks, 2020). Regulatory risk is perceived as the most crucial risk overall for both long-term and short-term investors. In contrast, physical and technological risks seem more important in longer-term horizons. However, it needs to be clarified to what extent investors consider the importance of climate risk relative to other risks. While investors perceive climate risk as less important than other types of risk, it does not imply that the effects of climate change are financially irrelevant. The majority of investors agree that regulatory risk is important to consider for investment decisions today (Krueger, Sautner, and Starks, 2020). Studies show a relationship between financial performance and high ESG, and especially in North America. ESG stock outperformance opportunities exist, which challenges our hypothesis(Friede, Busch, and Bassen, 2015). Furthermore, they conclude that investors should implement ESG in their investment decisions as an orientation towards a longer-term strategy towards the broader aspect of society and fulfill their duty of care. Additionally, we imply the view of investment decisions being profitable by reducing risk as well, in line withKrueger, Sautner, and Starks (2020). Their findings support the significance of climate risk for both long-term and short-term assets. Consequently, it is suggested that long-term investors prioritize the integration of climate risk into their investment decisions more so than short-term investors. However, their study may be biased as the information gathered at ESG conferences enhances the probability of respondents being more tilted toward ESG investing.

3 Hypothesis development

ESG-aware investors value ”greener” assets because they derive utility from investing in sustainable stocks. They are willing to pay a higher premium for companies with stronger ESG performance. Even investors who do not believe ESG performance influences shareholder value, would still pay a premium for companies with higher ESG scores((McKinsey, n.d.). The higher demand for ESG stocks will create an upward pressure on stock prices accordingly, and investors may experience lower cumulative abnormal returns than what would be expected solely based on their financial performance. Moreover, as investors integrate risk into their investment strategies, assets exhibiting stronger ESG performance are perceived as less susceptible to systematic risk compared to assets with poorer ESG performance.

The systematic risk component stems from companies' vulnerability to potential alterations in sustainable regulatory mandates concerning the achievement of net-zero emission goals, particularly in the context of attaining these goals by 2050. A more robust external value proposition can empower companies to attain better strategic flexibility by alleviating regulatory pressure and mitigating risks of unfavorable government intervention (Henisz, Koller, and Nuttall (2019)). This implies that companies with higher ESG scores are better to adapt to change by having a more holistic approach when managing risks (EY, n.d.). On the other hand, investors might expect firms to use their equity on value-destroying activities. Despite the expectation that higher ESG firms are expected to improve and prioritize social sustainability and environmental practices, studies reveal that they not only fail to deliver significant improvements in ESG performance but also do not generate financial returns (Bhagat (2022)). If investors do not find it attractive to invest in high ESG-rated companies, it would affect the stock prices negatively.

We put forward the following hypothesis:

H_1a : Higher ESG-rating yield lower cumulative abnormal returns around SEOs

ESG is a multidimensional construct assessed across numerous factors, whereas CO2 emissions constitute only a part of the overall ESG performance. The environmental pillar in ESG incorporates CO2 emissions in its measurement, and reflects the extent to which a company acts towards its environmental footprint. However, the environmental pillar comprises various other indicators of environmental impact besides CO2 emissions. This implies that companies could have relatively high ESG scores, even if they emit large amounts of CO2. Moreover, investors perceive climate risk as having substantial financial implications for their portfolios, as they acknowledge that regulatory risks have already begun to materialize. As a result, investors place greater importance on companies´ climate risk disclosure as they are already factoring it into their investment decisions (Krueger, Sautner, and Starks, 2020). Consequently, they demand higher expected returns on their investments in companies with higher total CO2 emissions (Bolton and M. Kacperczyk (2021b)). Additionally, investors price in carbon risk when evaluating assets as they pursue investment strategies that target companies holding different levels of ESG ratings. Hence, investors demand carbon risk premiums for stocks with higher total emissions. This implies that investors are aware of the potential costs of climate change, and adjust their expectations accordingly. When a company issue additional shares of high-carbon stock, the market will react more negatively by investors restricting their investments in these assets.

We thereby create an additional hypothesis:

H_1b : Higher CO2 emissions yield higher cumulative abnormal returns around SEOs

4 Methodology and Data

4.1 Data

4.1.1 Sample data

The process of constructing the data sample begins by obtaining data on publicly listed companies that have conducted a secondary equity offering. We retrieve the data from SDC Platinum covering the period from January 2004 to December 2022. Furthermore, we separate out companies not listed on New York Stock Exchange, NYSE MKT, or NASDAQ in the United States and then refine the sample excluding non-common stocks with SIC codes 4900 to 4999 (utilities), 6000 to 6999 (financials) and 9000 or higher (public service, international affairs, or nonoperating establishments). We were then left with 4270 observations(1477 between 2004-2013) and (2793 between 2014-2022). For the sample period spanning from 2004 to 2013, we obtain ESG scores only from Bloomberg due to the lack of available data on the Refinitiv ESG scores, which left us with 627 companies. For the 2014-2022 sample, we were left with 1165 observations with both Refinitiv and Bloomberg scores. Firm-level financial data is measured as annual fundamentals (fiscal year) and is retrieved from Compustat through the WRDS database. Furthermore, cumulative abnormal returns are obtained from CRSP and executive data is obtained from Execucomp, both through the WRDS database. We winsorized all the data at a 1% level. The final sample of the period from 2004 to 2013 with firm level-financial data from Compustat, CAR from CRSP, and ESG scores from Bloomberg consists of 413 companies. For the sample spanning from 2014-2022, we use both ESG scores from Refinitiv and Bloomberg, CAR from CRSP, and firm-level financial data from Compustat, and we end up with a data sample consisting of 763 companies. Since ESG scores first gained significant attention of interest in 2004, companies' requirement to disclose ESG data has increased dramatically in recent years. Consequently, this disparity in the data samples has become pronounced (McKinsey, n.d.)(UNEPFI, 2004).

ESG scores Refinitiv ESG scores rate companies on their level of disclosure of ESG data and evaluate a company's relative performance on fundamental ESG attributes, commitment, and effectiveness across Environmental (E), Social (S), and Governance (G) factors. These scores are data-driven and account for the most material industry metrics while minimizing biases related to company size and transparency. Refinitiv ESG scores capture and calculate over 630 company-level ESG measures, of which a subset of 186 of the most comparable and material per industry power the overall company assessment and scoring process. The scores are categorized by Refinitiv, as shown in table 19. (Refinitiv, 2023).

The Bloomberg score is a proprietary scoring system used to rate a company's level of Environmental, Social, and Governance (ESG) disclosure. The score ranges from 0 to 100, with 0 indicating no disclosure of any ESG data and 100 indicating full disclosure of all data points. The score is based on a consistent list of topics, data fields, and field weights that apply across all sectors and regions. The E, S, and G pillars are equally weighted within the overall ESG Disclosure Score, and each topic within a pillar is equally weighted. The score measures the amount of ESG data a company reports publicly, not its performance (Bloomberg, 2023). Companies not covered by Bloomberg for ESG data will receive a N/A score.

4.2 Dependent variable

4.2.1 CAR Estimation Window

The estimation window is a critical component in determining the cumulative abnormal returns before a secondary equity offering. We measure the normal returns and utilize them as a benchmark for comparing against expected returns, allowing us to quantify the CAR within the event window. The length of the estimation window must be carefully determined to avoid biased results. Further, we will set the estimation window before the event window to reduce the risk of biased normal returns(Fama, Fisher, Jensen, and Roll, 1969). Including the variation of returns from the event window in the estimation window would make biased results by not separating normal and abnormal returns. To establish the estimation window, we follow a traditional event study methodology(Brown and Warner, 1985). We measure the cumulative abnormal stock returns of all the companies in our data set in an estimation window ranging from 200 trading days before the event ending 60 days before the announcement date(Aktas, de Bodt, and Cousin, 2007).

4.2.2 CAR Event Window

The event window is crucial to the event study, as it sets the structure for our analysis. When selecting the event window, we consider the announcement date the most significant date to study. The announcement date is the date on which the market becomes aware of the new information regarding a company‘s future prospects and its capacity to raise capital. We have defined the event window as 0 days before the announcement of the equity offering and one day after the announcement; this is to capture the effect of the announcement made after the stock market closure (Aktas, de Bodt, and Cousin, 2007). This is consistent with research indicating that market imbalances following announcement news, typically last for a period ranging from five minutes to several hours (Chordia, Roll, and Subrahmanyam, 2005).

When setting the standards for the event window, the question that arises is whether the window will capture all the effects on CAR around SEO. If we set the window too small, we might not capture the whole reaction, and if we put the event window too big, we might capture other data that will create noise in our calculations and coherently weaken our results. A smaller window is preferred as longer event windows account for noisy measures of event dates; the biases will dominate the actual returns(Ahern, 2009). For the event window to explain all the relevant information and exclude all the information that is not relevant to the event, we check for pre-trends by extending the days prior to the announcement date. To test the robustness of our event window, we will use three different event windows: a 3-day window, an 11-day window, and a 1-day announcement day window(Campbell, Cowan, and Salotti (2010), Krüger (2015)). These three event windows are defined to capture the effects on both sides of the SEO announcement: (0,1), (-1,1), (-3,3), and (-11,11).

4.2.3 Factor Models

Regarding the dependent variable, we apply the estimation window and the event window to calculate cumulative abnormal return using The Adjusted Market Model, 3-Factor Fama-French Model, and Fama-French 3-factor + Momentum Model. In order to enhance our results, we compare each model's findings to improve consistency and accuracy. CAR is winsorized to reduce the impact of outliers and to improve the accuracy of the results.

The Adjusted Market Model is a one-factor model that accounts for market-wide movements in stock prices and is defined as (MacKinlay, 1997):

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{1}$$

$$E(\epsilon_{it}) = 0, \qquad Var(\epsilon_{it}) = \sigma^2_{\epsilon_{it}} \tag{2}$$

Where R_{it} is the normal returns of the stock i in period t while R_{mt} is the market returns at time t. β_i and α_i is the regression parameters while ϵ_{it} is the zero mean disturbance term. By using the market model to measure the normal returns over the estimation window we get the following equation for CAR:

$$\text{CAR}_{i,t_1,t_2} = \sum_{t=t_1}^{t_2}(R_{it} - \hat{\alpha}_i - \hat{\beta}_i(R_{mt})) \tag{3}$$

To further enhance the analysis we apply Fama-French 3-factor to calculate CAR, where we add size premium and value premium that relates to the risk of the underlying asset. $(R_{it} - R_{ft})$ is the stock return in excess of risk-free return. $(R_{mt} - R_{ft})$ is the market premium. $s_i SMB_t$ is the size premium between small and large stocks, $h_i HML_t$ is the value premium comprising assets with a low book value of equity to market value of equity ratio and a high book value of equity to market value of equity ratio. $w_i WML_t$ is the additional momentum factor. Using the 3-Factor Fama-French model to measure the cumulative abnormal returns we get the following equation:

$$\text{CAR}_{i,t_1,t_2} = \sum_{t=t_1}^{t_2} (R_{it} - \hat{\alpha}_i - \hat{\beta}_i(R_{mt}) - s_i SMB_t - h_i HML_t) \quad (4)$$

In addition to adding size premium and value premium, we extend our analysis by including a momentum factor. The momentum factor is the difference in stock returns of companies that have performed poorly in the past and assets that have performed well in the past. $w_i WML_t$ is the additional momentum factor. By using the 3-Factor Fama-French + momentum model to measure the cumulative abnormal returns, we get the following equation:

$$\text{CAR}_{i,t_1,t_2} = \sum_{t=t_1}^{t_2} (R_{it} - \hat{\alpha}_i - \hat{\beta}_i(R_{mt}) - s_i SMB_t - h_i HML_t - w_i WML_t) \quad (5)$$

4.3 Control variables

4.3.1 Firm- and offer characteristics

Firm-level and offer characteristics are included as control variables in our regression analysis to function as proxies for information asymmetry, debt capacity, valuation discrepancies, and growth opportunities in relation to Dutordoir, Strong, and Sun (2018). All control variables are listed in Appendix:A, for a more specific notation of calculations.

$Leverage$ is used as a control variable due to the impact it has on a company‘s financial structure. When companies have a higher debt ratio, it reduces the available free cash flow that can be allocated towards investments or dividend payments, as regular debt obligations need to be met(Dutordoir, Strong, and Sun, 2018,Jensen, 1986). $Leverage$ is measured as total liabilities to total assets. Since it signals that companies may be more restricted with their proceeds and use them in a more disciplined corporate manner, we believe leverage to have a positive impact on CAR around secondary equity offerings.

We include $RelOfrsize$ to adjust for the tendency of firms with higher offering proceeds to be overvalued(Krasker, 1986). $RelOfrsize$ is measured as the amount of proceeds a company is able to obtain through the SEO in $Mill divided by total assets. When companies issue a larger amount of equity relative to their size, it implies that companies send a signal to the investors that the company is overvalued. Consequently, the company takes advantage of higher valuations to raise capital, which negatively affects the stock price reaction when investors are asymmetrically informed. When a company‘s equity is overvalued, it issues new shares at a higher price than their actual worth. This enables the company to extract additional profits from new shareholders, as they end up paying more than the fair value for their investment. If the share price does not increase sufficiently to offset the initial overvaluation, it results in lower CAR (Dong, Hirshleifer, and Teoh (2012). Furthermore, the decrease in stock price could fall to a level where it is no longer attractive for companies to issue equity and affect the probability of companies doing SEOs (Krasker, 1986,Dutordoir, Strong, and Sun, 2018).

A wider bid-ask spread indicates that investors have a greater disagreement about the value of the asset, hence a higher level of information asymmetry. $Opacity$ measures the level of information asymmetry based on a combination of bid-ask spread and trading volume for a particular stock in relation to (Anderson, Duru, and Reeb, 2008,Dutordoir, Strong, and Sun, 2018). It is measured as the average quintile ranking of the natural logarithm of trading volume and bid-ask spread. Furthermore, we rank the two proxies into deciles, summarize them, and divide them by a factor of 20. We predict a higher value on $opacity$ to negatively impact CAR, as investors may experience greater uncertainty regarding a firm‘s value when higher a higher level of information asymmetry exists. Additionally, we include $volatility$ as a measure of risk. $Volatility$ is measured as the standard deviation of the stock returns and is normalized by multiplying the returns with the square root of 252 trading days in a year. When stocks undergo substantial price fluctuations in either direction, the increased likelihood of large losses signifies a higher risk for investors, leading them to respond more negatively to secondary equity offering announcements.

We employ $ExecOwnership$ as a proxy for assessing corporate governance influences on CAR in line with Dutordoir, Strong, and Sun (2018). $ExecOwnership$ is measured as the number of shares owned by executive management divided by the total shares outstanding. A higher degree of managerial ownership better aligns executive and shareholders' interests, which indicates that better governance practices increase investors´ confidence that equity proceeds are used in productive ways (Kim and Purnanandam, 2011). This could result in positive stock price reactions during SEO announcements. To analyze to what degree debt capacity may influence stock price reactions in relation to SEO announcements, we include ROA, $LnTA$, and $AssetTangibility$ in relation to Dutordoir, Strong, and Sun (2018). ROA is a measure of a company´s profitability relative to its total assets and reflects to which degree a company's ability to take on additional debt without causing financial distress. It is measured as total earnings before extraordinary items divided by total assets. $LnTa$ is the natural logarithm of total assets and is included because total assets provide insight into a company's ability to generate cash flows and repay outstanding debt. A higher value of $LnTa$ indicates an increased debt capacity because of the company´s larger asset base, which could make it easier to obtain additional debt financing. It is normalized to total assets to lower the effect of extreme values. $AssetTangibility$ refers to the amount of physical assets a company has and is measured as PPE divided by total assets. $AssetTangibility$ offers insight into the proportion of tangible assets of a company´s total assets. Tangible assets can be seized to recover outstanding debt. It makes it easier for the company to obtain debt financing as it may pledge its fixed assets as collateral to secure debt financing(Lemmon and Zender, 2010).

Furthermore, we include the market-to-book ratio as an indicator of growth opportunities. MTB is calculated as the company´s market value divided by the book value of equity. A higher MTB indicates that a company´s stock is overvalued, which makes firms issue equity as opposed to when it's undervalued, they repurchase equity. It makes it more attractive for companies to issue equity if the stock is overvalued, as it allows the company to raise capital at a lower cost, and investors pay more for the equity than its fundamental value. When the stock is undervalued, it is more attractive for the company to repurchase its shares because it buys back at a discount and increases the value of its equity (Baker and Wurgler, 2002). In relation to the pecking order theory, adverse selection may occur when a company is issuing equity to the market. To measure financial slack, we include $slack$ as a control variable in our regression analysis. $Slack$ is calculated as cash & short-term investments divided by total assets. As management has more information on the company´s financial health than market participants, they are able to take advantage of asymmetric information to issue new overvalued equity to the market. When investors pay more for the stocks than what they are actually worth, it increases adverse selection costs(Dutordoir, Strong, and Sun, 2018).

4.4 CO2 exposure

Going forward with our analysis, we introduced climate change exposure variables as a replacement for ESG scores in relation to (Sautner, van Lent, Vilkov, and R. Zhang, 2023, Bolton and M. Kacperczyk, 2021b). Cc_expo is developed through a machine learning keyword algorithm that identifies the attention paid by earnings call participants to firms‘ climate change exposures in relation to (Sautner, van Lent, Vilkov, and R. Zhang, 2023) and the data is retrieved from (Sautner, Lent, Vilkov, and R. Zhang (2020)). The method uses a transcript that analyzes the level of text frequency of earnings calls of firms and captures exposures of opportunities and physical and regulatory shocks in relation to climate change. The GHG protocol categorizes emissions into three distinct sources. Scope 1 emissions refer to direct GHG emissions arising from sources owned or controlled by the company. Scope 2 emissions are indirect GHG emissions that occur from purchased energy, while Score 3 emissions are indirect GHG emissions that occur from sources that are not owned directly or owned by the company but arise throughout the value chain. Total CO2 emissions are measured as the sum of Scope 1, Scope 2, and Scope 3 emissions. We measure $LnCO2$ as the natural logarithm of total CO2 emissions obtained from Refinitiv while controlling for the firm and offering characteristics as used in the ESG analysis. Furthermore, we include carbon intensity to analyze how much CO2 a company emits per unit of economic activity. We measure $CarbonIntensity$ as total CO2 emissions divided by a company´s revenue.

4.5 Equity proceeds and Probability

When measuring probability, we obtain firm characteristics of the entire Compustat database between 2014-2022. Due to limited data on ESG scores in the earlier period compared to SEO data, we base our probability sample on more recent years. First, we filter the data on SIC codes, removing 4900 to 4999 (utilities), 6000 to 6999 (financials), and 9000 or higher (public service, international affairs, or nonoperating establishments). We collect a total of 56,025 observations. Due to extraction limitations when obtaining Bloomberg ESG scores, we proceeded with the probability analysis with Refinitiv scores exclusively. To refine our data, we disregard all companies without Refinitiv ESG Scores, resulting in 6,003 observations of firms that did not undergo SEO, and 2,179 firms that did issue SEO.

To analyze equity proceeds, we gather annual company fundamentals from Compustat through WRDS using a time window of one fiscal year preceding SEO issuance date and one fiscal year following the SEO issuance date. We proceed with excluding firms with missing values or values less than zero on total assets and sales as well as companies with less than $5 million in physical capital(Peters and Taylor, 2017). Additionally, we replace missing values with zero for Selling, General and Administrative Expenses, Research, and Development Expense, In Process R&D Expenses, Sale of Common and Preferred Stock, Purchase of Common and Preferred Stock, and Dividends Common/Ordinary.

We continued with calculating our investment variables of interest such as Intangible investment rate, physical investment rate, total investment rate, R&D intensity, repurchase of shares, and payout. Intangible capital was gathered from ”Peters and Taylors Tobins Q” data available on WRDS. K^{Tot} is the variable for total capital and it is measured as gross PPE + intangible capital and functions as the baseline denominator for R&D intensity, Physical investment rate, and intangible investment rate. We lag total capital to analyze how much the companies invest in intangible assets, tangible assets, and R&D as a percentage of their existing capital base. I^{Phy} Is the physical investment rate and is measured as capital expenditures divided by lagged K^{Tot}. A higher ratio of physical investment rate indicates that companies are heavily investing in their physical assets. I^{Int} is the intangible investment rate and is measured as intangible investments divided by lagged K^{Tot}. Intangible investment is defined as R&D expense + (0,3 x SGA). SGA refers to investments in organizational capital and is defined as Selling, Administrative and General expenses - R&D expense - In Process R&D expense. SG&A expenses reflect the company´s investment in organizational capital. However, it is challenging to accurately measure SG&A because it varies across industries and is not separately reported in companies´ financial statements. Moreover, SG&A comprises various expenses, some of which may also contribute to other forms of intangible capital, such as the reputation or loyalty of existing customers. Hence, we follow the common practice of earlier studies and allocate 30% of SG&A expenses to intangible capital, assuming the remaining 70% to be included as operating costs essential for business operations (Peters and Taylor, 2017).

R&D intensity is measured as R&D expense divided by lagged K^{Tot} and indicates how much a firm invests in knowledge capital as a percentage of the company‘s existing capital base. $Payout$ indicates how much of the equity proceeds the company distributes as cash to its shareholders relative to its existing capital base. $Payout$ is measured as (Dividends Common/Ordinary + Purchase of common and preferred stock- Sale of common and preferred stock) divided by lagged K^{Tot}. $Repurchase$ is a measure of how much a firm buys back its own shares relative to its existing capital base. It is measured as (purchase of common and preferred stock - sale of common and preferred stock) divided by lagged K^{Tot}.

4.5.1 Data statistics

Table 2: **Correlation Matrix Sample 2014-2022**

The table presents the correlation matrix of the variables used in the augmented regression.

	Bloomberg	MTB	Slack	LnTA	RunUp	Leverage	Opacity	ROA	Volatility	RelOfersize	AssetTangibility
MTB	-0.01613										
Slack	-0.45027	0.04829									
LnTA	0.58766	-0.01006	-0.64717								
RunUp	-0.10006	-0.01116	0.18347	-0.07687							
Leverage	0.19663	-0.07496	-0.44918	0.22080	-0.03159						
Opacity	0.31377	0.08722	-0.17240	0.49565	0.05446	0.02231					
ROA	0.32522	0.01815	-0.57727	0.59669	-0.06533	0.04299	0.22097				
Volatility	-0.01535	-0.01491	0.04121	-0.00015	-0.00189	-0.04897	0.03908	0.01423			
RelOfersize	-0.27118	0.05832	0.46505	-0.55837	0.25907	-0.18782	-0.05677	-0.45973	0.05642		
AssetTangibility	0.32730	-0.08560	-0.50128	0.31916	-0.08888	0.33852	0.19649	0.20594	0.01026	-0.24386	
Car.MM.(0.1).	-0.08198	0.00737	0.17778	-0.05037	0.89746	-0.05443	0.05948	-0.03362	-0.00067	0.20097	-0.08477

Summary statistics analysis

The correlation matrix displayed in table 2, which displays the 2014-2022 sample, exhibits variations compared to the correlation matrix presented by Dutordoir, Strong, and Sun (2018). In particular, we observe differences in the correlation magnitude and direction between some of the variables. $LnTa$ and $Slack$ have the highest correlation among the independent variables, in both samples. Dutordoir, Strong, and Sun (2018) reported a correlation of -0.565 between $Slack$ and $LnTa$ while our sample shows a correlation of -0.65. We do not exclude any variables based on the correlation levels, and we address the potential issue of multicollinearity in the robustness section. Our ESG variable $Bloomberg$ has a notably higher positive correlation with the control variables compared to the Adjusted CSR score in (Dutordoir, Strong, and Sun, 2018). Our data sample suggests that there are inherent differences between the Adjusted CSR and $Bloomberg$ as main explanatory variables and that they capture different aspects of measuring factors of sustainability.

We compare the correlation matrices of our two data samples: 2004-2013 and 2014-2022, shown in table 21 and table 2, respectively. We observe two notable differences in the correlation coefficients involving $Bloomberg$. The correlation between $Bloomberg$ and $Slack$ decreases from -0.2396 to -0.44099, which means that the negative relationship between liquidity and ESG scores becomes more pronounced over time. The correlation between $Bloomberg$ and $LnTA$ increases from 0.4204 to 0.57489. An interpretation of this would be that the relationship between firm size and ESG score is becoming stronger over time.

Table 3: **Correlation Matrix of Explanatory variables Sample 2014-2022**

	Refinitiv	Bloomberg	LnCO2	Cc_expo
Refinitiv	1.00			
Bloomberg	0.57	1.00		
LnCO2	0.38	0.61	1.00	
Cc_expo	0.13	0.18	0.17	1.00

The correlation matrix of the different explanatory variables we use in our analysis is displayed in table 3. $Refinitiv$ and $Bloomberg$ exhibit a moderate positive correlation of 0.57, indicating that these rating agencies share similarities in their approach to evaluating companies on ESG metrics. However, it is worth noting that this correlation is lower than expected, despite research suggesting divergence between scores (Berg, Kölbel, and Rigobon, 2022. Another interesting observation is the positive correlation between $Bloomberg$ and $LnCO2$. Compared to $Refinitiv$, $Bloombergscores$ reflect CO2 emission more in their rating.

Table 4: **Summary statistics Key explanatory variables**

The table presents the summary statistics of the key explanatory variables.

Variable	Observations	Mean	Standard.Deviation	Min	25th.Percentile	50th.Percentile	75th.Percentile	Max
Refinitiv	1165	31.30	13.95	6.97	21.77	28.97	38.16	73.89
Bloomberg	1165	34.48	7.45	5.78	31.50	32.33	35.68	64.37

Table 4 reports the descriptive statistics of the scores from Refinitiv and Bloomberg. We notice that the standard deviation of Refinitiv scores is (13.95), which is much higher than the standard deviation of Bloomberg scores (7.45). This indicates that Refinitiv has a larger rating variation than Bloomberg. Additionally, our findings show that both the 50th and the 75th percentiles of the two ESG scores are comparatively low within our sample, suggesting that firms with higher ESG scores are not represented to the same extent as companies that have issued equity through a secondary equity offering, as firms with low ESG scores.

Table 5: **Control Variable characteristics**

The table presents the mean and median values of the control variables. The sample is divided by high and low Bloomberg scores, using the median value as the benchmark. The Pvalues are calculated by Wilcoxon Rank-sum and T-statistics.

	Full sample		High	Sample	Low	Sample	Difference	Difference	pvalue	pvalue
Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Bloomberg	34.4763	32.3308	38.4822	35.6202	30.3375	31.4656	8.1448	4.1546	6.855694e-90	7.140902e-192
MTB	4.6353	4.0547	4.6458	4.0439	4.6244	4.0602	0.0213	-0.0164	9.857260e-01	5.272006e-01
Slack	0.4703	0.4883	0.3205	0.1539	0.6275	0.7573	-0.3070	-0.6034	2.407129e-46	5.122131e-43
LnTA	6.0712	5.6721	6.9504	6.9608	5.1489	5.0787	1.8015	1.8821	1.076754e-72	6.899059e-64
RunUp	-0.0048	-0.0305	-0.0178	-0.0303	0.0085	-0.0307	-0.0263	0.0004	2.580620e-02	4.054626e-015
Leverage	0.5295	0.4619	0.6171	0.6006	0.4375	0.2990	0.1796	0.3016	3.394762e-13	4.354369e-22
Opacity	4.7965	4.8736	5.2979	5.2069	4.2992	4.4601	0.9988	0.7468	9.642964e-15	4.488745e-14
ROA	-0.2629	-0.1692	-0.1423	-0.0059	-0.3895	-0.3156	0.2473	0.3098	9.959310e-26	4.461738e-31
Volatility	2.8268	0.8876	3.2490	0.8509	2.4047	0.9049	0.8444	-0.0540	1.765992e-01	3.737393e-02
RelOfersize	0.5164	0.3669	0.3603	0.2005	0.6802	0.4921	-0.3199	-0.2915	3.316682e-20	2.729986e-35
AssetTangibility	0.2675	0.1356	0.3519	0.2072	0.1733	0.0816	0.1786	0.1255	2.976761e-18	2.329452e-23

Table 5. shows a significant difference between the subsets of high and low ESG scores, including all the control variables. We observe that the subset including companies with high ESG scores has significantly higher values on $LnTa$, $Volatility$, $Leverage$, ROA, and $Opacity$. Additionally, the subset including companies with lower ESG scores has significantly higher values on $Slack$ and $RelOfersize$.

Table 16 shows the mean and median values for the full sample and subsets divided by high and low Bloomberg scores in the different CAR estimation models with the event windows in parentheses. The p-value for the mean was calculated using a standard t-test, while the median was calculated using the Wilcoxon signed-rank test. When comparing Car MM (0,1) with Dutordoir, Strong, and Sun (2018)(Table 2.), we observed less variation in both the mean and median returns. It appears that during the period of 2004-2013, the average of market reactions was represented by a mean of

-4.51% and a median of -4.06%. In contrast, our sample indicated a mean of -2% and a median of -3%, which indicates that the market was more volatile during the earlier period as compared to 2014-2022.

Tabel 17 shows the mean median and standard deviation of the different cumulative abnormal returns. We see that as the event window increases, the standard deviation also increases. This suggests that there is more noise in the longer event windows and that they capture other factors than the market reaction.

In figure2, the upper graph displays the average Bloomberg and Refinitiv scores from 2014 to 2022. Similar cyclicality can be observed between 2014 and 2017, followed by a notable rise in companies with high Refinitiv ESG scores issuing seasonal equity. Conversely, there is a significant decline in Bloomberg scores from the year 2020. The graph also illustrates the low level of correlation between the two explanatory variables, as shown in table 4.In the lower graph, the mean value of CAR is presented with the adjusted market model and various event windows. By highlighting the differences in mean values of CAR based on the event window, we notice that longer event windows exhibit stronger and more positive values. However, we cannot discern any significant visual correlation between CAR and ESG scores.

4.6 Methodology

This section describes the methodology we use to test our hypotheses and answer our research question. We first explain how we measure the market reaction to secondary equity offerings using cumulative abnormal returns (CAR). We then describe the regression model we use to examine the effect of both Bloomberg and Refinitiv ESG scores on CAR, as well as the control variables we include in the model. In the second part of the methodology, we test the probability of issuing equity and the use of proceeds obtained in the offering by employing a logistic regression and a difference-in-differences method, respectively.

We use linear regression analysis to capture the effect of ESG scores on cumulative abnormal returns (CAR). We utilize CAR with the event window (0,1) as the dependent variable, Bloomberg scores as the main independent variable, and firm and offer characteristics as control variables in line with Dutordoir, Strong, and Sun (2018). In addition to the control variables, we include fixed effects for the industry with a 1-digit SIC code and time effect by the year of issuance to account for unobserved heterogeneity across industries and periods. (Wooldridge, 2012) The model includes a dummy variable to indicate whether a firm has announced a secondary equity offering. Our analysis begins with the following linear regression model:

$$
\begin{aligned}
\text{CAR} = \beta_0 &+ \beta_1 \text{ESG Score} + \beta_2 \text{Opacity} + \beta_3 \text{Volatility} + \beta_4 \text{Slack} \\
&+ \beta_5 \text{Runup} + \beta_6 \text{Leverage} + \beta_7 \text{ROA} + \beta_8 \text{AssetTangibility} \\
&+ \beta_9 \text{LnTA} + \beta_{10} \text{MTB} + \beta_{11} \text{RelOfrsize} + \beta_{12} D_{\text{SecondaryOffering}} \\
&+ \sum_{i=1}^{n} \gamma_i \times I_i + \sum_{j=1}^{m} \delta_j \times Y_j + \epsilon_i
\end{aligned}
$$

Where CAR_i represents the cumulative abnormal return for the firm, $ESGscore$ represents the ESG score for the firm, and β_1 - β_{12} represents the set of control variables for the firm. The control variables used in our analysis are detailed in the Appendix:A. The $I_{i,j}$ represents the j-th industry fixed effect for observation i, and $Y_{i,k}$ represents the k-th year fixed effect for observation i.

First, estimate the model without controls to examine the direct effect of the ESG score on CAR, and then incorporate fixed effects and control variables. The results are reported in table 6. Next, we repeat the same analysis with a more recent sample from 2014 to 2022. Additionally, we use Refinitiv and Bloomberg scores to measure the companies‘ ESG performance and robustness measures. The results are reported in table 7.

To optimize the results of our regression analysis, we implement several enhancements from the previous model that followed the methodology to Dutordoir, Strong, and Sun (2018). Firstly, we apply industry-fixed effects on 2-digit SIC codes instead of 1-digit SIC codes. 1-digit SIC codes might be a less specific industry classification, while 2-digit SIC codes are considered to result in more accurate industry benchmarks (Kahle and Walkling, 1996). Secondly, due to the possibility of over-fitting our model, we drop the $RunUp$ variable due to its high correlation with the dependent variable, as it could lead to an incorrect interpretation of our results table 2 (Wooldridge, 2012). Furthermore, we add a dummy variable for Penny Stocks, which takes a value of 1 if the stock price is below \$5 and 0 otherwise. Penny stocks are often considered more volatile due to their susceptibility to market movements. In contrast to our first two linear regression models, we include standard errors clustered by industry to account for heteroskedasticity. We formulate the linear regression model as:

$$\begin{aligned}\text{CAR} = \beta_0 + \beta_1 \times \text{ESG Score} + \beta_2 \times \text{Opacity} + \beta_3 \times \text{Volatility} + \beta_4 \times \text{Slack}\\ + \beta_5 \times \text{Leverage} + \beta_6 \times \text{ROA} + \beta_7 \times \text{AssetTangibility} + \beta_8 \times \text{LnTA}\\ + \beta_9 \times \text{MTB} + \beta_{11}\text{RelOfrsize} + \beta_{12} \times D_{\text{SecondaryOffering}}\\ D_{\text{Pennystock}} + \sum_{i=1}^{n} \gamma_i \times I_i + \sum_{j=1}^{m} \delta_j \times Y_j + \epsilon_i\end{aligned}$$

To deepen our analysis regarding sustainable impacts on CAR, we include $LnCO2$, Cc_{expo}, and $Carbonintensity$ as alternative explanatory variables to ESG scores table 8, In addition to the combined ESG regression analysis, we perform a linear regression model with pillar scores of environmental (E), social (S), and governance (G), obtained from Bloomberg on CAR. We conduct a truncated regression analysis using high ESG scores, calculated based on the mean ESG scores for Refinitiv and Bloomberg. The results are displayed in table 22.

Further on, performing a sensitivity analysis to capture the robustness and durability of the findings by utilizing various market models and estimation windows. In order to capture the market response both before and after the announcement date, we employ alternative market models such as the market-adjusted model, Fama-French 3-factor model, and Fama-French 3-factor model + momentum with different event windows; (-1,1), (-3,3), and (-3,11). The outcome of the sensitivity analyses is displayed in table 14 and table 15.

In the second part of our analysis, we will examine if there is a relationship between a firm's ESG score and the probability of issuing secondary equity. Specifically, we will analyze if higher ESG-scored companies or lower ESG-scored companies are more inclined to raise equity through a secondary equity offering. Furthermore, we test potential variations in how firms allocate their equity proceeds toward corporate purposes.

To estimate the probability of a firm raising external capital through an SEO, based on its level of ESG score, we apply a logistic regression model. This model allows us to capture the binary nature of the SEO decision and the non-linear relationship between ESG scores and SEO probability. We use SEO as the dependent variable taking the value of 1 if the firm issued SEO during the sample period 2014 -2022, and zero otherwise. The regression uses a sample comprising all U.S listed companies from the period of 2014 to 2022, which also hold a Refinitiv ESG score. The sample size, including all the relevant companies, consists of 6003 observations.

We apply the following model to examine the probability:

$$\text{logit(SEO)} = \beta_0 + \beta_1 \text{ESG} + \sum_{i=2}^{n} \beta_i \text{Year}_i + \epsilon \tag{6}$$

Where SEO is the probability of a firm issuing a seasonal equity offering and $\text{logit(SEO)} = \log\left(\frac{\text{SEO}}{1-\text{SEO}}\right)$ is the logit function. The independent variables include an intercept term β_0, Refinitiv ESG Score with coefficient β_1, and a set of year dummy variables with coefficients β_2 to β_n. The results are reported in table 21

In addition to examining the relationship between ESG score and the probability of a company issuing secondary equity, we extend our analysis to measure how companies decrease the ownership stake of current shareholders. We run a regression model with $dilution$ as the dependent variable and $Bloomberg$ as the independent variable. In addition, the analysis includes time-fixed effects and a dummy variable for if the company has conducted a secondary offering. The results are displayed in Table 18.

We perform an additional analysis on the variations in the allocation of equity proceeds from one fiscal year prior to the SEO, to one fiscal year following the SEO. Firstly, we explored the companies‘ statements on investment purposes, where out of the 1165 firms that have conducted an SEO in our data sample between 2014-2022, (943) reported that the proceeds were to be used for ”Corporate general purposes” 22. In contrast to the previous regression models where the announcement date was the event of interest, we now use the issue date as the event of interest when determining the dependent and independent variables. The issue date is defined as when the equity is issued to the market and the firm “receives” capital from issuing new equity. Firstly, we estimate the variables of interest following the methodology of (Peters and Taylor, 2017).

Furthermore, we apply a difference-in-difference equation to test how the allocation of proceeds differs between firms with high and low ESG scores. For the difference-in-difference regression model, $Bloomberg$ is used as the measure of ESG performance. This regression analysis method allows us to compare the changes in investment behavior of high and low ESG-scored companies before and after the SEO issuance. Using a binary dummy variable for post-SEO values and high ESG, we are able to estimate the average treatment effect of having a high ESG score on post-SEO investment behavior. In the equation $\beta_3(HighESG_i \times PostSEO_t)$, the coefficient β_3 measures the difference-in-difference effect of having a high ESG score on the investment behavior after issuing SEO.

We formulate the following equation:

$$Y_{it} = \beta_0 + \beta_1 HighESG_i + \beta_2 PostSEO_t + \beta_3(HighESG_i \times PostSEO_t) + \epsilon_{it} \quad (7)$$

Where Y_{it} represents the investment behavior of I^{Int}, I^{Tot} I^{Phy}, $R\&D$, $Capex/PPE$, $Repurchase$ and $Payout$ in relation to Peters and Taylor, 2017. $\beta_3(HighESG_i \times AfterSEO_t)$ is the interaction term between the dummy variables $\beta_1 HighESG_i$ and $\beta_2 PostSEO_t$ and is included to capture the differential effect. The results are presented in table 9.

4.6.1 Robustness

This section will address and discuss potential challenges and biases associated with our analysis and explain which measures we use to address them. We conduct several robustness tests for our analysis. First, we test the sensitivity of our results by running the regression models on several estimation windows and on different factor models. Additionally, we use ESG scores from two different ESG-rating providers. Furthermore, we use two different measures of CO2 exposure as alternatives to ESG ratings; $LnCO2$ and Cc_expo. The companies' total CO2 emissions are further scaled on revenue to get a more nuanced view of the impact that total CO2 emissions have on cumulative abnormal returns.

We use robust standard errors and clustered standard errors in our regression models to deal with the potential issues of heteroskedasticity and within-cluster correlation error. We chose to cluster only by industry and not by years as our sample only consists of 10 years. Consequently, including clustered standard errors by year could lead to biased clustered standard error estimates (Petersen, 2006). When there are too few clusters, they might incorrectly reject the null hypothesis and overestimate the true value of the standard errors. Earlier research also discusses how the definition of "few" clusters varies in the literature, suggesting that the number of few clusters varies from 5 to 50 (Colin Cameron and Miller, 2015). In our analysis, we cluster by industry and use clustered standard errors when there are more than 25 clusters, and robust standard errors when there are fewer than 25 clusters. Each table describes which method is used for the reported standard errors.

Multicollinearity refers to the situation where two or more independent variables are highly correlated with each other. This can cause problems such as inflated standard errors and incorrect inference of the results. To control for this, we examine the correlation matrices in table 2 and apply the variance inflation factor test to our results. The literature does not provide a clear cutoff level for VIF, and setting a clear cutoff level is not helpful (Wooldridge, 2012). However, we do not observe high levels of VIF through our analysis.

4.7 Limitations

First, we encountered some limitations while using the methodology in relation to Dutordoir, Strong, and Sun (2018). Unfortunately, we could not access the CSR data from the KLD database through Handelshøyskolen BI. Using Bloomberg as CSR measures in the sample 2004-2013 resulted in fewer observations, which may limit our analysis. Moreover, we were unable to retrieve analyst forecasts and institutional holdings to measure $Opacity$ due to unavailable data through I/B/E/S and MSCI. We believe these limitations may cause some disparity, but do not significantly affect the results of our regression analysis.

Endogeneity One of the main challenges of incorporating environmental, social, and governance (ESG) in research is the issue of endogeneity, especially the possibility of reverse causality or simultaneity. This refers to the possibility that firms with greater financial resources may allocate more resources towards ESG initiatives, thereby influencing their ESG scores. Such circumstances can potentially impact our findings, particularly with regard to the effect of ESG scores on the event of interest. As a result, our key explanatory variable may be endogenous, making it difficult to accurately estimate the causal effect that ESG scores have on cumulative abnormal returns. To address endogeneity in the analysis, we would need to isolate the exogenous variation in ESG scores. This can be achieved through the use of two-stage least squares regression (2SLS) with an instrumental variable. However, identifying a suitable instrumental variable could be challenging as it must meet two conditions: it must be exogenous and relevant (Wooldridge, 2012). This means that the instrumental variable must not be correlated with the error term in the regression (exogeneity), but it must also be correlated with the ESG score (relevance).

To identify an instrumental variable, it is important to first take a theoretical approach. One possible instrumental variable that could be used is one that captures regulatory changes affecting a firm's incentive to invest in ESG-enhancing initiatives. This variable would focus on reporting standards for ESG scores rather than the firm's financial performance. In order to better identify an instrumental variable, more research is needed to gain a better understanding of the methodology used by ESG score providers. Once a theoretical IV is identified, it needs to be tested against assumptions. Then, ESG scores would be regressed on the IV and other control variables in the first stage of the analysis. In the second stage of the 2SLS, the first regression's estimated values would be used as a proxy for the ESG score along with other control variables. This proxy would then capture the causal relationship between ESG scores and CAR. However, this is just a theoretical suggestion and is not implemented in our analysis.

Attenuation bias occurs when the measurement of a variable is noisy. It is widely known that the methodology of ESG ratings is unique for each rating provider, and the source of disagreement is the measurement (Berg, Kölbel, and Rigobon, 2022). Our results might be subject to wrong interference, or it can be challenging to replicate our results with other ESG-rating providers. Berg, Koelbel, Pavlova, and Rigobon (2022) discusses the problem of noise in ESG-rating and the attenuation bias that could occur when running regressions with ESG-rating data. We do not implement the countermeasures the paper suggests in this analysis but acknowledge the potential bias.

This thesis uses the intensive margin approach to analyze ESG ratings. This approach only considers firms that have issued a secondary equity offering and possess an ESG rating. The data section reveals that our sample size is significantly smaller compared to the total population of firms that have issued SEOs. Hence, our sample may not accurately represent the broader population of firms that have issued SEOs.

5 Results

Table 6: **Augmented model sample 2004-2013.**
The table presents the results of the augmented regression model. The initial regression model includes only Bloomberg score as an independent variable. Subsequent models introduce fixed effects and then control variables. The final two regressions represent fully augmented models. The industry fixed effects are by 1-digit SIC. Tstatistics, robust standard errors are reported in parentheses. Significance levels are denoted as follows *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

	Car Adjusted Market Model(0,1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Bloomberg	−0.0003	−0.0003	−0.0001	−0.0002		−0.0008
	(0.0005)	(0.0005)	(0.0003)	(0.0003)		(0.0006)
ExecOwnership					−0.0475	−0.0499
					(0.0506)	(0.0504)
Opacity			0.0008	0.0007	−0.0011	−0.0006
			(0.0008)	(0.0009)	(0.0014)	(0.0014)
Volatility			0.0001***	0.0002***	0.0005	0.0005
			(0.0000)	(0.0001)	(0.0003)	(0.0003)
Slack			−0.0009	0.0003	−0.0105	−0.0022
			(0.0076)	(0.0087)	(0.0163)	(0.0157)
Runup			0.6268***	0.6378***	0.5787***	0.5749***
			(0.0613)	(0.0582)	(0.0679)	(0.0662)
Leverage			0.0003	−0.0015	0.0012	−0.0035
			(0.0040)	(0.0043)	(0.0081)	(0.0083)
ROA			0.0028	0.0018	0.0041	0.0008
			(0.0081)	(0.0084)	(0.0140)	(0.0141)
AssetTangibility			−0.0123**	−0.0132**	−0.0078	−0.0081
			(0.0054)	(0.0059)	(0.0074)	(0.0076)
LnTA			−0.0040**	−0.0038*	−0.0052	−0.0034
			(0.0019)	(0.0021)	(0.0041)	(0.0039)
MTB			0.0000	−0.0000	0.0001	0.0001
			(0.0001)	(0.0001)	(0.0002)	(0.0002)
RelOfersize			−0.0008	−0.0020	0.0034	0.0009
			(0.0028)	(0.0028)	(0.0115)	(0.0115)
SecondaryOffering			−0.0017	−0.0033	0.0052	0.0035
			(0.0064)	(0.0065)	(0.0112)	(0.0116)
Constant	−0.0047		0.0198			
	(0.0137)		(0.0152)			
Year FE	No	Yes	No	Yes	Yes	Yes
Industry FE	No	Yes	No	Yes	Yes	Yes
Observations	433	428	413	408	219	218
Adjusted R^2	−0.0007	0.0363	0.6598	0.6628	0.6426	0.6498

Table 7: **Augmented model 2014-2022.**

The table presents the results of the augmented regression on the 2014-2022 data sample. Regression model 1 and 2 includes only key explanatory variable, with no controls. Subsequent models introduce control variables and fixed effects. Models 3, 4, and 5,6 represent fully augmented models. The industry fixed effects are by 1-digit SIC.T-statistics based on robust standard errors are reported in parentheses. Significance levels are denoted as follows *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

	Car Adjusted Market Model(0,1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Bloomberg	−0.0013 (0.0009)		0.0002 (0.0006)	0.0001 (0.0003)		
Refinitiv		0.0001 (0.0004)			−0.0009 (0.0005)	−0.0002 (0.0002)
ExecOwnership				0.0444* (0.0229)		0.0465** (0.0217)
Opacity			0.0002 (0.0049)	−0.0018 (0.0015)	0.0027 (0.0049)	−0.0013 (0.0015)
Volatility			0.0000 (0.0003)	0.0000 (0.0002)	−0.0001 (0.0003)	0.0000 (0.0002)
Slack			0.0298 (0.0258)	0.0313* (0.0169)	0.0333 (0.0259)	0.0320* (0.0174)
RunUp			0.6832*** (0.1799)	0.7478*** (0.0574)	0.6327*** (0.1786)	0.7564*** (0.0575)
Leverage			−0.0075 (0.0220)	−0.0078 (0.0078)	0.0093 (0.0221)	−0.0074 (0.0079)
ROA			0.0121 (0.0118)	0.0183 (0.0148)	0.0171 (0.0115)	0.0223 (0.0148)
AssetTangibility			0.0077 (0.0209)	0.0002 (0.0082)	−0.0093 (0.0191)	0.0032 (0.0085)
LnTA			0.0015 (0.0046)	0.0051 (0.0048)	0.0075 (0.0052)	0.0072 (0.0052)
MTB			0.0002*** (0.0001)	0.0002* (0.0001)	0.0000 (0.0001)	0.0002 (0.0001)
RelOfersize			−0.0108 (0.0225)	0.0125 (0.0224)	0.0216 (0.0229)	0.0166 (0.0228)
SecondaryOffering			0.0143 (0.0119)	0.0077 (0.0067)	0.0209* (0.0115)	0.0077 (0.0067)
Constant	0.0286 (0.0355)	−0.0113 (0.0168)				
Year FE	No	No	Yes	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes
Observations	1,014	1,014	762	235	762	235
Adjusted R^2	0.0033	−0.0008	0.8048	0.7778	0.8050	0.7795

5.1 Augmented regression analysis

When augmenting the existing research conducted by Dutordoir, Strong, and Sun (2018), we were unable to obtain the same results, both for the original sample of 2004-2013 and the sample of 2014-2022. Despite following the methodology outlined in the (Dutordoir, Strong, and Sun (2018). The adjusted R-squared is notably higher in our results which is due to the high correlation between $RunUp$ and CAR(0,1).

One of the leading causes of the discrepancy may be the use of different explanatory variables in our thesis compared to (Dutordoir, Strong, and Sun (2018)). In comparison, they incorporated $AdjustedCSR$ as an explanatory variable to measure the firm's sustainability, while we used $Refinitiv$ and $Bloomberg$ ESG-score as the main explanatory variables. The difference in variable selection may have contributed to the differences in our findings. $Refinitiv$ and $Bloomberg$ would capture different aspects of the cumulative abnormal return, leading to different results.

However, we find the variable $ExecutiveOwnership$ to be significant at 10% and 5% in the sample period of 2014-2022, regression (4) and (6). This implies that when executives hold more shares, the cumulative abnormal returns increase. Regarding conflict of interest, it indicates that investors view the managerial stock ownership to total shares outstanding as a critical factor for better governance practices. Additionally, a higher concentration of executive stock ownership is associated with companies being more productive when utilizing equity proceeds, preceding a secondary equity offering (Kim and Purnanandam (2011)).

Table 8: **Improved model**

The table displays the results of an enhanced regression model. 2-digit SIC codes determine industry fixed effects. We also introduce alternative climate exposure variables LnCO2 and Cc_expo. T-statistics, clustered by industry, are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Car Marked Adjusted Model(0,1)				
	(1)	(2)	(3)	(4)	(5)
Cc_expo	−7.7569				
	(4.9058)				
LnCO2		−0.0174***			
		(0.0063)			
Bloomberg			−0.0020		
			(0.0013)		
Refinitiv				−0.0003	
				(0.0005)	
Carbon Intensity					0.0000
Opacity	0.0014	0.0012	0.0012	0.0012	0.0017
	(0.0040)	(0.0039)	(0.0039)	(0.0039)	(0.0039)
Volatility	0.0002	−0.0002	−0.0005	−0.0004	0.0005
	(0.0004)	(0.0008)	(0.0006)	(0.0007)	(0.0007)
Slack	0.1187***	0.0742**	0.1271***	0.1270***	0.0727**
	(0.0371)	(0.0351)	(0.0344)	(0.0344)	(0.0344)
Leverage	0.0280	0.0360	0.0372	0.0361	0.0257
	(0.0274)	(0.0258)	(0.0248)	(0.0249)	(0.0249)
ROA	0.0669**	0.0594**	0.0716***	0.0724***	0.0409
	(0.0306)	(0.0256)	(0.0263)	(0.0260)	(0.0260)
AssetTangibility	−0.0210	0.0072	0.0100	0.0085	−0.0026
	(0.0240)	(0.0271)	(0.0251)	(0.0248)	(0.0248)
LnTA	0.0126**	0.0287***	0.0200***	0.0161**	0.0145**
	(0.0059)	(0.0087)	(0.0073)	(0.0071)	(0.0071)
MTB	0.0001	−0.0000	−0.0001	−0.0001	−0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)
RelOfersize	0.0405**	0.0620**	0.0740***	0.0719***	0.0836***
	(0.0189)	(0.0260)	(0.0247)	(0.0246)	(0.0246)
SecondaryOffering	0.0342***	0.0296*	0.0378**	0.0353*	0.0290
	(0.0132)	(0.0172)	(0.0184)	(0.0183)	(0.0183)
PennyStock	0.0302	−0.0046	0.0008	−0.0005	−0.0120
	(0.0278)	(0.0251)	(0.0228)	(0.0226)	(0.0226)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	588	675	763	763	580
Adjusted R^2	−0.0005	0.0135	0.0334	0.0296	0.0232

5.1.1 Improved model

We observe a significantly negative relationship between $LnCO2$ and CAR. This suggests that firms with higher carbon emissions are more exposed to carbon risk than firms with lower carbon emissions. Previous research finds a positive relationship between companies' total CO2 emissions and expected returns. This indicates that investors price in carbon risk and demand higher returns for companies with higher total CO2 emissions(Bolton and M. Kacperczyk, 2021b). Our results indicate that investors react more negatively to companies with higher CO2 emissions around a secondary equity offering event. Moreover, it implies that investors are rational and may avoid buying shares of firms with higher carbon emissions.

The sensitivity analysis presented in the tables 14 and 15 demonstrates a consistent negative relationship between total CO2 emissions and Cumulative Abnormal Returns across all factor models, and event windows. To address concerns about the potential influence of firm size and industry on this relationship, we control for these factors in our regression using the natural logarithm of total assets ($LnTA$) as a proxy for firm size and industry fixed effects. Our results suggest that, after accounting for the effects of firm size and industry, higher levels of CO2 emissions are still associated with lower abnormal returns. The magnitude of the coefficients ranges from -0.0174 to -0.023, indicating that the effect of CO2 emissions on the dependent variable is relatively small yet consistent across all models. We do not find $CarbonIntensity$ or Cc_expo to have a discernible impact on CAR during a secondary equity offering.

5.1.2 Results ESG score

Based on the additional regression analysis, it appears that ESG scores do not have a significant impact on CAR, table 8. Furthermore, our analysis, shown in table 12 and 13, indicates that there are no significant results when it comes to ESG pillar scores. Moreover, our truncated regression model with high ESG scores did not produce any significant results either. The findings are presented in table 23.

A possible drawback of using ESG scores as a proxy for cumulative abnormal returns, is their relatively infrequent publication. ESG scores are usually updated annually, while fundamental financial data is disclosed quarterly, and stock information is accessible in real-time daily. The data availability of ESG scores may reduce its relevance in the context of market reaction to a seasonal equity offering. It could be argued that rational investors would rely on the most recent information available, such as fundamental financial data and daily stock returns rather than ESG scores, which are updated on an annual basis. ESG scores are less reliable compared to fundamental data and are a more uncertain indicator of financial performance. The uncertainty is furthermore related to the divergence of ESG ratings (Berg, Kölbel, and Rigobon, 2022).

Investors are progressively integrating ESG considerations into their investment portfolios. They rely on information supplied by rating agencies regarding a company‘s ESG performance. Nevertheless, our findings indicate that investors do not depend on ESG data when responding to a secondary equity offering. This suggests that investors place a greater value on ESG when contemplating long-term investments rather than short-term investments.

5.2 ESG and SEO Proceeds and Probability

5.2.1 Probability of issuing SEO

Our result indicates that ESG scores are a highly significant predictor of the probability of a firm issuing a seasonal equity offering at the 1% significance level. The negative coefficient for ESG scores suggests that, as a firm's ESG score increases, the firm's log odds of issuing a seasonal equity offering decrease. The coefficients for the year dummy variables indicate that there are some differences in the response variable across years. We observe that there is a significant increase in the probability of issuing secondary equity in 2020 and 2021.

Table 9: **Probability**
Tabel shows the results of the logistic regression model for the probability of issuing SEO based on the ESG rating. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-0.6018	0.1280	-4.70	2.58e-06***
ESG	-0.0314	0.0014	-22.42	< 2e-16***
Year2015	0.0693	0.1546	0.45	0.6539
Year2016	-0.0466	0.1449	-0.32	0.7478
Year2017	0.2365	0.1352	1.75	0.0802
Year2018	0.3413	0.1330	2.57	0.0103*
Year2019	0.2774	0.1339	2.07	0.0383**
Year2020	0.7241	0.1300	5.57	2.55e-08***
Year2021	0.6226	0.1325	4.70	2.64e-06***
Year2022	-0.2523	0.1496	-1.69	0.0918

5.2.2 Probability

According to the pecking-order theory, firms prioritize capital-raising sources based on their respective costs. The least expensive is internal financing which is the preferred way of raising capital. The second is financing through debt, and the least preferred is issuing equity which is the most costly (S. C. Myers, 1984). As found in our analysis, firms with high ESG have a lower probability of issuing equity for financing to the same extent as firms with lower ESG scores. Firms with higher Bloomberg scores are associated with issuing fewer shares in a seasonal equity offering. Table**??**

High ESG firms that issue fewer shares also signal that they do not have the same need to raise as much capital as firms with lower ESG scores. Pedersen, Fitzgibbons, and Pomorski (2021) suggests that firms with high ESG scores may have a lower cost of capital because a higher ESG score increases the demand for the stock from ESG-motivated investors. Increased demand leads to higher stock prices and, therefore, a lower required return for the firm. A lower required return implies that high ESG firms can raise capital at a lower cost and may be able to rely more on internal financing and debt before resorting to issuing equity, compared to firms with lower ESG scores (Pedersen, Fitzgibbons, and Pomorski, 2021).

According to table 4, the ESG score for companies conducting SEO in our sample is generally low. This suggests that firms with higher ESG scores may not need to resort to SEO to secure external funding. A possible explanation is that firms with high ESG scores are associated with higher profitability and stock values (Gerard, 2019), which may reduce the need for external capital. Several studies have investigated the relationship between ESG performance and financial performance. Both (Orlitzky, Schmidt, and Rynes, 2003, Margolis, Elfenbein, and Walsh, 2009)found a positive correlation between corporate social performance and financial performance, which supports our observation that firms with high ESG scores do not have the same need for external capital to the same extent as firms with low ESG.

5.2.3 Use of equity proceeds

Table 10: **Proceeds**

We applied a difference-in-differences regression to calculate the use of proceeds. T-statistics and robust standard errors are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Total Investment	R&D	Capex/PPE	Payout	Physical Investment	Repurchase	Intangible Investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
high_esg	0.8201***	0.0771	−0.0202**	0.2683	0.3629***	−0.0143	0.4533***
	(0.1575)	(0.0481)	(0.0088)	(0.2517)	(0.0699)	(0.2254)	(0.1067)
after_seo	0.0159	0.0075	−0.0171*	0.3996***	−0.0011	0.1393**	0.0138
	(0.0320)	(0.0248)	(0.0089)	(0.0546)	(0.0076)	(0.0611)	(0.0287)
interaction	−0.2758	−0.0457	0.0067	0.8037**	−0.0972	0.1469	−0.1754
	(0.1752)	(0.0582)	(0.0112)	(0.4071)	(0.0807)	(0.2475)	(0.1199)
Constant	0.2398***	0.1616***	0.1587***	−0.3676***	0.0321***	−0.3719***	0.2082***
	(0.0217)	(0.0174)	(0.0072)	(0.0468)	(0.0056)	(0.0467)	(0.0194)
Observations	1,633	1,655	1,738	1,099	1,633	1,922	1,655
Adjusted R^2	0.0341	0.0007	0.0071	0.0089	0.0333	0.0002	0.0209

In the differnce-in-differneces regression, we analyze the interaction between the treatment, which is the high ESG, and the time indicator after SEO. This shows the treatment effect. In table 10, there is only a significant treatment effect for the variable payout at a 5% level, which indicates that firms with high ESG significantly allocate more resources to payout after the SEO compared to low ESG firms. Moreover, the variable after SEO indicates a significant change for all firms in payout and repurchase. This suggests that this is a common factor for all firms before and after SEO issuance.

$Interaction$ shows the difference-in-differences approach and measures the companies´ investment behavior changes between high and low-ESG issuers after a secondary equity offering. All firms have a significantly higher payout and repurchase after the SEO. Both payout, which refers to dividends, and repurchase are payout policies. Payout policy has a signaling effect on the stock market, signaling that the firm is confident about the future(Brealey, S. Myers, and Allen (2015)). The main difference between paying out dividends and repurchasing shares is that repurchasing is more flexible. The shareholders expect the firm to keep paying out dividends, and reducing the amount will have a negative signaling effect; on the other hand, there are no expectations to keep repurchasing shares. Therefore, repurchasing shares is not as committing as a dividend payout. High ESG firms pay out significantly more dividends after the SEO compared to firms with low ESG scores. This suggests that firms with high ESG scores are more confident about the future of the firm. However, we should also consider that younger firms have more growth and investment opportunities compared to more mature firms, as they might retain more excess cash to be used in future investments. The results could also reflect that high ESG firms are more mature, but we do not control for age in this analysis.

6 Conclusion

This thesis has explored the relationship between ESG scores and secondary equity offering, a topic that has received limited attention in the literature. Through analyzing a broad range of US companies and utilizing different statistical techniques, we have revealed insights about the impact of ESG ratings on raising external funds and added to the existing knowledge about ESG investments. The data did not support our hypothesis that high ESG scores yield lower cumulative abnormal returns. In addition, we do not find supporting evidence that higher CO2 emissions yield higher abnormal returns in the event of a secondary equity offering.

First, we illustrate that ESG scores are noisy and inconsistent predictors for the cumulative abnormal return in the event of a secondary equity offering. The study confirms that investors do not rely on ESG scores when reacting to an SEO but rather on more intangible information. Second, we have found that CO2 emissions are a more objective and reliable indicator of environmental impact and have a significant negative effect on the abnormal returns of firms that issue secondary equity. This suggests that investors penalize firms that are more carbon-intensive and less environmentally friendly. Third, we have demonstrated that firms with high ESG scores are less likely to issue secondary equity to raise external capital; this implies that high ESG firms have lower financing needs and rely more on internal or debt financing. Our research also finds evidence that the allocation of proceeds differs between firms with high and low ESG ratings, where firms with high ESG prioritize nurturing corporate policies in terms of payouts.

Our research has important implications for both academics and practitioners. For academics, it provides new insights into the role of ESG factors in corporate finance decisions and outcomes, and it calls for more standardized reporting and measurement of ESG performance. For practitioners, it highlights the potential pitfalls of relying on ESG scores as a proxy for a firm's performance in the event of an SEO, and it gives valuable insight for corporations raising capital.

6.1 Further research

Our research has some limitations that open up several avenues for future research. First, the sample used in this thesis is based on firms in the United States. According to Bolton, Halem, and M. T. Kacperczyk (2022), carbon transition risk is not priced in the American equity and debt markets to the same extent as in European markets. The Price-to-Earnings (P/E) discounts are similar for large-cap companies in the European Union and the United States. However, they are significantly larger for smaller-cap US companies than their European counterparts. This suggests that the results may have been different if the research had been conducted on European firms due to the EU's tighter carbon emissions regulations, disclosure requirements, and carbon pricing.

To better understand how ESG ratings affect the market's response to an SEO, conducting further research using an extensive margin to compare the impact of having an ESG rating versus not having one could provide a better understanding of how ESG ratings influence the market's reaction to an SEO. Third, using ESG providers such as MSCI and Sustainalytics, in addition to the ones already used, could offer more reliable and relevant ESG indicators for predicting the market's response to SEO. Moreover, regarding proceeds allocation, further research should incorporate the age of the firm to strengthen the evidence that high ESG firms prioritize payout policies after SEO.

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A Appendix

Variable	**Formula**	**Definition**
Refinitiv	Retrieved from Refinitiv	ESG-Score 0-100
Bloomberg	Retrieved from Bloomberg	ESG-Score 0-100
Executive Ownership	$\frac{\text{Shares owned by executives}}{\text{Total shares outstanding}}$	Amount of shares owned by executive officers last month of the year before announcement day, divided by total shares outstanding the year before the announcement date.
Volatility	$Std.daily.returns * \sqrt{252}$	Standard deviation of the daily returns * the square root of the total trading days in a year to annualize it.
Slack	$\frac{\text{Cash \& short term invest}}{\text{Total Assets}}$	Ratio shows a firms ability to meet short-term obligations
RunUp	Buy-hold abnormal returns	Buy-hold abnormal returns over 60 days ending 11 days before announcement day.
Leverage	$\frac{\text{Total liabilities}}{\text{Total Assets}}$	Ratio that shows the proportion of a firm's assets which is financed through debt
ROA	$\frac{\text{Earnings}}{\text{Total Assets}}$	Earnings before extraordinary items divide by Total Assets

Asset Tangibility	$\frac{\text{PPE}}{\text{Total Assets}}$	Ratio of the proportion of a firm's total assets which are invested in long-term investments.
Secondary offering	Dummy variable	Dummy variable equal to one for offerings including a secondary component, and zero otherwise.
LnTa	Ln(Total assets)	Natural logarithm of the total assets
MTB	$\frac{\text{Market Value}}{\text{Book Value of Equity}}$	Measure of market value relative to book value
Relofersize	$\frac{\text{Proceeds}}{\text{Total Assets}}$	Ratio of the magnitude of the SEO offer, compared to company size

Opacity	Ln(Trading volume) Bid-ask spread	LN of trading volume over 200 days ending 11 days before announcement day. Bid-ask spread over 200 days ending 11 days before announcement day. We then calculated the opacity by ranking the two individual proxies for opacity into deciles, with the most opaque (by information asymmetry) firms taking a value of 10. The two rankings were then summarized and divided by a factor of 20, representing the total possible points obtained and providing an index.
Pennystock	Dummy variable	Variable equal to one for offer-price less than 5$
LnCO2	Ln(CO2)	Natural Logarithm of totalt CO2 emissions. We take the Log to standardize the variable
Cc_expo	Retrieved from website	Represent a firm's exposures related to opportunity, physical, and regulatory shocks associated with climate change.
Dilution	$\frac{\text{Shares Offered}}{\text{Total Shares}}$	Reduction in the ownership percentage of existing shareholders

B Appendix

Table 12: **Pillar Score. E, S, and G**

Pillar score from Refintiv, first run without FE and then introduce FE. T-statistics standard errors are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Car Adjusted Market Model (0,1)					
	(1)	(2)	(3)	(4)	(5)	(6)
Governance	0.0003			0.0007		
	(0.0010)			(0.0011)		
Social		-0.0006			-0.0004	
		(0.0009)			(0.0011)	
Environmenal			0.0002			0.0002
			(0.0003)			(0.0003)
SecondaryOffering				0.0122	0.0118	0.0354^{**}
				(0.0169)	(0.0195)	(0.0157)
Constant	-0.0457	-0.0073	-0.0320^{***}			
	(0.0828)	(0.0122)	(0.0064)			
Year FE	No	No	No	Yes	Yes	Yes
Industry FE	No	No	No	Yes	Yes	Yes
Observations	964	891	242	964	891	242
Adjusted R^2	-0.0009	-0.0006	-0.0026	-0.0169	-0.0224	0.1437

Table 13: **Pillar Score. E, S, and G**

Table shows improved regression with Pillar scores from Refinitiv as explanatory variables. T-statistics robust standard errors are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Car Adjusted Market model(0,1)		
	(1)	(2)	(3)
Governance	0.0008		
	(0.0014)		
Social		−0.0010	
		(0.0013)	
Environmenal			0.0001
			(0.0004)
Opacity	0.0000	0.0010	−0.0069
	(0.0038)	(0.0040)	(0.0058)
Volatility	−0.0004	−0.0005	0.0003
	(0.0006)	(0.0006)	(0.0010)
Slack	0.1326***	0.1281***	0.1183**
	(0.0360)	(0.0381)	(0.0512)
Leverage	0.0350*	0.0343*	−0.0519**
	(0.0188)	(0.0199)	(0.0238)
ROA	0.0726***	0.0696***	0.0654
	(0.0238)	(0.0251)	(0.0505)
AssetTangibility	0.0090	0.0018	0.0194
	(0.0304)	(0.0322)	(0.0270)
LnTA	0.0174**	0.0185**	0.0203**
	(0.0072)	(0.0077)	(0.0096)
MTB	−0.0001	−0.0001	0.0000
	(0.0004)	(0.0004)	(0.0005)
RelOfersize	0.0748***	0.0734***	0.0380
	(0.0145)	(0.0151)	(0.0232)
SecondaryOffering	0.0227	0.0270	0.0441**
	(0.0208)	(0.0240)	(0.0194)
PennyStock	0.0064	0.0143	0.0984**
	(0.0228)	(0.0241)	(0.0406)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	728	683	181
Adjusted R^2	0.0303	0.0210	0.0878

Table 14: **Sensetivity LnCO2**

The table displays the results of sensitivity analysis of LnCO2 variable. Running the regression on several Models and event windows. T-statistics, clustered by industry, are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	‘CarMM(-1,1)‘	‘CarFF(-1,1)‘	‘CarFFM(-1,1)‘	‘CarMM(-3,3)‘	‘CarFF(-3,3)‘
	(1)	(2)	(3)	(4)	(5)
LnCO2	−0.023***	−0.022***	−0.023***	−0.019**	−0.019**
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Opacity	0.002	0.001	0.001	0.006	0.006
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Volatility	−0.000	−0.000	−0.000	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Slack	0.090**	0.082**	0.081*	0.051	0.040
	(0.042)	(0.041)	(0.042)	(0.055)	(0.055)
Leverage	0.062*	0.061*	0.059*	0.060	0.064
	(0.033)	(0.033)	(0.033)	(0.041)	(0.042)
ROA	0.071**	0.062*	0.065**	0.090**	0.087**
	(0.032)	(0.032)	(0.032)	(0.038)	(0.038)
AssetTangibility	−0.011	−0.015	−0.012	−0.015	−0.023
	(0.032)	(0.032)	(0.032)	(0.039)	(0.040)
LnTA	0.036***	0.036***	0.036***	0.014	0.014
	(0.011)	(0.011)	(0.012)	(0.015)	(0.015)
MTB	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RelOfersize	0.097***	0.093**	0.092**	0.086**	0.072*
	(0.038)	(0.038)	(0.038)	(0.042)	(0.042)
SecondaryOffering	0.022	0.022	0.022	0.031	0.035
	(0.020)	(0.020)	(0.020)	(0.038)	(0.038)
PennyStock	−0.005	−0.003	−0.001	−0.044	−0.036
	(0.028)	(0.028)	(0.028)	(0.038)	(0.037)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	646	646	646	641	641
Adjusted R^2	0.048	0.037	0.035	0.042	0.024

Table 15: **Sensetivity LnCO2**

The table displays the results of sensitivity analysis of LnCO2 variable. Running the regression on several models and event windows T-statistics, clustered by industry, are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	CarFFM(-3,3)	CarMM(-3,11)	CarFF(-3,11)	CarFFM(-3,11)
	(1)	(2)	(3)	(4)
LnCO2	−0.0199**	−0.0188*	−0.0207*	−0.0198*
	(0.0095)	(0.0108)	(0.0115)	(0.0114)
Opacity	0.0062	0.0084	0.0075	0.0074
	(0.0072)	(0.0072)	(0.0075)	(0.0075)
Volatility	−0.0008	−0.0010	−0.0006	−0.0006
	(0.0013)	(0.0012)	(0.0014)	(0.0014)
Slack	0.0402	0.0386	0.0314	0.0415
	(0.0550)	(0.0602)	(0.0618)	(0.0615)
Leverage	0.0637	0.0450	0.0604	0.0589
	(0.0429)	(0.0401)	(0.0432)	(0.0428)
ROA	0.0906**	0.0686	0.0610	0.0713
	(0.0380)	(0.0435)	(0.0449)	(0.0451)
AssetTangibility	−0.0254	−0.0077	−0.0262	−0.0152
	(0.0415)	(0.0422)	(0.0449)	(0.0443)
LnTA	0.0142	0.0086	0.0128	0.0122
	(0.0147)	(0.0163)	(0.0168)	(0.0170)
MTB	−0.0000	0.0000	0.0001	0.0000
	(0.0004)	(0.0005)	(0.0006)	(0.0006)
RelOfersize	0.0723*	0.0691	0.0435	0.0438
	(0.0427)	(0.0437)	(0.0459)	(0.0463)
SecondaryOffering	0.0349	0.0429	0.0478	0.0469
	(0.0378)	(0.0400)	(0.0415)	(0.0416)
PennyStock	−0.0347	−0.0165	0.0068	0.0117
	(0.0366)	(0.0435)	(0.0452)	(0.0453)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	641	641	641	641
Adjusted R^2	0.0233	0.0237	−0.0057	−0.0079

Table 16: **Mean and Median Values Sample 2014-2022**

The table displays the mean and median values of different Car models, with different event windows. The sample is divided by high and low Bloomberg scores, using the median value as the benchmark. The Pvalues are calculated by Wilcoxon Rank-sum and T- statistics

		Full sample		High	Sample	Low	Sample	Difference	Difference	p-value	p-value
	Variable	Mean	Median	Mean	Median	Mean	Median	Mean	Median	Mean	Median
1	Car MM (0,1)	-0.02	-0.03	-0.02	-0.03	-0.01	-0.03	-0.02	-0.00	0.08	0.34
2	CarMM(-1,1)	-0.00	-0.03	-0.01	-0.03	0.01	-0.03	-0.02	-0.00	0.06	0.26
3	CarFF(-1,1)	-0.01	-0.03	-0.02	-0.04	0.00	-0.03	-0.02	-0.00	0.06	0.34
4	CarFFM(-1,1)	-0.01	-0.03	-0.02	-0.03	0.00	-0.03	-0.02	-0.00	0.07	0.46
5	CarMM(-3,3)	0.01	-0.02	0.00	-0.02	0.03	-0.02	-0.02	0.00	0.14	0.91
6	CarFF(-3,3)	0.00	-0.03	-0.01	-0.03	0.01	-0.03	-0.02	0.00	0.16	0.88
7	CarFFM(-3,3)	0.00	-0.03	-0.01	-0.03	0.01	-0.04	-0.02	0.01	0.20	0.67
8	CarMM(-3,11)	0.02	-0.01	0.01	-0.02	0.03	-0.01	-0.03	-0.01	0.11	0.67
9	CarFF(-3,11)	-0.01	-0.03	-0.02	-0.03	0.01	-0.03	-0.02	-0.00	0.17	0.89
10	CarFFM(-3,11)	-0.01	-0.03	-0.02	-0.03	0.00	-0.04	-0.02	0.01	0.21	0.90

Table 17: **Explanatory variables Sample 2014-2022**

The table displays the results of the initial regression analysis. T-statistics with clustered errors by industry are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Car Adjusted Market Model (0,1)				
	(1)	(2)	(3)	(4)	(5)
Cc_expo	-7.7522^{**}				
	(3.5436)				
LnCO2		-0.0034			
		(0.0029)			
Bloomberg			-0.0005		
			(0.0008)		
Refinitiv				0.0002	
				(0.0003)	
Carbon Intensity					0.0000
					(0.0000)
SecondaryOffering	0.0202^{*}	0.0174	0.0207	0.0203	0.0165
	(0.0108)	(0.0139)	(0.0142)	(0.0141)	(0.0143)
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Observations	777	874	1,014	1,014	722
Adjusted R^2	-0.0144	-0.0196	-0.0134	-0.0136	-0.0072

Table 18: **Regression Dilution**

The regression shows how the dilution regressed on Bloomberg score, with secondary offerings as a dummy variable. Sample data 2005-2022.

$$\text{Dilution}_i = \beta_0 + \beta_1 \text{Bloomberg} i + \beta_{2\text{SecondaryOffering}} i + \sum_{i=1}^{n} \beta_{2+i} \times \text{Year}_i + \epsilon \tag{9}$$

T-statistics are reported in parentheses. Significance levels are indicated as follows *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

	Dilution
Bloomberg	-0.0015^{**}
	(0.0006)
SecondaryOffering	0.0051
	(0.0159)
Observations	1,252
Adjusted R^2	0.0105

Table 19: **Refinitiv Scoring Range for ESG Rating**

Score Range	Description
0 to 25	Indicate poor relative ESG performance and insufficient degree of transparency in reporting material ESG data publicly.
25 to 50	Indicate satisfactory relative ESG performance and moderate degree of transparency in reporting material ESG data publicly.
50 to 75	Indicate good relative ESG performance and above average degree of transparency in reporting material ESG data publicly.
75 to 100	Indicate excellent relative ESG performance and a high degree of transparency in reporting material ESG data publicly.

Figure 1: Mean Blommberg ESG Score by Year, sample 2004-2022

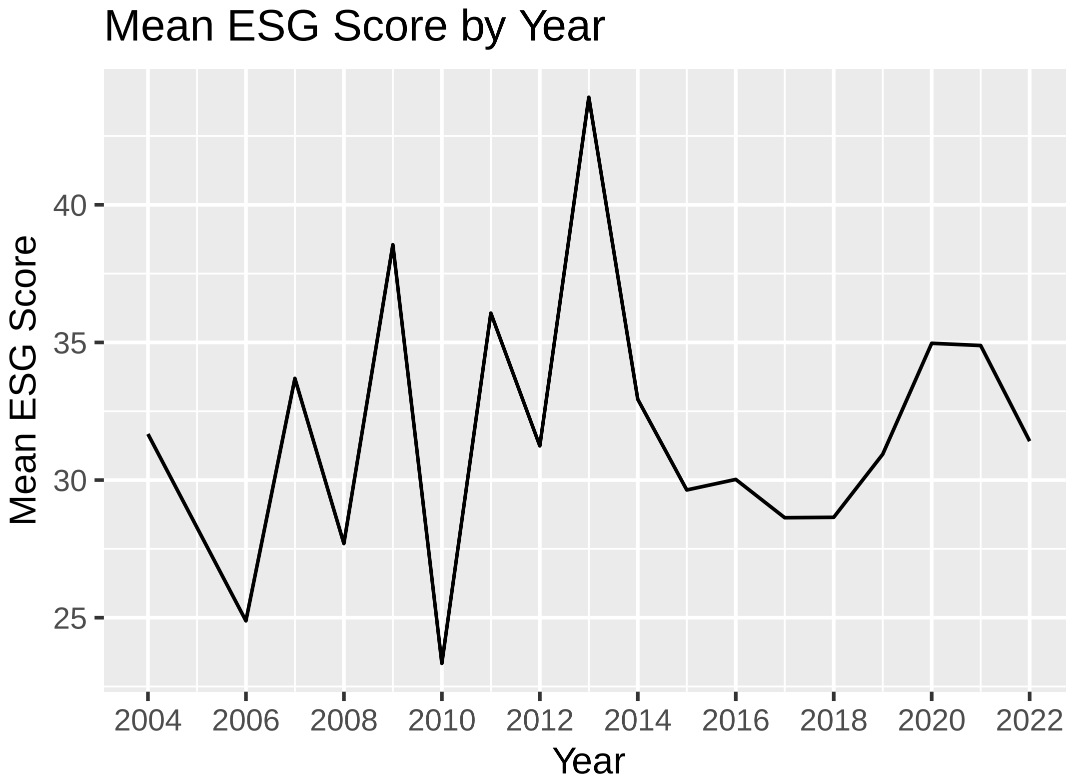
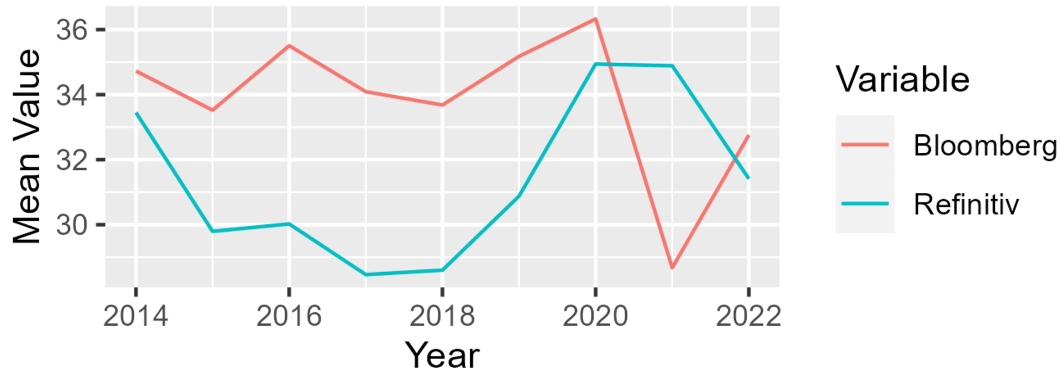


Table 20: **CAR Statistics, sample 2014-2022**

The table presents Mean, Median and standard deviation of the three market models, with different event windows.

Variable	Mean	Median	SD
Car MM (0,1)	-0.0091	-0.0304	0.2273
Car MM (-1,1)	0.0048	-0.0309	0.2781
Car FF (-1,1)	-0.0012	-0.0349	0.2775
Car FFM (-1,1)	-0.0016	-0.0338	0.2778
Car MM (-3,3)	0.0225	-0.0197	0.3078
Car FF (-3,3)	0.0097	-0.0307	0.3081
Car FFM (-3,3)	0.0092	-0.0310	0.3088
Car MM (-3,11)	0.0276	-0.0126	0.3234
Car FF (-3,11)	0.0028	-0.0312	0.3252
Car FFM (-3,11)	0.0019	-0.0319	0.3263

Figure 2: Upper graph shows the mean ESG score for Refinitiv and Bloomberg per year. The lower table shows the mean Car from Adjusted market model with event windows (0,1), (-1,1), (-3,3), and (-3,11)



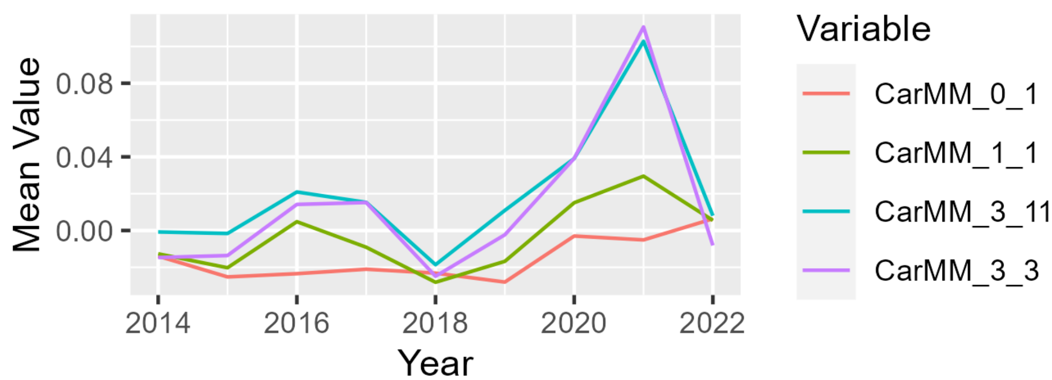


Table 21: **Correlation Matrix Sample 2004-2013**

The table presents the correlation matrix of the variables used in the augmented regression.

	Bloomberg	MTB	Slack	LnTA	RunUp	Leverage	Opacity	ROA	Volatility	RelOfersize
MTB	-0.0378									
Slack	-0.2396	0.1041								
LnTA	0.4204	-0.1332	-0.6619							
RunUp	0.0664	0.0250	0.0015	0.0763						
Leverage	-0.1349	0.0284	-0.2180	0.1419	0.0477					
Opacity	0.3285	-0.0001	-0.1728	0.4762	0.0806	-0.0900				
ROA	0.1799	-0.0962	-0.5767	0.5790	-0.0052	-0.0893	0.2361			
Volatility	0.0180	0.4012	-0.1024	0.1100	0.0290	0.0763	0.1069	0.1037		
RelOfersize	-0.1627	0.0867	0.5264	-0.5496	-0.0510	-0.1134	-0.0556	-0.3915	-0.0404	
AssetTangibility	0.1522	-0.0548	-0.4110	0.2411	0.0791	0.0488	0.2299	0.0632	-0.0709	-0.1644

Table 22: Showes the reported use of proceeds when announcing SEO. Obtained from SDC Platinum. Sample 2014-2022

Types of Observations	
Acq'n of Securities	1
Acquisition Fin.	5
Capital Expenditures	3
Future Acquisitions	8
General Corp. Purp.	943
Investment / Loan	6
Marketing & Sales	9
Medical	7
Pay Fees & Expenses	12
Payment on Borrowings	9
Prod Dev / R&D	10
Reduce Indebtedness	12
Secondary	123
Working Capital	17

Table 23: **Regression with High ESG**

The table shows regression with high ESG scores. T-statistics clustered standard errors by industry are reported in parentheses. Significance levels are indicated as follows: *** denotes significance at the 1 percent level, ** denotes significance at the 5 percent level, and * denotes significance at the 10 percent level.

Bloomberg	−0.0020			
	(0.0013)			
Refinitiv		−0.0003		
		(0.0005)		
HighESGBloomberg			−0.0188	
			(0.0249)	
HighESGRefintiv				−0.0117
				(0.0119)
Opacity	0.0012	0.0012	0.0011	0.0011
	(0.0035)	(0.0038)	(0.0037)	(0.0038)
Volatility	−0.0005	−0.0004	−0.0005	−0.0004
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Slack	0.1271***	0.1270***	0.1226***	0.1256***
	(0.0330)	(0.0347)	(0.0304)	(0.0333)
AssetTangibility	0.0099	0.0084	0.0079	0.0087
	(0.0149)	(0.0153)	(0.0141)	(0.0146)
Leverage	0.0371	0.0360	0.0363	0.0363
	(0.0265)	(0.0264)	(0.0270)	(0.0265)
ROA	0.0716***	0.0723***	0.0720***	0.0731***
	(0.0222)	(0.0231)	(0.0216)	(0.0233)
LnTA	0.0200***	0.0161***	0.0173***	0.0161***
	(0.0053)	(0.0058)	(0.0050)	(0.0041)
MTB	−0.0001	−0.0001	−0.0001	−0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)
RelOfersize	0.0740*	0.0719*	0.0725*	0.0720*
	(0.0406)	(0.0396)	(0.0399)	(0.0396)
SecondaryOffering	0.0379***	0.0353***	0.0341**	0.0354***
	(0.0139)	(0.0136)	(0.0137)	(0.0134)
PennyStock	0.0007	−0.0006	−0.0004	−0.0007
	(0.0199)	(0.0206)	(0.0202)	(0.0209)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	763	763	763	763
Adjusted R^2	0.0334	0.0296	0.0306	0.0302