THE COST OF A CLIMATE CONVERSATION

How climate and sustainability awareness affect the cost of capital for green and brown firms in the Nordics

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Abstract

This thesis empirically tests the relationship between changing public climate awareness and the weighted average cost of capital (WACC) for green and brown firms in the Nordics, one of the world's most ESG progressive regions. Using firm-level financial data and constructing the CSAI, a novel media-based index derived from textual analysis, we find that green firms enjoy a baseline WACC advantage, echoing previous findings that green firms are less exposed to climate-related risks, and therefore lowering investors' required return. However, periods of unexpectedly heightened public awareness surprisingly reduce financing costs for *both* green and brown firms, with moderately stronger effects observed for brown firms, suggesting a temporary "green convergence", whereby climate awareness shocks function as a market-wide repricing mechanism as opposed to penalizing brown firms. While we find partial support in existing literature, we discuss three additional explanations for this phenomenon: (1) the unique sustainability dynamics and ESG baseline within Nordic markets, (2) behavioral aspects such as halo effects, herding and investor optimism bias, and (3) methodological constraints, including potential endogeneity concerns.

Key words:

ESG; Nordic green and brown firms; WACC; climate change news; textual analysis

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List of abbreviations

ESG	Environmental, Social, and Governance
CSAI	Climate and Sustainability Awareness Index
WACC	Weighted Average Cost of Capital
BTM	Book-To-Market
LEV	Leverage
ROA	Return on Assets
H1	Hypothesis 1
H2	Hypothesis 2
H3	Hypothesis 3
OLS	Ordinary Least Squares
HC1	Heteroskedasticity-Consistent (standard errors type 1)
HC3	Heteroskedasticity-Consistent (standard errors type 3)
VIF	Variance Inflation Factor
GICS	Global Industry Classification Standard
SDG	Sustainable Development Goals
GHG	Greenhouse Gas
CSRD	Corporate Sustainability Reporting Directive
ESRS	European Sustainability Reporting Standards
IFRS	International Financial Reporting Standards
ISSB	International Sustainability Standards Board

1. Introduction

"Many people see our fight against climate change as a cost. Yes, it may be to a certain extent, but it's also a great opportunity" – Klaus Schwab[1], Founder, World Economic Forum

1.1 Background

Climate change is undoubtedly an issue of contemporary relevance with an increasing impact on societies worldwide, shaping economic, societal, and political landscapes in profound ways. As such, addressing and integrating sustainability considerations has become an increasingly prominent concern within global financial markets, reshaping investor perceptions and influencing corporate decision-making (Bolton & Kacperczyk, 2020; Friede et al., 2015; Giglio et al., 2021). Investors now recognize climate risk, both physical and transitional, as an influencing factor in corporate valuations, driving a profound shift toward integrating environmental, social, and governance (ESG) criteria into investment strategies and philosophies (Bolton & Kacperczyk, 2020; El Ghoul et al., 2011; Magnanelli & Izzo, 2017; Oikonomou et al., 2014). To this regard, prior literature proposes a risk-based perspective where firms classified as environmentally sustainable ("green") are perceived as lower-risk investments compared to less sustainable ("brown") counterparts, reflected in a lower required return, or cost of capital, for green companies. Concurrently, measuring public discourse and societal awareness around climate change have emerged as a relatively nascent research area, with scholars examining how a shifting sentiment around climate and sustainability influences investor behavior, and various dimensions of firm financial performance (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020).

1.2 Motivation

Understanding the financial implications of firm ESG performance and the effect of climate and sustainability awareness is of high relevance, both from a theoretical and practical perspective. Prior studies have demonstrated the existence of financial benefits for firms exhibiting superior ESG performance, mainly through reduced cost of equity and debt (Bolton & Kacperczyk, 2020; Chava, 2014; El Ghoul et al., 2011). However, as global climate concerns intensify and fluctuate, financial markets increasingly respond not only to firm-level ESG disclosures but also to broader shifts in public sentiment driven by media coverage (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020).

In light of these dynamics, this thesis investigates how changes in public climate and sustainability discourse interact with firm sustainability performance to influence corporate financing costs. Clarifying these relationships is particularly interesting within the context of the Nordic countries, recognized globally for its sustainability leadership and progressive investor base. As of December 2024, Denmark, Finland, Sweden, and Norway constituted the global top four countries in Robeco's annual country sustainability ranking, where each

[1] The quote was published in a Business Insider article (Ward, 2021).

country is assessed against the Sustainable Development Goals (SDG) and other criteria (Robeco, 2024; United Nations; 2025). As such, the Nordics provide a unique environment to study how public sustainability sentiment affects capital allocation. In particular, with the recent implementation of the European Reporting Standards (ESRS) under EU's Corporate Sustainability Reporting Directive (CSRD), understanding the financial implications of sentiment driven effects has gained increased contemporary relevance.

1.3 Research gap and question

Despite previous research investigating the areas of ESG performance, public sentiment around climate, and implications on firm-level financing costs, significant research gaps remain in combining these dimensions. Firstly, existing literature predominantly investigates ESG performance and implications for equity or debt financing separately, with relatively few studies explicitly examining the overall weighted average cost of capital (WACC) as a holistic measure of firm financing costs (Mariani et al., 2021; Piechocka-Kaluzna et al., 2021). Secondly, while the role of public climate sentiment has been explored with respect to stock returns and short-term asset pricing (Ardia et al., 2023; Engle et al., 2020; Kapfhammer et al., 2020), the direct influence of climate awareness on firms' financing conditions, more specifically firms' cost of capital as measured by WACC, remains underexplored. Thirdly, limited research has empirically tested how heightened public climate discourse might amplify existing financial disparities between green and brown firms, particularly within a regional context such as the Nordic market, despite its leading role in ESG. To the best of our knowledge, no previous study has combined these dimensions in a single analysis. As such, the research question, which aims to contribute to filling the aforementioned research gaps through a quantitative empirical analysis, is formulated as follows:

What is the effect of a changing public climate and sustainability awareness on the weighted average cost of capital for green and brown firms in the Nordics?

1.4 Contribution

Addressing these gaps, this thesis contributes to existing theory by empirically analyzing how unexpected public climate awareness affects the WACC of Nordic firms classified as green or brown based on their ESG performance during the five year time period 2020-2024. To capture this effect, a novel climate and sustainability awareness index (CSAI) has been developed based on textual analysis of articles from country-specific Nordic media outlets, as well as the Financial Times (FT) and the Wall Street Journal (WSJ).

Our findings present several contributions. Firstly, we find statistically significant support of green firms benefiting from a baseline cost of capital advantage relative to brown firms, aligning with risk-based theoretical perspectives in previous literature (Chava, 2014; El Ghoul et al., 2011; Oikonomou et al., 2014). Secondly, we observe a novel and counterintuitive phenomenon; heightened climate and sustainability awareness unexpectedly reduces the WACC for both green and brown firms, suggesting a market-wide repricing of climate-related risks rather than a selective penalty for lower ESG performers. This empirical

finding, which contradicts our prediction, challenges the expectation that climate awareness shocks primarily penalize brown firms. Rather, it introduces the concept of a "green convergence", whereby unexpected increased public climate attention temporarily compresses the financial gap between green and brown firms. These results were mirrored, though contextually nuanced, in a subsequent industry-specific analysis, which, despite low statistical power due to small sample sizes, proposed somewhat magnified and opposite effects in some industries, highlighting the sectoral heterogeneity in our sample and echoing that investor responses are context dependent (Ardia et al., 2023; Ilhan et al., 2021).

Overall, the results suggest that unexpected climate and sustainability awareness could function as an equalizer, rather than a discriminator, in ESG progressive capital markets. This could stem from behavioral dynamics such as herding, optimism bias, or structural context specific factors such as the relatively high ESG baseline even among firms classified as brown in the Nordic region. However, several methodological constraints, including the short time horizon with quarterly aggregations, potential flaws in the underlying ESG data, subsequent classification biases, and unaddressed endogeneity, underscore the need for interpretative caution. While these limitations do not undermine the empirical insights offered, they do frame the contribution of this thesis as exploratory in nature, providing a basis for further empirical testing rather than definitive causal claims. Within that scope, the results suggest a developing market logic in which firms' financing costs are shaped not only by ESG fundamentals, but also by shifts in public awareness, introducing a dynamic repricing mechanism that temporarily benefits both green and brown firms, albeit through potentially different channels.

These findings contribute to a more dynamic understanding of how ESG performance and external climate sentiment jointly influence capital allocation. They support the notion that capital markets do not always respond to sustainability narratives in a linear or static manner. Instead, investor reactions appear contingent on contextual and behavioral factors, and may temporarily generate convergence effects in financing costs across the ESG spectrum. Accordingly, the findings bear both theoretical and practical implications, e.g., for corporate managers in strategic sustainability communication and investors integrating dynamic ESG considerations into investment strategies.

1.5 Structure of the thesis

The remainder of the thesis is structured as follows. Section 2 provides a literature review and hypotheses development, covering previous academic articles exploring the role of ESG performance in shaping firms' financing costs, and prior literature examining the role of public climate and sustainability discourse and firm implications. Section 3 outlines the empirical data and methodology. Further, section 4 presents the results and empirical analyses, while section 5 discusses these findings relative to prior literature and their broader implications. Section 6 outlines limitations, and section 7 suggests directions for future research. Lastly, section 8 concludes the thesis by summarizing its core findings and contribution.

2. Literature review and hypotheses development

This part of the thesis first sets out to explore previous research findings and perspectives in the domain of firm sustainability performance and its effect on cost of capital. Said literature is mostly rooted in investors' risk-mitigation view with regards to the intersection of ESG performance and financing costs, supporting the formulation of the first hypothesis. Thereafter, we introduce the dimension of public discourse. Specifically, we explore previous academic papers examining the role of changing awareness around climate and sustainability and how said sentiment has been found to affect firm financial performance and capital costs. This latter part constitutes the basis against which the second and third hypotheses are developed.

2.1 Previous research on sustainability performance and cost of capital

Climate change has increasingly been recognized as a source of risk, reflected in a growing body of literature on the interplay between climate-related factors and financial markets (Friede et al., 2015; Giglio et al., 2021; Martinez-Diaz & Keenan, 2020; Nordhaus, 1977). Early research in sustainable finance has explored how both physical risks (e.g., extreme weather events) and transition risks (e.g., policy changes, technological shifts) associated with climate change are priced in assets ranging from real estate to equities and bonds (Giglio et al., 2021; Nordhaus, 1977), often finding a positive relationship between ESG and financial performance. In fact, when aggregating over 2,200 empirical studies on ESG and financial performance, Friede et al. (2015) found a positive relationship in roughly 90% of the articles.

A key question in this dynamic is whether firms with greater climate risk exposure or weaker sustainability profiles face a higher cost of capital. In theory, if investors anticipate that carbon-intensive or climate-vulnerable firms will incur future costs (such as carbon taxes, stricter regulations, or damage from climate events), they will demand higher returns for bearing these risks (Bolton & Kacperczyk, 2020; Chava, 2014). Conversely, companies with strong environmental performance or credible emission-reduction policies and strategies might be viewed as safer and attract long-term, sustainability-focused investors (e.g., sovereign wealth funds and pension funds), potentially lowering their required returns (Bolton & Kacperczyk, 2020; El Ghoul et al., 2011; Ng & Rezaee, 2015).

Accordingly, a central premise in this literature is that strong ESG performance signals better management of climate‑related and reputational risks, thereby mitigating perceived uncertainty and ESG-related risks, translating into lower financing costs (Chava, 2014; El Ghoul et al., 2011; Oikonomou et al., 2014). However, contradictory evidence also exists, where some studies find only a weak or inconsistent link between ESG and reduced cost of capital. Such discrepancies are often tied to contextual factors, for instance, varying definitions of firm-level financial performance and cost of capital, geographical differences, industry-level exposures, or evolving data availability, that shape how investors interpret sustainability metrics (Gonçalves et al., 2022; Magnanelli & Izzo, 2017; Menz, 2010). The

following subsections (2.1.1 and 2.1.2) elaborate on both perspectives, ultimately culminating in the formulation of the first hypothesis (section 2.1.3).

2.1.1 The risk perspective: a driver of lower cost of capital for green firms

Many researchers examining the intersection of sustainability performance and its implication on firms' financing costs posits that strong ESG performance leads to lower cost of capital, constituting a risk perspective where firms with a strong ESG performance are perceived as less risky. In other words, superior sustainability performance can serve as a risk mitigant where green firms (as opposed to brown firms), all else equal, have a lower exposure to climate-related risks. For example, El Ghoul et al. (2011) observe that higher CSR ratings correlate with significantly lower cost of equity, suggesting investors demand smaller risk premiums from green firms. Goss & Roberts (2011) find comparable patterns in U.S. debt markets, where banks impose lower loan spreads on green firms demonstrating strong corporate sustainability performance while penalizing those with major ESG concerns by 7-18 basis points. Caragnano et al. (2020) find a consistent pattern in European debt markets when analyzing firms' environmental risk profiles. Collectively, these findings reinforce the notion that by minimizing environmental liabilities, reputational damage, and governance shortfalls, superior ESG performance reduces the return required by capital providers, be it equity or debt investors (Apergis et al., 2022; El Ghoul et al., 2011; Goss & Roberts, 2011; Ng & Rezaee, 2015; Oikonomou et al., 2014; Sharfman & Fernando, 2008).

Notably, most of these studies have analyzed cost of equity and cost of debt separately, leaving relatively few that explicitly consider the weighted average cost of capital (WACC). Mariani et al. (2021) address this gap, showing that green firms in Europe, classified through a third‑party emissions score, enjoy a lower WACC, irrespective of industry membership. Similarly, Piechocka-Kaluzna et al. (2021) find consistent dynamics in a U.S. context. As such, the aforementioned scholars highlight that capital markets respond to environmental performance in ways that extend beyond isolated equity‑ or debt‑based effects. Despite these insights, a pronounced research gap remains in exploring how ESG‑driven risk mitigation translates to firms' overall cost of financing, thus warranting further empirical investigation into WACC outcomes specifically.

Complementary evidence on the risk‑cost of capital mechanism comes from the scholars examining firms' carbon emissions. For instance, Matsumura et al. (2014) found that higher‑emission firms face lower valuations, implying an elevated cost of capital. They also observe that firms concealing their emissions endure even steeper penalties, underscoring the value of climate transparency. Recent asset‑pricing work by Bolton & Kacperczyk (2020) mirrors these findings, showing that companies with greater carbon intensity earn higher subsequent returns (around 0.15% per standard deviation of emissions), a pattern consistent with investors demanding a carbon‑risk premium to offset perceived vulnerabilities. They also noted that institutional investors increasingly implement exclusionary screenings on certain sectors based on various ESG-criteria, including certain Nordic investors, e.g., the Swedish pension funds. In essence, their findings contribute to the notion that heavier emitters confront a higher cost of capital, aligning with the broader narrative that poor

environmental performance magnifies risk. Taken together, these emission-focused findings reinforce the core proposition that better climate stewardship alleviates investor concerns, translating into lower financing costs. (Bolton & Kacperczyk, 2020; Lemma et al., 2019; Maaloul, 2018; Matsumura et al., 2014)

2.1.2 Contradicting and contextual perspectives

Despite a broad academic consensus that stronger ESG performance can lower a firm's capital costs, a number of contradictory or inconclusive findings underscore the complexity of this relationship. For instance, Gonçalves et al. (2022) find that while better ESG scores often reduce the cost of equity, they can concurrently raise the cost of debt, suggesting that different capital providers react divergently to sustainability indicators. Similarly, Ernst & Woithe (2024) show that while firms in the S&P 500 with better ESG performance do enjoy lower costs of equity and debt, their higher ESG ratings do not necessarily translate into lower WACC, proposing that capital structure nuances can offset potential financing benefits. Magnanelli & Izzo (2017) also observe a positive link between leading ESG performance and the cost of debt, hypothesizing that over-investment in sustainability might prompt concerns about managerial agency or reduced shareholder returns. Similarly, Menz (2010) reports only a minor bond-pricing benefit for green firms, casting doubt on whether ESG consistently confers financial advantages across all debt markets.

Several contextual factors shed nuance to these inconsistencies. Firstly, the choice of financial dependent variable varies across studies, with some focusing on realized returns (alpha or excess returns), while others examine *ex ante* financing costs such as the cost of debt or equity. These methodological differences can complicate cross-study comparisons (Friede et al., 2015). Secondly, geographic considerations frequently reveal a U.S.-centric bias, leaving smaller or specialized markets, like the Nordics, relatively under-examined (Mariani et al., 2021). Thirdly, industry membership can moderate ESG's effect on financing costs, as carbon-intensive or resource-heavy sectors face distinct transition and regulatory risks (Ilhan et al., 2021). Lastly, a temporal dimension arises because investor awareness and ESG data quality have evolved considerably in recent years (Pástor et al., 2021), implying that older findings may no longer capture current market behavior.

Taken together, these studies reaffirm that while the dominant trajectory of the literature aligns with a risk-mitigation argument, ESG's impact on cost of capital is not unequivocally unidirectional. In particular, context, whether defined by measurement choices, regional factors, or industry characteristics, appears crucial in shaping the ESG-financing costs intersection. Thus, although the evidence broadly supports the notion that ESG leaders benefit from cheaper financing, inconsistencies in theory and a scarce number of studies explicitly exploring the effect on WACC, warrants further investigation into this relationship.

2.1.3 First hypothesis: Baseline difference in WACC between green and brown firms

Building on the risk perspective in section 2.1.1, the overall academic stance suggests that strong ESG performance reduces firms' overall risk, manifesting in cheaper equity and debt

financing (El Ghoul et al., 2011; Goss & Roberts, 2011; Oikonomou et al., 2014; Sharfman & Fernando, 2008). Mariani et al. (2021) and Piechocka-Kaluzna et al. (2021) extend this and demonstrate that green firms exhibit lower WACC, suggesting that capital markets do, in fact, reward strong ESG performance with a lower overall financing cost. Although certain studies have documented mixed or even opposite effects, as noted in section 2.1.2, the consensus still leans toward viewing robust a sustainability profile and rating as a strategic buffer against climate‑related and reputational liabilities (Bolton & Kacperczyk, 2020; Friede et al., 2015; Ng & Rezaee, 2015).

As such, we formulate following hypothesis:

H1: *Green* firms have a *lower* WACC than *brown* firms, all else equal.

2.2 Public climate awareness and cost of capital

A more nascent domain of research, which forms the basis for the second and third hypotheses of this thesis, is the role of climate change awareness and public discourse in shaping investor's financial decision-making, specifically concerning the cost of capital. As such, recent studies go beyond firm-specific ESG metrics and examine the broader effect of public sustainability sentiment on financial markets. This line of inquiry asks whether broader awareness of climate issues – reflected in media, politics, and society – can influence investor behavior, firm valuations and market prices (Ardia et al., 2023; Engle et al. 2020). If the world is talking more about climate change, do capital markets respond by reallocating capital toward greener firms, thus leading to a lower cost of capital? And how does this dynamic play out for brown firms?

This section first examines previous articles using media coverage as a proxy for public awareness (2.2.1), to then elaborate on previous scholars who have adopted this approach and leveraging textual analysis as the basis for empirical findings in the intersection of climate awareness and financial implications for green and brown firms (section 2.2.2). This literature then constitutes the foundation against which the second and third hypotheses are formulated (see section 2.2.3 and 2.2.4, respectively).

2.2.1 How media discourse serves as a proxy for public climate awareness

Several studies underscore that mass media serve as a powerful driver of public awareness regarding environmental issues, including climate change (Ardia et al., 2023; Boykoff & Boykoff, 2007; Hale, 2010; Sampei & Aoyagi-Usui, 2009; Schoenfeld et al., 1979; Slovic, 1986). Media influence on societal perceptions can be understood along two principal dimensions: first, through the substance of the information conveyed in news articles, and second, via the magnitude of coverage dedicated to a particular topic (Kasperson & Kasperson, 1996; McCombs & Shaw, 1972). Both dimensions are highly pertinent to climate change, where most individuals have limited direct exposure to severe climate-related impacts, many of which are projected to intensify in the future (Leiserowitz, 2005; Moser &

Dilling, 2007). In turn, media outlets become the predominant source of knowledge on environmental threats, effectively "setting the agenda" for public discourse and risk perceptions (Boykoff, 2011).

From a theoretical standpoint, the dependency model advanced by Ball-Rokeach & DeFleur (1976) further suggests that media narratives critically shape individual beliefs and attitudes, particularly when firsthand experience of an issue is scant. Since climate change is often perceived as complex, long-term, and geographically diffuse, the media's framing and frequency of coverage significantly influence public concern, policy preferences, and even investment behaviors (Ardia et al., 2023; Engle et al., 2020; Slovic, 1986). This dynamic underscores why fluctuations in media discourse, whether measured by the volume of climate-related reporting or the prominence of specific narratives, can serve as a meaningful barometer of evolving climate awareness and concerns (Ardia et al., 2023; Bua et al., 2022; Engle et al. , 2020; Sampei & Aoyagi-Usui, 2009).

Accordingly, changes in media discourse holds empirical legitimacy in being used as a practical proxy for broader shifts in public climate sentiment.

2.2.2 Previous research on public climate awareness and financial implications for firms

Following several studies on the impact of news and stock prices (Bollen et al., 2011; Chen et al., 2013; Hillert et al., 2014), Engle et al. (2020) were among the first to quantify climate change news and examine its financial impact, introducing a global "climate change news index" based on major news publications. By using textual analysis on outlets such as the Wall Street Journal, BBC, CNN, and the New York Times, Engle et al. (2020) created two media-based indices: one derived from a proprietary climate change vocabulary (CCV) and another from a third‐party software scanning for negative‐sentiment articles containing the search term "*climate change*". Their key finding is that unexpected changes in climate news can be traded as a risk factor, indicating that heightened discourse around climate issues influences asset pricing. Although Engle et al. (2020) focus primarily on stock returns and short‐term hedging strategies, their work establishes a methodological foundation for using media‐based climate awareness as a driver of market outcomes.

Building on Engle et al. (2020), and based on the Pástor et al. (2021) prediction that green firms outperform brown firms when climate change concerns increase unexpectedly, Ardia et al. (2023) introduced the media climate change concerns (MCCC) index, which tracks the frequency of "*climate change*" mentionings across ten prominent U.S. newspapers, regressed against S&P 500 companies. Ardia et al. (2023) confirmed the aforementioned prediction and highlighted that days with heightened unexpected climate change concerns often see green stocks outperform brown stocks. When running the same regressions on separate industry samples, the effect was found to be particularly pertinent in a handful of sectors (e.g., energy, utilities, and materials), while being smaller or statistically insignificant in others. Furthermore, Ardia et al. (2023) decomposed firms' returns into cash flow and discount rate components. Their evidence indicates that a substantial portion of green firms' outperformance stems from a lower discount rate for green firms during periods of

unexpected climate change concerns, implying that investors perceive these firms as less risky, or more favorably poised to handle environmental challenges. By contrast, brown firms face a higher discount rate (i.e., higher implied cost of capital), which can erode their market valuations. This decomposition is particularly relevant to the hypotheses in this thesis, suggesting that public awareness not only affects price levels but also the underlying financing costs of firms, as elaborated in section 2.2.3 and 2.2.4.

Other scholars adopt similar approaches, albeit often focusing on market returns. For instance, Bua et al. (2022) distinguish between physical climate risk news and transition risk news in European contexts. They find that both types of news coverage elevate risk premia for *brown* firms, with the effect intensifying post‑2015 (the Paris Agreement). Although Bua et al. (2022) do not explicitly analyze cost of capital, their results underscore the broader principle that heightened climate discourse systematically influences investor risk assessments, with investors demanding compensation for exposure to climate related risks. Bessec & Fouquau (2021), Faccini et al. (2021), Kapfhammer et al. (2020), and Maeso & O'Kane (2023) similarly investigate how climate‑related news or attention metrics feed into stock returns, real exchange rates, or commodity‑based currency pricing. While their specific contexts vary, ranging from U.S. equity markets to global exchange rates, the shared conclusion is that media‑driven climate sentiment can alter how investors price risk and allocate capital.

Thus, the unifying theme across these studies is the signaling power of climate‑related media coverage: as news volume or tone shifts, so too do investor perceptions of climate risks, amplifying the reward‑to‑risk trade‑off for green versus brown firms. Although most of this work emphasizes short‑term returns, the underlying mechanism, adjustments in risk premiums, logically extends to a firm's broader financing costs, including the weighted average cost of capital (WACC).

Comparison of media-based indices for climate and sustainability awareness

For a more nuanced understanding of how researchers previously have constructed media-based indices to capture public climate discourse, and, where applicable, classify firms as green or brown, table 1 provides a comparative overview of several key studies. It highlights each paper's research question, dependent variable, geographic scope, time frame, and the approach used to differentiate green from brown firms.

Table 1. Overview and comparison of textual analysis used to create climate change-related media index models

Paper	This paper (2025)	Engle et al. (2020)	Ardia et al. (2023)	Bua et al. (2022)	Kapfhammer et al. (2020)	Faccini et al. (2021)	Bessec & Fouquau (2021)	Maeso & O'Kane (2023)
Research question	The effect of changing climate awareness on WACC for green/brown firms	How climate change news could be used to hedge climate related risks	Climate change concerns and the effect on stock performance for green/brown firms	Climate risk premia for physical and transition in EU stock returns	Climate risk and its influence on pricing/returns of commodity-based currencies	Climate change risks and pricing in the U.S. stock market	Effect of environmental issues and stock prices in the US	The impact of climate change on low-minus-high carbon intensity portfolios
Dependent variable	WACC	Hedge portfolio return (CCt)	Returns, later decomposed	Excess return	Real exchange rate	Stock return	Excess return	Excess return
Geography	Nordic firms	Global (S&P 500)	U.S (S&P 500)	EU (SXXP)	Global	U.S. firms	U.S (S&P 500)	Global
Distinction of firms	Classification based on third party ESG-score	E-pillar scores from MSCI and Sustainalytics	Based on GHG-intensity	GHG-intensity, E-pillar score, and ESG-score	N.A	N.A	Based on GHG-intensity	Based on GHG-intensity
Time period	2020-2024	2008-2017	2010-2018	2005-2021	2001-2019	2012-2018	2010-2020	2005-2021
Index aims at capturing	Climate change awareness	Intensity of negative CC news	Climate change concerns (MCCC)	Intensity of climate risk news	Country-specific transition risks	Attention to climate risks	Attention and tonality about CC	Five dimensions about CC news
Corpus of news media	Nordic business newspapers, FT, and WSJ	Used software to search across 10k+ news outlets	Ten U.S. newspapers, two newswires	English articles on Reuters news	Dow Jones corpus, including WSJ	English articles on Reuters news	Four newspapers (NYT, WP, WSJ, and USA Today)	Five newspapers (FT, DT, UKG, LAT and NYT)
Articles' selection	Articles containing "climate change" and the equivalent in the Nordic languages	Articles containing "climate change", filtered for negative tonality	Articles tagged "climate change". Keyword filters applied	Only news with European focus	None	Articles containing "climate change" or "global warming"	Articles tagged "Economic news", "Commodity/financial market news"	Articles containing "climate change" and/or "global warming"
Relevant feature per article	Measures *attention* and *awareness*	Measures share of negative climate change news	Measures concerns, combination of attention and polarity	Same approach as Engle et al. (2020), with risk specific CCV	Measures attention between eight countries and climate risk	Measures attention using topic shares	Measures attention based on an environmental dictionary	Measures attention, concern, and tonality
Frequency	Daily/quarterly	Monthly	Daily/monthly	Daily	Monthly	Daily	Weekly	Daily

***Note**: Engle et al. (2020) constructed two indices, one based on CCV and WSJ and one index based on a third party software, which bears more relevance here.*

As shown in table 1, many of these papers focus on returns (e.g., Bua et al. (2022) and Engle et al. (2020) concentrate on equity pricing) or broader macro variables (e.g., real exchange rates in Kapfhammer et al. (2020)). Notably, few explicitly analyze the cost of capital. While Ardia et al. (2023) center on stock returns, their decomposition of returns into a cash‐flow component and a discount‐rate component effectively captures changes in cost of capital for green and brown firms, albeit without explicitly measuring WACC. Beyond that, the classification of green versus brown varies substantially: some authors rely on carbon intensity (Ardia et al., 2023; Bua et al., 2022; Maeso & O'Kane, 2023), others use different forms of ESG scores provided by third party data providers (e.g., MSCI, Refinitiv, and Sustainalytics), and others omit green versus brown distinctions altogether. This diversity reflects ongoing debates in sustainable finance over how best to define socially and environmentally responsible behavior (Berg et al., 2022; Cornell & Damodaran, 2020).

With these foundations in place, the next sections introduce our second and third hypotheses, which propose that heightened climate awareness exerts opposite effects on green and brown firms (H2) and potentially magnifies their WACC gap (H3).

2.2.3 Second hypothesis: Changing climate change awareness and the effect on WACC

While previous literature referenced in section 2.1 highlighted that firm-level ESG performance influences financing costs for green and brown firms, section 2.2 introduced the dimension of public climate awareness, which has been found to further amplify and affect these ESG-related dynamics. Therefore, as a natural extension of H1, and given the research question formulated in section 1.3, the second hypothesis, which is divided into two sub-hypotheses, aims investigate how unexpected spikes in media coverage and public sentiment around climate and sustainability affect the cost of capital of green and brown firms, respectively. Several recent studies suggest that heightened climate and sustainability awareness give rise to investors' being more mindful of environmental risks and opportunities (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020). By extrapolation, firms perceived as environmentally sustainable may experience a further reduction in their financing costs when climate and sustainability awareness unexpectedly increases, while brown firms could see a rising cost of capital due to heightened perceived risk.

Hence, the second hypothesis is subdivided into two complementary parts:

H2 (a): In periods of unexpected heightened climate and sustainability awareness, the WACC of Nordic *green* firms *decreases.*

H2 (b): In periods of unexpected heightened climate and sustainability awareness, the WACC of Nordic *brown* firms *increases.*

2.2.4 Third hypothesis: Magnification of WACC differences between green and brown firms

While H2 proposes that green and brown firms respond in opposite directions to heightened awareness, an outstanding question is whether these divergent effects magnify the hypothesized gap in their overall financing costs (i.e., H1). Put differently, if green firms see a more pronounced WACC reduction than brown firms' increase, the green-brown differential in financing costs could widen, especially when climate awareness is unexpectedly heightened.

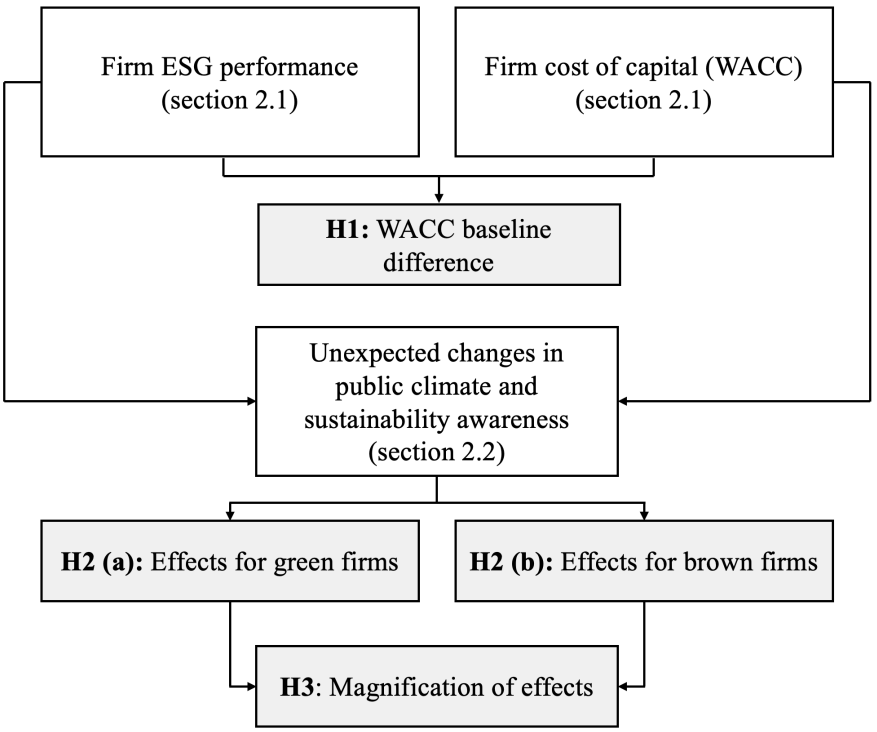
Empirical findings in sections 2.1 and 2.2 note that strong ESG performance can lower risk premiums (El Ghoul et al., 2011; Mariani et al., 2021), and that media coverage can intensify how markets value environmental performance (Ardia et al., 2023; Engle et al., 2020). Yet, few studies explicitly test the combined effect of firm‑level ESG profiles and real‑time shifts in climate awareness on blended financing costs. This gap suggests that green firms may reap disproportionate benefits, whereas brown firms endure sharper penalties, amplifying their WACC difference in periods of heightened climate news.

Based on this logic, we formulate:

H3: During periods of unexpected heightened climate and sustainability awareness, the WACC gap between green and brown firms *widens*.

Finally, all developed hypotheses in section 2 are summarized in table 2 below.

Table 2. Summary of the developed hypotheses and sections for underlying theoretical justification



3. Data and methodology

3.1 Research design

Building on the literature and research gaps outlined thus far, this study employs a quantitative approach on an unbalanced panel dataset to examine how unexpected changing climate change awareness, captured by a novel media-based index, affects the WACC for green and brown firms. Specifically, we focus on a cross section of publicly listed companies in Sweden, Norway, Denmark, and Finland, collectively referred to as the Nordics. We analyze quarterly firm-level financial data during a five year period between 2020-2024, including a conventional vector of controls used for WACC and other cost of capital metrics as the dependent variable (Caragnano et al., 2020; Friede et al., 2015; Lemma et al., 2019; Maaloul, 2018; Mariani et al., 2021).

To proxy public climate discourse, we construct a climate and sustainability awareness index (CSAI) using the open-source media data platform Media Cloud[2], following established text-analysis methods (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020). Firms are classified as green or brown based on ESG scores obtained from Refinitiv Eikon, consistent with methodological considerations based on e.g., Ardia et al. (2023) and Bolton & Kacperczyk (2020).

Our empirical models are multivariate OLS regressions with heteroskedasticity-robust standard errors type 3 (HC3), incorporating year-, industry-, and country-fixed effects. The dependent variable is WACC, while key explanatory variables are the CSAI and a green- versus brown-classification dummy. In order to facilitate an adequate testing of the formulated hypotheses, we will make adjustments in the model specification and the underlying data sample, i.e., running the regressions on the full sample for H1 and H3, and on a split sample for H2. For testing H3, we introduce an interaction term which will provide explanatory value and allow for interpretation of whether unexpected heightened public awareness around climate change exerts distinct impacts on financing costs for green versus brown firms. Accordingly, we run four regressions: one for H1, two split‑sample tests for H2 (a) and H2 (b), and one interaction model for H3.

In addition to the model specifications, variable definitions (section 3.3), sample selection (section 3.4), and pre-estimation diagnostics for multicollinearity (section 3.5) are also detailed in this section.

[2] Media Cloud is an open-source platform for analyzing digital media ecosystems, originally developed by the Harvard Berkman Klein Center and MIT Civic Media Center, that helps researchers study the flow of narratives in news media. Today Media Cloud is a consortium collaboration between University of Massachusetts Amherst, Northeastern University, and the Media Ecosystems Analysis Group.

3.2 Regression model

3.2.1 Regression model specifications

This study employs panel data OLS regressions to empirically test the four hypotheses (three main hypotheses, with H2 subdivided into H2 (a) and H2 (b)) developed in section 2. A multivariate specification allows for the inclusion of multiple explanatory variables, including an interaction term, thereby capturing the main effects and enabling a nuanced interpretation that differentiates between green and brown firms (Ardia et al., 2023; Gujarati, 2021; Wooldridge, 2010).

Beyond these key independent variables, the regression incorporates country-, year-, and industry-fixed effects to address unobserved heterogeneity and mitigate the risk of confounding shocks, which also helps reduce concerns related to endogeneity by controlling for time-invariant and contextual factors (Hsiao, 2014). Prior to specifying a fixed- or random-effects approach, we conduct a Hausman test (see table A1 in appendix), which evaluates the consistency of estimators under each framework (Hausman, 1978). The test results strongly indicate that we must reject the null hypothesis asserting equivalence between the random effects and fixed effects estimators. Consequently, a fixed effects specification is deemed more appropriate for our dataset, given the presence of potential correlation between firm-specific unobserved factors and the explanatory variables.

For the first hypothesis (H1), asserting that green firms have a structurally lower WACC compared to brown firms, the regression is conducted using the full sample of green and brown firms. The key explanatory variable of interest is the ESG classification dummy, D_{GREEN}, indicating whether a firm is classified as green (1) or brown (0). The main coefficient of interest is therefore β_1, and we anticipate a negative sign, reflecting lower baseline financing costs for green firms relative to brown counterparts, all else equal. The regression model is specified as follows:

$$WACC_{i,t} = \alpha + \beta_1 D_{GREEN_{i,t}} + \sum_k \beta_k X_{i,t,k} + \omega_{country} + \lambda_{year} + \delta_{industry} + \varepsilon_{i,t} \qquad (1)$$

where *i* denotes the firm index and *t* denotes the quarter.

For H2 (a) and H2 (b), we examine whether unexpected heightened climate awareness *decreases* $WACC$ for green firms (H2 (a)) and *increases* $WACC$ for brown firms (H2 (b)). For testing H2, we apply a split-sample approach, estimating two separate regressions.

H2 (a) investigates the effect of unexpected heightened climate and sustainability awareness on WACC for *green* firms *only*. Here, the green-firm subsample is exclusively analyzed, making $CSAI$ the main independent variable. The coefficient of primary interest is β_1 for $CSAI$ which is expected to be negative, indicating that heightened awareness leads to lower financing costs for green firms:

$$WACC_{i,t}^{GREEN} = \alpha + \beta_1 CSAI_{i,t} + \sum_k \beta_k X_{i,t,k} + \omega_{country} + \lambda_{year} + \delta_{industry} + \varepsilon_{i,t} \quad (2)$$

Conversely, H2 (b) examines whether unexpected heightened climate awareness increases WACC for *brown* firms. This regression uses only the brown-firm subsample. The main coefficient of interest remains β_1 for $CSAI$, but we now anticipate a positive sign, reflecting higher WACC for brown firms in response to unexpected spikes in climate awareness:

$$WACC_{i,t}^{BROWN} = \alpha + \beta_1 CSAI_{i,t} + \sum_k \beta_k X_{i,t,k} + \omega_{country} + \lambda_{year} + \delta_{industry} + \varepsilon_{i,t} \quad (3)$$

Finally, the third hypothesis (H3) addresses whether unexpected increases in climate awareness magnify the WACC gap between green and brown firms. The regression employs the full sample and introduces an interaction term between CSAI and the green/brown dummy to test whether unexpected changes in climate awareness impact financing costs differently for green and brown firms. Here, the interaction term $CSAI \times D_{GREEN}$ captures this differential effect, making its coefficient β_3 of primary interest. We expect this coefficient to be negative, suggesting that green firms experience a more pronounced reduction in WACC (or smaller increase) compared to brown firms, thereby widening the WACC gap during periods of unexpected increased climate awareness. The regression specification is:

$$WACC_{i,t} = \alpha + \beta_1 CSAI_{i,t} + \beta_2 D_{GREEN_{i,t}} + \beta_3 \left(CSAI_{i,t} \times D_{GREEN_{i,t}} \right) + \sum_k \beta_k X_{i,t,k} + \omega_{country} + \lambda_{year} + \delta_{industry} + \varepsilon_{i,t} \quad (4)$$

The following table 3 summarizes how each hypothesis corresponds to its respective model setup, including the main coefficient of interest and its expected sign:

Table 3. Hypotheses and regression model specifications overview

Hypothesis	Sample	Key coefficient	Expected sign
H1	Full sample	β_1 (D_{GREEN})	Negative (–)
H2 (a)	Green firms	β_1 ($CSAI$)	Negative (–)
H2 (b)	Brown firms	β_1 ($CSAI$)	Positive (+)
H3	Full sample	β_3 ($CSAI \times D_{GREEN}$)	Negative (–)

***Note**: All hypotheses and regressions control for firm-, country-, and industry-fixed effects.*

In all specifications, we employ heteroskedasticity-robust standard errors (HC3), ensuring the reliability of inference despite potential heterogeneity of variance across observations (White, 1980; Wooldridge, 2010). This detailed specification and explicit structuring clearly delineate our empirical approach and ensure transparency in hypothesis testing.

Table 4 below provides a brief description of each variable, which are outlined in detail in the next section.

Table 4. Regression model variable description

Variable	Description
$WACC_{i,t}$	Weighted average cost of capital for firm i in quarter t, see section 3.3.1
$CSAI_{i,t}$	Climate and sustainability awareness index, see section 3.3.2
$D_{GREEN_{i,t}}$	Dummy variable where green (brown) firms are coded as 1 (0), see section 3.3.2
$CSAI_{i,t} \times D_{GREEN_{i,t}}$	Interaction term capturing the differential effect for green versus brown firms, see 3.3.2
$\sum_k \beta_k X_{i,t,k}$	A vector of conventional control variables for cost of capital, see section 3.3.3
$\omega_{country}$	Country fixed effects
λ_{year}	Year fixed effects
$\delta_{industry}$	Industry fixed effects
$\varepsilon_{i,t}$	Idiosyncratic error term with heteroskedasticity-robust standard errors (HC3)

3.3 Variables

3.3.1 Dependent variable

The weighted average cost of capital ($WACC$), constitutes the dependent variable in the regression model specification used for all hypothesis testing. As the conventional metric for a firm's cost of obtaining financing, it inherently captures investors' perceived risk or opportunity cost for deploying capital into a specific project, which is reflected in both the equity component, commonly influenced by the firm-specific beta, and the cost of debt. Thus, WACC can be used as a proxy for firm-specific risk, which we hypothesize to be affected by changes in unexpected climate change awareness and underlying climate-related risk exposures. WACC is a critical parameter in investment decision-making and valuation, as it serves as the discount rate for future cash flows; a lower WACC means a lower hurdle rate for projects and a higher valuation for the firm, all else equal.

WACC, as defined in theory, is calculated as:

$$WACC = \frac{E}{E+D} r_E + \frac{D}{E+D} r_D (1 - \tau) \quad (5)$$

where, for a specific firm, τ denotes the applicable company tax rate, E denotes the market value of equity, D denotes the outstanding debt value, r_E denotes the equity cost of capital, and r_D denotes the cost of debt (Berk & DeMarzo, 2023).

3.3.2 Key independent variables

We use multiple independent variables in the regression model specifications to analyze various aspects of the relation between unexpected climate change awareness and WACC. These are (1) the novel CSAI, meant to capture how WACC is affected by a fluctuating public discourse around climate and sustainability, (2) a dummy variable classifying green and brown firms, intended to capture at what level green firms' WACC are higher or lower relative to brown firms. Notably, we also introduce an interaction term between (1) and (2) meant to investigate to what extent the observed CSAI effect with regards to WACC is stronger for green or brown firms. We deem these key independent variables, along with a vector of controls and the subsequent adjustments to the model specification and underlying data sample, sufficient to facilitate an interpretation of the regression results relative to the hypotheses developed in section 2. The methodology used to obtain each key independent variable is elaborated in the sections below.

Creating the climate and sustainability awareness index (CSAI)

The climate and sustainability awareness index (CSAI) is an attention-based model, drawing on the methodological approach used in previous literature (Ardia et al., 2023; Engle et al., 2020; O'Kane & Maeso, 2023). Our guiding assumption is that heightened public attention to climate-related topics correlates with periods when climate risks gain prominence. To capture this dynamic, we compile country-specific news data from major newspapers in Sweden, Norway, Denmark, and Finland, as well as the Wall Street Journal and Financial Times (see table A5 in appendix for specification of complete news corpus). While these latter two are international outlets, their broad readership within the Nordic investment community warrants their inclusion. We focus exclusively on written, online news articles and thus exclude social media content.

The data is sourced from Media Cloud, which provides the total number of articles and the subset of climate-related articles per country and quarter. We define a "climate-related article" as any item containing the English phrase *"climate change"* or its direct equivalent in the relevant Nordic language (see table A5 in appendix for list of search terms). The choice of limiting the search with two key terms per country is a deliberate precautionary measure to avoid potential issues with data mining and endogeneity, consistent with previous literature leveraging textual analysis in the creation of media indices for climate change- and sustainability-related research topics (Ardia et al., 2023; Engle et al., 2020; Faccini et al.,

2021; Maseo & O'Kane, 2023). In proceeding to create the CSAI, we first calculate the ratio of climate articles to total articles, $RCA_{c,t}$, for country c in quarter t, denoted:

$$RCA_{c,t} = \frac{CA_{c,t}}{TA_{c,t}} \tag{6}$$

where $CA_{c,t}$ is the count of climate-related articles, and $TA_{c,t}$ is the total number of articles for the same period and country.

To account for diminishing marginal effects in climate coverage (i.e., one additional climate article does not linearly increase awareness), we apply a natural logarithmic transformation:

$$LNRCA_{c,t} = ln\left(RCA_{c,t}\right) \tag{7}$$

This approach follows Ardia et al. (2023) and aligns with similar text-based research on media-derived sentiment indices, which often adopt a logarithmic scale to reflect the non-linear impact of incremental news coverage (Da et al., 2011; Tetlock, 2007). Finally, we mean-center this value by subtracting each country's average logarithmic ratio over the sample period:

$$CSAI_{c,t} = LNRCA_{c,t} - \overline{LNRCA}_{c} \tag{8}$$

where $\overline{LNRCA}_{c}$ is the mean of the natural logarithmic ratio for country c across the analyzed time period. Through mean-centering, we express each quarterly value as a deviation from its own country-specific baseline. This approach enhances interpretability by allowing us to isolate how above- or below-average (i.e., a proxy for unexpected) fluctuations in media coverage impact subsequent financial outcomes (Aiken & West, 1991; Brambor et al., 2006). Similar transformations for capturing *unexpectedness* appear in recent research, where text-derived indices are constructed to better capture unexpected shifts in public attention (Ardia et al., 2023; Engle et al., 2020). In our setting, mean-centering clarifies the interpretation of the CSAI variable and the interaction term, and mitigates potential multicollinearity between the index and other explanatory variables (see section 3.5).

Finally, since each firm (denoted by i) is always located in the same country for each quarter t respectively, we obtain that:

$$CSAI_{i,t} = CSAI_{c,t} \tag{9}$$

Consequently, $CSAI_{i,t}$ is the notation used for the media-index in the regression model and the subsequent analysis and discussion. Although the CSAI bears resemblance to the second index developed by Engle et al. (2020), it diverges by omitting explicit tonality analysis. Our intent is to capture heightened *unexpected* awareness rather than categorizing news content as positive or negative. Nonetheless, in line with Engle et al. (2020) which states that "no news

is good news", suggests that periods of minimal climate-related coverage might implicitly signal fewer negative developments. Consequently, while our index is not designed to measure *concern*, it may still partly reflect negative sentiment, given that media spikes often center on adverse climate-related events (Ardia et al., 2023; Engle et al., 2020).

It is essential to note that this index serves only as a proxy for unexpected public climate and sustainability awareness. Naturally, this infers limitations and imperfections. For instance, the CSAI does not differentiate between various types of climate risks (e.g., physical, climate, and transition), nor does it address nuances of intra-national local readership or editorial biases. These limitations mean that variations in the CSAI should be interpreted with caution. Nevertheless, within the scope of this thesis, the CSAI provides a tractable measure of how national media attention to climate issues evolves over time, thereby helping us explore the relationship between unexpected fluctuations in public climate awareness, firm-specific ESG characteristics, and financing costs in the Nordic context.

Dummy variable to differentiate between green and brown firms

As mentioned in section 2.2.2, labeling a firm as green or brown is indeed somewhat arbitrary and different methodologies have been adopted in adjacent studies. For this study, the green versus brown distinction is central to understanding whether public climate awareness influences financing conditions differently across firms with varying ESG performance. As such, this thesis draws on previous literature and differentiates between green and brown firms based on ESG scores (Apergis et al., 2022; Bua et al., 2022; El Ghoul et al., 2011; Ernst & Woithe, 2024; Gonçalves et al., 2022; Piechocka-Kaluzna et al., 2021). Specifically, we employ the ESG Score[3] from Refinitiv Eikon as our primary classification metric, thereby capturing a broad suite of sustainability factors relevant to investors.

In line with the methodology of Ardia et al. (2023), we define green (brown) firms as those whose ESG Score ranks in the top (bottom) 25th percentile within a given year and industry, computed on a quarterly basis, using annual scores as a proxy. This quarter-to-year approximation draws on the idea of the inherent stickiness of firms' ESG scores, as shown by e.g., Bouyé & Menville (2020) and Giese et al. (2021).

To integrate this classification into our panel regression, we create a dummy variable whereby green firms are coded as 1 and brown firms as 0 in each period they meet the respective percentile criterion. Thus, the dummy variable, where i refers to the specific company and t denotes the given quarter, is denoted as $D_{GREEN_{i,t}}$.

[3] This ESG score is defined as "*an overall company score based on the reported information in the environmental, social, and corporate governance pillars*"

3.3.3 Control variables

In line with empirical research on cost of capital and sustainability performance (Caragnano et al., 2020; Friede et al., 2015; Lemma et al., 2019; Maaloul, 2018; Mariani et al., 2021), this study includes a standard set of firm-level control variables, as well as country-, year-, and industry-fixed effects, to ensure our findings are both robust and comparable with existing literature. The control variables and fixed effects are included in all model specifications used for the hypothesis testing and are defined as follows:

Beta: Systematic risk is captured via a five-year quarterly $BETA$, reflecting the theoretical premise that market-wide fluctuations drive the cost of equity (Mossin, 1966; Ross, 1977; Sharpe, 1964).

Leverage: We measure leverage, denoted $LEV,$ as the ratio of total debt to total assets, following Modigliani & Miller's (1958) argument that equity risk rises with indebtedness, alongside evidence that heavily indebted firms face a higher probability of default (Altman & Hotchkiss, 2011).

Firm size: Firm size, measured by the natural logarithm of total assets, denoted $SIZE$, is included based on evidence from Brealey et al. (2020) and Fama & French (1993) suggesting that larger firms often enjoy better market access and greater diversification, thereby reducing perceived risk. To avoid issues with multicollinearity, $SIZE$ is mean-centered (see section 3.5 for elaboration).

Book-to-market: We also control for book-to-market (calculated as the ratio of book value of equity to market capitalization), denoted BTM. This recognizes that value- and growth-firms can exhibit distinct risk-return characteristics (Fama & French, 1993).

Return on assets: Profitability, captured by return on assets and denoted ROA, provides an additional control, as profitable firms are generally more financially resilient and thus carry lower risk for both equity and debt providers (Danielsen et al., 2016).

Fixed effects: Lastly, we include country-, year-, and industry[4]-fixed effects to account for regulatory differences, macroeconomic trends, and sectoral dynamics that could otherwise confound our estimates. These fixed effects reduce omitted-variable bias, thus reducing potential issues with endogeneity and help isolate the influence of our primary explanatory variables on $WACC$.

[4] Defined in accordance with The Global Industry Classification Standard (GICS) and reclassified for simplicity (see table A4 in appendix); GICS is a widely recognized taxonomy for categorizing public companies into distinct industry groups according to their primary business activities, co-developed by S&P Dow Jones Indices, and MSCI.

3.4 Data sources and sample selection

This section outlines the process for our sample selection and construction process, along with the filtering steps used to obtain the final samples for our empirical analysis. First we detail the financial data sources and the rationale behind key choices regarding currency and time frame. Secondly, we describe the ESG data used to classify firms between green and brown. Thirdly, we outline the media data used to construct our climate and sustainability awareness index. Finally, we explain our sample construction process, including the applied winsorization procedure.

3.4.1 Financial data

A central component of the dataset is firm-level financial information, collected on a quarterly basis from the Refinitiv Eikon database. To maintain consistency and minimize the confounding influence of currency fluctuations, all company financials are expressed in euros (EUR). This choice reflects several practical considerations. Firstly, Finland already uses the euro as its national currency, and Denmark's krone (DKK) is pegged to the euro (Danmarks Nationalbank, 2025). Secondly, although Sweden and Norway use the Swedish krona (SEK) and Norwegian krone (NOK) respectively, both currencies are generally well-correlated with the euro (European Central Bank Statistical Data Warehouse, 2024; Norges Bank, 2024; Sveriges Riksbank, 2024). Consequently, applying the euro as the uniform reporting currency mitigates potential distortions arising from exchange-rate volatility, thereby supporting clearer cross-country comparisons in our regression analysis (Erel et al., 2012; Ferreira & Matos, 2008).

We restrict our sample to publicly listed Nordic firms, as available accounting and market-based data are essential to compute the WACC and our control variables. Beyond the accounting-based metrics, we also retrieve data needed to compute market-based financial measures. We extract quarterly data between 2020-2024, which captures recent shifts in sustainability practices. Notably, daily observations would likely better capture the short term nature of unexpected changes in public climate sentiment, however, this presents an inherent limitation to our empirical analysis, as accounting-based data is only available on a quarterly basis.

3.4.2 ESG data

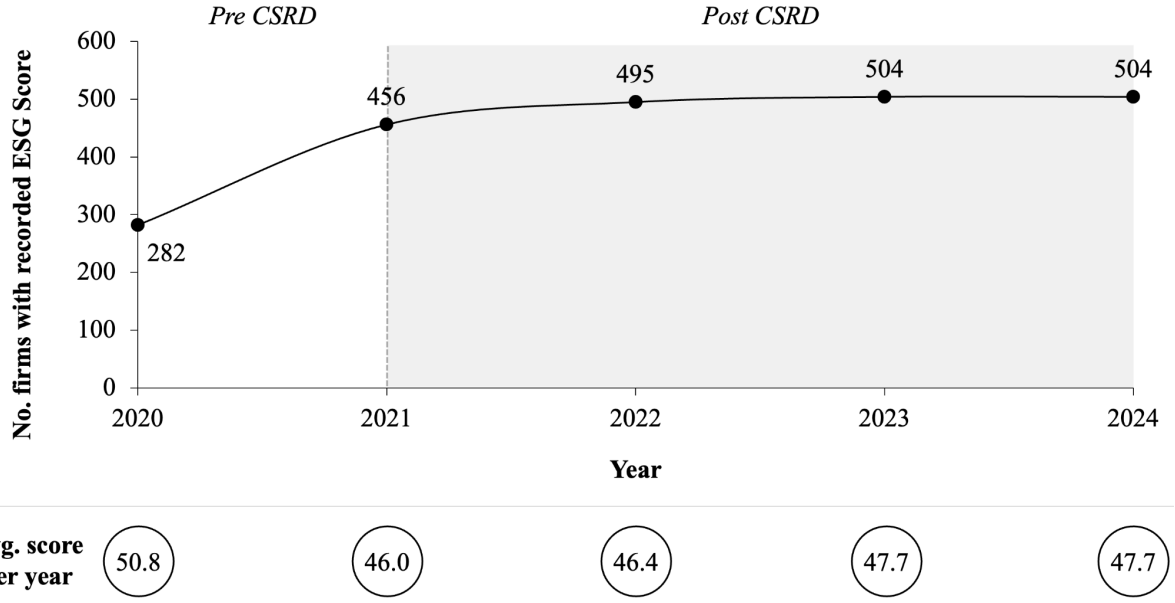
To classify firms as green or brown, we rely on ESG data from the Refinitiv Eikon database. We focus on the ESG Score, recorded on an annual basis and used as a proxy in quarterly observations following recent conventions that allow ESG scores to remain relatively "sticky" across quarters (Bouyé & Menville, 2020; Giese et al., 2021). Thus, for each quarter, the most recent annual ESG data serve as the relevant measure, as outlined in section 3.3.2.

Over the analyzed time period, the number of firms being graded has increased, which is depicted in table 5. Notably, this recorded uptick is in line with the regulatory environment prompting for a more extensive ESG reporting framework. In April 2021, for instance, the

European Commission proposed the Corporate Sustainability Reporting Directive (CSRD), which, through the European Sustainability Reporting Standards (ESRS), substantially enlarged the scope of EU companies subject to mandatory ESG disclosures (European Commission, 2025a; 2025b). Although Norway is not an EU member, it often aligns its legal and regulatory frameworks with EU directives. In parallel, the IFRS Foundation's International Sustainability Standards Board (ISSB) has recently introduced IFRS S1 and IFRS S2, which establish global benchmarks for sustainability and climate‑related disclosures that many jurisdictions, including Norway, may adopt or harmonize with their own regulations (EY, 2025). Taken together, these developments have affected Nordic firms' reporting practices, resulting in a greater number of companies providing ESG data over the period examined.

Additionally, the average Refinitiv Eikon ESG Score decreased over the period, potentially indicating that "early adopters" of ESG reporting, on average, had higher scores than "lagging" firms that received an ESG Score as of 2021 and onwards. To this regard, it also raises questions about the underlying data quality of the firms' reported ESG performance. Finally, our chosen time frame aligns with the overall trend in increased sustainability reporting, reflected in lower data availability prior to 2020.

Table 5. Total unique firms with recorded Refinitiv Eikon ESG Score and average score, 2020-2024

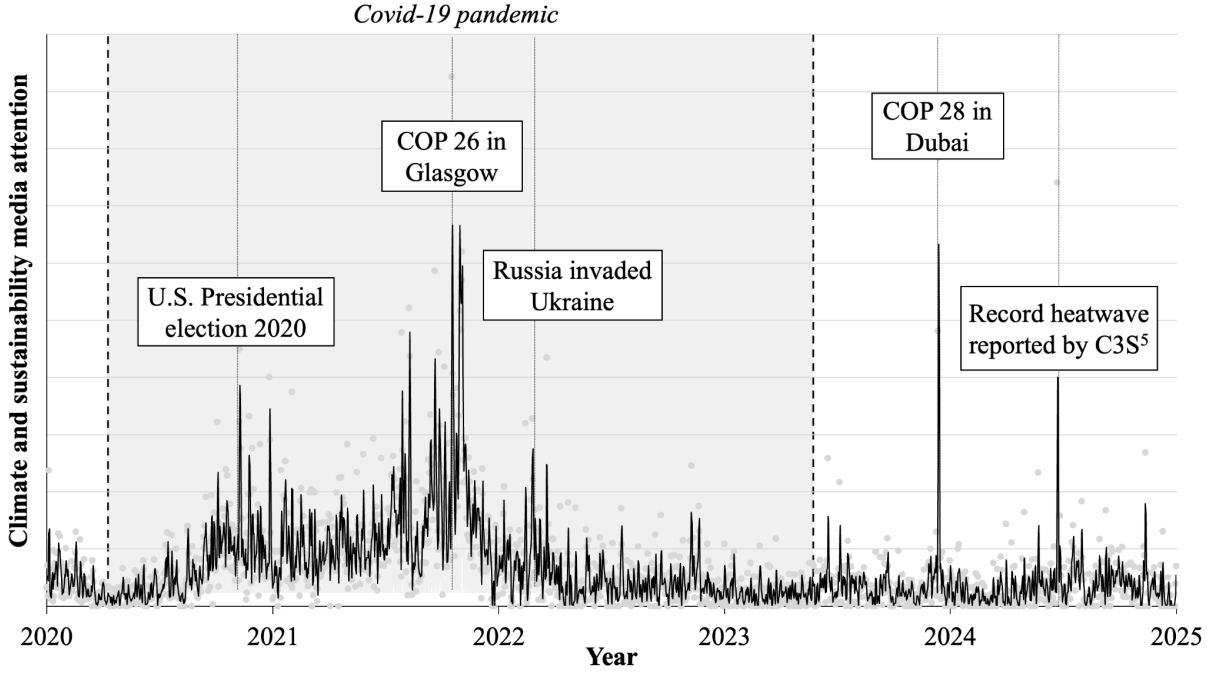


Note: *(1) CSRD and ESRS was announced in 2021, and is in effect as of financial year of 2024, see 2022/64/EU. (2) Total number of unique firms shown here are the gross amount prior to data cleaning for other independent variables in the regression model, see table 8 in section 3.4.4.*

3.4.3 Media data

The media data underpinning the creation of our climate and sustainability awareness index (CSAI) come from the Media Cloud platform. Media Cloud is a comprehensive, open-source tool that tracks digital news publications from numerous outlets across the world, and it is commonly utilized for textual analysis in academic papers (see for example Santillana (2024) and Zhang et al. (2024)). We described the index construction in section 3.3.2, highlighting how we identify climate-related articles through carefully selected search terms in each relevant language. Table 6 shows how the media attention around climate and sustainability has fluctuated during the studied time period, with significant events probable to have caused the aforementioned spikes marked throughout the time series. For instance, coverage increased during Q4 2023, concurrent with the COP 28 meeting being held in Dubai (UNFCCC, 2024).

Table 6. Climate and sustainability media attention in the Nordics



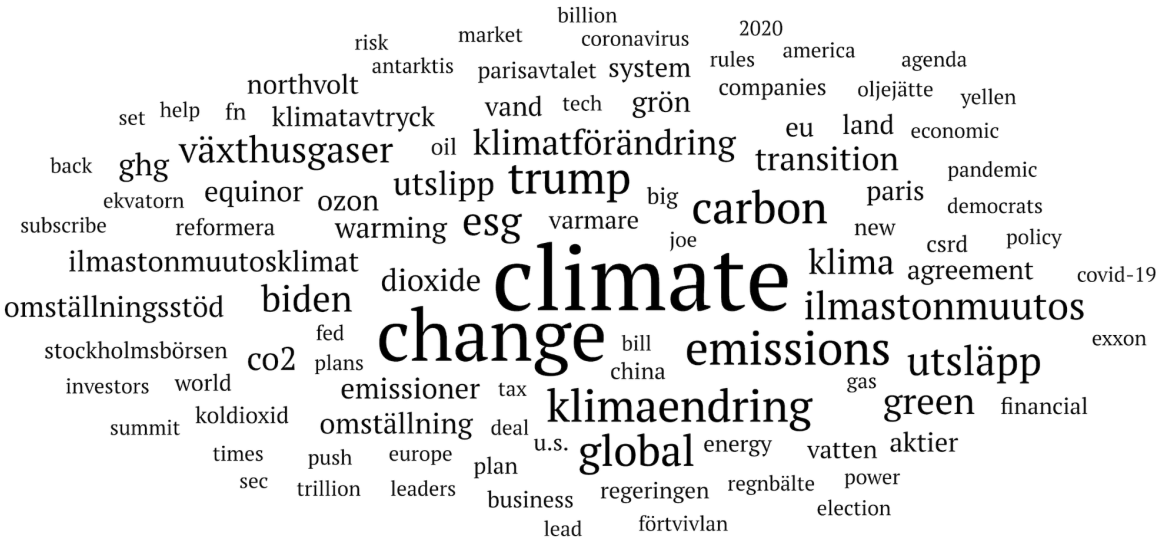
***Note**: The depicted data points and trend line are recorded on a daily basis, including weekends, for the period 2020-01-01 to 2024-12-31.*

As outlined in section 3.3.2, the media index has been constructed around a number of major news papers from the Nordic countries, as well as two major international news outlets commonly consumed by Nordic investors. In addition, "*climate change"* alongside the translated equivalent in the respective Nordic language (e.g., "*klimatförändring"* in Swedish etc.) was used as the search term[6] against the news corpus. A narrow set of key words follows the methodological approach applied by previous scholars creating climate news indices (see table 1 in section 2.2.2), aligned with the notion of avoiding data mining and potential issues with endogeneity (Ardia et al., 2023; Engle et al., 2020; Faccini et al., 2021; Maseo &

[5] Abbreviation for Copernicus Climate Change Service (C3S).
[6] The respective search terms include various conjugations i.e., *"klimatförändringarna"* and *"klimatförändringar"* etc. in Swedish.

O'Kane, 2023). Below in table 7 are the most common words found in Media Cloud articles during the construction of the CSAI. In table A5 in appendix, we provide full details regarding the specific newspapers included and the used search terms per country.

Table 7. Word cloud summary of most frequent words from Media Cloud articles



***Note**: The size of each word illustratively reflects its frequency across all articles extracted by Media Cloud.*

3.4.4 Sample construction process

After gathering these datasets, we merge the quarterly financials, the annual (proxy for quarterly) ESG scores, and the media-based CSAI into a single panel dataset. In table 8, we outline each stage of the sample construction process, including the initial pool of firms, exclusions due to missing data, and final inclusion counts by country and ESG classification As part of this cleaning procedure, we winsorize the continuous variables at the 1% level on both tails (except for CSAI), in line with conventional quantitative empirical research methods. This step mitigates the influence of extreme outliers, often driven by data errors or highly unusual events, thus enhancing the robustness of our regression estimates.

As evident from table 8, the main source of data loss from the total sample originates from the ESG Score, which results in a deduction of 15,075 observations. In combination with reductions from the other data points, the final sample, when deducting all observations relating to neutral firms, amounts to 3,522 observations, which is split evenly between green (1,760) and brown (1,762) firms. It is important to note that the number of observations for neutral firms is smaller than the combined number of observations for green and brown firms, even though they would intuitively be expected to be equally large. This discrepancy arises from the inclusive nature of the iterative quartile-based splitting process, which is applied separately for each year and industry based on ESG data, as outlined in section 3.3.2.

The final sample, as well as the subsamples of green and brown firms are used as inputs to the regression model specifications, which were detailed in section 3.2.1.

Table 8. Sample construction process

		No. of firm-quarter observations						No. of unique firms					
Country		Sweden	Norway	Denmark	Finland	Total	Δ	Sweden	Norway	Denmark	Finland	Total	Δ
Total Sample		**15,460**	**5,220**	**2,140**	**2,400**	**25,220**	***N.A.***	**773**	**261**	**107**	**120**	**1,261**	***N.A.***
Data metric adj.	**Variable(s)**												
WACC	$WACC$	13,890	4,403	1,985	2,214	**22,492**	*-2,728*	770	257	107	120	**1,254**	*-7*
ESG Score	D_{GREEN}	4,291	1,251	808	1,067	**7,417**	*-15,075*	253	73	44	59	**429**	*-825*
Total Assets	$SIZE; LEV$	4,204	1,231	761	996	**7,192**	*-225*	252	72	44	58	**426**	*-3*
Total Debt	LEV	3,815	1,227	729	986	**6,757**	*-435*	243	72	43	58	**416**	*-10*
Total Equity	BTM	3,815	1,226	729	986	**6,756**	*-1*	243	72	43	58	**416**	*0*
ROA	ROA	3,806	1,222	722	975	**6,725**	*-31*	243	72	43	57	**415**	*-1*
GICS	$\delta_{industry}$	3,791	1,222	722	975	**6,710**	*-15*	242	72	43	57	**414**	*-1*
Neutral firms	D_{GREEN}	2,020	610	318	574	**3,522**	*-3,188*	187	55	31	44	**317**	*-97*
Full sample used in regression		**2,020**	**610**	**318**	**574**	**3,522**	***N.A.***	**187**	**55**	**31**	**44**	**317**	***N.A.***
Of which green firms		*946*	*257*	*195*	*362*	***1,760***	*N.A.*	*71*	*21*	*16*	*25*	***133***	*N.A.*
Of which brown firms		*1,074*	*353*	*123*	*212*	***1,762***	*N.A.*	*116*	*34*	*15*	*19*	***184***	*N.A.*

Note: *(1) Removal of neutral firms refers to all firms that classify as neither green nor brown. (2) Firm, country, year, quarter, market cap, and beta did not remove any observations and are thus excluded from the table.*

3.5 Pre-estimation diagnostics: multicollinearity assessment

Before finalizing our regression model specification, it is critical to ensure that multicollinearity, defined as excessive correlation between explanatory variables, does not undermine the reliability of our estimates (Gujarati, 2021; Wooldridge, 2010). This section presents diagnostic tests conducted prior to estimation to evaluate whether multicollinearity poses a material concern. For this assessment, we employ two complementary diagnostic tools. First, we compute variance inflation factors (VIF) for each independent variable. Secondly, we construct a Pearson correlation coefficients matrix, which enables us to examine pairwise correlations and identify any overly strong linear dependencies (Chatfield & Xing, 2019). Both of these analyses are shown in table 9.

Table 9. Pearson correlation coefficient matrix and VIF for full sample

Variables	$WACC$	$CSAI$	D_{GREEN}	$SIZE$	BTM	LEV	ROA	$BETA$	VIF
$WACC$	1.000***								
$CSAI$	-0.145***	1.000***							3.5320
D_{GREEN}	0.016	-0.014	1.000***						4.0106
$SIZE$	-0.124***	0.004	0.641***	1.000***					2.4868
BTM	0.058***	-0.126***	-0.070***	0.121***	1.000***				3.4258
LEV	-0.219***	-0.036**	-0.033**	0.126***	0.143***	1.000***			3.9860
ROA	-0.043**	0.053***	0.114***	0.182***	-0.225***	-0.098***	1.000***		1.1723
$BETA$	0.727***	-0.008	0.111***	0.045***	0.230***	0.079***	-0.058***	1.000***	7.0011

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

Interpreting the VIF values in light of conventional guidelines (Hair, 2011), we find that none of our variables exceed a VIF of 10, indicating that collinearity is unlikely to undermine the stability of our regression estimates. Although $BETA$ shows a moderately elevated VIF of around 7, this does not surpass the typical threshold. Moreover, the correlation matrix confirms that no pairwise correlations approach critical levels, despite several statistically significant correlations, such as the moderate correlation between $SIZE$ and D_{GREEN}. These results reinforce our conclusion that high multicollinearity is not an issue (Nettleton, 2014).

Methodologically, we have preemptively acknowledged and accounted for potential issues with multicollinearity. Firstly, the methodological rationale of our construction of the $CSAI$, where we mean-center the natural logarithmic value for relevant articles, is twofold: (1) to capture unexpectedness in climate change awareness; and (2) mitigating potential collinearity issues, consistent with established practices in empirical research (Aiken & West, 1991; Brambor et al., 2006). Secondly, mean-centering the natural logarithm of total assets to derive the $SIZE$ variable was necessary to maintain acceptable multicollinearity levels, thereby

preserving its explanatory power. This procedure reduces VIF-values, and correlations between the interaction term and its constituent components, which improves both interpretability and model robustness. Lastly, we winsorize continuous variables at the 1% tails, as detailed in section 3.4.4, to limit the influence of extreme observations that can inflate correlation structures and variances.

Given these considerations and mitigation strategies, we conclude that although potential multicollinearity issues are mildly present, this does not pose a significant threat to our analysis. While we do observe moderate overlap among certain independent variables, the correlations remain within acceptable bounds, ensuring that the variables central to our research question can be reliably interpreted (Wooldridge, 2010). Although some studies present separate VIF and correlation matrices for each model specification or split sample, the results from our full‑sample diagnostics suffice to indicate that multicollinearity is unlikely to become problematic in these subsamples, thereby rendering additional tests optional. For robustness and post-estimation diagnostics, see section 4.3 and appendix B.

4. Results and analysis

4.1 Descriptive statistics

4.1.1 Sample composition by ESG classification

Table 10 provides an overview of the distribution of green and brown firms across industry, country, and year, resulting in a total of 3,522 firm‑quarter observations across the different dimensions. This classification scheme builds on the Refinitiv Eikon ESG Score approach described in section 3.3.2, where firms in the top 25th percentile, within each year and industry, are labeled green and those in the bottom 25th percentile are labeled brown, consistent with Ardia et al. (2023). As expected from this percentile‑based allocation, the final sample splits evenly: 1,760 green firm‑quarter observations and 1,762 brown.

From an industry perspective, industrials dominate the sample with the highest number of observations (897), with average GHG emissions[7] of 5.2 MtCO2e, during 2020-2024. Energy & utilities (27.3 MtCO2e), transportation & infrastructure (9.9 MtCO2e), and Materials (9.1 MtCO2e) sectors show the highest average GHG emissions. Consequently, these sectors, when viewed from an emissions perspective, can be regarded as the *brownest* in our sample, underscoring their significant environmental footprint. In contrast, the lowest average GHG emissions are observed in professional services (0.3 MtCO2e), finance & real estate (0.3 MtCO2e), and health care & life sciences (0.2 MtCO2e). These large differences in GHG emissions across industries largely mirror prior sectoral-based empirical findings (Ardia et al., 2023; Bua et al., 2022; Ilhan et al., 2021; Mariani et al., 2021).

Country-level analysis reveals notable variations. Sweden accounts for the majority of observations (57% of total), with a slight bias towards brown firms (53%). Norway, representing 17% of observations, demonstrates a higher proportion of brown firms (58%), possibly reflecting its industry composition skewed towards sectors with higher environmental impact such as the energy sector (e.g., oil and gas companies). Denmark and Finland, comprising 9% and 16% of the total observations respectively, both exhibit a more pronounced tilt towards green firms (Denmark at 61% green, Finland at 63% green), suggesting robust ESG performance in certain industries within these countries. Notably, the variation in observations across countries closely mirrors the distribution of listed firms within each market, thereby introducing a natural skewness in the dataset. These cross-country differences underscore the heterogeneity of the Nordic corporate landscape and further justify the inclusion of country-level fixed effects, as outlined in section 3.2.

[7] The total GHG emissions are based on data from Refinitiv Eikon and is the accumulated amount of tCO2e across scope 1, 2 and 3.

Turning to temporal distribution, the sample spans 2020-2024, which captures the evolving ESG reporting practices and regulatory landscape (see section 3.4.2). An initial increase of observations for both green and brown is visible early in the sample period (i.e., from 2020 to 2021), with a more balanced number of observations in later years. This development is consistent with the broader regulatory shift (e.g., CSRD) pushing more firms to disclose ESG data (European Commission, 2025a; IFRS Foundation, 2025). Finally, we see a decrease of total observations during 2024, which is likely due to unpublished 2024 Q4 financial statements at the time of writing this thesis.

Table 10. Industry GHG average and sample observations by ESG-classification per industry, country, and year

Industry	**GHG**	***Green***	***Brown***	**Total**	**Country / Year**	***Green***	***Brown***	**Total**
Energy & utilities	**27.3**	98 (50%)	98 (50%)	196 (6%)	**Sweden**	946 (47%)	1074 (53%)	2020 (57%)
Transportation & infrastructure	**9.9**	68 (51%)	66 (49%)	134 (4%)	**Norway**	257 (42%)	353 (58%)	610 (17%)
Materials	**9.1**	130 (51%)	126 (49%)	256 (7%)	**Denmark**	195 (61%)	123 (39%)	318 (9%)
Industrials	**5.2**	448 (50%)	449 (50%)	897 (25%)	**Finland**	362 (63%)	212 (37%)	574 (16%)
Consumer discretionary	**2.3**	230 (50%)	232 (50%)	462 (13%)	**Total (Country)**	**1,760**	**1,762**	**3,522 (100%)**
Consumer staples	**1.7**	110 (50%)	111 (50%)	221 (6%)	**2020**	231 (49%)	236 (51%)	467 (13%)
Technology & communication	**1.0**	224 (50%)	221 (50%)	445 (13%)	**2021**	330 (50%)	333 (50%)	663 (19%)
Finance & real estate	**0.3**	199 (50%)	200 (50%)	399 (11%)	**2022**	389 (50%)	393 (50%)	782 (22%)
Professional services	**0.3**	83 (49%)	86 (51%)	169 (5%)	**2023**	412 (50%)	407 (50%)	819 (23%)
Health care & life sciences	**0.2**	170 (50%)	173 (50%)	343 (10%)	**2024**	398 (50%)	393 (50%)	791 (22%)
Total (Industry)	**N.A**	**1,760**	**1,762**	**3,522 (100%)**	**Total (Year)**	**1,760**	**1,762**	**3,522 (100%)**

Note: *(1) Industry classification has been based on GICS and reclassified for simplification purposes, see table A4 in appendix for methodology used for reclassification. (2) GHG refers to the full sample average per industry group expressed in MtCO2e for total emissions across Scope 1, 2, and 3.*

4.1.2 Descriptive statistics of key regression variables

Table 11 presents descriptive statistics for the variables used in the regression analyses. Looking at $WACC$, the dependent variable in all regression model specifications, we see a range from roughly two percent to around 15 percent in the full sample, reflecting an ample variation in cost of capital in the Nordics. When analyzing the key independent variables, it is evident that the $CSAI$ fluctuates significantly throughout the sample period, consistent with the time series presented in table 6 in section 3.4.3, i.e., we see periods of both unexpectedly heightened awareness (positive sign) as well as observations where coverage falls below the mean (negative sign). As mentioned under section 3.3.2, we mean-centered the index to capture said above- and below-average (i.e., a proxy for *unexpected*) fluctuations. As such, the mean of the $CSAI$ is relatively close to zero. Meanwhile, the green-brown classification dummy variable assumes values of 1 and 0, and the interaction term between the aforementioned variables mirrors the observed variations of the $CSAI$ and D_{GREEN}.

Similarly to the key independent variables, we observe no unusual patterns for the controls. Notably, $SIZE$, which was mean-centered for multicollinearity purposes also has a mean of zero, albeit preserving its explanatory value as a conventional control. Additionally, $BETA$ has a mean close to one (1.0729), indicating that the full sample, on average, has a market risk exposure that is roughly on par with the market.

Table 11. Descriptive statistics for regression variables, full sample

Variables	n	mean	std	min	25%	50%	75%	max
$WACC$	3,522	7.4722	2.4382	1.8325	5.9376	7.3591	8.8899	14.6634
$CSAI$	3,522	-0.0231	0.5973	-1.0528	-0.4259	-0.1861	0.4477	1.6685
D_{GREEN}	3,522	0.4997	0.5000	0.0000	0.0000	0.0000	1.0000	1.0000
$CSAI \times D_{GREEN}$	3,522	-0.0156	0.4267	-1.0528	-0.1861	0.0000	0.0000	1.6685
$SIZE$	3,522	0.0000	1.9460	-4.3495	-1.5171	0.0509	1.5536	4.1643
BTM	3,522	0.6607	0.5864	0.0352	0.2624	0.4822	0.8668	3.0637
LEV	3,522	0.2615	0.1660	0.0045	0.1390	0.2400	0.3571	0.7754
ROA	3,522	0.8729	3.3161	-15.9317	0.1258	1.1141	2.1585	9.6992
$BETA$	3,522	1.0729	0.4656	-0.0222	0.7729	1.0606	1.3510	2.6463

Note: *(1) CSAI and SIZE are mean-centered, see sections 3.3.2., 3.3.3, and 3.5. (2) CSAI has a mean that deviates slightly from zero, as it is mean-centered separately within each country, resulting in values specific to each country-quarter observation; an uneven distribution across these groups contributes to the deviation. In contrast, SIZE has a mean of exactly zero, as it is mean-centered across the entire sample. This outcome follows naturally from the chosen methodological approach. (3) WACC and ROA are expressed in percentage points, whereas all remaining accounting-based ratios are in decimal form.*

4.2 Hypothesis testing

In this section, we present the outcomes of four OLS regressions aimed at examining the impact of unexpected climate and sustainability awareness, as measured by our CSAI, on the WACC for green versus brown firms. Building on the literature from the intersection of sustainability performance and financing costs and media‐based measures of public climate awareness, we relate these results directly to the hypotheses developed in section 2 (Apergis et al., 2022; Ardia et al., 2023; Bua et al., 2022; El Ghoul et al., 2011; Engle et al., 2020; Goss & Roberts, 2011; Mariani et al., 2021; Ng & Rezaee, 2015; Oikonomou et al., 2014; Piechocka-Kaluzna et al., 2021; Sharfman & Fernando, 2008).

Table 12 summarizes the regression coefficients, including their direction, magnitude, and statistical significance, after controlling for both firm‐ and macro‐level fixed effects (country, year, and industry), as outlined in section 3. In the following subsections, we further analyze each hypothesis and provide a detailed interpretation.

To investigate whether the effect of CSAI on WACC differs systematically across sectors for green and brown firms, we also re-estimate the most comprehensive form of our regression model (equation 4 used for H3) and re-run regressions on ten industry subsamples. As noted in section 2, industries vary substantially in e.g., carbon intensity, exclusionary screenings from institutional investors, and other stakeholder pressures, all of which can condition how unexpected climate awareness translates into financing cost dynamics (Ardia et al., 2023; Bolton & Kacperczyk, 2020; Ilhan et al., 2021). By running these additional regressions, we aim to uncover any sectoral heterogeneity that may be obscured in the pooled estimates and to assess whether our hypotheses hold uniformly across, for example, high‐emitting versus low‐emitting industries.

Table 12. OLS panel regression results for hypothesis testing

Regression no.	**(1)**	**(2)**	**(3)**	**(4)**
Hypothesis	H1	H2 (a)	H2 (b)	H3
Sample	Full sample	Green sample	Brown sample	Full sample
Dependent variable	$WACC$	$WACC^{GREEN}$	$WACC^{BROWN}$	$WACC$
Key variables				
D_{GREEN}	-0.1737*** (0.063)	-	-	-0.1722*** (0.063)
$CSAI$	-	-0.2906*** (0.080)	-0.1606** (0.076)	-0.2841*** (0.066)
$CSAI \times D_{GREEN}$	-	-	-	0.1317* (0.070)
Control variables				
$SIZE$	-0.0414** (0.016)	-0.1327*** (0.024)	-0.0070 (0.026)	-0.0419*** (0.016)
BTM	-0.4175*** (0.057)	-0.6324*** (0.119)	-0.3334*** (0.063)	-0.4234*** (0.057)
LEV	-3.9585*** (0.176)	-4.6811*** (0.306)	-3.3669*** (0.206)	-3.9668*** (0.175)
ROA	0.0051 (0.007)	0.0070 (0.017)	0.0012 (0.008)	0.0038 (0.007)
$BETA$	3.9656*** (0.061)	3.8906*** (0.095)	4.0334*** (0.083)	3.9702*** (0.061)
Fixed effects				
Time	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Model diagnostics				
Observations	3,522	1,760	1,762	3,522
Adj. R-squared	0.757	0.761	0.770	0.758
Condition number	36.6	35.0	40.4	36.7
Kurtosis	8.223	9.434	7.478	8.033
Skew	0.017	0.695	-0.168	0.188
Standard errors	Heteroskedasticity robust type 3 (HC3)			

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

***Note**: (1) Standard error in parentheses. (2) All continuous independent variables are winsorized at 1%, except for CSAI. (3) D_{GREEN} = 1 for top quartile ESG Score within each year and industry, and 0 = bottom quartile ESG Score within each year and industry. Neutral firms are removed.*

4.2.1 First hypothesis: results and analysis

Hypothesis 1 (H1) posited that *green firms have a lower WACC than brown firms, all else equal*. Analyzing regression (1), we find empirical evidence supporting that green firms indeed exhibit a lower WACC than brown firms, consistent with the risk-based view, outlined in section 2.1.1, stating that superior ESG performance reduces investors perceived market risk and therefore the cost of capital.

Conceptually, the results support the notion of green firms signalling stronger environmental stewardship and governance quality, and are thus less exposed to climate-related risks, reputational setbacks, and cash‑flow volatility (Bolton & Kacperczyk, 2020; Sharfman & Fernando, 2008). Investors and lenders consequently demand a smaller risk premium, lowering both the cost of equity (El Ghoul et al., 2011) and the cost of debt (Goss & Roberts, 2011). When these components are aggregated, the effect persists at the level of WACC, echoing previous empirical evidence from European and U.S. samples (Mariani et al., 2021; Piechocka‑Kaluzna et al., 2021).

Specifically, the regression finds a negative coefficient of -0.1737 on D_{GREEN}, which is in line with the expected sign and statistically significant at the 1% level. This translates into a WACC discount of roughly 17 basis points for green firms relative to otherwise comparable brown firms. Hence, while the difference is economically moderate, the statistically significant result suggests that we reject the null hypothesis in support of H1. As such, the bottom line empirical interpretation is that in the Nordic context, strong ESG credentials are associated with a tangible, if incremental, financing advantage that persists after introducing conventional control variables and fixed effects.

Having found statistical significant evidence for a baseline WACC differential, the next question is whether unexpectedly changing public climate and sustainability awareness modify this advantage. Sections 4.2.2 and 4.2.3 therefore turn to the second and third hypotheses, analysing how unexpected movements in CSAI affect WACC for green and brown firms and whether those shifts widen or narrow the gap documented here.

4.2.2 Second hypothesis: results and analysis

Hypothesis 2 (H2) is divided into two parts: H2 (a) predicted that a positive shock to CSAI would *decrease* the WACC for green firms, whereas H2 (b) anticipated an *increase* in the WACC for brown firms. The split-sample regressions reveal that spikes in CSAI lower WACC for *both* green and brown firms. This contradicts the hypothesized assumption that brown firms would face an outright penalty and only partly support the hypotheses.

Regression (2), testing H2 (a), estimated on the green‑firm subsample (1,760 observations), shows a negative relationship between $CSAI$ and $WACC$. The key coefficient is that of $CSAI$ which, in line with our prediction, is negative (-0.2906) and statistically significant at the 1% level. In other words, a one‑unit rise in unexpected climate awareness lowers the average green‑firm WACC by roughly 29 basis points. This finding is in line with prior empirical

evidence suggesting that investors reallocate capital toward green firms during periods of heightened climate concern (Ardia et al., 2023; Pástor et al., 2021). It also reinforces the view that public discourse can act as an amplifier of ESG-related risk perceptions, ultimately compressing required returns for green firms. However, it is important to note that, despite the strong statistical significance for the green-firm sample, methodological considerations warrant some caution in interpretation. Since the sample is considerably smaller than the full sample, this could affect the statistical power of the model specification, and limit the generalizability of the results. Moreover, potential differences in ESG ratings and sectoral exposures across the sample may introduce structural heterogeneity that is not fully captured by the model specification, even though HC3-robust standard errors adjust for residual variance differences. Accordingly, while we acknowledge the need for interpretative caution, we reject the null hypothesis and accept H2 (a).

Regression (3), which tests H2 (b) on the brown-firm subsample (1,762 observations), yields a *CSAI* coefficient of -0.1606, significant at the 5% level. This result contradicts the theoretical expectation that brown firms would face a higher cost of capital during climate awareness shocks due to their elevated exposure to climate related-risks. However, this observation is not unique. Similar ambiguous or inverted dynamics have been observed in prior studies (Ernst & Woithe, 2024; Gonçalves et al., 2022; Magnanelli & Izzo, 2017), which emphasize that ESG-financing relationships are often contingent on contextual factors such as geography, data timing, and classification thresholds. Additionally, as with the green-firm subsample, reduced sample size and intragroup heterogeneity may partly explain the observed effect. Nonetheless and interestingly, when omitting fixed effects (table A2 in appendix), the magnitude of the $CSAI$ coefficient on green and brown firms becomes even more pronounced, further supporting the view that both firm types experience WACC compression during periods of unexpected heightened awareness. Notably, the omission of fixed effects amplifies the potential concerns related to unobserved endogeneity.

Taken together, we find empirical support for H2 (a) and, contrary to expectations, also observe a statistically significant WACC reduction for brown firms. As such, the directionality of H2 (b) is not supported and we fail to reject the null hypothesis. Nonetheless, the overall significance of CSAI in both samples suggests a systemic role in shaping financing conditions during climate awareness shocks, although the results should be interpreted with caution due to sample-related limitations and the inherent complexity of ESG-related financing cost dynamics, as evidenced in prior research (Ilhan et al., 2021). A more in-depth exploration of these patterns will be offered in the discussion in section 5.

4.2.3 Third hypothesis: results and analysis

Hypothesis 3 (H3) builds on the preceding tests by evaluating whether unexpected climate and sustainability awareness magnifies the green-brown gap in WACC. As such, it tests whether the CSAI-induced WACC change systematically differs between firm types, captured by the $CSAI$ and D_{GREEN} interaction term. If green firms benefit more from CSAI shocks than brown firms, the interaction term should be negative and significant.

Looking at the results for regression (4), we observe, consistent with the split-sample evidence in section 4.2.2, that the main effect and coefficient of $CSAI$ remains negative (-0.2841) and statistically significant at the 1% level. We also observe that the coefficient for the interaction term is 0.1317 and statistically significant at the 10% level. These results suggest that unexpected spikes in climate awareness are associated with lower WACC across the full sample. For brown firms, this effect is captured directly by the $CSAI$ coefficient, further supporting H2 (b), with an observed effect of -0.2841. For green firms, the effect of climate shocks corresponds to the sum of the $CSAI$ and interaction term coefficients (-0.1524), implying a negative effect on WACC as well, thus aligning with the findings under H2 (a).

In addition, and consistent with the results from H1, the D_{GREEN} coefficient is negative (-0.1722) and statistically significant at the 1% level, indicating a structural baseline WACC advantage for green firms, which reflects the average difference in WACC between green and brown firms under normal conditions, independent of changes in climate awareness. While the total WACC levels for each firm type include this structural baseline effect, the CSAI and interaction coefficients capture how unexpected climate awareness shocks modulate these levels.

Crucially, however, the critical test and key coefficient of H3 lies in the interaction term. The positive and statistically significant coefficient of the interaction term indicates that, while both green and brown firms experience a reduction in WACC when climate awareness unexpectedly increases, the magnitude of this reduction is somewhat smaller for green firms relative to brown firms. As such, heightened CSAI appears to reduce WACC broadly, but does so more strongly for brown firms than green firms, implying a narrowing, rather than widening, of the green-brown WACC gap during periods of heightened unexpected climate awareness. Thus, although these findings contrast with the expected magnification proposed in H3, they remain consistent with earlier individual split sample regression results, showing CSAI-driven reductions in WACC for both firm types. However, the statistical significance of the interaction term is marginal, and the findings indicate no strong support for differential widening effects benefiting green firms relative to brown. Thus, we are unable to reject the null hypothesis of H3.

This empirical pattern highlights the complex interplay between ESG profiles and investor behavior under shifting public narratives. Prior research has identified similar reversals or converging effects under certain conditions (Ernst & Woithe, 2024; Gonçalves et al., 2022). It is also worth noting that the effect persists, and becomes even stronger, when excluding fixed effects (table A2 in appendix), where the interaction term reaches 5% significance and increases in magnitude. As such, the results suggest that both green and brown firms experience lower financing costs during periods of unexpectedly heightened climate awareness, but not in a way that magnifies the relative advantage of green firms. A deeper qualitative exploration of potential explanatory factors and broader implications of these inconclusive results will be provided in the discussion in section 5.

4.2.4 Industry analysis

Due to the inconclusive nature of the hypothesis testing, another dimension of empirical interest is that of potential sectoral differences. As noted under section 2.1.2, several contextual factors, including industry membership, can moderate the effect of ESG performance and financing costs (Ilhan et al., 2021). Ardia et al. (2023) illuminated this when re-running their regression model specification on specific industry-group subsamples, finding that certain sectors saw amplified effects with regards to climate change concerns affecting stock performance and the underlying discount rate component (i.e., cost of capital) for green and brown firms. Additionally, Bolton & Kacperczyk (2020) found that institutional investors (e.g., sovereign wealth funds and pension funds) in the Nordics increasingly base their investment decisions on exclusionary screenings on certain industry groups.

Further, as mentioned in section 4.1, we see a substantial variation in GHG emissions between industries in our sample of Nordic firms. As such, the negative relationship between exposure to unexpected changes in climate and sustainability awareness and WACC observed for both green and brown firms under H2 and H3 may be further explained by industry effects, thus warranting an extended empirical exploration into the sectoral dynamics of our research question.

To empirically test this, we re-estimate the regression model specification used for testing H3 (equation 4), separately within each of the GICS-based industry group segments but exclude industry fixed effects. As such, the coefficients of $CSAI$, D_{GREEN}, and their interaction term constitutes the ones of main interest for each industry subsample.

The results, presented in table 13, indicate that unexpectedly heightened climate and sustainability awareness has a statistically meaningful effect in several industries. However, we acknowledge that these findings must be interpreted with caution. Most of the sectoral regressions are based on relatively small subsamples, ranging between 134 and 897 observations, which may reduce the statistical power and precision of the estimates. As such, the risk of Type II errors is non-trivial, and observed significance patterns should not be overstated. Nonetheless, a number of patterns emerge when interpreting the industry-specific regression results.

Table 13. Panel regression results for GICS-based industry subsamples

			Dependent variable = $WACC$					
Industry	**GHG**	**No. of obs.**	$CSAI$		D_{GREEN}		$CSAI \times D_{GREEN}$	
			Coeff	Std error	Coeff	Std error	Coeff	Std error
Energy & utilities	**27.3**	**196**	-0.9333**	0.411	1.3542**	0.575	0.3878	0.472
Transportation & infrastructure	**9.9**	**134**	-1.1021**	0.434	-0.3813	0.591	0.9711***	0.302
Materials	**9.1**	**256**	-0.6013***	0.220	-0.2060	0.336	0.2199	0.206
Industrials	**5.2**	**897**	-0.1933*	0.112	-0.3882***	0.123	0.2988***	0.113
Consumer discretionary	**2.3**	**462**	-0.2271	0.220	-0.1872	0.165	0.0295	0.225
Consumer staples	**1.7**	**221**	-0.4437**	0.189	-0.0756	0.275	0.2458	0.168
Technology & communication	**1.0**	**445**	0.1831	0.166	-0.1512	0.166	-0.3412**	0.166
Finance & real estate	**0.3**	**399**	-0.3495**	0.172	-0.1376	0.130	0.1822	0.208
Professional services	**0.3**	**169**	-0.2031	0.177	0.0241	0.185	0.1680	0.246
Health care & life sciences	**0.2**	**343**	0.1692	0.152	0.4391***	0.163	-0.0961	0.178
Total	**N.A.**	**3,522**	**N.A.**	**N.A.**	**N.A.**	**N.A.**	**N.A.**	**N.A.**

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

Note: *(1) All control variables and fixed effects (except for industry) are included in the industry-specific regression model specifications. (2) All continuous variables are winsorized at 1%, except for CSAI. (3) Industry observations are split 50/50 between green and brown firms. (4) GHG refers to the full sample average per industry group expressed in MtCO2e for total emissions across Scope 1, 2, and 3.*

We observe considerable variation in results across industries, although the proportion of statistically significant outcomes remains low. This is likely a consequence of the reduced sample sizes, which, as previously stated, constrain statistical power and thus warrant interpretative caution. Nonetheless, notable patterns emerge in certain high-emitting sectors. In particular, energy & utilities and transportation & infrastructure, the most carbon-intensive sectors in our sample (see table 10), exhibit relatively large and statistically significant effects. This reinforces the notion that climate awareness shocks have a stronger effect on industries that are sensitive to transition risks (Ardia et al., 2023). More broadly, when comparing results across all ten industry groups, we find that unexpected climate and sustainability awareness generally lowers WACC, though the effect does not systematically favor green firms. Instead, in line with our findings in H3, it suggests a convergence rather than a magnification of ESG-related financing advantages between green and brown firms, which underlines the importance of industry-based contextualization when analyzing how climate awareness shocks translate into financing cost differences.

4.3 Robustness and post-estimation diagnostics

In addition to the baseline multicollinearity diagnostics, presented in section 3.5, we probe whether our main results are sensitive to other modelling choices. Robustness tests[8] are crucial for ensuring that our core findings on the interplay between unexpected climate and sustainability awareness, ESG classification, and WACC are not artifacts of particular modeling choices, sample characteristics, or extreme observations (Gujarati, 2021; Wooldridge, 2010).

Aligning with previous literature in the research domain of sustainability performance and cost of capital (Apergis et al., 2022; El Ghoul et al., 2011; Goss & Roberts, 2011; Ng & Rezaee, 2015; Oikonomou et al., 2014; Sharfman & Fernando, 2008), and those involving media-based indices on climate change and financial effects on firms (Ardia et al., 2023; Bua et al., 2022; Engle et al., 2020), we subject our baseline results to four supplementary robustness tests: (1) Heteroskedasticity correction and diagnostics, (2) bootstrapped inference, (3) outlier control, and (4) an alternative ESG classification.

Across these tests, all of which presented in appendix B, our main coefficients of interest, $CSAI$, D_{GREEN}, and their interaction term, remain qualitatively stable and directionally consistent with the baseline models. However, as some magnitude and significance levels are reduced, the results moderately reinforce the robustness of our findings. As such, this observed variation underlines the need for interpretative caution, especially when drawing strong inferences from results near conventional significance thresholds.

Finally, while our modelling choices mitigate specification risks, we acknowledge that none of the post-estimation diagnostics explicitly address potential endogeneity concerns, such as reverse causality or omitted variable bias. These issues, while difficult to resolve within the scope of this thesis, may still be present and are discussed further in sections 6 and 7.

4.4 Summary of findings

Overall, the regression results are inconclusive yet informative. While we find statistically significant results in support of H1 and H2 (a), we fail to reject the null hypothesis in H2 (b) and H3 as the regression results, albeit being statistically significant, run counter to our prediction. Consequently, these results highlight a considerable complexity, particularly regarding the hypothesized magnification in WACC-gap between green and brown firms during periods of unexpectedly heightened climate awareness. In several instances, the data reveals convergence rather than divergence, suggesting that investor responses to sustainability narratives may be more multifaceted than initially expected.

Specifically, H1 is supported by a statistically significant baseline difference in WACC where green firms are observed to enjoy a discount of approximately 17 basis points, which is also supported in H3. This result aligns with the risk-based investor perspective, where signals of

[8] All robustness tests are outlined in detail in appendix B.

lower exposure to climate-related risks, reduces the perceived market risk and therefore the cost of capital (El Ghoul et al., 2011; Goss & Roberts, 2011; Sharfman & Fernando, 2008).

Turning to H2, the results are mixed. H2 (a) is confirmed by a statistically significant reduction of approximately 29 basis points in WACC for green firms during periods of unexpected climate awareness, echoing findings from Ardia et al. (2023) and Pástor et al. (2021) on investor reallocation toward green firms. However, H2 (b) is not supported. Contrary to the hypothesis, brown firms also experience a statistically significant WACC reduction of roughly 16 basis points, suggesting that climate awareness shocks act as a generalized repricing force rather than a mechanism of penalization, an unexpected pattern that is not unprecedented in adjacent literature (Ernst & Woithe, 2024; Gonçalves et al., 2022; Magnanelli & Izzo, 2017).

Finally, H3 is not supported. While the results substantiate the established observations in H1 and H2, the positive and significant interaction term indicates that brown firms benefit more than green firms during climate awareness shocks, effectively compressing the green–brown WACC gap. This empirical pattern reinforces the notion of convergence and underscores the non-linear, contingent nature of ESG pricing in capital markets.

The industry-level regressions reinforce and contextualize the patterns described above. In six out of ten sectors, CSAI has a statistically significant negative effect on WACC, with the largest effects observed in carbon-intensive sectors. This supports the notion that the financial materiality of climate sentiment is greatest in industries with high transition risk exposure (Ardia et al., 2023; Bua et al., 2022). The industry analysis thus demonstrates that investor reactions remain context-dependent. As such, the industry analysis sheds additional nuance on the heterogeneity of the sample and the complex inter-relationship between ESG performance and firms' financing costs during periods of unexpected climate awareness.

Notably, the post-estimation diagnostics performed in section 4.3 offer partial support for the robustness of our findings, as the key coefficients remained directionally identical, although slightly reduced in magnitude and significance levels. In addition, the statistical power of the split-sample regressions may be limited due to smaller samples, constraining the generalizability of the results. Accordingly, caution is warranted in interpreting the main findings as the regression specifications appear somewhat sensitive to model choices.

While we acknowledge these interpretative constraints, the empirical results nonetheless support that ESG performance is rewarded with a baseline WACC advantage in the Nordics. However, during episodes of unexpectedly heightened sustainability awareness, this advantage appears to erode as financing costs fall across the board. While green firms benefit from climate awareness shocks, brown firms do so as well, generally even more strongly, leading to a narrowing of the green-brown WACC gap. These findings underscore the dynamic and contextual nature of ESG-financing relationships, suggesting that the public sentiment for sustainability topics act as a repricing mechanism rather than a selective reward function. The broader implications of these results, including possible explanations for this "green convergence" and its relevance for firms and investors, will be discussed in section 5.

5. Discussion

5.1 Discussion of findings

The empirical results presented in section 4 offer a nuanced and at times unexpected view of how climate and sustainability awareness interacts with firms' ESG performance to shape financing costs. However, given the methodological limitations of our study and the partial support for model robustness, our findings should be interpreted with caution and viewed as exploratory. Nonetheless, consistent with H1, our results confirm a baseline WACC discount for green firms relative to brown firms in the Nordic capital markets. This aligns with the established risk-based perspective, where superior ESG performance signals lower exposure to climate-related regulatory, reputational, and transition risks (Chava, 2014; Mariani et al., 2021; Oikonomou et al., 2014; Sharfman & Fernando, 2008). Nonetheless, given the Nordic context, often considered a global ESG frontrunner both in policy and corporate ESG performance (Bolton & Kacperczyk, 2020; Robeco, 2024; United Nations; 2025), it is plausible that even firms categorized as brown in this market possess relatively higher baseline ESG standards compared to global peers. Consequently, contrary to our expectation, the differentiation effects between green and brown firms observed across the hypothesis testing may partly reflect the region's inherently strong ESG orientation, potentially influencing investors' uniform responses to climate awareness shocks.

Building on this geographical context-perspective, the partially unexpected results for H2 indicate a more intricate investor response to climate and sustainability shocks, captured by the CSAI. While H2 (a) aligns with previous findings (Ardia et al., 2023; Pástor et al., 2021) by demonstrating a WACC reduction for green firms during unexpected heightened climate discourse, H2 (b) contradicts theoretical expectations. Rather than penalizing brown firms, increased CSAI surprisingly appears to reduce their WACC. This finding suggests that climate awareness shocks may trigger a generalized market-wide repricing of climate-related risk, consistent with Engle et al. (2020).

Moreover, as Ernst & Woithe (2024) argue, potential differences in capital structure could naturally also influence the observed decreasing WACC pattern for brown firms. Consequently, companies with lower ESG ratings may rely more heavily on debt financing, thus having structurally lower WACC despite higher perceived transition risks, highlighting the need to carefully interpret results within financial and capital structure contexts. Additionally, other prior literature with inconclusive or contradicting results notes that capital market responses to ESG signals are often inconsistent and contingent on external factors such as investor composition, regulatory expectations, and prevailing macroeconomic sentiment. In particular, Gonçalves et al. (2022) observe divergent effects between cost of equity and cost of debt, while Magnanelli & Izzo (2017) suggest that ESG overinvestment could introduce concerns about managerial inefficiency or "greenwashing", further complicating the interpretation of sustainability-related advantages. In our empirical setting, such theoretical perspectives could thus contextualize the deviations from hypothesized outcomes observed in our results.

The full-sample regression used to test H3 further supports this complex narrative. Green and brown firms both benefit from climate awareness shocks, but brown firms experience greater incremental benefits. The positive and statistically significant interaction term implies a narrowing WACC gap, contradicting the hypothesized magnification mechanism and instead suggests a green convergence. Several structural and behavioral mechanisms may underpin this observation. Firstly, heightened unexpected climate awareness might produce sectoral ”halo effects”, whereby positive sustainability sentiment extends to brown firms perceived as transitioning or likely policy beneficiaries. Secondly, investor optimism bias and “herding behavior” may induce generalized market optimism during periods of intensified unexpected climate-related media attention, potentially affecting firms market-wide. Thirdly, investors may anticipate future regulatory support, green subsidies, or favorable transition policies for brown firms, temporarily reducing their perceived transition risks – possibly amplified during climate awareness shocks. While these theoretical explanations are plausible, they cannot be directly tested within the scope of this study and should thus be interpreted cautiously (see section 6 for further discussion on methodological constraints).

Finally, our industry-specific regressions indicate sectoral differences while mirroring the overall green convergence patterns observed in the hypothesis testing. Unexpected climate and sustainability awareness appears to reduce WACC, especially in GHG-intensive sectors. These industries, with high transition risks and the highest CO_2 contaminations in our sample, are characterized by heightened investor sensitivity to climate risk and experience strong effects, in line with previous literature (Ardia et al., 2023; Bua et al., 2022; Ilhan et al., 2021). Although these results suggest strong reactions to unexpected climate awareness across sectors, they counterintuitively point to disproportionately benefitting brown firms, similarly to the main regressions. Nonetheless, it is important to note that the results are based on model specifications characterized by low statistical power due to small sample sizes and thus a non-trivial risk for Type II errors, limiting the interpretation and generalizability of the results. As the primary objective of this thesis was not to conduct in-depth industry-level analysis, and given that industry-level regressions are split from the full sample, these constraints are an inherent limitation. Regardless, this analysis highlights the importance of considering sector-specific characteristics, such as GHG-emissions, regulatory exposure, and investor scrutiny, when interpreting ESG-financing dynamics (Ilhan et al., 2021).

Collectively, our findings suggest that strong sustainability credentials, while associated with a baseline WACC advantage under normal conditions for green firms, may be partially overshadowed during periods of unexpected heightened climate awareness. This pattern could reflect an evolving market dynamic in which shifts in public sentiment do not consistently reinforce baseline ESG risk premiums but instead trigger a more generalized repricing of climate-related risks that benefit both green and brown firms, albeit through potentially different channels. While conceptually plausible and empirically suggestive, these dynamics, particularly those observed under H2 (b) and H3, appear somewhat sensitive to modeling assumptions, classification thresholds, and sample design. As such, they should be interpreted with appropriate caution.

5.2 Implications of findings

Building on the discussion of the exploratory patterns observed in our results, this section reflects on their broader implications. While the methodological constraints discussed earlier limit the generalizability of our conclusions, the findings nonetheless offer meaningful insights into how shifting climate awareness and firm-level ESG performance interact in shaping WACC. Against this backdrop, several implications emerge, both for how sustainability is conceptualized in theory and how ESG dynamics are navigated in practice for investors and management teams.

Our findings have important theoretical implications for the ESG-finance literature. While the baseline advantage for green firms aligns well with traditional risk-based theories (El Ghoul et al., 2011; Goss & Roberts, 2011), the observed convergence during periods of unexpected heightened climate awareness suggests a possible extended and nuanced theoretical lens that integrates behavioral finance perspectives and investor sentiment dynamics. The market-wide WACC convergence pattern during climate awareness shocks (Engle et al., 2020), where brown firms benefit alongside green firms, indicates that ESG pricing is less linearly determined by static ESG scores than previously assumed in adjacent literature (Mariani et al., 2021; Piechocka-Kaluzna et al., 2021). Accordingly, our findings suggest that it could be of relevance to incorporate dynamic external factors, such as media-driven climate awareness, into theoretical frameworks modeling ESG impacts on capital allocation.

Beyond theoretical implications, these results carry practical considerations for various stakeholders. For example, from an investor perspective, we show that public sustainability narratives influence market pricing beyond simple ESG classifications. As such, we propose that investors could consider not just firm-level ESG performance, but also place a larger emphasis on how shifts in public climate sentiment and expected policy actions could affect market-wide pricing of climate risks, similar to Engle et al. (2020). Particularly in markets like the Nordics, where ESG integration is advanced and institutional investors increasingly incorporate stringent ESG criteria (Bolton & Kacperczyk, 2020), investment strategies should reflect dynamic rather than static approaches to ESG risk management.

Our findings also highlight the strategic importance of credible ESG communication for firms. While green firms consistently benefit from ESG transparency through reduced financing costs, brown firms could leverage periods of unexpected elevated climate awareness to effectively communicate their transition pathways and sustainability initiatives. ESG disclosures thus remain strategically valuable but could be complemented by proactive narrative-building to capitalize on periods of changing public climate sentiment.

These implications, while instructive, ultimately rest on findings that are subject to statistical and contextual limitations (section 6), reinforcing the need for further empirical validation in other markets and over longer timeframes (see section 7).

6. Limitations and quality of study

This thesis has a number of inherent methodological limitations and constraints which inevitably affects the quality of the study and, in turn, the generalizability of the results. Firstly, a primary limitation concerns the time horizon of our empirical analysis, constrained by the availability of data from Media Cloud, covering only a relatively short five-year period (2020-2024). Extending the study to a longer timeframe (e.g., 10 years or more) would have enhanced robustness and comparability with prior research (e.g., Ardia et al., 2023; Engle et al., 2020). Moreover, the chosen sample period includes significant macroeconomic and geopolitical disruptions, such as the Covid-19 pandemic, Russia-Ukraine war and global recessionary pressures. Such events may significantly influence market dynamics, potentially confounding or exaggerating the observed effects on WACC. Additionally, the decision to focus on the Nordic region, where firms categorized as brown could exhibit relatively high baseline ESG standards, limits the extent to which our findings can be generalized to larger economies such as the United States or China, where ESG practices, disclosure frameworks, and investor behavior differ markedly.

Secondly, the classification of firms into green and brown is inherently sensitive to the ESG scoring methodology applied. ESG scores vary substantially across providers (Engle et al., 2020; Giese et al., 2021), and our use of Refinitiv Eikon may not fully align with other rating frameworks. Although an alternative ESG classification, using the Emission Score was employed as a robustness test (see table B6 in appendix B), our quartile-based classification could oversimplify complex sustainability profiles, potentially misclassifying firms. This is further complicated by the nascency of regulatory ESG reporting practices in the Nordics, where the new ESRS and CSRD frameworks only took full effect in 2024. As a result, the underlying data quality of ESG disclosures across firms may lack consistency, reducing the reliability of third-party ESG data. Furthermore, the multiplicity of ESG reporting standards (e.g., IFRS S1, IFRS S2, and ESRS) imposes a considerable reporting burden on companies, possibly undermining consistency and comparability of ESG disclosures. In addition, the relatively small sample sizes in our industry-specific and green-brown split-sample regressions limit statistical power and increase the risk of Type II errors, further constraining the generalizability of those findings.

Thirdly, limitations also stem from the construction and granularity of our CSAI and other key independent variables. While the CSAI captures shifts in public awareness through textual media coverage, its quarterly aggregation, constrained by accounting-based financial data availability, may overlook short-term investor responses to climate media shocks. A daily frequency would likely provide a more accurate depiction of sentiment effects, particularly given the volatile nature of climate discourse. In addition, the index does not account for sentiment tonality (i.e., positive or negative tone), nor does it incorporate other news formats such as radio, TV, or social media, thereby limiting the comprehensiveness of our proxy for public climate awareness.

Lastly, while the construction of our media index followed methodological considerations from previous literature (Ardia et al., 2023; Engle et al., 2020) aimed at minimizing data mining and reverse causality, potential endogeneity in the regression models, such as omitted variable bias or simultaneous causality between WACC and CSAI, remains a limitation. For example, reverse causality could arise if changes in a firm's WACC influence public or media attention to sustainability issues, rather than the other way around. Similarly, omitted variables, such as concurrent regulatory changes, firm-specific climate events, or macroeconomic shocks, may simultaneously affect both CSAI and WACC. Although these concerns are partly mitigated through fixed effects and careful variable construction, these concerns could not be fully addressed econometrically within the scope of this study.

Taken together, these limitations do not undermine the exploratory value of the study. Rather they define empirical and methodological boundaries. Insofar, they highlight areas for improvement and contextual expansion, issues which are addressed in section 7.

7. Suggestions for future research

The empirical findings and limitations identified in this thesis open several avenues for further exploration.

First, given the five-year time horizon analyzed (2020-2024), future studies should extend the temporal scope to examine whether the observed convergence patterns persist over longer periods. A longitudinal design spanning 10-20 years would allow researchers to capture evolving investor expectations, changing regulatory regimes, and broader shifts in climate discourse over time, offering stronger temporal validity and a more robust test of the dynamics observed here. Similarly, expanding the geographic scope beyond the Nordic context, could test the generalizability of our findings in regions with more fragmented or less mature ESG ecosystems. Conducting the same study to larger regions, or emerging markets, could reveal whether the observed "green convergence" phenomenon is context-specific and related to the empirical setting and methodological considerations applied here, or more universally applicable.

Moreover, while our CSAI captures the volume of media-based climate discourse within our news corpus and, to that capacity, functions as a proxy for unexpected climate and sustainability awareness in the Nordics, it could be refined in future studies. For example, although unattainable with Media Cloud, incorporating sentiment analysis and using higher-frequency media data (e.g., daily) may offer a more detailed understanding of how different types of climate narratives influence capital market outcomes.

Given the methodological limitation associated with using ESG ratings from one provider, future studies could test alternative ESG metrics or composite scores derived from multiple rating agencies (e.g., MSCI, Sustainalytics, Bloomberg) to validate the robustness of the green-brown classification. Alternatively, exploring such classification in combination with ESG sub-scores or using other types of classification metrics such as GHG-intensity[9], could offer additional insights into specific drivers behind WACC differentials. Relatedly, future research could also address potential endogeneity concerns more explicitly. For example, the use of instrumental variables, lag structures, or panel data techniques may help disentangle causal effects from correlated shocks and better isolate the directional influence of climate awareness on firm financing conditions.

Finally, while sector-specific dynamics were explored as a complementary dimension in this thesis, future research could further investigate how these effects vary by industry. Expanding the sample size and incorporating more granular firm-level or policy-specific data may clarify how different sectors respond to sustainability awareness shocks. Beyond financing costs, future studies could also examine whether similar dynamics affect other aspects of firm financial performance, such as stock returns, credit spreads, or volatility.

[9] GHG-intensity is defined as the volume of emissions produced per unit of economic activity (e.g., revenue).

8. Conclusion

This thesis has examined the research question of how unexpected public climate and sustainability awareness influences the WACC for green and brown firms in the Nordics. By combining firm-level financial and ESG data with a novel media-based climate and sustainability awareness index (CSAI) for the period 2020-2024, this quantitative study provides empirical insights into how public climate sentiment shocks interact with firm characteristics to shape financing costs in one of the world's most ESG-progressive regions.

The results confirm a baseline WACC advantage for green firms, consistent with established risk-based theories suggesting that superior ESG performance reduces exposure to climate-related risks. However, the study also contradicts previous research in climate discourse and firm financial effects, revealing a counterintuitive pattern; during periods of climate awareness shocks, WACC decreases for *both* green and brown firms. Rather than reinforcing a reward-penalty mechanism, unexpected climate awareness spikes suggest a WACC convergence. This observation, described here as a "green convergence", was also discovered, albeit with sector-specific nuances, in the subsequent industry-level regressions.

These findings contribute to the ESG-finance literature by advancing a more dynamic understanding of market responses to sustainability narratives. They imply that investor behavior may be shaped not only by firm-level ESG profiles, but also by media-driven sentiment, behavioral factors (e.g., optimism bias or herding), and sectoral as well as regional context. Thus, the thesis challenges the static assumption that markets consistently price climate risk in a linear fashion, providing both theoretical and practical implications.

However, the results must be interpreted with caution. The study's empirical design is subject to methodological limitations and model sensitivity. Most notably, the interaction term capturing the "green convergence"-effect proved sensitive to classification methodology, albeit directionally consistent. Moreover, the five-year time frame, quarterly data aggregation, and reliance on ESG ratings from one provider, limit the ability to draw strong causal inferences. Additional concerns, such as potential endogeneity, unobserved heterogeneity, and reduced statistical power in subsample regressions, further constrain the generalizability of the results. The Nordic focus, while analytically valuable, further limits external geographical validity, as ESG standards and investor behavior differ significantly across global markets. These limitations do not invalidate the empirical contributions, but they do frame them as exploratory and suggestive rather than statistical certainties.

Conclusively, this study offers a useful starting point for further inquiry. Future research could replicate the analysis across longer time periods and more diverse geographies, refine ESG classifications or media-based awareness proxies, and investigate whether similar convergence patterns appear in other financial or operational performance metrics. In doing so, scholars and practitioners alike can deepen their understanding of how public sentiment, firm sustainability efforts, and capital market dynamics are intertwined, and thus further explore the cost of a climate conversation in the age of the green transition.

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10. Appendix

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Appendix A: Additional tables

Table A1. Hausman test, full sample[10]

	Fixed effects (FE)	**Random Effects (RE)**	
Dep. variable	WACC	WACC	
Estimator	Panel OLS	Random effects	
No. of observations	n = 3,522	n = 3,522	
Cov. Est.	Robust	Robust	
R-squared	0.3561	0.5105	
F-statistic	221.53	458.02	
P-value (F-stat)	0.0000	0.0000	
	Coefficients		**Difference**
Const.	3.8663	4.1727	-0.3064
$CSAI$	-0.5937	-0.6588	0.0651
D_{GREEN}	0.5551	0.0065	0.5485
$CSAI \times D_{GREEN}$	0.1404	0.1473	-0.0069
$SIZE$	1.1935	-0.0749	1.2685
BTM	-0.0010	-0.1147	0.1137
LEV	-3.7657	-3.7033	-0.0623
ROA	-0.0001	-0.0011	0.0010
$BETA$	4.0102	4.0479	-0.0376
Hausman chi2 (d.f. = 8)	186.22		
p-value	0.000		
Decision	Reject null hypothesis, FE specification preferred		

Note: *D_{GREEN} is recalculated each period within each year and industry and therefore varies over time for a subset of firms. Because it is not perfectly time-invariant, it is estimated on both the RE and FE specifications and enters the Hausman chi2 test together with all other time-varying regressors. Robust (HC3) standard errors are clustered at the firm level in both estimators.*

[10] We re-ran the Hausman test separately for the green and brown sample splits. In both cases, the chi2 statistic remained highly significant, leading to the same conclusion that FEs are preferred.

Table A2. OLS panel regression results for hypothesis testing, no FE

Regression no.	**(1)**	**(2)**	**(3)**	**(4)**
Hypothesis	H1	H2 (a)	H2 (b)	H3
Sample	Full sample	Green sample	Brown sample	Full sample
Dependent variable	$WACC$	$WACC^{GREEN}$	$WACC^{BROWN}$	$WACC$
Key variables				
D_{GREEN}	-0.0675 (0.071)	-	-	-0.1165* (0.068)
$CSAI$	-	-0.5710*** (0.056)	-0.7326*** (0.059)	-0.7431*** (0.059)
$CSAI \times D_{GREEN}$	-	-	-	0.1810** (0.024)
Control variables				
$SIZE$	-0.1311*** (0.017)	-0.1860*** (0.023)	-0.0893*** (0.026)	-0.1190*** (0.017)
BTM	-0.3081*** (0.051)	-0.4599*** (0.095)	-0.3666*** (0.064)	-0.4025*** (0.053)
LEV	-3.7875*** (0.183)	-4.9636*** (0.295)	-3.1758*** (0.218)	-3.8427*** (0.175)
ROA	-0.0143* (0.008)	-0.0251 (0.017)	-0.0121 (0.009)	-0.0127 (0.008)
$BETA$	4.0314*** (0.067)	4.0010*** (0.088)	4.1054*** (0.090)	4.0564*** (0.063)
Fixed effects				
Time	No	No	No	No
Country	No	No	No	No
Industry	No	No	No	No
Model diagnostics				
Observations	3,522	1,760	1,762	3,522
Adj. R-squared	0.625	0.658	0.652	0.650
Condition number	22.7	21.7	25.3	22.7
Kurtosis	5.455	5.334	5.983	5.460
Skew	0.186	0.342	0.016	0.131
Standard errors	Heteroskedasticity robust type 3 (HC3)			

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

***Note**: (1) Standard error in parentheses. (2) All continuous independent variables are winsorized at 1%, except for CSAI. (3)* D_{GREEN} *= 1 for top quartile ESG Score within each year and industry, and 0 = bottom quartile ESG Score within each year and industry. Neutral firms are removed.*

Table A3. OLS panel regression results for hypothesis testing, no FE and controls

Regression no.	**(1)**	**(2)**	**(3)**	**(4)**
Hypothesis	H1	H2 (a)	H2 (b)	H3
Sample	Full sample	Green sample	Brown sample	Full sample
Dependent variable	$WACC$	$WACC^{GREEN}$	$WACC^{BROWN}$	$WACC$
Key variables				
D_{GREEN}	0.0802 (0.082)	-	-	-0.7392*** (0.101)
$CSAI$	-	-0.4475*** (0.099)	-0.7392*** (0.101)	0.0773 (0.082)
$CSAI \times D_{GREEN}$	-	-	-	0.2917** (0.141)
Control variables				
$SIZE$	-	-	-	-
BTM	-	-	-	-
LEV	-	-	-	-
ROA	-	-	-	-
$BETA$	-	-	-	-
Fixed effects				
Time	No	No	No	No
Country	No	No	No	No
Industry	No	No	No	No
Model diagnostics				
Observations	3,522	1,760	1,762	3,522
Adj. R-squared	0.000	0.013	0.031	0.022
Condition number	2.62	1.66	1.69	4.41
Kurtosis	3.415	3.541	3.236	3.386
Skew	0.347	0.434	0.367	0.400
Standard errors	Heteroskedasticity robust type 3 (HC3)			

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

***Note**: (1) Standard error in parentheses. (2) D_{GREEN} = 1 for top quartile ESG Score within each year and industry, and 0 = bottom quartile ESG Score within each year and industry. Neutral firms are removed.*

Table A4. Overview and reclassification of GICS industries

Industries used in thesis	GICS industries reclassified
Energy & utilities	Energy Equipment & Services; Independent Power and Renewable Electricity Producers; Oil, Gas & Consumable Fuels; Electric Utilities; Water Utilities
Materials	Metals & Mining; Chemicals; Paper & Forest Products; Construction Materials; Containers & Packaging
Industrials	Aerospace & Defense; Building Products; Electrical Equipment; Machinery; Industrial Conglomerates; Construction & Engineering; Trading Companies & Distributors; Distributors; Electronic Equipment, Instruments & Components
Transportation & infrastructure	Marine Transportation; Ground Transportation; Air Freight & Logistics; Passenger Airlines; Transportation Infrastructure
Technology & communication services	Software; IT Services; Technology Hardware, Storage & Peripherals; Semiconductors & Semiconductor Equipment; Communications Equipment; Interactive Media & Services; Diversified Telecommunication Services; Wireless Telecommunication Services; Media
Consumer discretionary	Automobiles; Automobile Components; Household Durables; Leisure Products; Textiles, Apparel & Luxury Goods; Specialty Retail; Broadline Retail; Hotels, Restaurants & Leisure; Entertainment
Consumer staples	Food Products; Beverages; Household Products; Personal Care Products; Tobacco; Consumer Staples Distribution & Retail
Health care & life sciences	Health Care Providers & Services; Health Care Equipment & Supplies; Health Care Technology; Life Sciences Tools & Services; Biotechnology; Pharmaceuticals
Financials & real estate	Banks; Capital Markets; Insurance; Consumer Finance; Financial Services; Real Estate Management & Development
Professional & commercial services	Professional Services; Commercial Services & Supplies; Diversified Consumer Services

Table A5. Keywords used as input in Media Cloud and newspapers included

Country	Keywords used for search	Sources in news corpus
Sweden	Swedish: "*klimatförändring**" English: "*climate change**"	FT, WSJ, Dagens Industri (DI), Svenska Dagbladet (SvD), Affärsvärlden, EFN
Norway	Norwegian: "*klimaendring**" English: "*climate change**"	FT, WSJ, Dagens Næringsliv (DN), E24, Verdens Gang (VG), Aftenposten
Denmark	Danish: "*klimaforandring**" English: "*climate change**"	FT, WSJ, Berlingske, Børsen, Jyllands Posten
Finland	Finnish: "*ilmastonmuutos**" English: "*climate change**"	FT, WSJ, Helsinki Times, Kauppalehti, Etelä-Saimaa, Savonsanomat

Note: *The star sign (*) in the end of the word allows the search engine to include different conjugations of the word, i.e., "klimatförändringarna" and "klimatförändringar" etc. in Swedish.*

Appendix B: Robustness tests

Heteroskedasticity

A first set of tests centers on heteroskedasticity, which can invalidate standard errors if left unaddressed (White, 1980; Wooldridge, 2010). Given the firm‐level panel structure and the potential for residual variance to differ across industries, countries, or firm sizes, we first test for heteroskedasticity using the Breusch & Pagan (1979) procedure (see table B1). The tests strongly reject the null hypothesis of constant variance, confirming the need for robust inference. Accordingly, all regressions reported in section 4.2 employ heteroskedasticity‐robust standard errors type 3 (HC3) (White, 1980; Wooldridge, 2010). To further verify that our t‐statistics are not unduly influenced by the choice of correction, we also re‐estimate all regression model specifications with heteroskedasticity‐robust standard errors type 1 (HC1) and with firm‐level clustering; in each case, the sign, magnitude, significance levels of $CSAI$, D_{GREEN}, and their interaction term remain largely intact[11], underscoring that our core inferences are insensitive to the form of variance adjustment.

Table B1. Breusch-Pagan tests for heteroskedasticity for H1, H2, and H3

Test type H1	**Statistic**	**p-value**	**F-statistic**	**F p-value**
Breusch-Pagan LM	336.9337	3.6946e-58	16.8247	2.0527e-6

Test type H2 (a)	**Statistic**	**p-value**	**F-statistic**	**F p-value**
Breusch-Pagan LM	216.4945	6.5295e-34	11.0743	1.9191e-36

Test type H2 (b)	**Statistic**	**p-value**	**F-statistic**	**F p-value**
Breusch-Pagan LM	145.6719	3.1227e-20	7.1240	3.2107e-21

Test type H3	**Statistic**	**p-value**	**F-statistic**	**F p-value**
Breusch-Pagan LM	336.8646	5.8810e-57	15.4102	3.5997e-60

Note: *As all p-values are essentially zero, we strongly reject the null hypothesis of homoskedasticity. Accordingly, all reported OLS regressions (regression (1)-(4) and the sector specific regressions) employ HC3 heteroskedasticity-robust standard errors to ensure valid inference.*

[11] We observe marginal changes in significance levels for regression (1) and (4), testing H1 and H3, where the green-brown classification dummy loses its significance from the 1% level to the 10% level when re-estimated using firm-level clustering in regression (1), with the similar pattern emerging in regression (4) where the interaction term also loses its statistical significance with firm-level clustering.

Bootstrap confidence intervals

To assess whether our estimates depend on specific data draws or distributional assumptions, we implement a non-parametric bootstrap with 1,000 replications, re-sampling at the firm-quarter level (Cameron & Trivedi, 2005; Efron & Tibshirani, 1993). The bootstrapped 95% confidence intervals for the key coefficients closely mirror those based on HC3 standard errors: the $CSAI$ effect in the full and split samples remains negative and never crosses zero, the D_{GREEN} baseline is consistently negative in regression models (1) and (4), and the interaction term remains positive and significant. These bootstrap results (see table B2-B5) therefore confirm that our findings are not driven by sampling variability or outlier-induced leverage.

Table B2. Bootstrap results on regression (1), full sample

Coefficient	Mean	95 % CI Lower	95 % CI Upper	Bootstrap p-value
D_{GREEN}	-0.1762	-0.3013	-0.0523	0.0060
$SIZE$	-0.0407	-0.0720	-0.0088	0.0050
BTM	-0.4157	-0.5293	-0.3019	0.0000
LEV	-3.9556	-4.3176	-3.6218	0.0000
ROA	0.0054	-0.0096	0.0199	0.2310
$BETA$	3.9665	3.8477	4.0906	0.0000

Table B3. Bootstrap results on regression (2), split sample (green firms)

Coefficient	Mean	95 % CI Lower	95 % CI Upper	Bootstrap p-value
$CSAI$	-0.2933	-0.4517	-0.1435	0.0000
$SIZE$	-0.1317	-0.1791	-0.0856	0.0000
BTM	-0.6369	-0.8447	-0.4158	0.0000
LEV	-4.6672	-5.1955	-4.0665	0.0000
ROA	0.0063	-0.0241	0.0406	0.3710
$BETA$	3.8904	3.6969	4.0835	0.0000

Table B4. Bootstrap results on regression (3), split sample (brown firms)

Coefficient	Mean	95 % CI Lower	95 % CI Upper	Bootstrap p-value
$CSAI$	-0.1605	-0.3099	-0.0203	0.0130
$SIZE$	-0.0063	-0.0556	0.0444	0.4010
BTM	-0.3380	-0.4537	-0.2152	0.0000
LEV	-3.3769	-3.7504	-3.0064	0.0000
ROA	0.0013	-0.0147	0.0161	0.4320
$BETA$	4.0338	3.8884	4.1966	0.0000

Table B5. Bootstrap results for model specification on regression (4), full sample

Coefficient	Mean	95 % CI Lower	95 % CI Upper	Bootstrap p-value
D_{GREEN}	-0.2856	-0.4078	-0.1556	0.0000
$CSAI$	-0.1717	-0.2924	-0.0428	0.0040
$CSAI \times D_{GREEN}$	0.1333	-0.0004	0.2725	0.0260
$SIZE$	-0.0419	-0.0728	-0.0113	0.0020
BTM	-0.4238	-0.5313	-0.3120	0.0000
LEV	-3.9773	-4.2933	-3.6519	0.0000
ROA	0.0036	-0.0105	0.0177	0.3000
$BETA$	3.9675	3.8401	4.0776	0.0000

Dealing with outliers

Extreme observations in WACC or firm characteristics risk disproportionately influence OLS estimates (Rousseeuw & Leroy, 1987). As stipulated in the sample construction process outlined in section 3.4.4, we apply a two-tailed 1% winsorization to all continuous regressors (except $CSAI$) to mitigate this risk, consistent with conventional quantitative empirical research methods. To verify that this choice does not drive our results, we re-run the full suite of regressions on the un-winsorized sample and again on a sample winsorized at the 2.5% level, in accordance with Bolton & Kacperczyk (2020) and El Ghoul et al. (2011). In every case, the direction, magnitude, and statistical significance of $CSAI$, D_{GREEN}, and their interaction term remain essentially unchanged, demonstrating that our inferences are robust to reasonable alternative treatments of outliers.

Alternative ESG classification

To test the sensitivity of the ESG classification of green and brown firms, we re-estimate the regression models used for the hypothesis testing, including all controls and fixed effects, with the Emission Score[12] from Refinitiv Eikon, following the same percentile cut-off as previously deployed. As such, this classification methodology also follows that of previous literature (Ardia et al., 2023; Bessec & Fouquau, 2021; Maeso & O'Kane, 2023), and the D_{GREEN} variable is coded as 1 (green) for each firm that ranks within the top 25th percentile within each year and industry. Accordingly, the bottom 25th percentile is coded as 0 (brown) and neutral firms (i.e., 26th to 74th percentile) are removed.

As evident from table B6 below, the direction and significance levels of the main coefficients of interest largely replicate that of the ESG Score-classification, although reduced levels of magnitudes and significance reinforce the need for interpretative caution in our overall findings and contributions. Notably, the number of observations under this classification methodology differs slightly from our main regressions (3,574 vs 3,522) due to data availability.

Specifically, the baseline WACC discount for green firms in H1, interpreted through D_{GREEN}, remains negative and significant, albeit at a lower magnitude and significance level, indicating a slightly weaker financing cost-advantage with emission-based classification. Similarly, the $CSAI$ coefficient under H2 maintains its significantly negative relationship with WACC for green firms (H2 (a)), however the brown firm subsample shows an insignificant result, although with a maintained negative coefficient. The negative and statistically significant $CSAI$ coefficient in regression (4) does however indicate confidence in the observed negative CSAI-induced effect in WACC for brown firms. However, as the interaction term under H3 remains directionally consistent but becomes statistically insignificant, this somewhat diminishes the confidence in the robustness of the differential effect previously observed between green and brown firms.

Overall, the supplemental alternative ESG classification regressions reinforce our original findings related to green firms' baseline financing advantage and a broader market-wide repricing of climate risks under unexpectedly heightened climate awareness. Nonetheless, the weaker statistical significance and reduced economic magnitude observed here underline that the "green convergence" phenomenon is somewhat sensitive to ESG classification methodologies and should therefore be interpreted cautiously.

[12] Defined as "*a category score that measure a company's commitment and effectiveness toward reducing environmental emission in the production and operational processes".*

Table B6. OLS panel regression results for hypothesis testing, alternative ESG classification

Regression no.	**(1)**	**(2)**	**(3)**	**(4)**
Hypothesis	H1	H2 (a)	H2 (b)	H3
Sample	Full sample	Green sample	Brown sample	Full sample
Dependent variable	$WACC$	$WACC^{GREEN}$	$WACC^{BROWN}$	$WACC$
Key variables				
D_{GREEN}	-0.0880* (0.055)	-	-	-0.0902* (0.055)
$CSAI$	-	-0.3106*** (0.078)	-0.1264 (0.077)	-0.2296*** (0.066)
$CSAI \times D_{GREEN}$	-	-	-	0.0389 (0.068)
Control variables				
$SIZE$	-0.0532*** (0.015)	-0.1270*** (0.021)	0.0017 (0.025)	-0.0536*** (0.015)
BTM	-0.3118*** (0.050)	-0.2751** (0.109)	-0.3253*** (0.053)	-0.3145*** (0.050)
LEV	-4.0977*** (0.168)	-4.6980*** (0.285)	-3.6786*** (0.221)	-4.1118*** (0.168)
ROA	0.0057 (0.007)	0.0162 (0.017)	-0.0044 (0.008)	0.0045 (0.007)
$BETA$	4.1005*** (0.062)	3.9454*** (0.093)	4.1883*** (0.085)	4.1079*** (0.061)
Fixed effects				
Time	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Model diagnostics				
Observations	3,574	1,768	1,779	3,574
Adj. R-squared	0.767	0.768	0.779	0.768
Condition number	37.3	33.4	42.0	37.3
Kurtosis	7.785	10.426	5.711	7.628
Skew	0.389	0.850	0.109	0.391
Standard errors	Heteroskedasticity robust type 3 (HC3)			

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

***Note**: (1) Standard error in parentheses. (2) All continuous independent variables are winsorized at 1%, except for CSAI. (3) D_{GREEN} = 1 for top quartile Emissions Score within each year and industry, and 0 = bottom quartile Emissions Score within each year and industry. Neutral firms are removed.*

Appendix C: Disclosure on the use of artificial intelligence (AI) tools

During the process of writing this thesis, AI-tools were sporadically used to support our work. For instance, ChatGPT was employed as a sounding board to assist in troubleshooting the Python script for the regression models as well as retrieving data from the Media Cloud database through an API, which was deployed in JupyterLab. Its use was limited to debugging errors, and offering general programming guidance. All code outputs were critically reviewed, tested, and adjusted to align with our methodological standards and cross-checked against other sources (e.g., methodological literature and other online resources).

For grammar-related tasks, ChatGPT and DeepL[13] were used. These tools supported the writing process through spelling corrections, and occasional translation tasks. However, final decisions regarding wording and structure were always based on our own judgment, and any critical content was cross-verified with academic sources or underlying data. Furthermore, in interpreting our results, ChatGPT was occasionally used to clarify statistical concepts. One example of this was to help us conceptualize our interpretation of the interaction term, where ChatGPT, in combination with other non-AI based resources, was helpful in enhancing our understanding of our regression results. Notably, this was done to inform our own thinking and did not generate answers nor conclusions, and in several instances we ended up disregarding the AI-generated guidance as it was providing factually incorrect statements.

[13] DeepL is a AI-powered translation software.