Mind the Green Gap: Climate Attention and the Green Premium in Sweden

Liv Nyström & Olivia Jernhall

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Abstract

This thesis investigates the existence and dynamics of the green premium in Swedish equity markets. Using daily data on Swedish large-cap stocks between 2016 and 2025, we examine whether environmental characteristics are priced in firms' expected returns, and how this pricing varies with investor attention to climate change. To capture climate-related concern among Swedish investors, we construct a novel Climate Change News Index (CCNI) based on articles published by Dagens industri. We regress excess returns on firms' ESG scores and on the interaction between ESG scores and the CCNI, and complement the analysis with an examination of second moment dynamics in green and brown portfolios. Our findings are three-fold. First, a negative green premium exists over the period 2016–2024 but reverses in 2025, coinciding with a broad decline in ESG-related sentiment. Second, the green premium narrows during periods of heightened climate news coverage, suggesting that investors reallocate capital toward green assets when climate change is more salient in the media. Third, green firms exhibit lower volatility and lower downside risk than brown firms, indicating that environmental characteristics are reflected not only in expected returns but also in the broader risk profile of equities.

Keywords: Green Premium, Climate Finance, ESG Investing
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Contents

1. Introduction

At the time of writing, public and political attention in Sweden and elsewhere has shifted toward a range of pressing short-term concerns, including geopolitical conflict and energy security. In this environment, climate change, once at the center of public debate and financial discourse, has receded from immediate focus. This shift reflects changing salience rather than diminished importance, but could have implications for how climate risk is perceived and priced in financial markets. Climate change remains a fundamental long-term societal risk with far-reaching economic implications, and its relevance for financial markets persists even as attention is temporarily drawn elsewhere. The World Meteorological Organization has confirmed that 2025 was one of the three warmest years on record, continuing the streak of extraordinary global temperatures (WMO, 2026). Understanding how climate change risk is reflected in asset prices therefore remains a timely and important research question.

At the core of climate finance lies the question of whether climate-related characteristics are incorporated into asset prices. As climate change represents a largely systematic risk, its effects on firms' future cash flows should, in principle, be anticipated and priced by rational investors. Mispricing of climate risk could lead to inefficient capital allocation, and correcting this is essential for mitigation of climate change. Consequently, the interaction between climate change, public policy, and financial markets has become an issue of growing interest for both investors and policymakers.

A central concept in this literature is the existence of a green premium, which posits that sustainable, "green", firms may benefit from a lower cost of capital, while "brown" firms face higher expected returns as compensation for climate change risk. That is, green firms are associated with lower expected returns, capturing a negative green premium. As will be discussed in the literature review, there is substantial evidence supporting the existence of a negative green premium. Evidence, however, is mixed regarding the size of the premium across time.

One potential explanation for this time variation lies in changing investor attention to climate risk. A growing body of literature proposes text-based approaches to capture climate risk through climate news coverage. Engle, Giglio, Lee, Kelly, and Stroebel (2020) construct a climate news index to study how climate-related information affects asset prices, while Bua, Kapp, Ramella, and Rognone (2024) use textual analysis to estimate the pricing of climate risk in European financial markets. These approaches interpret climate news intensity as a proxy for investors' perception of climate risk. Periods of heightened climate news intensity are assumed to coincide with increased investor attention to climate change, potentially leading to a reallocation of capital across firms with differing exposure to climate change. Existing studies primarily rely on large international news sources and less is known about how local information contexts shape the pricing of climate risk.

Building on this literature, we construct a Climate Change News Index (CCNI) using the complete collection of articles published by Dagens industri, the leading Swedish business outlet, over the past ten years. As a central source of financial information for Swedish investors, Dagens industri provides a relevant proxy for climate-related information flows in the Swedish market. By linking variation in climate news coverage to stock returns, this approach allows us to examine how investor attention interacts with the pricing of climate characteristics.

Beyond expected returns, climate characteristics may also shape the risk profile of asset returns. Climate risk often materialises through rare but severe adverse events, such as regulatory shocks or physical climate disasters, implying an asymmetric and non-linear impact on firm valuations. Climate characteristics may therefore be visible in measures of volatility and downside risk. Assessing whether green firms differ from brown firms along these dimensions is essential to painting a complete picture of how climate exposure is reflected in equity markets.

The Swedish equity market provides a particularly interesting setting for studying climate risk pricing. Sweden is widely regarded as a frontrunner in the green transition, characterised by ambitious climate policies, relatively low reliance on fossil energy, and an active green technology sector. It is therefore plausible that climate considerations play a more prominent role in investment decisions in Sweden than in many other markets. Moreover, Stockholm was recently crowned the European "capital of capital" by The Economist (2025). This could suggest that insights into Swedish climate risk pricing bear relevance beyond the domestic market, as such phenomena are expected to proliferate across Europe.

This thesis investigates how climate risk is priced in Swedish equity markets and how it evolves over time. Using data from 2016 to 2025, we analyse both the existence and the dynamics of the green premium in a period of changing climate sentiment. By combining firm-level climate measures with a novel CCNI, we examine whether climate risk pricing is sensitive to changes in investor attention. In addition, we assess whether these effects extend beyond expected returns to risk characteristics of asset returns, namely volatility and downside risk.

The paper is structured as follows: it will begin with a review of previous literature on the subject. Chapter 3 outlines the theoretical foundation of the study and presents the hypotheses. Chapter 4 describes the data and chapter 5 the empirical methodology. Chapter 6 reports the results, as well as a discussion of their implications for finance, followed by chapter 7 which addresses the limitations of the study, and suggests avenues for future research. Finally, chapter 8 concludes and summarises the key findings.

2. Literature review

2.1 Green premia in equity markets

Growing awareness and increased knowledge about climate change has expanded climate finance literature. Scholars are interested in how financial markets react to this relatively new source of risk, in part to improve understanding of how financial markets play into the complex regulatory frameworks designed to mitigate the consequences of a changing climate.

Theory predicts that climate risk should command a premium, as it is non-diversifiable. Pástor, Stambaugh, and Taylor (2021) study the hypothesis in a well-cited paper. In their equilibrium model, green assets have low expected returns because investors enjoy holding them and because these assets provide a hedge against climate risk. Paradoxically, the authors show that green assets have higher realised returns when investors are surprised by climate change concerns. The puzzle is attested by Tang, Dias, Mo, and Tian (2025), who find that green stocks substantially outperform brown stocks over the period 2010–2023.

Bolton and Kacperczyk (2021) examine whether carbon emissions affect US stock returns. They find statistical evidence of a carbon premium, wherein higher emission levels are associated with higher expected returns.

Eskildsen, Ibert, Jensen, and Pedersen (2025) construct an aggregated green score and find a negative green premium. The magnitude of the premium is greater in 'greener' countries, and it has become increasingly negative across the studied period 2009–2022. Similarly, Kranias, Psychoyios, and Refenes (2024) find that improved environmental performance is associated with lower returns.

2.2 Green premia in other asset classes

Another considerable research area concerns green premia in the bond market. Bonds present an appealing context for studying the green premium, as the same company can issue green and non-green bonds with similar maturities. Pietsch and Salakhova (2025) study the pricing of green bonds in European markets, and find a small but significant green premium. Moreover, they document time variation: the premium grew stronger from 2020 to early 2022, and weakened between 2022 and 2023. A similar analysis is conducted by Caramichael and Rapp (2024), who study the global primary bond market. They find a green premium emerging in 2019 and tightening during 2020–2021. They link it to demand for sustainable assets, suggesting investor demand as a primary driver. Building on this evidence of time variation, Wollny, Derwall, Galema, and Koedijk (2025) look at corporate green bonds and find a reversal in 2024, which they connect to a general ESG backlash.

Earlier studies also support the existence of a green premium. Baker, Bergstresser, Serafeim, and Wurgler (2018) document such a premium in US bond markets between 2010 and 2016. Similarly, Koziol, Proelss, Roßmann, and Schweizer (2022) show that investors are willing to accept a lower return on green bonds as the funds are used for sustainable investments and because of the informational advantages associated with proceeds disclosures.

More recent evidence points to a decline of the premium: Bachmann and Jespersen (2025) show that an initially negative yield spread between green and non-green bonds diminishes over time, becomes negligible by 2020, and turns positive by 2024.

Hartzmark and Sussman (2019) explore investor demand for sustainable assets. Using Morningstar's 2016 ESG ratings, they document that the highest-rated funds attract substantial net inflows while the lowest-rated funds instead experience net outflows. Moreover, they compare investor responses to different types of ratings: more detailed, versus simple categorical. They find that investors respond to simple categorical ratings while largely ignoring more detailed scores.

Climate change risk is typically divided into two categories: transition risk and physical risk. The first captures risk to businesses caused by costs related to transitioning to a low-carbon economy. The latter captures risks related to physical impacts of climate change, such as flooding or drought. While the lion's share of current literature focuses on transition risk, some studies examine physical risk. Schubert (2024) finds that banks with high flood-risk exposure through mortgages underperform relative to banks with low exposure.

2.3 Text-based approaches to modeling climate change risk

Identifying green premia is complicated by the lack of agreed-upon metrics to assess firms' exposure to climate risk. One approach to addressing this challenge is to add an intermediary step, using media coverage to capture investor attention and concern. The underlying assumption is that investors use news media to update their beliefs about economic and environmental risks, implying that variation in media coverage can serve as a proxy for time-varying climate-related concern.

There is convincing evidence for the agenda-setting function of news media, and its influence of public opinion (McCombs and Shaw, 1972). Baker, Bloom, and Davis (2016) are among the first to develop a newspaper-based index to measure economic policy uncertainty, demonstrating how media content can be transformed into economically meaningful indicators. Their methodology has since inspired a growing literature within climate finance.

Engle et al. (2020) construct a Climate Change News Index based on textual analysis of the Wall Street Journal, using a predefined climate vocabulary derived from official reports and policy documents. They show that exposure to climate change news represents a priced risk and propose a mimicking portfolio designed to hedge against fluctuations in the index. Their methodological framework is directly relevant for studies of climate risk pricing.

Similarly, Bua et al. (2024) apply textual analysis of news outlets to construct two daily climate risk indicators: physical risk index and transition risk index. Their indices spike on days when discussion on the risk types increases, and time-series regressions reveal significant premia associated with both risk types.

Ardia, Bluteau, Boudt, and Inghelbrecht (2023) test the second prediction by Pástor et al. (2021), that green firms outperform brown firms when concerns about climate change increase unexpectedly. Using a daily media index, they find that on days when climate change concern rises, prices of green stocks increase, whereas prices of brown stocks decrease.

2.4 Second moment effects of greenness

If climate exposure constitutes a systematic source of risk, its relevance should extend beyond average return differentials. Financial markets are characterised by time-varying conditional volatility, as shown by Engle and Ng (1993), and new information on climate risk may therefore be reflected in higher-order moments such as volatility and tail risk.

Albuquerque, Koskinen, Yang, and Zhang (2020) show that firms with high environmental and social scores exhibited lower return volatility during the COVID-19 pandemic. Looking beyond crisis periods, Hoepner, Oikonomou, Sautner, Starks, and Zhou (2023) identify that investor engagement in ESG issues reduces downside risk. Mishra and Modi (2013) study corporate social responsibility (CSR) actions of firms. They find that positive CSR efforts are successful in reducing the risk of firms. Consistent with this, Clark, Krieger, and Mauck (2026) demonstrate that among the S&P 500, firms with high ESG scores are less likely to exhibit extreme volatility.

Evidence from option markets provides further support of reduced volatility. Ilhan, Sautner, and Vilkov (2020) show that options written on more carbon-intensive firms are systematically more expensive, indicating a higher cost of insuring against extreme negative outcomes. Moreover, this effect strengthens when public attention to climate change increases, suggesting that climate risk is not only priced in expected returns but also in the higher moments of the return distribution.

2.5 Our contribution

Our contribution to the literature is threefold.

First, we provide novel evidence on the green premium by extending the analysis into 2025. Prior literature documents mixed findings regarding both the existence and magnitude of the green premium (Pietsch and Salakhova, 2025; Caramichael and Rapp, 2024; Wollny et al., 2025), but these studies are confined to earlier samples. By contrast, our analysis documents a green premium over 2016–2024, and its reversal in 2025.

Second, we extend the text-based approach of Engle et al. (2020) by constructing a CCNI tailored to the Swedish equity market. Our index is built on articles published by Dagens industri, Sweden's leading business outlet. This allows us to capture climate-related information flows relevant to Swedish investors. This represents the first Swedish CCNI, thereby extending the empirical climate finance literature to a new institutional and geographical setting.

Third, we extend the analysis beyond average returns by incorporating the second-moment effects of climate exposure. While much of the existing literature focuses on return differentials, climate risk is inherently asymmetric and likely to materialise through tail events. By analysing volatility dynamics, we provide a more comprehensive assessment of how climate risk is priced in financial markets and whether green assets offer downside protection.

Taken together, our findings contribute to a more nuanced understanding of climate risk pricing by showing the role of local information environments and risk characteristics of asset returns.

3. Theory and hypotheses

Standard asset pricing theory, building on the work of Sharpe (1964), Lintner (1965), and Markowitz (1952), posits that assets with greater exposure to systematic, non-diversifiable risk must compensate investors through higher expected returns. Climate change can be viewed as such a systematic risk, given its economy-wide impact across industries.

Within this framework, firms with high exposure to climate risk should command higher expected returns as compensation for bearing this risk. Conversely, firms with lower exposure may serve as a hedge and investors should consequently accept lower expected returns for these firms. In this study, the resulting difference in expected returns between green and brown firms is referred to as the *green premium*.

Hypothesis 1. Firms with low exposure to climate risk have lower expected returns than firms with high exposure to climate risk.

If climate risk is priced in equity markets, its associated premium should vary with changes in the perception of this risk. Building on the framework of Pástor et al. (2021), green firms are expected to outperform brown firms during periods of elevated climate-related concern, as investors revise the valuations of climate-resilient assets upward. Using the Climate Change News Index (CCNI) as a proxy for climate concern in the Swedish market, we therefore expect higher CCNI values to coincide with a narrowing of the (negative) green premium as it becomes less negative.

Hypothesis 2. The green premium is time-varying and depends on investor attention to climate change. During periods of heightened climate-related concern, as measured by the CCNI, the green premium narrows.

In an efficient market, differences in expected returns should reflect corresponding differences in risk. If green stocks have lower expected returns than brown stocks, this return discount should be matched by a more favourable risk profile. Climate risk is also likely to materialise through rare adverse events, suggesting that the relevant risk dimension may be particularly visible in measures of downside risk.

Hypothesis 3. Firms with high exposure to climate risk have higher volatility and higher downside risk.

4. Data

4.1 Stock prices, firm data, and control factors

We compile a firm-level panel with variables of daily frequency for Swedish large-cap companies, listed on the Nasdaq Stockholm Exchange, for the period 2016–2025. LSEG Workspace is used to collect closing prices, climate variables and industry codes, while Fama-French European factors are obtained from the Kenneth R. French Data Library.

Closing prices are collected at daily frequency. The use of daily closing prices is motivated by the need to align return data with the daily frequency of the constructed CCNI and capture high-frequency movements in the stock market. Moreover, daily returns are preferred for the volatility analysis, which further motivates the use of daily data throughout the study. Based on the retrieved closing prices, we calculate daily stock returns. Log returns are chosen over simple returns because of their time-additive features, and their mathematical properties which automatically preserve the natural lower price bound of zero.

To ensure comparability of the firms in our sample, ensure sufficient trading frequency, and maximise availability of ESG ratings, we restrict the sample to firms with a market capitalisation of at least SEK 10 billion on the date of data retrieval. This results in an initial sample of 130 firms, similar to the OMX Stockholm Large Cap Index. Daily stock prices, ESG scores, and E scores are collected for this set of firms. ESG data are missing for 14 firms, which are subsequently excluded from the analysis. Our final sample therefore consists of 116 firms.

The ESG scores range from 0 to 100, where a higher score reflects superior performance across the three ESG dimensions: environmental, social, and governance. ESG scores are reported at an annual frequency. To align them with the daily frequency of stock returns, we lag the ESG scores by one year and assign each firm's ESG score from year $t-1$ to all trading days in year t. This approach avoids look-ahead bias. Table 1 presents descriptive statistics of ESG scores by year.

Table 1: Descriptive Statistics for ESG Score

	Mean	Std	Min	Max	*N*
Full sample	58	17	21	93	204,696
2016	59	19	21	89	10,980
2017	60	19	21	83	11,664
2018	61	18	21	86	12,584
2019	56	18	21	88	19,680
2020	57	18	21	90	20,998
2021	58	17	21	93	27,134
2022	59	17	21	92	27,233
2023	59	16	21	91	28,272
2024	58	15	25	89	23,712
2025	59	15	22	84	22,439

As control variables we use the Fama–French 3 factors (the market risk premium, the size factor, and the value factor) at daily frequency, which is in line with conventions in financial literature. The Fama–French factors are provided at the European level rather than the individual country level. Under the assumption of relatively efficient and integrated capital markets, European risk factors are expected to co-move closely with their Swedish counterparts, rendering this approach a reasonable approximation.

Industry codes are used as a second set of control variables to ensure robustness. For our sample, this results in a total of 10 different industries, listed in Table 2.

Table 2: Industry Distribution

Industry	Number of Firms
Industrials	36
Real Estate	14
Health Care	13
Consumer Discretionary	12
Financials	12
Information Technology	9
Communication Services	7
Materials	7
Consumer Staples	4
Energy	1

In addition, we construct a corresponding monthly data set. Month-end closing prices are collected from LSEG, and monthly Fama–French 3 factors are retrieved from the Kenneth R. French Data Library. Monthly returns are computed in line with the daily specification. Also in the monthly data set, ESG scores are incorporated on an annual basis.

The time period, 2016–2025, allows us to capture both variations over time and recent developments. The time period also features significant variations in macroeconomic conditions, which could potentially impact the existence and size of the green premium. Importantly, we have opted for data collection post the Paris Agreement in 2015, a widely recognised turning point that significantly elevated climate change on the global political agenda and accelerated public, corporate, and policy engagement (Dröge, 2016).

To address high kurtosis in our data sample, winsorisation is applied to limit the disproportionate impact of outliers. All variables are winsorised at the 1st and 99th percentiles.

4.2 Climate Change News Index

To construct the CCNI, we first define a Climate Change Vocabulary (CCV). This vocabulary consists of a list of words derived from nine environmental reports published by different organisations, primarily governmental, including the Swedish Environmental Protection Agency and the Swedish Climate Policy Council (full list in Appendix 1). The reports used for the CCV are selected based on the criteria of (1) being published recently, ideally within the past year and no older than five years, (2) being issued by the most prominent and environmentally influential organisations in Sweden, and (3) maintaining a neutral and non-partisan perspective. After removing stopwords, a word frequency analysis is performed on the compiled reports to identify the most common terms, with a frequency of at least 50 across the selected reports. The CCV is illustrated by the word cloud in Figure 1.

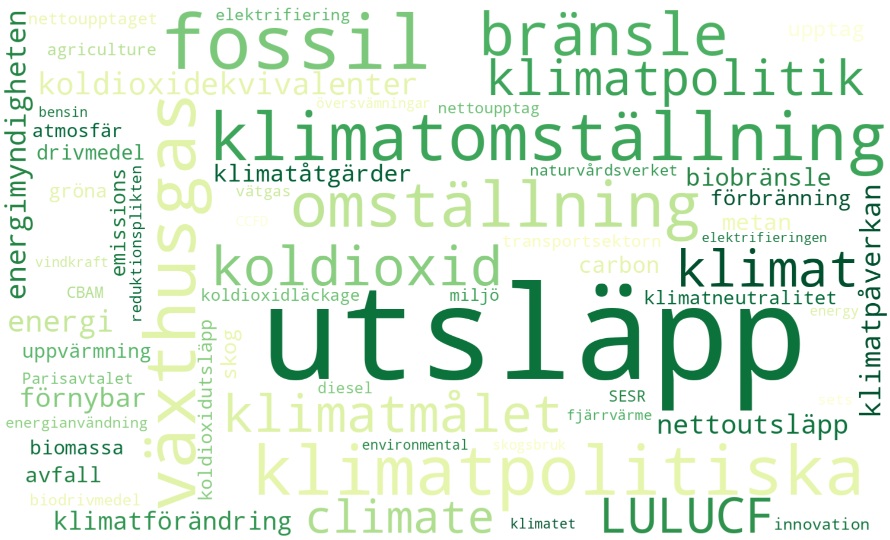

Figure 1: Climate Change Vocabulary, word cloud

Some English terms appear among the most frequent words, reflecting that climate change is often described using international terminology. The initial set is subsequently refined to exclude non-environmental terms, resulting in a final vocabulary of 64 terms. Notably, the CCV is heavily skewed toward transition-risk terms, with comparatively few terms relating to physical climate risk. This likely reflects the Swedish context: with limited exposure to physical climate effects such as drought, wildfires, or coastal flooding, public discourse and policy reports concentrate primarily on the economic and regulatory dimensions of the green transition. The full CCV, along with the corresponding word frequencies, is presented in Appendix 1.

Dagens industri was selected as the news outlet on which to construct the CCNI. This choice is motivated by the newspaper's position as the leading business news outlet in Sweden and its central role covering Swedish financial markets. To build the index, we used Retriever to collect the full set of articles published by Dagens industri during our sample period 2016–2025 (ca. 120,000 articles). The articles were compiled into a single document, and using the Python library pdfplumber, we extracted the full text, which was then sorted by date of publication, and subsequently matched to trading days on the Stockholm Stock Exchange.

5. Methodology

5.1 Estimation method

We estimate linear panel regressions to examine the relationship between firm-level climate exposure and stock returns. The data set, consisting of daily observations for 116 firms, is unbalanced as the availability of ESG scores differs, and some firms in the sample have been listed during the period.

We employ pooled Ordinary Least Squares (OLS) to estimate effects on the mean in a linear model specification. Under the assumption of conditional exogeneity, OLS yields consistent parameter estimates and provides a transparent benchmark framework widely used in empirical asset pricing research.

However, financial return data are known to violate several of the standard OLS assumptions. In particular, returns typically exhibit heteroskedasticity, serial correlation, and non-normality, including excess kurtosis. While these features do not affect the consistency of the OLS estimators, they invalidate results based on assumptions of homoskedastic and independently distributed errors. To account for this, we report heteroskedasticity-robust standard errors. In the panel regressions, standard errors are clustered at both the firm and time level to allow for cross-sectional and temporal dependence. In the portfolio regression, we instead employ Newey-West (HAC) standard errors to account for serial correlation and heteroskedasticity in the residuals. To mitigate concerns related to omitted variable bias, we further control for industry effects and restrict the sample to large-cap firms, thereby limiting variation in firm size.

The analysis is conducted on the full sample (2016–2025), a main subsample (2016–2024) and a separate analysis of 2025. This structure reflects evidence in previous literature of time-varying ESG characteristics and shifts in ESG-related sentiment, discussed in further detail in the results chapter.

5.2 Baseline regression model

To examine the existence of a green premium, firm-level climate risk exposure must first be assigned. In the baseline specification, ESG scores serve as a proxy for firms' overall exposure to climate risk. While ESG scores do not constitute a precise measure of climate risk exposure, they provide a natural and observable starting point for the analysis.

The baseline regression is specified as:

$$R^e_{i,t} = \alpha + \beta_1(Mkt\text{-}RF)_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 ESG_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

As a robustness test, we re-estimate the baseline specification using the E score. In addition, industry fixed effects are included to control for unobserved, time-invariant industry characteristics that may influence both ESG score and stock returns.

Furthermore, the baseline regression is re-estimated using monthly data as a robustness check to reduce daily noise. Apart from the change in data frequency, the model specification is identical.

5.3 Constructing the Climate Change News Index

The initial models capture firm-level exposure to climate risk based on reported figures and evaluations made by rating platforms. To complement these with a market-wide, data-driven measure of perceived climate risk, we construct the CCNI which captures variation in climate news intensity and thereby reflects changes in climate risk awareness among Swedish investors. This approach allows for the analysis of how financial markets respond when climate risk becomes more or less salient.

Two alternative versions of the index are constructed and subsequently used in the empirical analysis. The first index, hereafter referred to as the Raw Frequency CCNI, is computed as the daily aggregate frequency of terms from the predefined CCV appearing in articles published in Dagens industri. For each trading day, the total number of occurrences of CCV terms across all published articles is summed to obtain the index value. Figure 2 illustrates the time series of the Raw Frequency CCNI, together with a 30-day Moving Average (MA) to show trends.

The index shows a steady increase in climate news reporting between 2016 and 2020, with a sharp decline at the outbreak of the COVID-19 pandemic, which absorbed media bandwidth. The pronounced spike at the end of 2021 coincides with unusually high energy prices in Sweden and Europe, stemming from re-opening of society post pandemic, and rising prices on natural gas (Energimyndigheten, 2022).

From 2022 onwards, media attention devoted to climate change trends downward, likely reflecting competing sources of public concern, among them the Russian full-scale invasion of Ukraine in 2022 and unfolding conflict in the Middle East.

The spike in late 2024 likely relates to Trump's victory of the US presidential election, which prompted coverage of climate policy reversal, Paris Agreement withdrawal, and rollback of the Inflation Reduction Act, a landmark reform which in part targeted clean energy.

Our index appears to track meaningful shifts in the salience of climate change relative to competing news narratives, supporting its validity as a proxy for attention to climate change in the Swedish media environment.

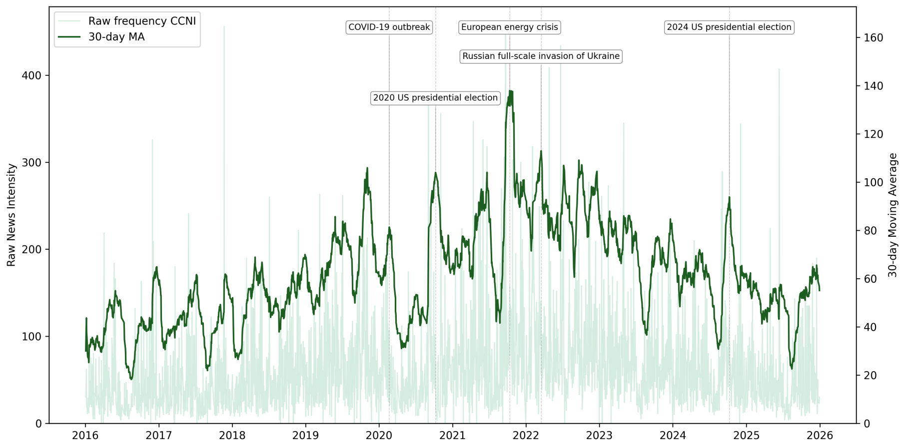

Figure 2: Climate Change News Index, Raw frequency

The second index is constructed using term frequency-inverse document frequency (TF-IDF), hereafter referred to as the TF-IDF CCNI. TF-IDF weights are estimated on the full corpus of news articles, with the CCV included as a reference in the estimation. Each document is represented as a vector in a high-dimensional term space, where each element corresponds to the TF-IDF weight of a specific term.

To quantify the degree to which a news article relates to climate change, cosine similarity is computed between the TF-IDF vector of each news article and the

TF-IDF vector of the climate reference corpus. Cosine similarity is defined as:

$$\cos(d, c) = \frac{d \cdot c}{\|d\| \, \|c\|} \tag{2}$$

where d denotes the TF-IDF vector of a news article and c denotes the TF-IDF vector of the climate reference corpus. The resulting similarity measure takes values between 0 and 1, with higher values indicating greater similarity to climate-related content. These similarity scores are aggregated to the daily level to obtain the TF-IDF CCNI, shown in Figure 3. In contrast to the Raw Frequency CCNI, this index has a normalised, weighted structure, whereby particular climate-related events show up less clearly. What is clear, however, is the downward trend from 2022 and onwards, attesting to the reduced salience of climate change in news media.

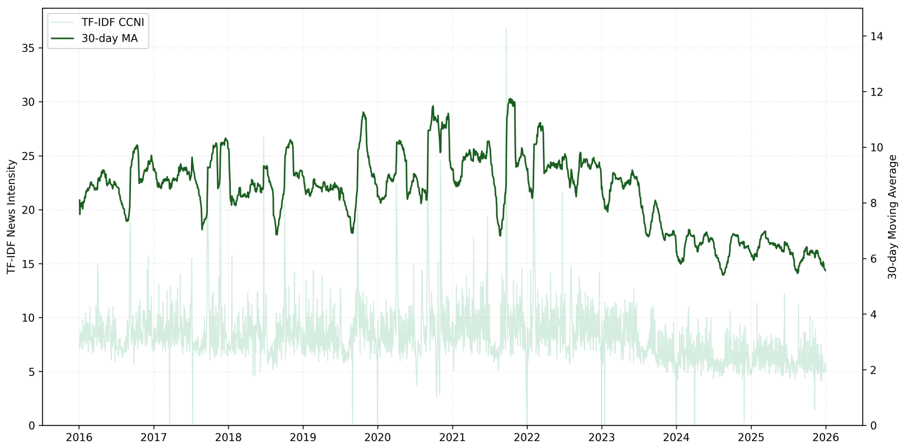

Figure 3: Climate Change News Index, TF-IDF

Both index measures are constructed at daily frequency and aligned with trading days on the Nasdaq Stockholm Exchange. To facilitate interpretation, the index variables are standardised to have zero mean and unit variance. The two indices capture different aspects of climate change reporting, the Raw Frequency CCNI captures the intensity in reporting, while the TF-IDF CCNI captures the relative importance of articles depending on their climate-related content.

5.4 Modeling returns together with climate-related concern

To examine whether the pricing of firm-level climate exposure varies with changes in climate-related concern, we extend the baseline specification by including the CCNI and an interaction term between the CCNI and firm-level climate exposure. This allows the relationship between ESG characteristics and returns to vary with the intensity of climate news coverage. The extended model is specified as:

$$\begin{aligned} R^e_{i,t} = \alpha &+ \beta_1 (Mkt\text{-}RF)_t + \beta_2 SMB_t + \beta_3 HML_t \\ &+ \beta_4 ESG_{i,t-1} + \beta_5 CCNI_t \\ &+ \beta_6 (ESG_{i,t-1} \times CCNI_t) + \varepsilon_{i,t} \end{aligned} \tag{3}$$

5.5 Constructing the hedging portfolio

Next, we investigate the possibility of creating an investment strategy that exploits potential return differences driven by environmental characteristics. To do this, we construct a characteristic-managed mimicking portfolio inspired by Engle et al. (2020). We base portfolio weights on firms' relative ESG scores.

On each trading day, each firm is assigned a weight proportional to its ESG score, demeaned and standardised across firms. The weight z for each firm i at time t is given by:

$$z_{i,t} = \frac{ESG_{i,t} - E\bar{S}G_t}{\sigma(ESG_t)} \tag{4}$$

This results in a long-short portfolio, which takes a long position in firms with a above-average ESG score and a short position in firms with a below-average ESG score, with position sizes proportional to the relative ESG score each day. The portfolio return x_t is then computed as the weighted average sum of individual stock returns using the z_{it} weights.

$$x_t = \sum_{i=1}^{N} z_{i,t} R_{i,t} \tag{5}$$

To assess if the portfolio successfully captures exposure to climate risk, we regress the CCNI on the mimicking portfolio return together with our control factors:

$$CCNI_t = \alpha + \beta x_t + \gamma_1 (Mkt\text{-}RF)_t + \gamma_2 SMB_t + \gamma_3 HML_t + \varepsilon_t \tag{6}$$

A positive and statistically significant coefficient on x_t indicates that the ESG portfolio co-moves with the CCNI.

5.6 Modeling conditional volatility and downside risk

To complement the return-based analysis, we examine whether climate risk exposure is reflected in second moment dynamics. For this, we construct two portfolios based on ESG scores: first, sorting the firms in quartiles, we classify firms with ESG scores in the upper quartile as green, and firms in the bottom quartile as brown. The use of quartiles balances the trade-off between achieving a sufficient sample size and a clear differentiation in climate exposure between green and brown firms.

We estimate a non-linear GARCH (NGARCH) to model the time-varying volatility, to investigate if green firms exhibit lower conditional volatility than brown firms. This specification allows for asymmetric responses to shocks, which is appropriate when working with financial market returns, as negative return shocks tend to have a more persistent impact on volatility than positive shocks (Engle and Ng, 1993).

To quantify the downside risk, we compute Expected Shortfall (ES) at the 5% level using a 250-day rolling window. ES measures the average loss in the left tail of the return distribution and is widely regarded as a suitable risk measure.

6. Results

6.1 Pricing of greenness in Swedish equities

To examine whether firms with lower climate risk exposure earn lower expected returns, we regress daily excess returns on ESG score.

Table 3: Pooled OLS, ESG Score and Excess Returns

Variable	(1) Full sample 2016–2025	(2) Main sample 2016–2024	(3) 2025
const	0.0004	0.0006**	−0.0017**
	(0.0003)	(0.0003)	(0.0007)
Mkt-RF	0.8660***	0.8672***	0.8584***
	(0.0299)	(0.0312)	(0.0549)
SMB	0.2984***	0.3048***	0.2270*
	(0.0645)	(0.0671)	(0.1379)
HML	−0.2825***	−0.2806***	−0.2898***
	(0.0511)	(0.0523)	(0.1058)
ESG Score	-4.963×10^{-6}	-7.301×10^{-6}**	20.460×10^{-6}**
	(3.131×10^{-6})	(3.418×10^{-6})	(8.917×10^{-6})
R^2	0.2222	0.2264	0.1851
N	204,696	182,257	22,439

Note: Standard errors in parentheses. Clustered standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.1.1 Baseline regressions, 2016–2024

The baseline regression on the full sample period does not yield a statistically significant coefficient on the ESG score at any conventional level of significance (Table 3). The estimated coefficient is negative, consistent with the hypothesis that investors accept lower expected returns for firms with a lower exposure to climate risk, but it is not statistically different from zero. As a result, no meaningful conclusion can be drawn based on the full-sample regression alone.

Motivated by previous documentation of the green premium changing over time, we extend the analysis to the period 2016–2024. Focusing on this period, the ESG coefficient is significant at the 5% level and reveals a green premium of $-7.301 * 10^{-6}$. Financially, a ten-point ESG score increase, equivalent to one letter grade improvement, is accompanied by an annual return discount of approximately 1.8% (Table 3), in line with Hypothesis 1.

Both the market risk premium (Mkt-RF) and the size factor (SMB) load positively and significantly, in line with expectations. The value factor (HML), by contrast, carries a negative and statistically significant coefficient of approximately -0.28 across all three specifications. This indicates that returns in our sample co-move inversely with the European value factor, consistent with the Swedish large-cap universe, where industrials, engineering, and technology firms trading at premium multiples are heavily represented.

To address the concern that the observed return discount may be driven by industry-level rather than firm-level dynamics, we re-estimate the baseline specification with industry fixed effects in Section 6.4, Table 10. The ESG coefficient remains negative and statistically significant, confirming that the result reflects the pricing of greenness rather than industry composition.

In addition to industry characteristics, other firm-specific variables could in principle affect both returns and ESG scores. Restricting the sample to firms with market capitalisation above SEK 10 billion limits cross-sectional variation in size, liquidity, analyst coverage, and disclosure quality, which collectively act as implicit controls for many of the standard return-driving characteristics. Combined with the Fama–French 3 factors, this helps mitigate omitted-variable concerns without introducing excessive controls.

6.1.2 The 2025 reversal: Evidence of a regime shift

Excluding 2025 from the main-analysis is justified by a notable shift in ESG-related sentiment during 2025, a year when ESG investing faced a broad backlash, originating in the United States and spreading to Europe. This shift is exemplified by fund flow data. According to Morningstar (2026), global sustainable funds saw net outflows of approximately USD 84 million during 2025, a sharp decrease in relation to previous years. Notably, Europe recorded the first net outflow since measurement began in 2018, indicating a broad decline in investor demand for green equities.

When restricting the sample to 2025, the ESG coefficient is instead positive and statistically significant at the 5% level ($20.460 * 10^{-6}$) (Table 3), indicating a reversal of the previously observed relationship. In this period, green firms earn higher returns than brown firms. Specifically, a ten-point increase in ESG score is associated with an annualised return increase of 5.1%. In addition to being of different sign, the magnitude of this estimated premium is large compared to the return discount of green firms observed in the period 2016–2024, which further supports the decision to analyse 2025 in isolation.

The reversal in 2025 is difficult to reconcile with a pure risk-based interpretation of the green premium. If the premium was solely a compensation for bearing climate change risk, it would arguably remain stable over time. Instead, our results point toward investor preferences as a primary driver: when demand for green stocks is broad, supply-and-demand pressure raises prices and lowers subsequent returns; when demand weakens, the relationship inverts. This interpretation aligns with the outflows from sustainable funds, and the work of Wollny et al. (2025), who document a reversal of green premia in the bond market during 2024.

The descriptive comparison in Table 4 reinforces this view. The mean ESG score is virtually unchanged between the two periods. This confirms that the reversal of the green premium is not driven by a change in firms' climate change exposure itself. In contrast, broader market conditions differ starkly between the two periods: the market risk premium is substantially higher in 2025 than in 2016–2024. Also, the mean CCNI shifts from positive to negative, indicating a sharp decline in climate news intensity during 2025. These trends are consistent with a sentiment driven story, rather than a fundamental repricing of climate change risk.

Table 4: Descriptive Statistics: 2016–2024 vs. 2025

Variable	2016–2024 Mean	2025 Mean	Δ
Mkt-RF	0.0002	0.0011	0.0009
ESG Score	58.3962	58.5646	0.1684
CCNI Raw Frequency	0.1305	-0.2251	-0.3557

The 2025 findings therefore do not invalidate the earlier results, but refine them. Return differences between green and brown stocks appear sensitive to investor preferences, which themselves vary with macroeconomic conditions and the salience of climate change. Whether 2025 represents a persistent regime shift or a temporary deviation cannot be determined within our sample and is left to future research.

6.2 The interacting role of climate change news

The previous section confirms that there are return discrepancies between green and brown firms listed on the Nasdaq Stockholm Exchange during the sample period 2016–2024. As a next step, we set out to investigate whether the differences in return increase during periods of heightened climate change concern. The CCNI, calculated in two different ways, is used as a proxy for climate risk awareness.

Table 5: Pooled OLS, ESG Score and Excess Returns with CCNI Interaction, 2016–2024

Variable	(1) Baseline	(2) Raw Freq. CCNI	(3) TFIDF CCNI
const	0.0006**	0.0006**	0.0006**
	(0.0003)	(0.0003)	(0.0003)
Mkt-RF	0.8672***	0.8674***	0.8672***
	(0.0312)	(0.0312)	(0.0312)
SMB	0.3048***	0.3043***	0.3038***
	(0.0671)	(0.0670)	(0.0670)
HML	−0.2806***	−0.2802***	−0.2801***
	(0.0523)	(0.0523)	(0.0523)
ESG Score	-7.301×10^{-6}**	-8.161×10^{-6}**	-7.964×10^{-6}**
	(3.418×10^{-6})	(3.430×10^{-6})	(3.396×10^{-6})
Raw Freq. CCNI	—	−0.0005*	—
		(0.0003)	
TFIDF CCNI	—	—	−0.0004
			(0.0003)
ESG × Raw Freq. CCNI	—	7.281×10^{-6}**	—
		(3.420×10^{-6})	
ESG × TFIDF CCNI	—	—	4.057×10^{-6}
			(3.689×10^{-6})
R^2	0.2264	0.2264	0.2264
N	182,257	182,257	182,257

Note: Standard errors in parentheses. Clustered standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.2.1 CCNI: The effect of climate news intensity

The first specification uses the Raw Frequency CCNI. In addition to the simple ESG score, the model includes an interaction term combining the ESG score with the CCNI.

In this model specification, the ESG coefficient remains statistically significant and negative at $-8.161 * 10^{-6}$ (Table 5), consistent with a baseline negative green premium that persists independently of climate-related news reporting. Moreover, the interaction term between the ESG score and the raw CCNI yields a statistically significant, positive coefficient of $7.281 * 10^{-6}$ (Table 5). The positive coefficient on the interaction term indicates that during periods of elevated climate news intensity, the negative ESG coefficient narrows, or may even reverse briefly, consistent with Hypothesis 2.

To further explore the impact of media attention, we perform an identical regression, instead using the TF-IDF CCNI.

This model does not yield a statistically significant coefficient on the interaction term (Table 5). This indicates that investors in the Swedish market react more strongly to the frequency of reporting rather than the uniqueness of the terms. While Engle et al. (2020) found more sizable market reactions to their TF-IDF index, the Swedish market is seemingly more driven by binary attention shocks.

Financially, our results using the Raw Frequency CCNI indicate that media attention reduces the green premium temporarily as investors in such periods appear to rebalance towards green assets, consistent with their role as hedging instruments against climate risk. This is in line with prior research on the influence of media on public opinion and concern (McCombs and Shaw, 1972). When climate news intensity increases, investors rebalance their portfolios to achieve a climate hedge. However, the long-term return discount of green stocks persists independently.

Our results suggest that Swedish investors respond quickly to intensified climate change reporting. This observed behavioral pattern has two important implications. First, it indicates that financial markets are sensitive to new information about climate change. Instead of waiting for regulatory changes or physical climate events to occur, media coverage is sufficient to trigger capital reallocation among investors.

Second, this highlights the important role and responsibility of the financial community as a driver of climate change responsiveness. Periods of heightened media attention coincide with increased capital allocation toward green firms, providing listed firms with an incentive for improving climate risk management. Thus, the financial markets have great potential in accelerating the green transition.

6.2.2 From pricing to portfolio: A hedging strategy for Swedish climate risk

Given the CCNI–return relationship documented in the previous section, we now ask: can we build an investable portfolio that loads on the underlying climate news factor, in order to hedge against climate change risk? We construct a portfolio using the mimicking portfolio approach, and regress the Raw Frequency CCNI on the return of the mimicking portfolio.

Table 6: OLS: Regression on Hedging Portfolio, 2016–2024

Variable	Coefficient
const	0.0478
	(0.034)
x_t	14.0990
	(9.306)
Mkt-RF	2.5707
	(2.347)
SMB	−2.9688
	(7.307)
HML	2.8406
	(4.729)
R^2	0.004
N	2,168

Note: Standard errors in parentheses. HAC (Newey-West) standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The regression on the mimicking portfolio return shows a positive but statistically insignificant loading on the ESG factor (Table 6), indicating that the ESG-based portfolio does not significantly co-move with the Raw Frequency CCNI. The low explanatory power ($R^2 = 0.004$) further confirms that the model captures little of the variation in climate news intensity. Together, these results suggest that while green assets may respond to climate-related information shocks at the firm-return level, this signal is not strong enough to construct a reliable hedging portfolio against fluctuations in the CCNI using ESG weights alone.

This null result does not invalidate the earlier findings, but rather highlights the difficulty of translating return-level climate risk pricing into an actionable hedging strategy.

6.3 Second moment effects of greenness

As a next step in the study, we proceed with a second moment analysis.

The NGARCH result, shown in Figure 4, reveals a persistently higher volatility of the returns of brown firms compared to green firms. Throughout most of the sample period, the annualised conditional volatility of the brown portfolio exceeds, in relative, that of the green portfolio in line with Hypothesis 3. These findings align with Clark et al. (2026), who identify a connection between low volatility and high ESG scores in equities.

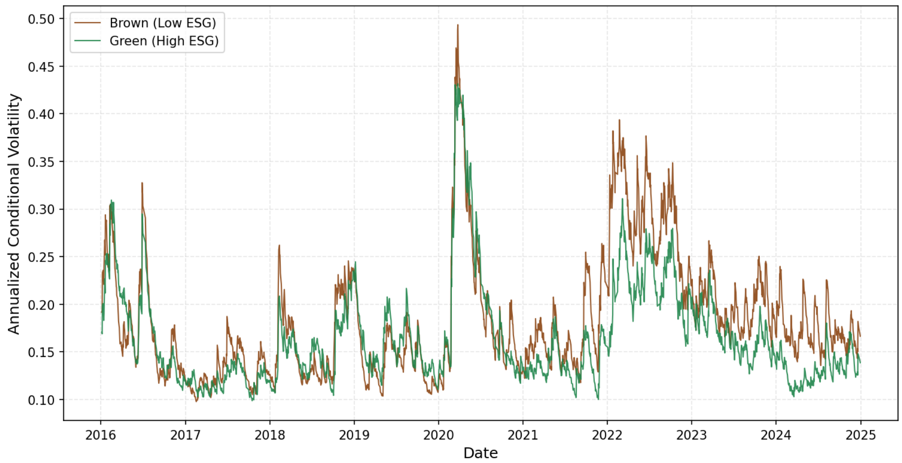

Figure 4: NGARCH-t conditional volatility

Connecting conditional volatility to expected return via ES provides a comprehensive view of downside risk, as it integrates first and second moments into one single analysis.

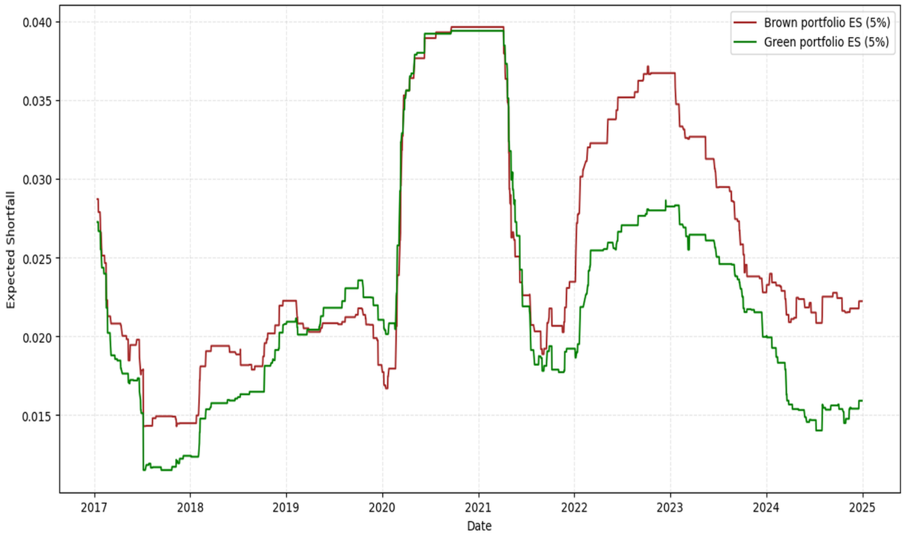

Figure 5: 250-Day Rolling ES 5%

As expected, the time-series movement of the ES resembles that of the NGARCH volatility (Figure 5). Throughout the period, green firms exhibit a lower shortfall.

The descriptive statistics in Table 7 summarise the second moment characteristics of the brown and green portfolio, highlighting important differences in both volatility and downside risk.

Table 7: Second Moment Risk Measures: Brown vs. Green Portfolio, 2016–2024

	Brown Portfolio	Green Portfolio
Conditional Volatility (NGARCH)		
Mean volatility	0.1842	0.1646
Expected Shortfall (5%, 250-day rolling)		
Mean ES	0.0256	0.0226
Max ES	0.0396	0.0394

Note: Brown and Green portfolios correspond to the bottom and top ESG-score quartiles, respectively.

Under standard mean-variance preferences, the lower returns of green stocks documented in Section 6.1 can therefore be justified, at least in part, by their overall lower risk profile, here illustrated through volatility and, in particular, ES. Given the general aversion to losses among investors, this property is especially valuable. To most investors, protection from downside risk weighs more heavily than an equivalent reduction in upside potential. Therefore, the return discount on green stocks appears to be compensated by the favourable risk characteristics they offer, in line with the risk-mitigation view of ESG assets supported by Hoepner et al. (2019).

6.4 Robustness

6.4.1 Monthly frequency

To ensure that the statistical significance observed in the regressions using daily data is not driven by noise, we re-estimate the baseline model using monthly data.

As can be seen in Table 8, the ESG coefficient remains negative and statistically significant at the 10% level. This equals an annualised return discount of approximately 2.4% for a one-grade ESG score improvement. While the statistical significance is slightly weaker, the direction remains consistent. This persistence suggests that the green premium is not a result of short-term noise, but reflects a relationship between green firms and expected returns. The reduced statistical significance could be a result of the lower number of observations, which increases standard errors.

We also re-estimate the regression including the interaction term between the ESG score and the Raw Frequency CCNI using monthly data. To align with the use of month-end closing prices in the return calculation, the Raw Frequency CCNI observation from the last trading day of each month is used. The ESG score coefficient remains negative and statistically significant at the 5% level, and the Raw Frequency CCNI coefficient remains negative, strengthening from 10% to 5% significance. The interaction term remains positive and statistically significant at the 5% level. The strengthening of statistical significance across terms relative to the daily specification likely reflects reduced high-frequency noise, and provides further support that climate news intensity meaningfully influences the pricing of environmental characteristics in Swedish equity markets, consistent with our earlier findings.

Table 8: Pooled OLS using monthly data, 2016–2024

Variable	(1) Baseline	(2) Raw Freq. CCNI
const	0.0140**	0.0162**
	(0.0069)	(0.0064)
Mkt-RF	0.8436***	0.8428***
	(0.0651)	(0.0645)
SMB	0.6094***	0.6124***
	(0.1892)	(0.1940)
HML	−0.2528***	−0.2510**
	(0.0964)	(0.1007)
ESG Score	−0.0002*	−0.0002**
	(9.867×10^{-5})	(9.041×10^{-5})
Raw Freq. CCNI		−0.0124**
		(0.0063)
ESG × Raw Freq. CCNI		0.0002**
		(8.889×10^{-5})
R^2	0.2639	0.2654
N	5,990	5,990

Note: Standard errors in parentheses. Clustered standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.4.2 E score as an alternative greenness proxy

To ensure that the observed green premium is driven by environmental performance rather than social or governance factors, we investigate whether the standalone E score generates a significant result. This regression yields a statistically significant negative coefficient of $-5.022 * 10^{-6}$ (Table 9), reflecting a 1.3% annual discount for a ten-point increase in the E score, compared to the 1.8% observed for the complete ESG score. The result provides evidence that social and governance factors do contribute to the lower expected returns of firms with high ESG scores, but also that the return difference is primarily driven by the isolated environmental factor. The use of the ESG score as the primary variable is therefore defensible. Particularly as previous studies have found that investors tend to favour simpler sustainability metrics over more detailed ones (Hartzmark and Sussman, 2019).

Table 9: Pooled OLS, E Score and Excess Returns, 2016–2024

Variable	Coefficient
const	0.0004**
	(0.0002)
Mkt-RF	0.8672***
	(0.0312)
SMB	0.3049***
	(0.0671)
HML	-0.2806***
	(0.0523)
E Score	-5.022×10^{-6}**
	(2.326×10^{-6})
R^2	0.2264
N	182,257

Note: Standard errors in parentheses. Clustered standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.4.3 Industry fixed effects

To confirm that the significance of the ESG score coefficient is not only a byproduct of industry-level dynamics, we expand the model specification to include industry dummy variables. After controlling for industry-specific effects, the ESG score maintains a significant negative coefficient of $-7.094*10^{-6}$ (Table 10). This confirms that the return discount is not driven by industry-level effects. The market is not simply pricing clean industries; it is rewarding specific firms that demonstrate successful climate risk management.

Table 10: Pooled OLS, ESG Score with Industry Fixed Effects, 2016–2024

Variable	Coefficient
const	0.0005*
	(0.0003)
Mkt-RF	0.8672***
	(0.0312)
SMB	0.3049***
	(0.0671)
HML	−0.2806***
	(0.0523)
ESG Score	-7.094×10^{-6}**
	(3.052×10^{-6})
Consumer Discretionary	-7.417×10^{-5}
	(0.0002)
Consumer Staples	8.228×10^{-5}
	(0.0002)
Energy	0.0014***
	(0.0002)
Financials	0.0002
	(0.0002)
Health Care	0.0002
	(0.0002)
Industrials	0.0002
	(0.0002)
Information Technology	0.0003
	(0.0002)
Materials	0.0001
	(0.0002)
Real Estate	−0.0002
	(0.0003)
R^2	0.2265
N	182,257

Note: Standard errors in parentheses. Clustered standard errors.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

7. Limitations and suggestions for future research

7.1 Limitations

Several limitations should be acknowledged when interpreting the results of this study.

First, ESG scores are imperfect proxies for firms' climate risk exposure. In addition, the use of annual ESG scores risk concealing short-term variations in climate risk that may be relevant to daily returns.

Second, in the CCNI, we have relied on the assumption that no news is good news, meaning we have not differentiated between good and bad climate change news. Should a significant portion of the articles cover positive climate news, the value of the CCNI as a proxy for climate-related concern is reduced.

While a significant relationship is identified between climate news coverage and the green premium, the analysis does not establish causality. It remains unclear whether increased media attention drives investor behavior or whether developments in financial markets influence the extent of climate-related reporting.

Moreover, omitted variables, such as the introduction of new climate policies, macroeconomic shocks, and increased energy prices, could simultaneously influence media coverage and the returns of green firms, creating biased results. As such, the results should be interpreted with a certain amount of caution.

Finally, the increasing prevalence of algorithmic trading may influence the speed and manner in which information is incorporated into asset prices. If trading strategies are designed to respond to news signals, this could amplify the observed relationship between media coverage and market outcomes.

7.2 Suggestions for future research

Building on the findings of this study, several avenues for future research emerge.

First, as additional data becomes available, it would be valuable to reassess the shift observed in 2025. A longer time horizon would allow for a clearer determination of whether the reversal of the green premium reflects a persistent structural change or a temporary deviation driven by short-term factors, such as political developments or shifts in ESG-related discourse.

Second, future research could examine inter-industry differences in greater detail. Expanding the sample would enable a more granular analysis of sectoral heterogeneity, providing insight into whether the observed effects are concentrated in specific industries or represent a broader market pattern.

Finally, using ML models to classify news as positive or negative could potentially generate more nuanced results, and could be an interesting path for future research.

8. Conclusion

This study set out to examine the existence and evolution of the green premium, as well as the role of climate news coverage in shaping investor behavior. The findings provide evidence of a marked shift over time. While a negative green return premium is observed in the period 2016–2024, it turns positive in 2025. Green firms went from having a lower cost of capital compared to brown firms, to having a higher cost of capital. The result confirms what has become a well-documented theory among financial analysts: that the ESG-era is on the decline.

Jointly, the results indicate that investor preferences and sentiment may play an important role in explaining the observed green premium, potentially alongside traditional risk-based explanations. In particular, the findings raise questions as to whether the premium reflects compensation for climate risk, or rather, changing demand for sustainable assets.

The text-based analysis offers further insight into these dynamics. A positive association is identified between climate news intensity and the magnitude of the green premium, suggesting that heightened attention to climate issues may coincide with increased investor demand for green firms. Conversely, the decline in both climate-related reporting and the green premium in 2025 points to a potential link between reduced public attention and diminished market valuation of sustainability characteristics.

These findings highlight the importance of financial markets in influencing capital allocation toward sustainable firms. Our results suggest that market-based mechanisms, particularly those driven by investor attention and preferences, can be a significant part of the solution to one of the defining challenges of our time. In this context, media coverage of climate-related topics may indirectly affect firms' cost of capital and thereby contribute to the pace of the green transition.

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A. Appendix

A.1 Climate vocabulary

Table 11: Reports Used for the Climate Change Vocabulary

Issuing Authority	**Report Title**
OECD	Environmental Performance Reviews 2025: Sweden
Swedish Civil Contingencies Agency (MSB)	Naturolyckor i Sverige: Hur förändras risken i ett förändrat klimat (Eng: Natural Hazards in Sweden: How Risk Changes in a Changing Climate), 2025
National Institute of Economic Research (Konjunkturinstitutet)	Miljö, ekonomi och politik 2025 (Eng: Environment, Economy and Policy 2025)
Swedish Environmental Protection Agency (Naturvårdsverket)	Fördjupad analys av den svenska klimatomställningen (Eng: In-Depth Analysis of Sweden's Climate Transition), 2021
Swedish Energy Agency (Energimyndigheten) & Swedish Environmental Protection Agency	Industrins klimatomställning (Eng: The Climate Transition of Industry)
Swedish Climate Policy Council (Klimatpolitiska rådet)	Klimatpolitiska rådets rapport 2025 (Eng: Climate Policy Council Report 2025)
Swedish Society for Nature Conservation (Naturskyddsföreningen)	Miljön i siffror 2025 (Eng: The Environment in Figures 2025)
Government Offices of Sweden (Regeringskansliet)	Sveriges klimatstrategi (Eng: Sweden's Climate Strategy), John Hassler
Sveriges Riksbank (Swedish Central Bank)	Riksbankens klimatrapport, februari 2025 (Eng: Climate Report, February 2025)

Table 12: Climate Change Vocabulary

Term	**Frequency**	**Term**	**Frequency**
utsläpp	4217	nettoupptaget	77
fossil	650	agriculture	77
växthusgas	558	elektrifiering	73
klimatpolitiska	530	innovation	72
klimatomställning	515	CBAM	68
omställning	448	vätgas	67
bränsle	406	SESR	67
koldioxid	336	nettoupptag	66
klimatmålet	306	Parisavtalet	65
klimat	296	reduktionsplikten	64
klimatpolitik	266	biodrivmedel	63
LULUCF	263	naturvårdsverket	62
climate	224	diesel	62
koldioxidekvivalenter	194	energianvändning	59
energi	183	sets	58
energimyndigheten	165	fjärrvärme	54
klimatpåverkan	161	energy	51
nettoutsläpp	150	environmental	51
förnybar	147	vindkraft	51
klimatförändring	145	översvämningar	51
biobränsle	140	CCFD	50
klimatåtgärder	134	klimatet	50
metan	130	skogsbruk	49
carbon	124	bensin	48
förbränning	113	elektrifieringen	47
avfall	113		
skog	110		
upptag	108		
emissions	94		
drivmedel	94		
biomassa	90		
gröna	90		
uppvärmning	90		
koldioxidutsläpp	83		
atmosfär	83		
klimatneutralitet	83		
transportsektorn	81		
miljö	80		
koldioxidläckage	79		

A.2 The use of AI

We have used generative AI tools, including ChatGPT and Claude, to support the execution of this study. These tools were primarily utilised for assistance with data handling, code development, and text editing. In addition, generative AI was used to produce a word cloud visualisation presented in Chapter 4.

The use of AI enabled us to implement more complex models and conduct more advanced data analyses than would otherwise have been feasible, given our limited programming experience. In this sense, AI functioned as a technical support tool, helping translate analytical ideas into executable code.

We did not use AI for idea generation or creative conceptual development. All research questions, hypotheses, and interpretations were developed independently by us. Instead, AI was used as a supplementary tool for refining language, improving clarity, and providing a secondary review of both code and written text.

While the use of AI improved efficiency and analytical scope, it also introduced potential risks, such as incorrect or misleading code suggestions. To mitigate these risks, all AI-generated content was carefully reviewed, tested, and validated before inclusion in the study.

Overall, AI contributed to improving the technical execution and clarity of the thesis, while we retain full responsibility for the study's design, analysis, and conclusions.