# Broken promises: The failure of green stock outperformance in Europe

**The importance of rating coherence**

**ELLEN HÅDÉN**
**EBBA GRAFF-LONNEVIG**

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**Abstract**

Increasing interest for sustainable investment have caused a trend within the investment sector towards more ESG engagements. Our study finds no outperformance of green portfolios over brown portfolios, when using industry-adjusted environmental pillar scores. The same applies when controlling for unexpected climate concerns. However, we do find evidence of across-industry greenness having more impact on stock returns when including both measures of greenness. This indicates that within-industry alone does not have the capacity to capture stock return variations to explain any green outperformance. Lastly, we provide evidence that the choice of model in calculating unexpected climate concerns significantly impacts the interaction between greenness and unexpected climate concerns.

**Keywords**

Sustainable investing; ESG; Environment; Climate change; Green stocks

**Authors**

Ellen Hådén (24947)
Ebba Graff-Lonnevig (24937)

**Supervisor**

Mehran Ebraheimian, Assistant Professor, Department of Finance

**Examiner**

Adrien d'Avernas, Assistant Professor, Department of Finance

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Over the past decade the importance of sustainable investments has been widely debated in financial literature. In 2022, $2.5 trillion were invested in Global ESG fund assets, where Europe accounted for $2.1 trillion of these, which corresponds to the region representing 83% of investments in Global ESG fund assets (Baker, 2023). Thus, the demand for sustainability in the investment sector can be viewed as high, however, discussions remain regarding the impact of these more specific investments.

Furthermore, there are divergences in literature on whether CSR and ESG investments benefit corporations. Relating back to Milton Friedman's doctrine (Friedman, 1970), the agency theory view on corporate responsibility aligns with Friedmans questioning on the claim that firms have responsibilities towards society other than to increase profits. A summarizing study by Friede, Busch and Bassen (2015) examine the results from over 2000 studies within the field of ESG relation to financial performance, where 90% of the studies demonstrates a non-negative relationship between ESG and company financial performance. Likewise, there is a trend within the investment sector towards more extended ESG engagement (Uzoki 2020). Zerbib (2019) suggests there is a green bond premium because of investor non-pecuniary motives. Baldauf, Garlappi and Yannelis (2020) detects changes in consumer preferences in the real estate market, where climate crises are shown to cause a more conscious consumer behavior. Large asset management companies also advise their customers to invest in ESG stocks. For example, BlackRock in a recent report claims that sustainability is their "standard for investing" while also promoting their product screener to match customer preferences with companies' sustainability goals (BlackRock, 2023). From this we can conclude that there is a clear demand for ESG investments in the stock market, both from asset managers and private investors.

Previous research investigating the impact of ESG engagements on financial performance as well as stock returns, have examined regional as well as global markets. However, the primary focus of these studies has been with regards to the US stock market (or markets with global actors)[1]. Thus, factors such as emerging vs developed markets, high-income vs developing countries and varying regulations and jurisdictions with regards to ESG reporting might be overlooked due to gaps in the body of research. In most of Europe, laws and jurisdictions now demand firms to take action, for example, as ESG reporting is mandatory in the EU due to the non-financial reporting directive, founded by the European Commission in 2014 (Directive 2014/95/EU of the European Parliament and of the Council, 2014). As a result of differences in regulation in Europe and the US, EU firms outperform US firms in ESG disclosures (Rezaee, Homayoun, Poursoleyman and Rezaee, 2023). Additionally, the European market performs better on average in terms of Environmental and Social scores (Auer, Schuhmacher, 2016) and Liang and Renneboog (2017) find a strong correlation between the firm's legal origin and their CSR score, where Scandinavian legal origins give the highest correlation with high CSR scores. One of the main objectives of this study is therefore to address the question of stock performance of green portfolios vs brown portfolios in Europe.

The fact that ESG data providers differ in their nature is well established. One of the main objectives of these organizations is to prevent information asymmetry. However, the differences in these agencies' processes to obtain ESG scores, creates obstacles that are hard to combat. Several previous studies have examined the differences and biases of the major ESG agencies that today gather and provide ESG scores for firms worldwide. Even among the prominent global ESG rating agencies, Dorfleitner, Halbritter and Nguyen and Sparrer (2015)

[1] Top 10 most cited articles when searching on ESG and stock returns on google scholar, adopt a sample set either from firms listed on S&P 500 or use a global universe as sample for their studies.

and Chatterji Durand, Levine, and Touboul (2016) highlight the absence of consistent ESG measurement frameworks, where they also report a lack of homogeneity amongst ESG rating agencies. A study by Berg, Kolbel and Rigobon (2022) examines the divergence between the scoring system that rating agencies use. The study investigates categories and their respective scores from six global ESG agencies. Their findings suggest that the main issue of divergence in scores is due to measurement divergence, i.e., the difference in choice of methodology to realize the scores. However, there are also instances of the same methodology being applied using different databases where results have been similar (Demers, Hendrikse et al. 2021). Another objective of our study is therefore to use the methodology of Pástor, Stambaugh et al. (2022) to examine stock returns of green vs brown portfolios using a different ESG database than the original paper.

The aim of the study is to replicate the green-minus-brown estimation of *Dissecting Green Returns* (Pástor, Stambaugh et al. 2022) to answer the following research question:

Do green portfolios outperform brown portfolios in the European market?

There are several challenges in examining green stock performance. Firstly, there is a great disparity in methodologies used and few replications in the field. We address this by applying the same methodology as Pastor, Stambaugh et al (2022) with another database for ESG scores to examine European and US stock returns separately. Secondly, green stock can temporarily outperform brown stocks due to immediate stock price effects occurring from unexpected climate concerns (Pástor, Stambaugh et al. 2021). The outperformance is explained through two aspects; Firstly, the demand from investors for green assets which directly increases these assets prices, and secondly, the demand from consumers for green products, which increases company profits that consequently drives up stock prices (Pástor, Stambaugh et al. 2021). We address this by incorporating unexpected climate concerns in our regressions by using the MCCC index as a proxy for climate sentiment.

To address the first challenge, we estimate the green-minus-brown factor (from now on referred to as GMB factor) for a sample of 723 European firms during the period November 2012 to December 2020. The greenness measure used is the Refinitiv Eikon environmental pillar score, which is industry-adjusted. Brown portfolios contain firms with the ⅓ lowest environmental scores, while the green portfolios contain the firms with the ⅓ highest environmental scores. The portfolios are constructed in June each year and the returns are value weighted. Time series regressions are performed on the difference of monthly green and brown value-weighted portfolio returns which are performed according to the methodology of Fama and French (Fama, French 2015) (Fama, French 1992) and Carhart (Carhart 1997). For comparison objectives, we repeat this analysis for a sample of 674 US firms. Our results give no incentive to believe that there is an outperformance of green portfolios over brown portfolios for either geographic region, when using industry-adjusted environmental pillar scores. However, we find evidence for differences between the regions as our estimates of the US GMB factors are negative and significant whilst we cannot find evidence for the European GMB factors differing from zero.

To address the second challenge, two different analyses are conducted. The MCCC index (both 2020 and updated 2022 version) is used to calculate unexpected climate concerns through a rolling AR (1) model with an estimation period of 36 months. First, an aggregated analysis with regular OLS regressions is used to analyze GMB returns and GMB alphas when controlled for unexpected climate concerns (for both current and previous month). Then, we use a fixed effects panel regressions to analyze the effect of within-industry and across-industry greenness on firm stock performance at individual level. Here, the two measures of greenness are interacted with both same and previous month unexpected climate concern. The across-industry greenness here is the industry-averages of GICS categories and subcategories, as collected from Pástor et. al (2022). For comparison objectives, we repeat this analysis for US firms. After having included across-industry greenness, we find evidence of across-industry greenness having more impact on stock returns. This in turn indicates that within-industry alone does not have the capacity to capture stock return variations to explain any green outperformance.

In a further analysis, we also examine the difference between using a rolling AR (1) and rolling AR (2) model to estimate unexpected climate concerns. The intuition behind this is that since the regressions containing unexpected climate concerns are in principle multi-step regressions due to the calculations of unexpected climate concerns, small changes in unexpected climate concerns can greatly impact the regression results. Furthermore, there is a risk of a rolling AR (1) model not being able to properly capture trends lasting several months, which a model containing more months might be able to do. Therefore, we concentrate the last part of our analysis on this issue, constructing a new index for unexpected climate concerns from the rolling AR (2) model. First, an aggregated analysis with regular OLS regressions were used to analyze GMB returns and GMB alphas when controlled for unexpected climate concerns (for both current and previous month). Then, we use a fixed effects panel regressions to analyze the effect of within-industry and across-industry greenness on firm stock performance at individual level. The results from these are later compared with the results from the regressions having used the rolling AR (1) model. Here, we provide evidence that the choice of model in calculating unexpected climate concerns significantly impacts the interaction between greenness and unexpected climate concerns.

The remainder of the paper will be structured as follows. Section I. Covers close papers on the key concepts applied, as well as our contribution to current body of literature. Section II. Presents the data and methodology used. Section III. Consists of the empirical analysis on the performance of green stocks in the EU. Whilst Section IV. Discusses the results guided by the results from the empirical analysis as well as the key concepts of previous literature. Finally, Section V. concludes the paper.

# I. Related Literature

## 1.1 Divergence in literature; Perspective and Methodology

There is various literature covering ESG stock performance and its implications. However, the variation in perspective, procedures and methodology applied are distinctive even though the studies seem to investigate and explain the same phenomenon at first. For example, *Dissecting green returns* by Pástor et. al (2022) applies the lens of the investor through examining how well environmental scores can predict future stock returns, while *ESG controversies and controversial ESG: about silent saints and small sinners* by Dorfleitner et. al (2020) instead explains the relationship between *Corporate Financial Performance* and *Corporate Social Performance* from a firm perspective, suggesting the importance of how companies are presented in the light of ESG engagement. These two articles reflect the widespread differences that compose the current gaps in literature. Despite the similarities in applied methodology for the two articles, as both studies apply the Fama and French five factor model, the starting point and fundamental approaches cause divergence.

Similar to the approach by Pástor et. al (2022), Ardia, Bluteau, Boudt, and Inghelbrecht (2020) examines the effect of increasing climate concerns on green stock performance, by both portfolio-analysis and individual-level fixed effects regression. The main difference between the studies is the construction of the greenness measure, as greenness is defined as greenhouse gas emission scaled by firm revenue in the study by Ardia et. al (2020).

Thus, consistency of methodology in literature is limited to the extent that studies on ESG stock performance often apply different procedures while focusing on different explaining factors to justify their results. We contribute to this existing gap in literature through applying a different ESG database (Refinitiv Eikon), while replicating the procedure by Pástor et. al (2022), thus withstanding our stance on consistency in the subject of ESG stock performance. Further, the MCCC index used in Pástor et. al (2022) has since been updated so that the index covers a larger scope of newspapers. We will thus use this more extensive sample in our analysis with the aim to contribute through as accurate and up-to-date results as possible with regards to current available data.

## 1.2 Geographic and regulatory factors effect on the stock market

Few studies have examined sample sets that are limited to stock markets connected to geographically smaller countries. However, a study that focuses on the stock market in a smaller country was conducted in 2020 by Fiskerstrand, Fjeldavli, Leirvik, Antoniuk, and Nenadić (2020). The main conclusion and accordingly the contribution of the paper is that an abnormal risk-adjusted return should not be expected by investors that decide to invest in portfolios with high ESG scores (Fiskerstrand, Fjeldavli et al. 2020).

Further, a study by Bermejo Climent, Figuerola-Ferretti Garrigues, Paraskevopoulos, and Santos (2021) uses a two step-regression according to Fama and McBeth (1973) on monthly stock returns from a sample of 6211 European firms. From analyzing the ESG disclosure effect on returns, they find evidence for a significant governmental effect on returns, suggesting that firms are more likely to report transparent information with governmental character. However, it should be noted that they find no significant effect of the environmental pillar or the social pillar.

The European market consists of a broad range of companies characterized by strategies aligning with ESG as well as legal regulation by the European Non-financial reporting directive. As mentioned before, a sample of the European market is seldomly used when examining ESG stock performance, however there are several cultural factors interfering with the prerequisites of this market in relation to the US market. For instance, Norway is a country where the energy sector (mostly oil and gas) accounts for high financial performance, which demonstrates geographically conditioned prerequisites. To prevent few economically stronger companies from creating skewed results, Fiskerstrand et. al (2020) adjust for these through using a logarithmic market capitalization methodology for value-weighting.

The results from a study by Schultz (2002) also reflect that there are significant differences between Europe and the United States with regards to the collective stance on sustainability. The findings suggest that citizens of the United States overall, have less concern with regards to climate change in comparison to the other regions investigated (Europe, amongst others). The study also explains the reasoning behind this to stem from differences in cultures, where the United States are said to have a more individualistic culture, in comparison to for example Europe that is said to foster a *biospheric* attitude, where the collectivistic culture encourages social relationships.

The studies presented, indicate the importance of realizing the impact that the geographical position with regards to governmental, regulatory, and cultural effects have on stock markets, and further ESG stock performance. Thus, taking the different findings above into consideration, narrowing the sample down to this particular market could possibly give results that vary from previous studies. By focusing on the European market as a sample, a further extension inspired by Fiskerstrand et. al (2020) contributes to current gaps in literature.

## 1.3 Industry-adjustment in ESG data

The view on rating agencies' choice to constrain ESG scores to either industry-adjusted or industry-unadjusted is dispersed. Some claim that industry-relative scores provide a more accurate picture as they rely on industry averages, while some prefer the raw scores to be reflected. This also poses yet another factor contributing to the heterogeneity in the debate on the widespread differences in procedures that problematize the rating agency industry.

As Larcker, Pomorski, Tayan and Watts (2022) propose, industry-adjustment of ESG scores mitigates the risk of industry-biases as it narrows the perspective to industry levels, which could be more efficient when comparing within-industry scores. On the other hand, Halbritter and Dorfleitner (2015) argues that companies within a *brown or dirty* industry could still be viewed as appropriate for a *green or clean* portfolio as a repercussion of industry-adjusted scores. Consequently, the industry-adjusted scores could be misleading, which in turn expose investors towards the risk of firms exploiting scores with the incentive to appear more appropriate, hence there is an increased risk of greenwashing.

Empirical findings regarding industry-adjustment in ESG scores are also disparate. Ilhan, Sautner, and Vilkov (2020) find that a greenness measure only capturing industry-emissions can explain variation in asset prices in the option market due to unexpected climate concerns. A study by Ardia et. al (2020) concludes that industry greenness is a good predictor of firm exposure against unanticipated increases in climate concerns and that a within-industry effect is only observed for few industries, such as machinery, business suppliers, computers, and construction materials (Ardia, Bluteau et al. 2020).

Through combining an acknowledged methodology with an ESG database characterized by industry-adjusted scores, we can compare our findings with the results from Pástor et. al (2022) that use industry-unadjusted ESG data. Hence, we contribute to the existing body of literature through providing evidence on how well industry-adjusted ESG data can be used to examine green stock performance and thus provide valuable insights for investors.

# II. Data & Methodology

This section introduces which databases are used in the study and explains the nature of the data used. First, initial data and screening is explained by factors such as time and geographic area. Furthermore, the construction of variables as well as the data needed for the variables are explained. This includes greenness score, portfolio factors, GMB stock returns, GMB alphas and unexpected climate concern.

## 2.1 Initial Data and Screening

Sample data for the European stock return analysis and US stock return analysis were collected from the database Refinitiv Eikon, Kenneth French Data Library and MCCC index. We classify European firms as those having headquarters in Europe and US firms as those having headquarters in the US.

After having removed firms for which there are any missing values, the European sample contains 723 firms, and the US sample contains 674 firms for the period 30 November 2012 to 31 December 2020. For the European sample, we have data for a total of 24 countries since Refinitiv Eikon does not present ESG data for all European countries. These countries are presented in table 2. These samples are the ones used for the aggregated portfolio-level analysis.

In further screening, the previous two samples were matched with industry averages of environmental score from Pástor et. al (2022) through GICS industry and sub-industry which further decreased the sample size. This led to the European sample containing 670 firms and the US sample containing 604 firms during the period November 2012 to June 2018. The sample sizes throughout the analysis are presented in table 1.

**Table 1:** The table shows the number of firms for each region, and where in the analysis the sample sizes are applied.

Number of Firms

| | EU Sample | US Sample |
|---|---|---|
| Used in Portfolio analysis | 723 | 674 |
| Used on individual level | 670 | 604 |

From the summarizing tables of the number of companies and their respective origin country, we can also identify that there is a skewed distribution in how much each country is represented in our sample (table 2). For example, there are 194 companies that origins from the United Kingdom, in contrast to the 2 companies that have their headquarter in Cyprus. Further, regulations such as the non-Financial disclosure directive from the European Commission is applicable to all member states of the EU, which in turn is applicable to roughly 96% of our sample. Since only 4% of the firms in the sample are European firms, but not in the EU or EEA, we argue that these few countries still have similar culture and business conduct due to their geographic location and history. Thus, we argue that the companies can be equated as similarities in culture and trading patterns are applicable in this region. On the same note, the United Kingdom left the European Union on the 31st of December 2020. As our sample period extends from 30 November 2012 to 31 December 2020, the impact of this is neither relevant nor applicable and as such disregarded from the analysis.

**Table 2:** The table shows the countries represented in the European sample, as well as how many firms are included for each country.

| Country | Number of firms |
|---|---|
| Austria | 14 |
| Belgium | 21 |
| Cyprus | 2 |
| Czech Republic | 2 |
| Denmark | 23 |
| Finland | 23 |
| France | 79 |
| Germany | 69 |
| Guernsey | 1 |
| Hungary | 4 |
| Ireland; Republic of | 26 |
| Italy | 30 |
| Jersey | 2 |
| Luxemburg | 4 |
| Netherlands | 24 |
| Norway | 17 |
| Poland | 20 |
| Portugal | 7 |
| Russia | 25 |
| Spain | 36 |
| Sweden | 43 |
| Switzerland | 57 |
| Ukraine | 1 |
| United Kingdom | 193 |

## 2.2 Construction of variables

**Greenness score**

For the environmental score, ESG data from Refinitiv Eikon was used, specifically the annual environmental pillar score. Refinitiv Eikon provides industry-adjusted ESG scores, leading to its score reflecting within-industry greenness. Refinitiv Eikon is a world class provider of financial ESG data containing information about companies all over the world. Since 2021 Refinitiv Eikon has been part of London Stock Exchange Group (LSEG), which has enabled a broader capacity of delivery (Eikon Refinitiv, 2021). Refinitiv Eikon has also been used as an ESG data source for several previous studies (Demers, Hendrikse et al. 2021), (Dorfleitner, Kreuzer et al. 2020, Sassen, Hinze et al. 2016, Ciciretti, Dalò et al. 2023).

The data is mostly updated (at least) once a year and Refinitiv has committed to not re-calculating any scores older than 5 years (i.e. in 2023 ESG scores later in time than 2018 can still be updated). The ESG data which is the basis of the ESG scores are collected from several sources, such as annual reports, company websites, NGO websites, stock exchange filings, CSR reports and news sources. Refinitiv captures 630 company ESG measures which are later grouped into 10 categories which are used to calculate the three ESG scores (environmental, social, and governmental). For the environmental pillar score, the three subcategories are resource use, emissions, and innovation. The ESG scores are based on relative performance in either the company's sector (environmental or social) or the country (governmental). Hence, the scores are industry-adjusted for the environmental pillar score and industry- and country adjusted for the combined ESG pillar score. The pillar scores are in the range 0.00-100 (Refinitiv: ESG company scores, 2023).

For across-industry greenness, the industry-average of MSCI environmental score is collected from Pástor et. al (2022) which presents this data for 2019. Environmental scores at industry level (GICS sub-industry classification) were collected from Pástor et. al (2022) which present their g-score for 62 industries at the end of 2019. These are manually merged with the GICS classifications from Refinitiv by following the MSCI industry classification definitions (MSCI, 2023). The data is merged either by industry-classification or sub-industry classification as the data from the two data sources were inconsistent in which of the ones they provided. In the regressions where both across-industry and within-industry greenness is used at the same time, the g-scores are normalized using the scale() function in R.

**Portfolio factors**

For the portfolio factors that are used in the portfolios regressions to estimate GMB returns, we collect factors from the Kenneth French Data Library. Portfolio factors used are the Fama-French three factors, and five factors and Carhart momentum factor. For the European sample, we use the European factors and for the US sample, we use the US factors. All factors are the monthly factors.

**GMB stock returns**

The monthly stock returns are collected from Refinitiv Eikon, using the 1 month return on the last day of each month period 30 November 2012 to 31 December 2020. To calculate green-minus-brown (GMB) stock returns, the portfolios for the green-minus-brown factor time series regressions are constructed according to the methodology in Pástor et. al (2022). This means the brown portfolios contain firms with the ⅓ lowest environmental pillar scores, while the green portfolios contain the firms with the ⅓ highest environmental pillar scores as collected from Refinitiv Eikon. In other words, only the high and low portfolio are used to create the GMB portfolio returns, while the neutral portfolio is not used at all. The portfolios are value weighted with the market capitalization for each firm and they are created in June each year. The GMB portfolio return is the difference between the green portfolio returns and the brown portfolio returns. The green and brown portfolio returns are presented in figure 1.

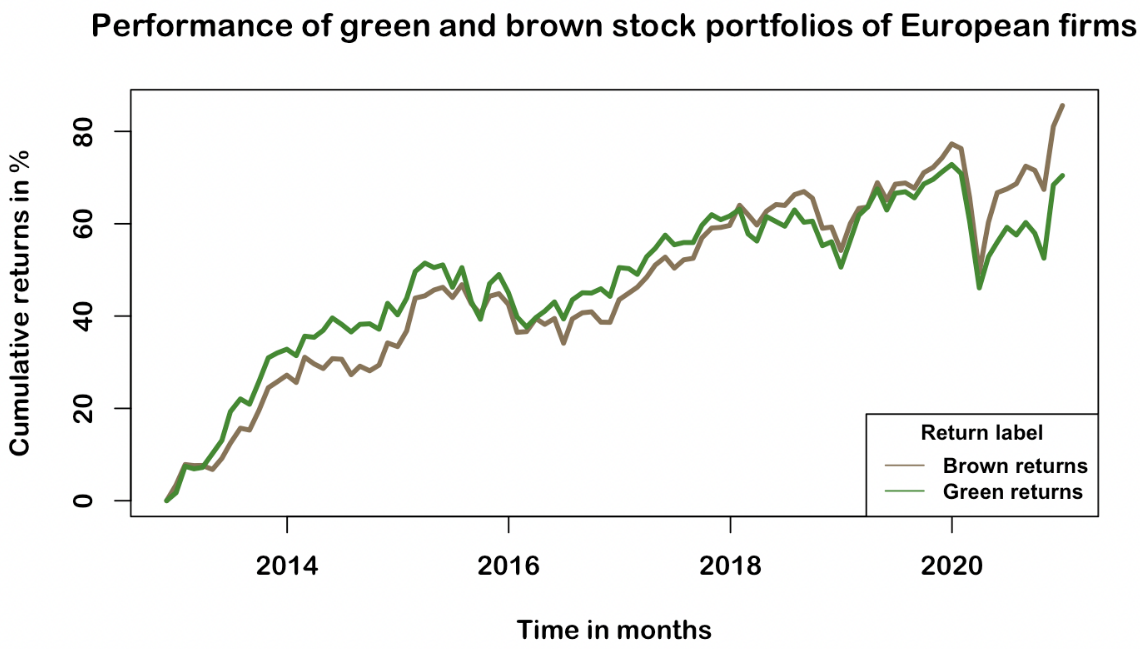


**Figure 1:** The figure shows the cumulative brown and green returns of European firms in the period November 2012-December 2020. Returns are in percentages.

**GMB alphas**

The green-minus-brown alphas are an estimate of the GMB factors. GMB alphas are estimated as the sum of intercept and the residuals received from the Fama French 3 factor regression.

**Unexpected climate concern**

For climate sentiment, we use the daily Media Climate Change Concerns (MCCC) index from Ardia et al (2020)[2]. The monthly climate concern is calculated as the average of all the daily average within the month. For the main analysis, we use the updated version from 2022 This dataset is based on news from 10 different US newspapers and 2 newswires for the period of January 2010 - June 2018. The index can be used to capture unanticipated changes in climate concerns. We also use the older version from 2020 which is based on news from 8 different US newspapers (Ardia, Bluteau et al. 2020). This is the same dataset as the one used in Pástor et. al (2022) and can be used for climate sentiment in analyses regarding US firms. We use the older version for a closer comparison with Pástor et. al (2022), with the results presented in the appendix, but use the updated version for the main analysis. The figure below shows the climate concerns over time, from the updated MCCC index.

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[2] Ardia, D., Bluteau, K., Boudt, K. & Inghelbrecht, K. (2022). Climate change concerns and the performance of green versus brown stocks. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3717722.

The MCCC index is from this website: https://sentometrics-research.com. We only aim to use the data provided by Ardia et al for research purposes.

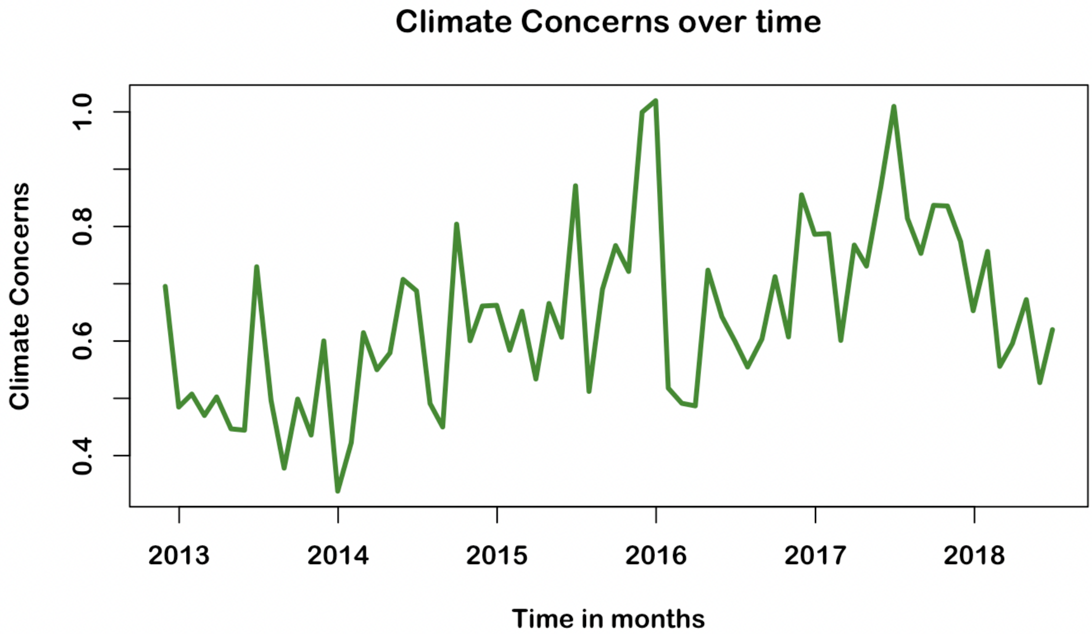


**Figure 2:** The figure shows climate concerns monthly over time.

To estimate the unexpected climate concern, we use a rolling autoregressive model with an estimation window of 36 months. Here, the unexpected climate concern is estimated as the prediction error, $\varepsilon_t$ , from the rolling AR model. We use two different specifications; an AR(1) model, as seen in equation 1, where the climate concern is predicted from the previous month climate concern and an AR(2), as seen in equation 2, model where the climate concern is predicted from the previous month climate concern and the climate concern the month before that.

$$CC_t = \varsigma \times CC_{t-1} + \varepsilon_t \tag{1}$$

$$CC_t = \varsigma_1 \times CC_{t-1} + \varsigma_2 \times CC_{t-2} + \varepsilon_t \tag{2}$$

The digitalization era has enabled a quicker and broader flow of news, as well as opened the media landscape to new and stronger news delivery actors. The restructuring of the media landscape has also facilitated a more international scenery where regional news can become global issues overnight. A study made by Rabitz, Telešienė and Zolubienė (2020) uses topic modeling to investigate the influences behind the Lithuanian regional news regarding climate change. Through their analysis they find clear evidence of international media presence within roughly a third of their corpus, which consequently leads to the conclusion that there in fact is strong global influence on climate change news reflected in Lithuanian media (Rabitz, Telešienė et al. 2020). The takeaway from this article proposes that the division between regional and global news with regards to climate change is not that distinct. Hence, we argue that it is possible to use climate sentiment in the US as a proxy for climate sentiment in Europe and therefore use the MCCC index for analyses regarding the European sample as well.

# III. Main Empirical Analysis

In this section, we present the main results from our analysis and interpret these results further. First, time series regressions are performed with five different model specifications to analyze GMB performance of European firms. Furthermore, we do monthly time series regressions including same and previous month change in climate concern with both GMB returns and GMB alphas as dependent variables. Last, fixed effects panel regressions are used to further examine within and between-industry greenness as well as interaction effects with change in climate concerns. The findings from our results are further analyzed in the last part of this section where we relate these findings to US firms as well as to previous literature.

## 3.1 European Market Returns and GMB Performance

Cumulative returns obtained from the portfolio construction for the green and brown portfolios, respectively, were plotted against time. As can be seen in the figure showing cumulative returns (figure 1), the cumulative return of each portfolio varies in which one is the highest and it is not possible to discern any clear pattern from observation. Monthly time series regressions were performed. The dependent variable was the difference in stock returns between green and brown stock portfolios, where the green and brown portfolios are created based on the simple g-score. The independent variables were the CAPM factor, Fama French 3 factor, Fama French 3 factor, and momentum factor, and lastly the Fama French 5 factors. The returns were in percent per month and standard deviations are in parentheses. This was repeated for a smaller sample, only covering the period November 2012 to June 2018, to receive a closer comparison to the regressions presented in 3.2 and 3.3.

**Table 3:** Regression results for the European sample when using the within-industry g-score. The constant is the estimate of the GMB factor.

**European Market Returns and GMB Performance**

| | GMB | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Mkt-Rf | | -0.006 | -0.017 | -0.039 | -0.071 |
| | | (0.039) | (0.044) | (0.045) | (0.047) |
| SMB | | | 0.118 | 0.096 | 0.080 |
| | | | (0.102) | (0.101) | (0.104) |
| HML | | | 0.021 | -0.044 | 0.415*** |
| | | | (0.072) | (0.078) | (0.145) |
| MOM | | | | -0.115* | |
| | | | | (0.058) | |
| RMW | | | | | 0.568*** |
| | | | | | (0.185) |
| CMA | | | | | -0.322 |
| | | | | | (0.206) |
| Constant | -0.147 | -0.143 | -0.166 | -0.144 | -0.231 |
| | (0.171) | (0.174) | (0.180) | (0.178) | (0.173) |
| Observations | 98 | 98 | 98 | 98 | 98 |
| $R^2$ | 0.000 | 0.000 | 0.015 | 0.055 | 0.122 |
| Adjusted $R^2$ | 0.000 | -0.010 | -0.017 | 0.014 | 0.075 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

For all regressions the GMB factor estimate is negative and insignificant. The factor estimates are also smaller than for the US sample in our study which are negative and significant. They are also smaller in magnitude than in Pástor et. al (2022), in which the factor estimates are positive and significant. Further analyses are motivated by investigating the cause of the EU GMB estimate as to why it differs from other studies as well as from the corresponding regression for US stock returns.

**Table 4:** Regression results for the European sample when using the within-industry g-score for the years 2012-2018. The constant is the estimate of the GMB factor. For the years 2012–2018.

**European Market Returns and GMB Performance 2012-2018**

| | GMB | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Mkt-Rf | | 0.026 | 0.061 | 0.044 | 0.013 |
| | | (0.058) | (0.065) | (0.061) | (0.066) |
| SMB | | | 0.161 | 0.120 | 0.155 |
| | | | (0.136) | (0.129) | (0.138) |
| HML | | | -0.092 | -0.203* | 0.481** |
| | | | (0.101) | (0.102) | (0.207) |
| MOM | | | | -0.220*** | |
| | | | | (0.073) | |
| RMW | | | | | 0.656** |
| | | | | | (0.247) |
| CMA | | | | | -0.461* |
| | | | | | (0.248) |
| Constant | -0.049 | -0.068 | -0.153 | -0.072 | -0.260 |
| | (0.204) | (0.209) | (0.218) | (0.207) | (0.221) |
| Observations | 68 | 68 | 68 | 68 | 68 |
| $R^2$ | 0.000 | 0.003 | 0.034 | 0.157 | 0.171 |
| Adjusted $R^2$ | 0.000 | -0.012 | -0.011 | 0.104 | 0.104 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

The GMB constant estimates in table 4 are in general of less magnitude than in table 3, while also being negative and insignificant. The factor estimates are also smaller than for the US sample in our study which are negative and significant. They are also smaller in magnitude than in Pástor et al. (2022) in which the factor estimates are positive and significant.

## 3.2 Sources of GMB Performance

Monthly time-series regressions were performed with data from November 2012 through June 2018. The dependent variables are GMB returns and GMB alphas in column 1 and 2, respectively. According to the methodology of Pástor et. al (2022), changes in climate concerns ($\Delta\ Climate\ Concern$) were estimated as the prediction error from a rolling AR(1) model of the MCCC index with a time-period of three years. The updated version of the MCCC index was used here. Furthermore, GMB alphas were estimated from the previous Fama French three factor regression where the alphas were estimated as the regression's intercept plus residual. Returns are in percent and standard deviations are presented in parentheses below coefficient estimates.

**Table 5:** Regression results for the European sample when using the within-industry g-score when including unexpected change in climate concerns for the same month and previous month.

**Climate Concerns and GMB Performance**

| | GMB return | GMB Alpha |
|---|---|---|
| | (1) | (2) |
| ΔClimate Concern (previous month) | -0.490 | -0.386 |
| | (1.679) | (1.675) |
| ΔClimate Concern (same month) | 0.056 | 0.102 |
| | (1.685) | (1.681) |
| Constant | -0.026 | -0.062 |
| | (0.242) | (0.242) |
| Observations | 68 | 68 |
| $R^2$ | 0.001 | 0.001 |
| Adjusted $R^2$ | -0.029 | -0.030 |
| *Notes:* | ***Significant at the 1 percent level. | |
| | **Significant at the 5 percent level. | |
| | *Significant at the 10 percent level. | |

Previously, all estimates of GMB returns were negative and insignificant for European firms (table 3 and 4). When including unanticipated climate concern shocks, $\Delta CC_{t-1}$ and $\Delta CC_t$, the constant estimates of GMB returns and GMB alphas are still negative and insignificant. This gives no incentive to believe there is an equity greenium for European firms. $\Delta CC_t$ is positive for both regressions, as in the study by Pástor et. al (2022). The $\Delta CC_{t-1}$ the estimate is negative and insignificant, which contradicts the results found in Pástor et. al (2022). It should also be noted that the corresponding regression for US stock returns are similar to the European stock returns, with negative $\Delta CC_{t-1}$ and positive $\Delta CC_t$ with both being insignificant. However, the US GMB returns and GMB alphas constant estimates are both negative and significant.

Lastly, it should be noted that the results do not differ substantially regarding if the original MCCC index (presented in appendix A) or updated MCCC index is used as a proxy for climate sentiment.

## 3.3 Greenness and individual stock returns: Effects within and across industries

Panel regressions were performed with data from November 2012 through June 2018. The dependent variables are monthly stock returns for individual firms. According to the methodology of Pástor et. al (2022), changes in climate concern ($\Delta\ Climate\ Concern$) were estimated as the prediction error, $\varepsilon_t$ , from a rolling AR(1) model of the MCCC index with a time-period of three years. The updated version of the MCCC index was used here. Four different model specifications were examined. The first model only includes the within-industry greenness, as presented in column 1. The second model only includes within and between industry-greenness, as presented in column 2. The third model includes only data gathered from Refinitiv Eikon/MCCC index and therefore only contains within-industry metrics, as presented in column 3. The fourth column presents the regression for both within and across industry-greenness, as well as greenness interaction effect with change in climate concern (current and previous month). All models include time fixed effects, cluster by month and include robust standard errors. Returns are in percent and standard deviations are presented in parentheses below coefficient estimates.

**Table 6:** Regression results for the European sample when using both within-industry and across-industry greenness score. All regressions include unexpected change in climate concerns for the same month and previous month.

**Greenness and individual stock returns: Effects within and across industries**

| | Stock monthly returns | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Within g-score | 0.044 | 0.040 | 0.000 | -0.023 |
| | (0.038) | (0.038) | (0.045) | (0.045) |
| Across g-score | | -0.041 | | -0.209*** |
| | | (0.039) | | (0.045) |
| Within g-score *ΔCC | | | 0.560* | 0.758** |
| | | | (0.311) | (0.312) |
| Across g-score *ΔCC | | | | 1.867*** |
| | | | | (0.314) |
| Within g-score *ΔCC (t-1) | | | 0.248 | 0.387 |
| | | | (0.310) | (0.311) |
| Across g-score * ΔCC (t-1) | | | | 1.259*** |
| | | | | (0.313) |
| Observations | 45,560 | 45,560 | 45,560 | 45,560 |
| $R^2$ | 0.000 | 0.000 | 0.000 | 0.001 |
| Adjusted $R^2$ | -0.001 | -0.001 | -0.001 | -0.000 |
| *Notes:* | ***Significant at the 1 percent level. | | | |
| | **Significant at the 5 percent level. | | | |
| | *Significant at the 10 percent level. | | | |

Firstly, the regression only including the within g-score is positive and insignificant. The regression including only within-industry and across-industry greenness without any interaction effects gives almost identical estimates of opposite signs for within and across greenness, as seen in regression column (2). This is the opposite result of Pástor et. al (2022), where a similar fixed effect panel regression results in positive estimate of across-greenness and negative estimate of within-greenness. It should be mentioned though that the results from our US regression are in line with the results of Pástor et. al (2022), indicating that any difference stems from differences in sample and not method. Furthermore, we do not place much importance in this reversal, as neither estimate in column 2 of table 6 are significant and it is more likely to be a consequence of a non-specific estimate.

The opposite signs of within and across greenness could explain why table 4:s constant estimates are all insignificant, as it is expected that a g-score only capturing within-industry greenness would have difficulty in predicting higher returns stemming from an equity greenium due to variation from the uncaptured across-industry greenness. This is supported from the results from column (3) where the within g-score is zero and insignificant by itself, but its interaction effect with $\Delta CC_t$ is positive and significant at the 10% level.

In contrast from table 5 where interaction effects with $\Delta CC_t$ are positive while interaction effects with $\Delta CC_{t-1}$ are negative, all interaction effects for all four model specifications here are positive, although not all of them are statistically significant. This is in line with the results of Pástor et. al (2022), where both $\Delta CC_{t-1}$ and $\Delta CC_t$ are positive. Similar results are also observed for US stock returns (appendix) with roughly the same magnitude and significance level.

It should also be noted that the estimates relating to across-industry greenness are consistently of larger magnitude than the estimates relating to within-industry greenness. This is consistent with Pástor et. al (2022) where across-industry greenness repeatedly was shown to be of higher economic significance than within-greenness.

Lastly, it should be noted that the results do not differ substantially regarding if the original MCCC index (presented in appendix A) or updated MCCC index is used as a proxy for climate sentiment.

## 3.4 Using an AR(2) Model to account for unexpected climate concern

The two different data of unexpected climate concern is presented in the figure below. As can be observed in the figure, the results obtained are different based upon if calculated through a rolling AR(1) or AR(2) model. Since this data is the input in further regressions, our belief is that the differences can impact the end results substantially. Therefore, we redo the results from 3.2 and 3.3 based on the unexpected climate concern calculated by the rolling AR(2) model. These results are presented below in figure 3.

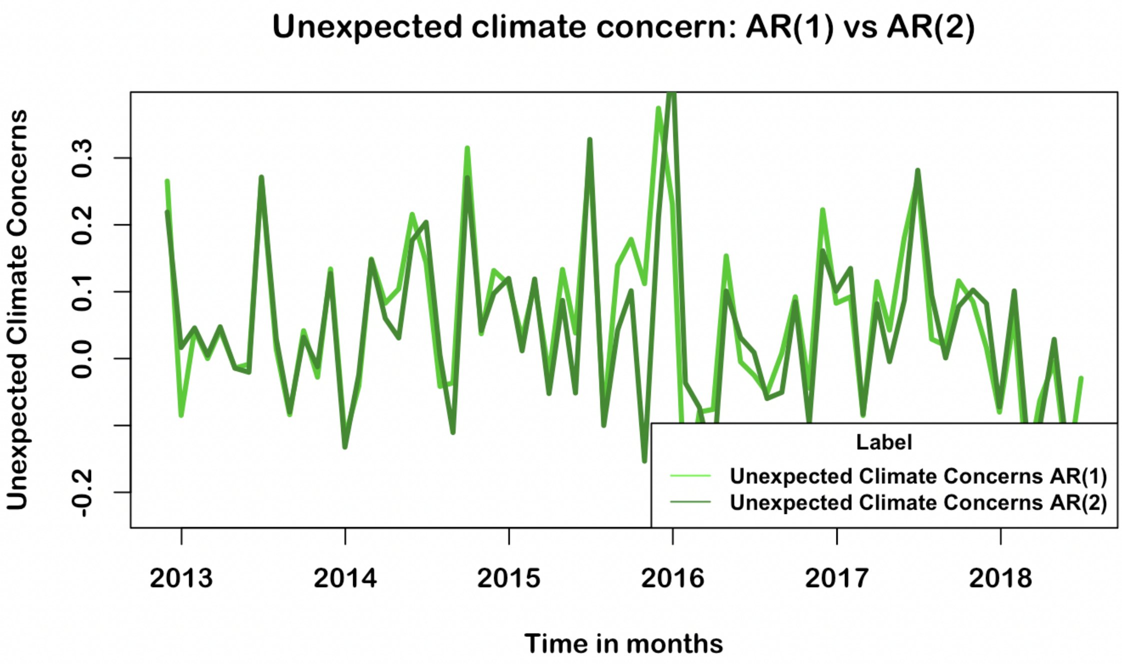


**Figure 3:** The figure shows the unexpected climate concern when calculated through a rolling AR(1) model vs a rolling AR(2) model.

Monthly time-series regressions were performed with data from November 2012 through June 2018. The dependent variables are GMB returns and GMB alphas in column 1 and 2, respectively. The changes in climate concerns ($\Delta\ Climate\ Concern$) were estimated as the prediction error, $\varepsilon_t$ , from a rolling AR(2) model of the MCCC index with a time-period of three years. By using this methodology, the climate concern is always predicted from the previous two months climate concerns. The updated version of the MCCC index was used here. Furthermore, GMB alphas were estimated from the previous Fama French three factor regression where the alphas were estimated as the regression's intercept plus residual.

**Table 7:** Regression results for the European sample when using the within-industry g-score when including unexpected change in climate concerns for the same month and previous two months. Here the unexpected climate concern is calculated through a rolling AR(2) model.

**Climate Concerns and GMB Performance**

| | GMB return (1) | GMB Alpha (2) |
|---|---|---|
| ΔClimate Concern (2 months back) | -1.330 | -1.214 |
| | (1.736) | (1.730) |
| ΔClimate Concern (previous month) | -1.078 | -1.273 |
| | (1.808) | (1.802) |
| ΔClimate Concern (same month) | -1.456 | -1.255 |
| | (1.785) | (1.780) |
| Constant | 0.122 | 0.087 |
| | (0.266) | (0.265) |
| Observations | 66 | 66 |
| $R^2$ | 0.020 | 0.018 |
| Adjusted $R^2$ | -0.027 | -0.029 |
| *Notes:* | ***Significant at the 1 percent level. | |
| | **Significant at the 5 percent level. | |
| | *Significant at the 10 percent level. | |

In contrast to table 5, the constant terms for both GMB returns and alphas are positive, while still being statistically insignificant. We do not place much importance in this reversal, as neither estimate is significant for any of the regressions, and it is more likely to be a consequence of a non-specific estimate. It can also be observed that using different data for unexpected climate concerns changes the signs of the climate concerns estimates. Here, the sign is negative for same month, previous month, and 2 months back for both columns. This is a difference to the results of Pástor et. al (2022), which receive positive estimates for all month's climate concerns which are included in their regression.

Panel regressions were also performed with data from November 2012 through June 2018. Four different model specifications were examined. The first model only includes the within-industry greenness, as presented in column 1. The second model only includes within and between industry-greenness, as presented in column 2. The third model includes only data gathered from Refinitiv Eikon/MCCC index and therefore only contains within-industry metrics, as presented in column 3. The fourth column presents the regression for both within and across industry-greenness, as well as greenness interaction effect with change in climate concern (current and the previous 2 months). All fixed effects models include time fixed effects, cluster by month and include robust standard errors.

**Table 8:** Regression results for the European sample when using both within-industry and across-industry greenness score. All regressions include unexpected change in climate concerns for the same month and previous two months.

**Greenness and individual stock returns: Effects within and across industries**

| | Stock monthly returns | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Within g-score | 0.034 | 0.029 | 0.116** | 0.112** |
| | (0.039) | (0.039) | (0.049) | (0.049) |
| Across g-score | | -0.044 | | -0.031 |
| | | (0.039) | | (0.049) |
| Within g-score *ΔCC | | | -0.678** | -0.523 |
| | | | (0.329) | (0.330) |
| Across g-score *ΔCC | | | | 1.528*** |
| | | | | (0.331) |
| Within g-score *ΔCC (t-1) | | | -0.152 | -0.139 |
| | | | (0.333) | (0.334) |
| Across g-score * ΔCC (t-1) | | | | 0.105 |
| | | | | (0.335) |
| Within g-score * ΔCC (t-2) | | | -0.849*** | -1.036*** |
| | | | (0.319) | (0.320) |
| Across g-score * ΔCC (t-2) | | | | -1.917*** |
| | | | | (0.322) |
| Observations | 44,890 | 44,890 | 44,220 | 44,220 |
| $R^2$ | 0.000 | 0.000 | 0.000 | 0.002 |
| Adjusted $R^2$ | -0.001 | -0.001 | -0.001 | 0.000 |
| *Notes:* | ***Significant at the 1 percent level. | | | |
| | **Significant at the 5 percent level. | | | |
| | *Significant at the 10 percent level. | | | |

For the results from table 8, it can be observed that the within-industry g-score alone is positive for all four model specifications while the significance level differs. However, its interaction effect with $\Delta CC_t$ , $\Delta CC_{t-1}$ and $\Delta CC_{t-2}$ are all negative, as can be seen in column 3 and 4. These interaction effects are also larger in magnitude than the magnitude of within-industry g-score alone. It should also be mentioned that the within-industry g-score alone before (table 5) varied in both magnitude and sign, which differs from the results here. This could be seen as a 're-allocation' of the negative correlation to the interaction effects, which all had positive estimates when using the unexpected climate concerns from the AR(1) model.

The interaction effects from two months ago are negative for both within-industry and across-industry greenness for all model specifications when these variables are included. This differs from the previous analysis of within and across-industry greenness where all interaction effects were positive (table 6), as in the article by Pástor et. al (2022). Furthermore, the effects of the across-industry greenness alone are negative and similar in both sign and magnitude as the previous estimates (table 6).

# IV. Interpretation of Empirical Findings

By comparing the regression results from the EU sample with the US sample, the GMB factor estimates are negative and significant for the US. For European stocks, the GMB factor estimates are still negative, but smaller in magnitude and insignificant. Furthermore, when including climate concerns, the estimate for GMB returns and alphas are negative and significant for the US, while negative and insignificant for the European samples. Furthermore, these estimates are much smaller in magnitude than for the US sample. In total, we argue these differences provide evidence for a negative equity greenium for US stocks while it seems the equity greenium is close to zero for European stocks.

When controlling for unexpected climate concerns in Pástor et. al (2022), the equity greenium estimate has a slight fluctuation between negative and positive values, hence a small magnitude, where none of the regression results in economic significance. In the study by Pástor et. al (2021), unexpected climate shocks and other sources of increased demand for green assets is said to be the single factor explaining the outperformance of green returns, according to the PST model. The result from this study supports this for European firms, for which we find the equity greenium to be close to zero. However, for the US sample, we find the equity greenium to be negative, indicating that brown stocks outperform green stocks.

It is thus reasonable to suggest that the underlying cause of the difference in equity greenium is due to what has previously been shown in studies to have a significant effect, namely the geographical regulatory differences, and thus the legislations imposed by the European Commission (Directive 2014/95/EU of the European Parliament and of the Council, 2014) as well as local legislations imposed by the individual countries.

Additionally, the differences in culture as discussed by Schultz (2002) could partially explain the divergence seen on magnitude between the European and US market. Since the results indicate ESG investing has an economically larger significance in the European market, it is viable to assume in accordance with Auer and Schuhmacher (2016), that the European market is suitable for investors wanting to participate in socially responsible investing.

As previously mentioned, across-industry greenness has a consistently larger effect on individual stock performance of green firms than within-industry greenness. For example, in table 6, column 4, all estimates including across-industry greenness are larger than estimates containing within-industry greenness. Also, when using the AR(2) model for unexpected climate concerns, the interaction effects for same and previous month are negative for within-industry greenness and positive for across-industry greenness. Furthermore, when not including unexpected change in climate concerns, all estimates of the GMB factor are negative and insignificant when using the g-score only accounting for within-industry greenness. This indicates that within-industry alone does not have the capacity to capture stock return variations to explain any green outperformance, while a mixed score containing both within and across-industry greenness can explain green outperformance for certain periods. It is also possible that using only across-industry greenness measure might be enough to predict stock returns, as suggested by the authors of *Carbon Tail Risk* (Ilhan, Sautner et al. 2020).

Investors aiming to use ESG data for stock prediction should be aware of this difference, as only ESG data capturing across-industry greenness can be expected to predict green outperformance. At the same time, there is a high risk of greenwashing with regards to using within-industry ESG data as it is possible to profile a 'better than average' firm in a brown industry as green despite it receiving no equity greenium. Both NGOs and investors should pay attention to this, as various agents such as firm managers, brokers and fund managers have incentives in participating in such greenwashing. Therefore, the choice of rating agency as well as knowledge regarding the rating system is of utmost importance.

Further studies could focus on both examining which industries, if any, where within-industry greenness can explain green stock outperformance, as motivated by the study by Ardia et. al (2020) where within-industry greenness was found important in some industries. This could also guide investors regarding which industries where within-industry greenness is an important metric in predicting stock performance.

The PST model states that unexpected climate concerns can explain outperformance of green stocks (Pástor, Stambaugh et al. 2021) during shorter periods. Figure 2 shows that there are periods where there is a trend in climate concern over time, such as the trend of decreasing climate concerns in 2018. We call this a *prolonged shock period* and argue that when the climate shock is near constant over a period, this is actually anticipated climate shocks and not unexpected climate shock. According to the PST model, only unexpected climate shocks can explain green stock outperformance, since asset prices react immediately to new information (Pástor, Stambaugh et al. 2021). A prolonged shock period indicates that despite high climate concerns, investors and consumers have already reacted from previous positive unanticipated climate shocks and the increase in climate concerns is already reflected in asset prices. Therefore, they are less sensitive to current climate shocks leading to no increased demands for green assets from either consumers or investors.

According to the PST model, agents tilt their portfolios based on ESG preferences and this tilt is larger in times of higher climate concerns (Pástor, Stambaugh et al. 2021). Investors and consumers having reacted to previous month climate shocks might therefore be less inclined to react to a further increase in climate concerns as they already have adjusted their portfolio in reaction to previous climate shocks.

As previously stated, a proxy for unexpected climate concern is important for investors aiming for sustainable investing. However, the evidence of prolonged shock periods where change in climate concerns is anticipated, and thus irrelevant for investors, leads to question if there is a better way to proxy for this. Pástor, Stambaugh et. al (2022) states that "The AR(1) model's intercept absorbs the recent level and trend in the climate index", meaning that current trends should be captured by the rolling AR(1) model. However, since the rolling AR(1) model is based on data from 36 months, it is possible that the trends very close to next month being predicted are not captured enough. We propose either changing the model to place more weight on months close in time or increasing the number of lags in the AR model.

When testing the AR(2) model as a method for estimating unexpected climate concern, figure 3 shows that there are differences in unexpected climate concern to the ones estimated through an AR(1) model. Furthermore, the regression results show that especially the within-industry greenness effects change based on usage of AR(1) or AR(2) model. For example, in the most extensive model, the within-industry greenness alone changes signs from negative from positive, while the within-industry greenness interaction effects changes sign from positive to negative. This indicates that there is a re-allocation of the negative effect from within-industry alone to interaction effects. Also, when using the AR(2) model, the difference in magnitude between within-industry and across-industry greenness decreases. Consequently, there are substantial differences in how within-industry greenness effects stock performance based upon which of the models are used for unexpected climate concern. However, at this point, it is unclear which one of the model specifications captures the effect of greenness and unexpected climate concern best. Thus, further studies are required to determine how to depict the effect of unexpected climate concerns most accurately.

# V. Conclusion

This study investigates whether green stock returns outperform brown stock returns in the European market. Environmental scores are collected from the Refinitv Eikon database which provide industry-adjusted ESG data. Firstly, we address the research question through examining the green minus brown factor and performing a portfolio analysis.

Here, we find no evidence of a positive GMB factor for European firms indicating that green portfolio returns are not higher than brown portfolio returns. Furthermore, our findings are not coherent with *Dissecting green returns* by Pástor et. al (2022). After including the effects of unexpected increase in climate concerns, we find no significant results. The lack of consistent results motivates an examination of greenness and individual stock returns. Panel time-fixed effects regressions are used to examine within-industry and across-industry greenness, after including the interaction effect with unexpected climate concerns. This is done by applying a rolling AR (1) model. The results suggests that only across-industry ESG data can be expected to capture green outperformance on its own. This highlights the challenge in using within-industry greenness alone as a predictor for stock performance. Thus, we call attention to the importance for investors to carefully select rating agency as well as an overall risk of greenwashing.

We also introduce the subject of *prolonged shock periods* and thus propose looking into a rolling AR (2) model as a method for estimating unexpected climate concerns. In a further analysis, we investigate this by using this new data for unexpected climate concern to both examine climate concerns and GMB performance, as well as within-industry and across-industry greenness at an individual level. The findings indicate substantial differences in the result based upon which model is used to calculate unexpected climate concerns. We suggest future studies should analyze this further.

Regarding limitations of the study, we consider the choice of MCCC index as a proxy for climate sentiment to be a potential limitation. It is assumed that US sentiment can be applied to Europe. However, the geographical differences previously mentioned, cannot be fully disregarded. For example, the risk of potential political influence should be emphasized since there are fundamental differences between the US and EU with regards to elections and presidential campaigns (Sampugnaro, Montemagno 2021).

Furthermore, the distribution of companies within Europe is considered as a potential limitation. Refinitiv Eikon does not report ESG data for all European companies, which could be an issue if there are systematic differences regarding which countries ESG data is reported for. For example, if more brown countries are excluded. Furthermore, when the firms are mapped based upon GICS sub-industry and industry classification, the sample size decreases due to some firms not having matches. Here, it is also a possibility that this leads to a more skewed distribution.

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# Appendix A: Climate Concern and GMB Performance

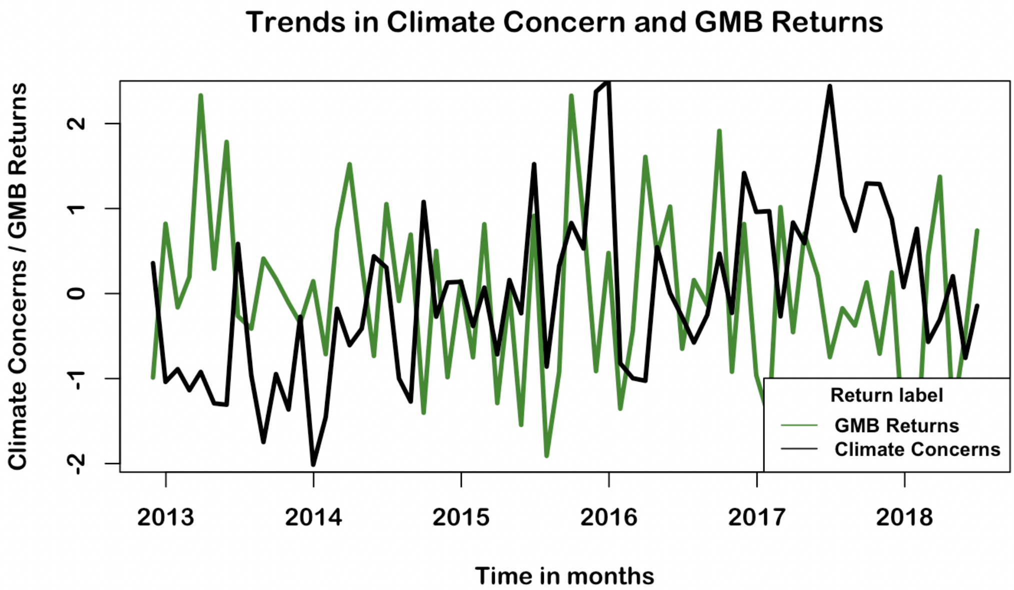


**Figure A1:** The figure shows climate concern (note; not change in climate concerns) and GMB returns over time, specifically November 2012 - June 2018. Both climate concerns and GMB returns are normalized using the R function scale() in order to receive a comparable magnitude.

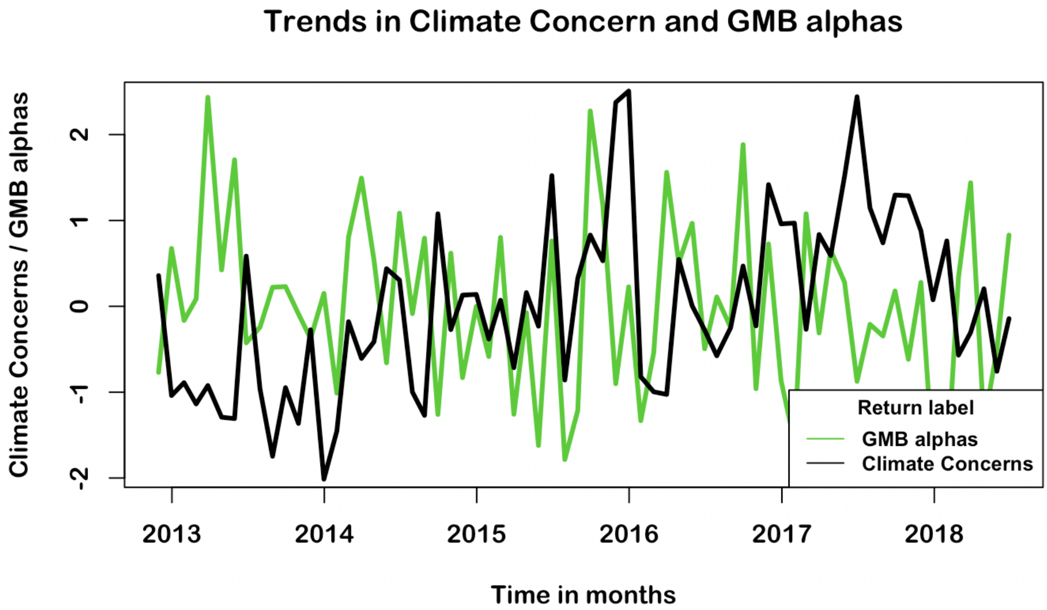


**Figure A2:** The figure shows climate concern (note; not change in climate concerns) and GMB alphas over time, specifically November 2012 - June 2018. Both climate concerns and GMB alphas are normalized using the R function scale() in order to receive a comparable magnitude.

**Table A1:** Regression results for the European sample when using the within-industry g-score when including unexpected change in climate concerns for the same month and previous month. Here the unexpected climate concern is calculated through a rolling AR(1) model and the 2020 version of the MCCC index is used as a proxy for climate sentiment.

**Climate Concerns and GMB Performance, using data available 2020**

| | *Dependent variable:* | |
|---|---|---|
| | GMB return | GMB Alpha |
| | (1) | (2) |
| Previous Month Climate Concern | -0.887 | -0.760 |
| | (1.633) | (1.629) |
| Current Month Climate Concern | -0.078 | -0.046 |
| | (1.643) | (1.639) |
| Constant | -0.004 | -0.040 |
| | (0.231) | (0.231) |
| Observations | 68 | 68 |
| $R^2$ | 0.005 | 0.003 |
| Adjusted $R^2$ | -0.026 | -0.027 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

**Table A2:** Regression results for the European sample when using the within-industry g-score and the across-industry g-score, when including unexpected change in climate concerns for the same month and previous month. Here the unexpected climate concern is calculated through a rolling AR(1) model and the 2020 version of the MCCC index is used as a proxy for climate sentiment.

**Greenness and individual stock returns: Effects within and across industries, using data available 2020**

| | Stock monthly returns | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within g-score | 0.040 | 0.009 | -0.008 |
| | (0.038) | (0.043) | (0.043) |
| Across g-score | -0.041 | | $-0.153^{***}$ |
| | (0.039) | | (0.043) |
| Within g-score *ΔCC | | $0.500^{*}$ | $0.659^{**}$ |
| | | (0.303) | (0.305) |
| Across g-score *ΔCC | | | $1.507^{***}$ |
| | | | (0.307) |
| Within g-score *ΔCC (t-1) | | 0.246 | 0.345 |
| | | (0.301) | (0.303) |
| Across g-score * ΔCC (t-1) | | | $0.901^{***}$ |
| | | | (0.305) |
| Observations | 45,560 | 45,560 | 45,560 |
| $R^2$ | 0.000 | 0.000 | 0.001 |
| Adjusted $R^2$ | -0.001 | -0.001 | -0.001 |
| *Notes:* | $^{***}$Significant at the 1 percent level. | | |
| | $^{**}$Significant at the 5 percent level. | | |
| | $^{*}$Significant at the 10 percent level. | | |

# Appendix B: US firms, GMB performance and greenness

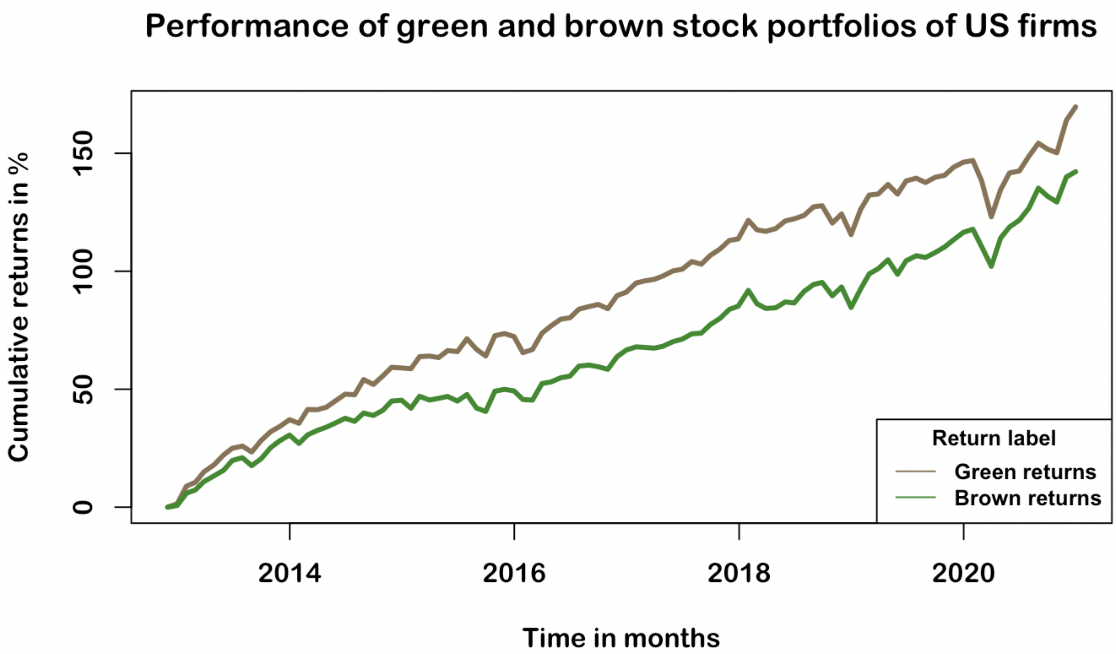


**Figure B1:** The figure shows the cumulative brown and green returns of European firms in the time period November 2012-December 2020. Returns are in percentages.

**Table B1:** Regression results for the US sample when using the within-industry g-score. The constant is the estimate of the GMB factor.

**US Market Returns and GMB Performance**

| | GMB | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Mkt-Rf | | -0.004** | -0.025 | -0.016 | -0.020 |
| | | (0.002) | (0.043) | (0.045) | (0.046) |
| SMB | | | 0.026 | 0.033 | 0.046 |
| | | | (0.070) | (0.071) | (0.079) |
| HML | | | -0.110* | -0.087 | -0.159** |
| | | | (0.059) | (0.069) | (0.074) |
| MOM | | | | 0.038 | |
| | | | | (0.059) | |
| RMW | | | | | 0.073 |
| | | | | | (0.121) |
| CMA | | | | | 0.135 |
| | | | | | (0.132) |
| Constant | -0.274* | -0.546*** | -0.302* | -0.309* | -0.306* |
| | (0.162) | (0.203) | (0.173) | (0.174) | (0.174) |
| Observations | 98 | 98 | 98 | 98 | 98 |
| $R^2$ | 0.000 | 0.046 | 0.044 | 0.048 | 0.058 |
| Adjusted $R^2$ | 0.000 | 0.037 | 0.014 | 0.007 | 0.007 |

*Notes:* ***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

**Table B2:** Regression results for the US sample when using the within-industry g-score when including unexpected change in climate concerns for the same month and previous month. Here the unexpected climate concern is calculated through a rolling AR(1) model and the 2020 version of the MCCC index is used as a proxy for climate sentiment.

**Climate Concerns and GMB Performance of US firms**

| | *Dependent variable:* | |
|---|---|---|
| | GMB return | GMB Alpha |
| | (1) | (2) |
| Previous Month Climate Concern | -0.642 | -0.578 |
| | (1.293) | (1.297) |
| Current Month Climate Concern | 2.052 | 2.144 |
| | (1.301) | (1.305) |
| Constant | $-0.540^{***}$ | $-0.531^{***}$ |
| | (0.183) | (0.184) |
| Observations | 68 | 68 |
| $R^2$ | 0.039 | 0.042 |
| Adjusted $R^2$ | 0.010 | 0.012 |
| *Note:* | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 | |

**Table B3:** Regression results for the US sample when using the within-industry g-score and the across-industry g-score, when including unexpected change in climate concerns for the same month and previous month. Here the unexpected climate concern is calculated through a rolling AR(1) model and the 2020 version of the MCCC index is used as a proxy for climate sentiment.

**Greenness and individual stock returns of US firms: Effects within and across industries**

| | Stock monthly returns | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Within g-score | -0.101** | -0.081* | -0.189*** | -0.204*** |
| | (0.049) | (0.049) | (0.054) | (0.055) |
| Across g-score | | 0.113** | | -0.072 |
| | | (0.048) | | (0.054) |
| Within g-score *ΔCC | | | 0.240 | 0.667* |
| | | | (0.387) | (0.392) |
| Across g-score *ΔCC | | | | 2.392*** |
| | | | | (0.386) |
| Within g-score *ΔCC (t-1) | | | 1.723*** | 2.006*** |
| | | | (0.384) | (0.390) |
| Across g-score * ΔCC (t-1) | | | | 1.567*** |
| | | | | (0.383) |
| Observations | 41,072 | 41,072 | 41,072 | 41,072 |
| $R^2$ | 0.000 | 0.000 | 0.001 | 0.002 |
| Adjusted $R^2$ | -0.002 | -0.001 | -0.001 | 0.000 |
| *Notes:* | ***Significant at the 1 percent level. | | | |
| | **Significant at the 5 percent level. | | | |
| | *Significant at the 10 percent level. | | | |