In Search of the True Greenium

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Abstract

The greenium (the expected return of green securities relative to brown) is a central impact measure for ESG investors. Replicating the literature's wide range of equity greenium estimates based on realized returns, we find that these are not robust to changing the greenness measure or time period. Instead, we propose a robust green score combined with forward-looking expected returns, yielding a more precisely estimated annual equity greenium of −25 basis points per standard deviation increase in greenness. The greenium is more negative in greener countries and over time. Finally, we provide greeniums for corporate bonds, weighted-average costs of capital, and sovereign bonds.

Keywords: Greenium, cost of capital, ESG, replication, climate, sustainable finance

JEL Codes: G11, G12, H23, Q5

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ESG investors and sustainable finance regulators seek to improve the environment by lowering the cost of capital for green firms while raising it for brown firms. The success of this mechanism depends on the size of the greenium—the cost of capital of green relative to brown firms—so estimating this greenium is focal in a rapidly growing literature. However, greenium estimates vary tremendously across papers and, while most academic papers report a negative greenium, many practitioners expect a positive one.[1] So, what is the true greenium?

To address this question, the first part of the paper replicates and extends existing papers that estimate the equity greenium based on realized returns. Collecting data for 23 greenness measures from the literature, we estimate the corresponding greeniums based on a unified methodology and data samples that are extended over time and across the world. Our first main result is that all these greenium estimates are insignificant when we account for multiple testing. Indeed, all greenium estimates have wide standard errors and all 23 greenness measures from the literature lead to insignificant greeniums in the US and globally for a range of risk adjustments. More broadly, we show that estimating the greenium using realized returns requires centuries of data, while the literature often uses little over a decade.

The second part of the paper seeks to estimate the greenium with less noise and study its properties. We reduce the noise by constructing a "robust green score" (the right-hand-side variable) and by using forward-looking expected returns instead of realized returns (the left-hand-side variable). Using these measures, we estimate a statistically significant equity greenium of −25 basis points (bps) annualized per standard deviation increase in the robust green score. This greenium corresponds to an expected return of −50 bps per year for a green-minus-brown (GMB) tercile portfolio due to the portfolio's two-standard-deviation spread in greenness. This greenium is economically meaningful but more modest than prominent estimates in the literature and a modest part of the overall equity premium.

Further, we show that the equity greenium has become more negative over time and is more negative in greener countries. Finally, we also estimate the greeniums for corporate

[1] As an example of practitioner views, 60% of participants in the 2019 BNP Paribas Global ESG Survey expect their ESG portfolios to outperform over the next five years.

bonds, the weighted-average cost of capital (WACC), and sovereign bonds. We explain each of these findings in turn.

Replication problems with realized returns and green confusion. The literature contains a wide range of greenium estimates. In fact, the various papers even disagree on whether green stocks have under- or outperformed![2]

As a recent example, Hsu et al. (2023) find that a GMB portfolio based on toxic emission intensity generates a significant annual return of -4.42%. This effect is extremely large economically, but when we construct a similar factor using their greenness measure in an updated sample, we find an insignificant effect.[3]

Bolton and Kacperczyk (2021, 2023) find that green stocks underperform brown ones when greenness is measured based on total carbon emissions, but not when measured based on emissions scaled by sales (emission intensity). Aswani et al. (2024) find no effect with total emissions when focusing on the subset of firms with reported (as opposed to estimated) emissions. Zhang (2023) notes that estimated emissions correlate with firm fundamentals and are released with significant lags, causing a potential look-ahead bias. When lagging the data, Zhang (2023) finds that green US stocks have actually outperformed, not underperformed. When we extend the sample period and similarly use data only when available to investors, we show that green stocks have neither out- nor underperformed in a statistically significant way, regardless of whether we use total emissions or emissions intensity.

Pástor et al. (2022) report a 174% cumulative outperformance of green over brown stocks

[2] A large literature examines the realized returns of green-versus-brown stocks using different greenness measures. This literature includes papers that find green outperformance (see, e.g, Garvey, Iyer, and Nash, 2018; In, Park, and Monk, 2019; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2021; Cheema-Fox, LaPerla, Serfaeim, Turkington, and Wang, 2021; Giese, Nagy, and Rauis, 2021; Huij, Dries, Stork, and Zwinkels, 2021; Ardia, Bluteau, Boudt, and Inghelbrecht, 2022; Bauer, Huber, Rudebusch, and Wilms, 2022; Pástor, Stambaugh, and Taylor, 2022; Zhang, 2023; Berg, Lo, Rigobon, Singh, and Zhang, 2023; Karolyi, Wu, and Xiong, 2023), papers that find the opposite (see, e.g., Alessi, Ossola, and Panzica, 2020; Bolton and Kacperczyk, 2021, 2023; Hsu, Li, and Tsou, 2023), and papers that find no significant difference (see, e.g., Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens, 2020; Pedersen, Fitzgibbons, and Pomorski, 2021; Aswani, Raghunandan, and Rajgopal, 2024; Alves, Krüger, and van Dijk, 2023; Lindsey, Pruitt, and Schiller, 2023).

[3] We use a scientific replication method following Jensen, Kelly, and Pedersen (2023). In particular, we use the robust factor construction similar to Jensen et al. (2023), allowing our methodology to differ from Hsu et al. (2023).

from 2012 to 2020. When we update this sample period and use their greenness measure, the realized outperformance again becomes insignificant. In any event, Pástor et al. (2022) attribute the high realized green returns to a repricing and, controlling for changes in climate concerns and earnings news, they report a negative and insignificant greenium.

To analyze the greenium broadly, we estimate it using 23 different greenness measures in the US. For each measure, we compute the return of a GMB portfolio, either industry-neutral (used by some papers) or industry-agnostic (used by other papers). These 46 GMB portfolio returns are plotted in Figure 1(a). To further account for the variation across papers, we compute the realized GMB performance in five different ways for each measure by varying the risk controls (excess returns, CAPM alphas, Fama-French three-factor alphas, etc.). Looking across these $23 \times 2 \times 5$ estimates of the US equity greenium, we show that none of these is statistically significant when controlling for multiple-testing effects.

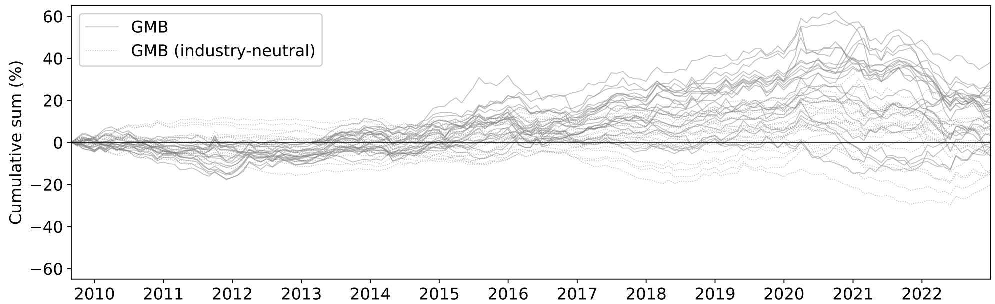
Further, we also consider global estimates of the greenium. Specifically, we estimate the greenium in each of 48 countries using each of the available greenness measures and each way to control for risk. Across all these specifications, the realized GMB performance is globally insignificant. In fact, the distribution of these greenium estimates is bell-shaped with a center near zero.

To shed light on the source of these widespread replication issues, we show that a GMB factor based on the robust green score has a low predicted annual Sharpe ratio of -0.10, computed as the ratio of the modest greenium (estimated using forward-looking returns, defined below) to the high realized GMB volatility—implying that one needs more than 300 years of realized returns to identify the greenium. Hence, a lack of robustness is not surprising given that the literature is generally based on less than 20 years of data.

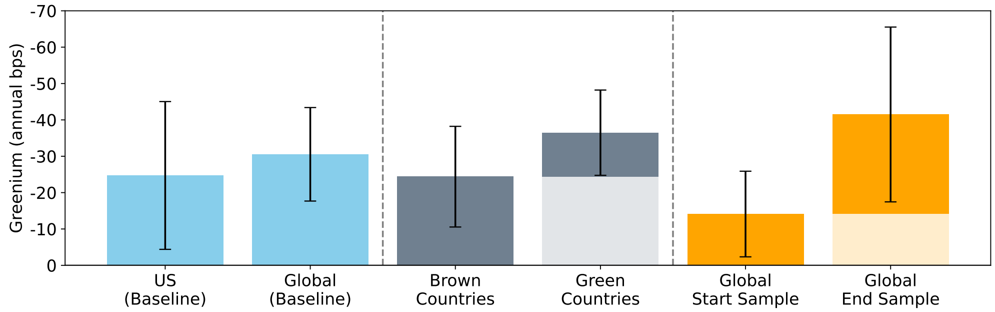
A robust green score: clarity instead of confusion. Part of the reason for the differences in the literature is the modest correlation of different ESG measures, termed an "aggregate confusion" by Berg, Koelbel, and Rigobon (2022). To address this problem, we construct a robust green score. The robust green score is the average of the key greenness measures from several leading data providers.

Figure 1: Summary of findings: Greenium estimates

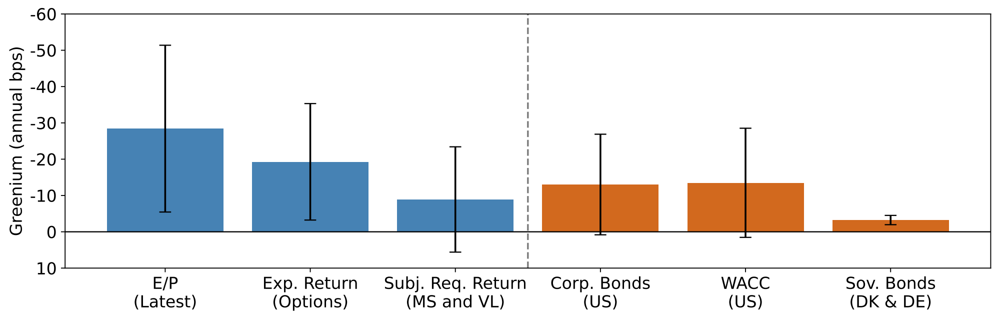
(a) Realized returns of green-minus-brown using 46 different methods



(b) Equity greenium globally and over time



(c) Robustness tests and greenium across asset classes



Panel (a) illustrates the replication problems in the literature by plotting cumulative realized returns of 46 green-minus-brown (GMB) US equity factors constructed using 23 different greenness measures with either an industry-neutral or industry-agnostic approach. Panels (b) and (c) show annualized greenium estimates and 95% confidence bands based on standard errors clustered by industry and month. We estimate the greenium by regressing forward-looking expected return proxies on our robust green score. Panel (b) shows the equity greenium estimated using the average implied cost of capital as the measure of expected returns. The first two bars contain our baseline results for US and global equities, respectively. The two middle bars show brown and green countries, respectively, where the darker part of the latter bar shows the additional greenium in green countries. The second-to-last bar shows the greenium at the start of the sample, and the darker park of the last bar shows the increase in the greenium by the end of our sample (Aug-2009 vs. Dec-2022). In Panel (c), the first three bars show US robustness estimates using earnings-to-price, option-implied expected returns, and subjective required returns from Morningstar and Value Line. The last three bars show greenium estimates for corporate bonds, the weighted-average cost of capital (WACC) using both equities and corporate bonds, and sovereign bonds based on the relative yields of twin bonds.

The robust green score appears to capture each firm's greenness with less noise. Indeed, the average correlation between the robust green score and each individual greenness measure is much higher than the average pairwise correlation of the underlying measures. Further, the robust green score predicts changes in the underlying greenness measures, suggesting that it is more informative. For instance, when the robust green score is above an individual greenness measure, then the individual greenness measure tends to adjust upward in the future.

More precisely estimated equity greenium. Having a less noisy green score is helpful, but we also need to address the noise in realized returns. Estimating expected returns from realized returns requires an exceedingly long sample, but most greenness measures have only been available since around 2009. Moreover, concerns about the environment have arguably intensified over recent years and a resulting potential repricing of green versus brown stocks makes it even more challenging to infer expected returns from realized returns.

To address these issues, we use forward-looking measures of expected returns. In our baseline specification, we first compute each stock's implied cost of capital (ICC) using the method of Mohanram and Gode (2013) who take an average of four different measures from the accounting literature. We then estimate the greenium, g, as the slope coefficient in the regression of each stock's implied cost of capital, $\hat{E}(r_t^i)$, on its robust green score, s_t^i, which is normalized to have zero mean and unit standard deviation in the cross-section:

$$\hat{E}(r_t^i) = g \times s_t^i + \text{controls} + \varepsilon_t^i. \tag{1}$$

The baseline estimate of the greenium g is -25 bps per year, which is also illustrated in Figure 1(b). This estimate is significantly negative, but economically more modest than many estimates from the literature. The 95% confidence interval is $(-45, -4)$ bps in the US and $(-44, -17)$ globally, which identifies the magnitude far better than estimates from the literature for which the width of the confidence interval is typically in the hundreds of bps. Our confidence interval is tighter because of our use of a robust green score and forward-looking returns. The confidence interval would be even tighter with standard errors computed as in the ICC literature, but our coarse clustering (by industry and time) raises standard errors to an arguably more appropriate level.[4]

We analyze the robustness of our greenium estimate in a multitude of ways. In particular, we estimate the greenium with only time-fixed effects as well as with standard risk controls—corresponding to considering raw and risk-adjusted returns. Another specification has industry-by-time fixed effects—corresponding to comparing returns within each industry at a given point in time. Our baseline estimate in Figure 1(b) controls for time-fixed effects and risk, but we note that it is quite reassuring that we find similar results with more or fewer controls and fixed effects.[5]

As further robustness tests, we consider a range of forward-looking expected returns measures: i) each individual implied cost of capital measure from Mohanram and Gode (2013); ii) a number of valuation ratios; iii) option-implied expected returns based on Martin and Wagner (2019) and Chabi-Yo, Dim, and Vilkov (2023) across three different horizons; and iv) analysts' required returns from Morningstar and ValueLine. Some of these robustness tests are reported as the first three bars in Figure 1(c).

The greenium has become more negative over time. Based on our framework, we can even consider more detailed questions, such as whether the greenium has changed over time. Indeed, we find that the global equity greenium has become more negative over time

[4]E.g., our confidence interval is much narrower than the 511 bps width of the confidence interval in Hsu et al. (2023), Table II.A. We note that Pástor et al. (2022) also consider an ICC, but only using a single measure of ICC, using their greenness measure, and only in a single country (US), and their only statistical analysis (their Internet Appendix Table A.1) has no controls and their standard errors are likely too small, as we show in Figure 2 given that they only cluster by firm. Having no controls and too narrow standard errors means that it is difficult to assess whether the modest GMB expected return is spurious or due to risk differences, industry effects, or other differences across stocks. We also note that their measure of greenness is based on a transformation that almost mechanically classifies firms in industries (e.g., technology) with low environmental effects as the greenest. Our estimate of the greenium is based on an average of several greenness measures and is robust to a battery of controls and expected-return proxies—and we provide estimates of the greenium globally, over time, and across asset classes. See also Chava (2014) who finds evidence of a negative greenium with data ending in 2007, even before the major rise in ESG investing, but using standard errors that are likely too small (only clustered by firm).

[5]When choosing which specification to present as the "baseline" greenium estimate, we face the standard trade-off between having too many controls and fixed effects (over-differencing) or too few controls and fixed effects (omitted-variable bias). Figure 1 therefore has an intermediate number of controls and fixed effects (risk controls and time-fixed effects), but all our results are also presented with fewer and more controls—and the order of magnitude of the greenium is consistent across all these specifications.

as illustrated in the last two bars in Figure 1(b). A decreasing greenium is consistent with the idea that the importance of ESG investors has increased over time or that perceived environmental risks have increased.

The greenium is more negative in greener countries. We find a significantly negative greenium both in the US and outside the US using two non-overlapping samples. Further, we uncover interesting global variation in the greenium. We find that the greenium is significant in most countries, but has a bigger magnitude in greener countries as seen in the middle bars of Figure 1(b).

The greenium beyond equities. Finally, we consider the greenium in other asset classes. The literature contains a range of greenium estimates for green corporate bonds (see, e.g., Zerbib, 2019; Larcker and Watts, 2020; Tang and Zhang, 2020; Flammer, 2021; Baker, Bergstresser, Serafeim, and Wurgler, 2022; Caramichael and Rapp, 2022). However, the literature is rather silent on the more basic question of the greenium of "regular" corporate bonds across green versus brown firms, which is more comparable to the analysis of the equity greenium.

We find a meaningful greenium of −13 bps for regular corporate bonds as seen in Figure 1(c). Aggregating each firm's equity and bonds, we find a greenium for the weighted average cost of capital (WACC) of −13 bps as seen in Figure 1(c). Lastly, we estimate the sovereign bond greenium. As seen in Figure 1(c), we find a small negative greenium, consistent with findings in Pástor et al. (2022), Feldhütter and Pedersen (2023), and D'Amico, Klausmann, and Pancost (2023).

Related literature. We complement the literature on green returns. Most of this literature relies on realized returns (see references above), and we document replication issues with this approach. Papers using other approaches include Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu (2023), who find that Vanguard investors expect ESG investments to underperform the overall stock market by −1.4% annually over a ten-year horizon. Gormsen, Huber, and Oh (2023) find that corporate managers' perceived cost of capital is lower for green firms than brown, especially since 2016. Sautner, van Lent, Vilkov, and Zhang (2023) find that, controlling for emissions, firms with a larger fraction of earnings calls dedicated to discussing climate change have higher option-implied expected returns, mostly between 2011 and 2014.[6] Going beyond the literature, we consider a range of forward-looking expected return proxies across geographies and asset classes, a range of greenness measures aggregated into our robust green score, and uncover a greenium, which is consistently negative, more negative for greener countries, and trending down over time.

A few recent papers seek to tackle the noise in ESG measures. Berg, Kölbel, Pavlova, and Rigobon (2023) instrument a given ESG rating with ratings of other ESG rating providers and find that green stocks realize larger returns than brown stocks and Berg et al. (2023) reach a similar conclusion. Alves et al. (2023) construct two composite ESG measures to reduce the noise and find no systematic relation between ESG and stock returns globally. Analyzing net-zero carbon portfolio alignment, Cenedese, Han, and Kacperczyk (2023) create an "ambition score" consisting of several components to measure firms' ambition to decarbonize. We find that, even with a more robust green score, the time-series of realized returns is too short and noisy to identify a greenium, so we estimate the greenium with forward-looking returns instead.

Our paper also complements the theoretical ESG literature. A capital asset pricing model with ESG investors is provided by Pástor, Stambaugh, and Taylor (2021), Pedersen et al. (2021), and Zerbib (2022). Berk and van Binsbergen (2021) provide a calibration in which they predict a tiny equity greenium of 0.44 bps per year with one particular set of parameters. While our greenium is smaller than most estimates in the literature, we can reject that it is as small as that particular version of Berk and van Binsbergen (2021). Pedersen (2023) shows how to "translate" a carbon tax on emissions into a cost-of-capital premium for brown firms above green ones. His results suggest that the cost of capital of the brownest firms must be raised by more than 400 bps relative to green to implement the carbon tax of Nordhaus (2019), a number that must grow more than fivefold over time to transition to a net-zero economy. We can reject that the greenium is that high, suggesting that ESG investing in its

[6] Controlling for emissions means that the finding of Sautner et al. (2023) is difficult to interpret as a greenium, which is also not their stated intention.

current form cannot replace a carbon tax.

In summary, we complement the literature by providing (i) a replication analysis of the ESG literature, highlighting a lack of robustness, (ii) a robust green score (to be made public), (iii) estimates of the equity greenium in the US and globally across a host of specifications that are more precise than those in the literature, (iv) evidence that the greenium is more negative in greener countries and over time, and (iv) the greenium across asset classes.

1 Methodology and Robust Green Score

1.1 Greenness measures and our robust green score

We consider 24 different ways to measure a firm's greenness: 23 individual greenness measures and our robust green score. The greenness measures are based on data from Trucost, MSCI, Sustainalytics, and the Environmental Protection Agency's (EPA) Toxics Release Inventory as shown in Table 1. The EPA data are only available in the US, so our global ex-US sample contains 19 individual greenness measures. We sign each greenness measures such that a higher value means being greener. The 23 individual measures cover greenness measures considered in the literature, and Table 1 also shows the corresponding references. For completeness, the 23 measures also include ones that appear of similar relevance even if they have not been studied in connection to realized returns. For each measure, we seek to only use the data when they are available to investors.

To overcome the green confusion highlighted by Berg et al. (2022), we seek to construct a more robust greenness measure. In constructing this measure, we focus on simplicity, taking an average across a range of measures to reduce the noise in any individual greenness measure. A similar approach has been taken in the cross-sectional asset pricing literature (see, e.g., Stambaugh, Yu, and Yuan, 2015; Stambaugh and Yuan, 2017).

Apart from simplicity, we aim to use measures that many investors consider in practice (see, e.g., ERM Sustainability Institute, 2023). The actual score is, therefore, an equal-weighted average of three pillars that many investors may consider. The first pillar captures

Table 1: Greenness measures

Name	Source	References
Robust green score	Below	This paper
Components of green score:		
S1INT (Sales)	Trucost	Bolton and Kacperczyk (2021, 2023), Busch, Bassen, Lewandowski, and Sump (2022)[c], Aswani et al. (2024), Atilgan, Demirtas, Edmans, and Gunaydin (2023), Zhang (2023)
S1+2INT (Sales)	Trucost	Griffin, Lont, and Sun (2017), Garvey et al. (2018)[a], Görgen et al. (2020)[a], Cheema-Fox et al. (2021), Cheema-Fox et al. (2021), Giese et al. (2021), Huij et al. (2021), Pedersen et al. (2021), Bauer et al. (2022)[a], Shakdwipee, Giese, and Nagy (2023)
S1+2+3INT (Sales)	Trucost	In et al. (2019), Cheema-Fox et al. (2021), Ardia et al. (2022)[a,c], Busch et al. (2022)[c]
S1INT (Assets)	Trucost	Shakdwipee et al. (2023)[b]
S1+2INT (Assets)	Trucost	Shakdwipee et al. (2023)[b]
S1+2+3INT (Assets)	Trucost	S&P Dow Jones Indices (2020)[b]
Weighted ESG score	MSCI	Ang, van Beek, Li, Tamoni, and Zhang (2023), Lindsey et al. (2023)
Environment score	MSCI	Engle, Giglio, Kelly, Lee, and Stroebel (2020), Görgen et al. (2020), Berg et al. (2023), Lindsey et al. (2023)
Total ESG score	Sustainalytics	Alves et al. (2023), Lindsey et al. (2023)
Environmental score	Sustainalytics	Engle et al. (2020), Görgen et al. (2020), Seltzer, Starks, and Zhu (2022), Alves et al. (2023), Lindsey et al. (2023)
Other, not in green score:		
LOG(S1TOT)	Trucost	Bolton and Kacperczyk (2021, 2023), Aswani et al. (2024), Atilgan et al. (2023), Zhang (2023)
LOG(S1+2TOT)	Trucost	Huij et al. (2021), Bauer et al. (2022)[a]
LOG(S1+2+3TOT)	Trucost	Matsumura, Prakash, and Vera-Muñoz (2014)[a,b], Delmas, Nairn-Birch, and Lim (2015)[c], Busch et al. (2022)[c]
Ind.-adj. ESG score	MSCI	Görgen et al. (2020), Pedersen et al. (2021), Alves et al. (2023), Ang et al. (2023), Berg et al. (2023), Berg et al. (2023), Lindsey et al. (2023)
Greenness (PST)	MSCI	Pástor et al. (2022), Karolyi et al. (2023)
E climate score	MSCI	Cheema-Fox et al. (2021), Kacperczyk and Peydró (2022)[c]
E nat. res. score	MSCI	Kacperczyk and Peydró (2022)[c]
E waste score	MSCI	Kacperczyk and Peydró (2022)[c]
E env. opps. score	MSCI	Cheema-Fox et al. (2021), Kacperczyk and Peydró (2022)[c]
TPWINT (Sales)	EPA TRI	Hsu et al. (2023)
TPWINT (Assets)	EPA TRI	Hsu et al. (2023)
TRINT (Sales)	EPA TRI	Akey and Appel (2021)[d]
TRINT (Assets)	EPA TRI	Akey and Appel (2021)[d]

The table shows data sources for 23 individual greenness measures and our robust green score, constructed from the first 10 individual greenness measures. The table also shows the academic papers which use a particular greenness measure when studying realized financial performance, in particular realized stock returns. S1TOT, S1+2TOT, and S1+2+3TOT refer to the absolute amount of carbon emissions using scope 1, the sum of scope 1 and 2, and the sum of scope 1, 2, and 3 carbon emissions, respectively. S1INT, S1+2INT, and S1+2+3INT refer to the respective carbon intensities, i.e., total emissions scaled by sales or assets. Greenness (PST) refers to the measure of Pástor et al. (2022). Ind-adj. ESG score refers to MSCI's industry-adjusted ESG score. E nat. res. score and E env. opps. score refer to MSCI's natural resource and environmental opportunities scores. TPWINT and TRINT refer to toxic release intensity and toxic production waste intensity from the Environmental Protection Agency. The superscript [a] indicates a paper using carbon emissions, but from another data source than Trucost. The superscript [b] indicates references showing that practitioners and regulators also scale emissions by assets, typically EVIC (enterprise value including cash), which we proxy for by book assets to avoid introducing biases by having market values on the right-hand side. The superscript [c] indicates a paper using a dependent variable other than realized stock returns. The superscript [d] indicates a paper uses toxic releases (which is arguably more relevant for pollution than the toxic production waste used in Hsu et al. (2023)), which we then scale as in Hsu et al. (2023).

a firm's carbon intensity based on Trucost data, and it is computed by averaging six measures, namely total emissions under scope 1, 1+2, or 1+2+3, each scaled by sales or assets.[7] The second pillar is an average of the E and ESG score from MCSI and, likewise, the third pillar

[7]Scope 3 refers only to upstream emissions as downstream emissions are only available from 2017.

is an average of the E and ESG score from Sustainalytics.[8] These scores are central metrics from these providers and we include the overall ESG scores as many green investors may use these as catch-all sustainability metrics.[9] To put these pillars on the same scale, we standardize each of the three pillars to have zero mean and unit standard deviation within each month and country. Finally, we average the three pillars, re-standardize this average within each month and country, and thus arrive at our green score.

The components of the green score are listed in Table 1, which also contains greenness measures that are not included in the green score. The measures that we do not include are based on (i) a firm's total carbon emissions, since these measures are highly correlated with firm size, (ii) EPA data, which sums the pound emissions of chemicals with very different toxicity levels,[10] or (iii) a sub-component of, or derived from, the MSCI E score, as we do not want to overweight the MSCI E score. We have verified that the results in Figure 1 are similar if we instead take an equal-weighted average of the 23 measures or even use random weights.

We construct the robust green score since August 2009, when data from all constituent providers are available. In contrast, in our replication study using the 23 individual greenness measures, we use the entire time series for each greenness measure. We indicate the sample period used for each greenness measure in Table A1 and describe the (standard) data on realized returns used for the replication study in Appendix A.1.

To validate the robust green score, we perform two exercises. First, for each month we

[8] The Sustainalytics methodology started to transition from ESG scores to risk ratings in 2018. We use the legacy ESG scores from 2009 and until they are phased out towards the end of 2019. We extend this data until Dec-2022 using indicator scores and weights from the new data which closely matches the legacy methodology. The average correlation between the old and re-created new scores is above 80% in the overlapping period when both scores are available.

[9] As an example, in BlackRock's 2020 Global Sustainable Investing Survey, 88% of respondents rank Environment as their top priority among the ESG factors.

[10] The EPA metric used by Hsu et al. (2023) does not even distinguish whether such chemicals have been recycled vs. released into the air/water/ground. As an example, it does not distinguish 1 lb of cyanide released into the water versus 1 lb of paint waste that is recycled. The other EPA measures in Table 1 are focused on released chemicals, but, again, add chemicals with toxicity levels that can differ by a factor of many millions. Hsu et al. (2023) do consider toxicity in their internet appendix using a county-level mortality model (as opposed to simply scaling by EPA's toxicity estimates), but the relation to realized returns appears difficult to ascertain for the reasons explained in Section 2.5.

Table 2: Pairwise correlations of greenness measures

	Panel A: US			
	Robust Green Score	Trucost	MSCI	Sustainalytics
Robust Green Score	100	56.6	75.5	63.2
Trucost	56.6	100	11.9	-9.1
MSCI	75.5	11.9	100	39.6
Sustainalytics	63.2	-9.1	39.6	100
	Panel B: Global ex-US			
	Robust Green Score	Trucost	MSCI	Sustainalytics
Robust Green Score	100	56.1	74.4	61.9
Trucost	56.1	100	12.7	-10.4
MSCI	74.4	12.7	100	35.6
Sustainalytics	61.9	-10.4	35.6	100

The table shows average pairwise Pearson correlations between the Robust Green Score and its three components (see Section 1.1) for the US (Panel A) and the Global ex-US (Panel B) samples. For each pair of variables, we report the time-series average of the monthly cross-sectional Pearson correlation coefficients. The sample is restricted to firms which have data on all three components of the robust green score.

compute the pairwise Pearson rank correlations across US stocks between the robust green score, the average Trucost measure, the average MSCI measure, and the average Sustainalytics measure. We then compute the time-series average of these pairwise correlations and report the resulting correlation matrix in Panel A of Table 2. Panel B is similar, but considers the sample of global ex-US stocks. The table shows that the robust green score has a considerably higher pairwise correlation with any of the three alternative greenness measures than any of the three alternative measures themselves. This suggests that the robust green score indeed averages out some of the idiosyncratic noise in alternative greenness measures.

Second, for each individual greenness measure m, we regress the one-year change in greenness, $s_{t+12}^{m,i} - s_t^{m,i}$, of any stock i on the difference between the lagged robust green score, s_t^i, and the individual greenness score, $s_t^{m,i}$:

$$s_{t+12}^{m,i} - s_t^{m,i} = a^m + b^m(s_t^i - s_t^{m,i}) + \varepsilon_{t+12}^{m,i} \tag{2}$$

Table 3 reports the slope coefficient estimates, $\hat{b}^m$, and the corresponding t-statistics. Most estimated slope coefficient estimates in the US and global ex-US stock samples are significantly positive. That is, when an individual greenness measure is below the robust green score, the individual measure tends to move up toward the robust green score in the future. This finding suggests that the robust green score is informative and helps reduce the noise in individual greenness measures.

1.2 Forward-looking expected returns

Apart from the robust green score, the second ingredient to obtaining precise estimates of the greenium is measures of forward-looking expected returns.

Implied cost of capital

We estimate a stock's implied cost of capital, ICC, as the equal-weighted average of four measures from the accounting literature, following Mohanram and Gode (2013). The underlying measures, $\text{ICC}^{GLS}, \text{ICC}^{CT}, \text{ICC}^{PEG}, \text{ICC}^{OJ}$, are based on Gebhardt, Lee, and Swaminathan (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005).

In short, each ICC measure computes the implied cost of capital as the internal rate of return that makes the discounted value of future expected cash flows equal to the current stock price. As such, each ICC is a forward-looking measure of the expected equity return based on the current price. To estimate expected future cash flows, these methods use analyst forecasts (consensus earnings-per-share forecasts and long-term-growth in earnings-per-share, from I/B/E/S), past dividends payout ratios, past return on equity in each industry, and a Treasury yield, combined with different economic assumptions. The original papers rely on US data, and we try to use as similar methods as possible outside the US. We describe each of the ICCs in detail in Appendix A.2.

Of course, ICCs are not perfect measures of expected returns. On one hand, having random noise in the left-hand-side variable does not create a bias. Such noise simply raises

Table 3: Convergence of individual greenness measures to robust green score

	US		Global ex-US	
	Coeff. estimate	t-statistic	Coeff. estimate	t-statistic
S1INT (Sales)	-0.01	-1.48	0.03	4.20
S1+2INT (Sales)	-0.01	-1.41	0.03	4.50
S1+2+3INT (Sales)	-0.01	-1.57	0.03	4.29
S1INT (Assets)	0.00	0.16	0.03	5.58
S1+2INT (Assets)	0.00	0.13	0.03	5.67
S1+2+3INT (Assets)	0.01	1.12	0.02	5.96
Weighted ESG score	0.11	6.04	0.14	12.16
Environment score	0.09	3.93	0.12	7.18
Total ESG score	0.06	6.54	0.07	7.82
Environmental score	0.07	5.43	0.11	6.69
LOG(S1TOT)	0.02	4.18	0.02	7.62
LOG(S1+2TOT)	0.02	4.25	0.02	7.44
LOG(S1+2+3TOT)	0.03	4.40	0.02	7.43
Ind.-adj. ESG score	0.10	10.31	0.11	14.65
Greenness (PST)	0.03	5.42	0.05	8.57
E climate score	0.08	4.03	0.08	10.79
E nat. res. score	0.15	6.67	0.14	12.24
E waste score	0.11	6.76	0.11	9.47
E env. opps. score	0.09	3.42	0.09	6.50
TRINT (Sales)	0.03	3.66	n.a.	n.a.
TPWINT (Sales)	0.03	3.28	n.a.	n.a.
TRINT (Assets)	0.03	3.30	n.a.	n.a.
TPWINT (Assets)	0.03	3.13	n.a.	n.a.

The table shows slope coefficient estimates and corresponding t-statistics for the null hypothesis of a zero slope coefficient in panel regressions of one-year changes in individual greenness measures on the contemporaneous differences between the robust green score and the individual greenness measure. Specifically, we estimate $s_{t+12}^{m,i} - s_t^{m,i} = a^m + b^m(s_t^i - s_t^{m,i}) + \varepsilon_{t+12}^{m,i}$, where m refers to an individual greenness measure, i to a stock, and t to a month. Standard errors are two-way clustered by industry and month. Details on the individual greenness measures are in Table 1.

standard errors. On the other hand, systematic biases in ICC could affect our estimation of the greenium. Therefore, we also consider several other measures of forward-looking expected returns, which we discuss next.

Option-implied expected returns

We use two option-implied expected returns: The SVIX from Martin and Wagner (2019) and the generalized lower bound (GLB) from Chabi-Yo et al. (2023).[11] The SVIX is based on the stock's risk-neutral variance as implied by option prices and captures expected returns for a log utility investor who chooses to be fully invested in the stock market. The GLB is based on the full risk-neutral distribution and captures the expected return of an investor with a general utility function. The option-implied expected returns are available from 1996 to 2022. The data are at a daily frequency, but we convert it to the monthly frequency by taking the average of daily expected returns within each month, following Chabi-Yo et al. (2023).

Subjective required and expected returns

We use the same subjective required and expected returns as Jensen (2023). We consider two subjective required returns. The first is the cost of equity from Morningstar. This measure reflects Morningstar's assessment of the stock's systematic risk. The second is based on the safety rank from Value Line. The safety rank reflects Value Line's assessment of the stock's price stability and the financial strength of the underlying firm.[12] To convert the safety rank to a required return, we follow Jensen (2023) and multiply it by 1.5%, which comes from regressing the average expected return of Value Line, Morningstar, and I/B/E/S on the safety rank.

We obtain subjective expected returns from three different providers: Four-year expected returns from Value Line, three-year expected returns from Morningstar, and one-year expected returns from I/B/E/S. Each expected return is computed as the future "price target" plus expected dividends from now until the "target date," divided by the current stock price.

[11] The data are provided by Grigory Vilkov at doi.org/10.17605/OSF.IO/Z2486.

[12] The safety rank is a discrete number between 1 (safe) and 5 (risky), and it is based on the average score of a stock on two sub-components related to price stability and financial strength. To avoid losing information from the discrete nature of the original safety rank, we follow Jensen (2023) and instead use the stock's average ranking on the price stability and financial strength. We further standardize the modified safety rank to have a cross-sectional mean of zero and a cross-sectional variance of one.

These expected returns are then annualized using geometric compounding.[13]

Forward-looking corporate bond returns

We compute the expected bond return by taking the bond's yield and subtracting its expected default loss, computed as the probability of loss times one minus the expected recovery rate:

$$E[r_{b,t+1}] = \text{yield}_{b,t} - \text{prob. of default}_{b,t} \times (1 - \text{recovery rate}_{b,t}), \tag{3}$$

where $E[r_{b,t+1}]$ is the expected return of bond b over the next year. Following Campello, Chen, and Zhang (2008), we compute the probability of default as the average default rate over the past three years for bonds with the same rating as bond b. For recovery rates, we use estimates from Altman and Kishore (1998).[14]

The corporate bond data are from the dataset of Dick-Nielsen, Feldhütter, Pedersen, and Stolborg (2023). The data are based on quoted prices from Warga (1973-1985) and Merrill Lynch/ICE, as well as traded prices from Trace (2002-2022).

1.3 Standard errors

An important part of our paper is to quantify the uncertainty around our greenium point estimates. The standard errors for the greenium estimates based on realized returns must account for cross-sectional correlation, while there is little auto-correlation in realized returns. To account for the cross-sectional correlation of the errors in our regressions of realized returns on greenness measures, we cluster the standard errors by month. We additionally cluster the standard errors by industry but, because of minor auto-correlation in realized

[13]For a detailed description of how the subjective expected returns are constructed, see Jensen (2023, Section A.2.2).

[14]The annual default rates for broad rating categories (AAA, AA, A, BBB, BB, B, and CCC/C) from 1981 to 2022 provided by S&P Global Ratings (2023, Table 3). For observations before 1981, we use the average default rate over the full sample. Recovery rates are from Exhibit 6 in Altman and Kishore (1998) using corporate bond data from 1971 to 1999: AAA=68.34%, AA=59.59%, A=62.07%, BBB=45.59%, BB=36.82%, and CCC/C=38.19%.

returns, this makes little difference.

The standard errors for the greenium estimates based on forward-looking returns, notably ICC, must account for potential correlation in the errors over time. Existing research on ICC (mostly related to issues other than ESG) computes standard errors with the Fama and MacBeth (1973) procedure, which is similar to clustering by time (see Petersen, 2009), by clustering by firm, or by clustering by both firm and time.[15] In contrast, we cluster standard errors by industry and time in all our analyses.

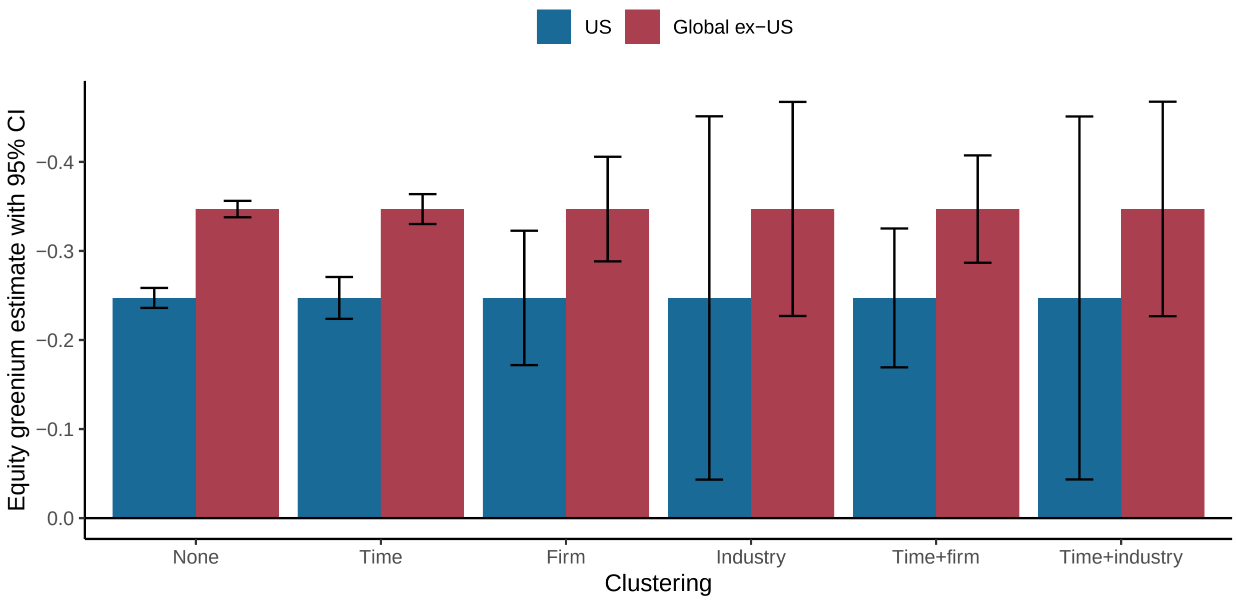
The clustering method matters for the analysis using ICCs. Figure 2 shows the estimated equity greenium in the US and global ex-US samples using ICCs along with the 95% confidence intervals based on six different methods to compute standard errors: i) OLS standard errors, ii) clustering by time (i.e., month), iii) clustering by firm, iv) clustering by industry, v) clustering by both time and firm, and vi) clustering by both time and industry.

The figure shows that clustering by industry leads to considerably wider standard errors. One reason for the apparent correlation of errors across firms over time within industries could be industry-wide shocks to analysts' cash-flow expectations that analysts incorporate into firms' cash-flow forecasts at different points in time.

The literature on clustered standard errors seeks to cluster the standard errors at the "right" level: Coarse enough such that all major correlations across error terms are captured, but finely enough that the number of clusters is sufficiently large for asymptotic theory to work (see, e.g., MacKinnon, Nielsen, and Webb, 2023a). Recommendations from the literature suggest that, in our case, 169 industries (we use GICS8 codes) and 161 months,

[15]For ICC papers that compute standard errors with the Fama-MacBeth procedure or cluster by time see Gebhardt et al. (2001, Table 7), Francis, LaFond, Olsson, and Schipper (2004, Table 5), Fu (2009, Table 7), Chava and Purnanandam (2010, Table 3), Botosan, Plumlee, and Wen (2011, Table 7), Mohanram and Gode (2013, Table 9). For papers that cluster by firm see Campbell, Dhaliwal, and Schwartz Jr (2012, Table 5), Hwang, Lee, Lim, and Park (2013, Table 5), Donangelo (2014, Table 7), Chava (2014, Table 1), Cao, Myers, Myers, and Omer (2015, Table 4), Goh, Lee, Lim, and Shevlin (2016, Table 4), and Pástor et al. (2022, I.A. Table A.1). For papers that cluster by firm and time see Naiker, Navissi, and Truong (2013, Table 4), Lee, So, and Wang (2021, Table 10), and Dick-Nielsen, Gyntelberg, and Thimsen (2022, Table 3). To find these papers, we were inspired by the list compiled by the internet appendix of Lee et al. (2021), which shows 98 papers published in top finance or accounting papers that use ICCs as the primary dependent variable. In our (non-exhaustive) search, we only identified one paper that clustered by industry, namely Chen, Miao, and Shevlin (2015, Table 6).

Figure 2: Estimating correct standard errors: The role of clustering



The figure shows the confidence intervals for our estimate of the equity greenium based standard errors with different levels of clustering. Specifically, we first estimate the equity greenium by regressing the implied cost of capital on our robust green score, a time-fixed effect, and four controls (market beta, log book equity, net debt-to-assets, and EBIT-to-assets) separately for the sample of US and global ex-US stocks. The bars show the equity greenium estimate, that is, the estimated coefficient on the robust green score. We then compute the 95% confidence interval based on standard errors clustered at different levels, as indicated by the label on the x-axis.

represent sufficiently many clusters.[16] Clustering errors this way happens to produce the most conservative standard errors—another rule-of-thumb for choosing at which level to cluster (see Angrist and Pischke, 2008). In summary, our standard errors are computed in a way that creates considerably wider confidence intervals than prevailing methods in the ICC literature, but we believe that this method is most appropriate.

[16] With a balanced panel and equally-sized clusters, having at least 50 clusters is a common recommendation for the asymptotic theory of clustered standard errors to work. Another recommendation from the literature on clustered standard errors is to compute p-values using a wild cluster bootstrap if the numbers of clusters is small. Bootstrapping by industry, we have estimated such p-values and they generally yield similar results as clustering by industry, which suggests that the number of industries (clusters) is sufficiently large in our application. Also, we tested whether one should cluster by firm or industry as in MacKinnon, Nielsen, and Webb (2023b), rejecting that firm clustering is enough against the alternative of industry clustering (this test does not allow for double-clustering also by time).

2 Greenium via realized returns: replication problems

As discussed in the introduction, the literature contains a wide range of greenium estimates and even disagrees on the sign of the performance of green-versus-brown stocks. This first part of the paper seeks to reconcile the evidence in the literature and to investigate what can be learned from the agglomeration of evidence. Following the literature, we consider the realized returns of green-minus-brown portfolios based on a range of greenness measures.

We perform a "scientific replication," meaning that we examine the results from the literature using a common framework for all greenness measures. Specifically, we potentially use a different sample period, different population, and a similar, but not identical model relative to the original papers. In other words, we are interested in the robustness of the results, not whether they can be reproduced by following each paper's different specific steps (as in "pure replication" or "reproduction").

Our analysis goes beyond the literature along several dimensions. First, while the literature is US centric, we consider global evidence based on 48 additional countries. Second, while the literature considers one greenness measure per paper, each with a specific sample period, industry adjustment, and risk adjustment, we jointly consider 23 greenness measures combined with a range of combinations of industry- and risk adjustments. Third, the literature has no multiple-testing adjustment, while we consider the whole distribution of p-values and perform a Benjamini-Hochberg adjustment.

2.1 Replication problems: portfolio sorts

While many papers in the literature focus on industry-agnostic portfolios (e.g., Pástor et al., 2022; Zhang, 2023), others focus on within-industry variation (e.g., Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023)). Therefore, we construct both industry-neutral and industry-agnostic portfolios for each of the 23 individual greenness measures from Table 1. This process yields $2 \times 23 = 46$ GMB factors in each country.

Starting with the US, to construct each industry-agnostic green-minus-brown (GMB) factor, we sort US stocks into terciles each month according to each greenness measure. We then compute next month's portfolio return for each tercile by value-weighting stocks with a cap on market capitalization at the NYSE 80th percentile, as in Jensen et al. (2023).

Likewise, to construct industry-neutral GMB factors, we first sort stocks into terciles within each industry, then combine these terciles across industries, and then compute value-weighted capped returns. Finally, we compute a GMB portfolio return for each greenness measure as the return difference between the top tercile (the green portfolio return) and the bottom tercile (the brown portfolio return).

Figure 1(a) plots the cumulative returns of the 46 US GMB portfolios from September-2009 to December-2022. The figure shows that, on average, green stocks outperform brown stocks from 2009 to 2020 and that this outperformance is partly reversed after 2020. However, the returns differ substantially across greenness measures, portfolio construction methods, and sample periods. Over the entire sample period, the return of the average GMB portfolio is not significantly different from zero.

Figure 3(a) plots a histogram of the alphas of the 23 industry-agnostic and 23 industry-neutral GMB factors. For each of these 46 factors, we compute the alpha in five different ways to account for risk exposures measured in different standard ways: 1) no risk adjustment (excess returns), 2) the CAPM, 3) the Fama-French three-factor model, 4) the Fama-French five-factor model augmented with momentum, and 5) the *q5*-factor model (Hou, Xue, and Zhang, 2015, 2021).

Figure 3(b) plots a histogram of the t-statistics corresponding to the 46-by-5 alphas of the GMB portfolios. As can be seen in the figure, most of the t-statistics are less than 1.96 in absolute value, meaning that the corresponding alphas are insignificant at the conventional level. However, there are a number of larger t-statistics, which helps explain why the literature sometimes finds a significant greenium. We show in the next subsection that none of these larger t-statistics survive a multiple testing adjustment.

Details on the performance of each individual GMB factor are reported in Tables A9 and A10 in the appendix. For example, Pástor et al. (2022) find that their GMB factor earns a monthly average return of 0.65% from 2012 to 2020. While we can reproduce their finding with their sample and method, we find a statistically insignificant 0.04% average monthly return using their greenness measure with our extended sample period and method. Likewise, Zhang (2023) finds a 0.39% monthly GMB return based on scope-1 carbon intensity (carbon emissions scaled by sales) from 2009 to 2021, whereas we find a statistically insignificant 0.13% return. More broadly, the few individual factors that are significant at the conventional 5% level in a given specification (e.g., the 6-factor alpha without industry adjustment) are often not significant at the 5% level in many of the other specifications (e.g., with other risk controls or with industry adjustment)—an indication of a lack of robustness of these results.

2.2 No significance with multiple-testing adjustment

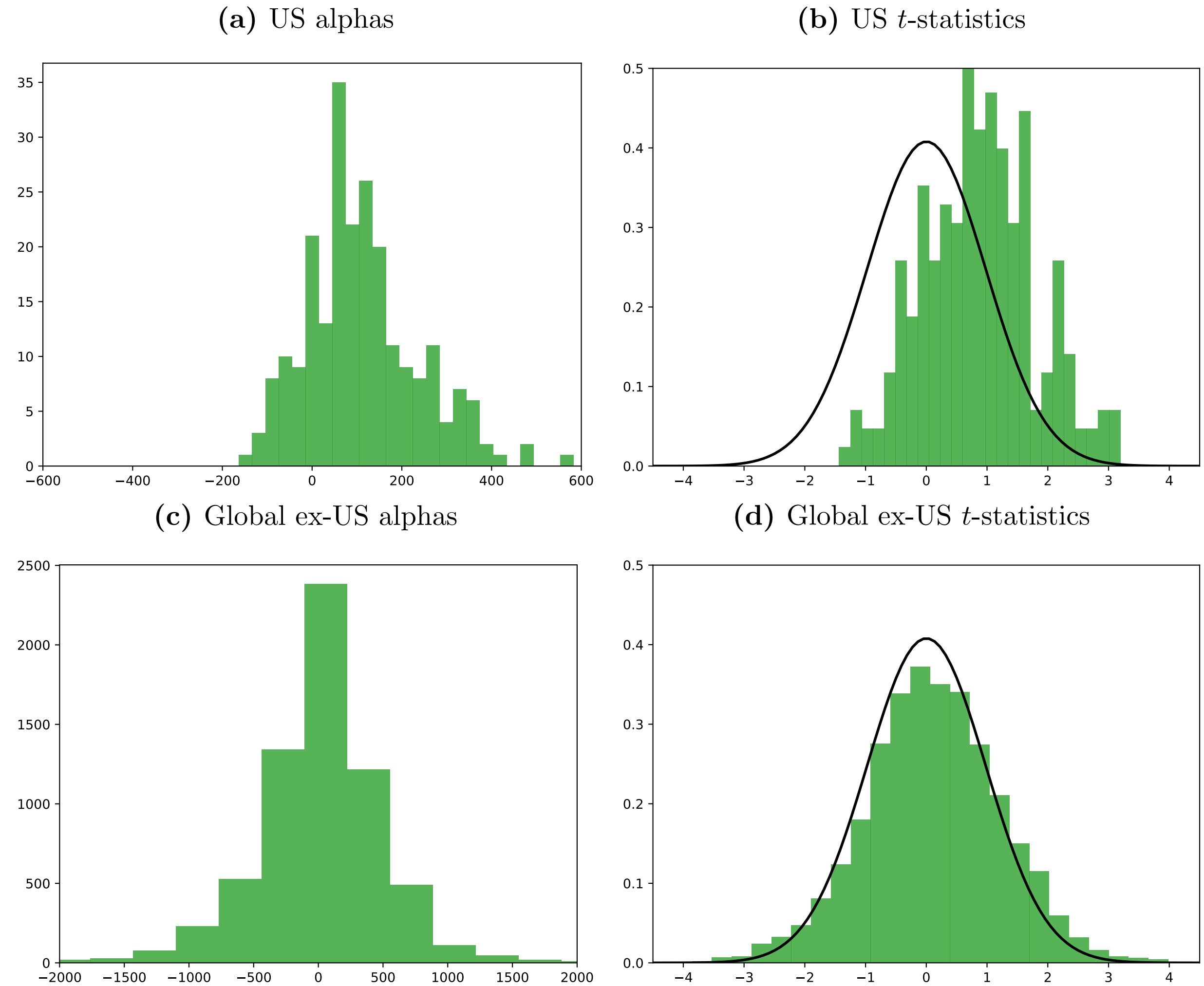
Figure 3(b) shows the results of 230 simultaneous tests. Indeed, we consider 23 greenness measures, industry-agnostic and industry-neutral portfolios, and 5 different risk adjustments. Given the large number of tests of essentially the same economic question, we should account for multiple testing, as some tests may indicate significance purely by chance.

We compute the multiple-testing adjustment of Benjamini and Hochberg (1995). The Benjamini-Hochberg method considers the p-values from all tests and classifies them as significant or not in a way that controls the false discovery rate. This method is one of the most commonly used for multiple testing as it is not as conservative as other methods (e.g., the Bonferroni correction), meaning that the Benjamini-Hochberg method is more likely to reject the null. Despite this method being less conservative than other methods, we find that none of the alphas is significant when accounting for multiple testing using the Benjamini-Hochberg method. In sum, there is no significant evidence of green versus brown realized return differences in the US using any greenness measure.

2.3 Out-of-sample evidence: global replication problems

So far, we have focused on US stocks. We next study realized return differences of global ex-US green and brown stocks. Figure 3, Panels (c) and (d) show histograms of alphas and their t-statistics of global ex-US GMB factors. Specifically, we compute a GMB factor for

Figure 3: Replication problems: GMB alphas and corresponding t-statistics



The figure shows histograms of the alphas of green-minus-brown (GMB) factors and their corresponding t-statistics. We construct the GMB factors using 23 (US) and 19 (Global ex-US) individual greenness measures, separately for the US and 48 other countries, and with and without industry adjustment. We estimate alphas with respect to 1) no risk adjustment (excess returns), 2) the CAPM, 3) the Fama-French three-factor model, 4) the Fama-French five-factor model augmented by momentum, and, in case of a US GMB factor, 5) the $q5$-factor model. For instance, Panel (a) contains $23 \times 2 \times 5 = 230$ alphas. An industry-agnostic GMB factor's return is the value-weighted capped return of stocks in the top tercile of the corresponding greenness measure less the value-weighted capped return of stocks in the bottom tercile, with a cap on market capitalization at the NYSE 80th percentile. We construct an industry-neutral GMB factor in a similar way, but sort stocks into terciles within each industry and then combine these terciles across industries. In a given country and month, we require at least ten stocks to construct a GMB factor, and in a given country a GMB factor must have at least 60 months of non-missing returns. All returns are measured in USD. Standard errors are Newey and West (1987) adjusted with three lags. Panels (b) and (d) overlay the standard normal distribution.

each country and greenness measure in the same way as the US factors. We then compute its alpha with respect to local risk models corresponding to the US Fama-French models: 1) no risk adjustment, 2) the local market, 3) the local market, size, and value, and 4) the local market, size, value, operating profitability, asset growth, and momentum. The local risk models are based on factors from Jensen et al. (2023), as Fama-French factors are not available in many countries.

The figure shows that alphas of the global ex-US GMB portfolios are dispersed and centered near zero. Further, the distribution of the t-statistics is close to Normal and centered near zero. Not surprisingly, none of these alphas are statistically significant according to the multiple-testing method of Benjamini and Hochberg (1995). In sum, we do not find evidence that green stocks realize different (risk-adjusted) returns than brown stocks outside the US.

2.4 Combining realized returns with the robust green score

The first ingredient in our search for the true greenium is the robust green score, constructed as an average of the ex-ante most reasonable measures as described in Section 1.1. Using the robust green score, we investigate whether greener stocks realize different returns from brown stocks via the following regression using monthly data,

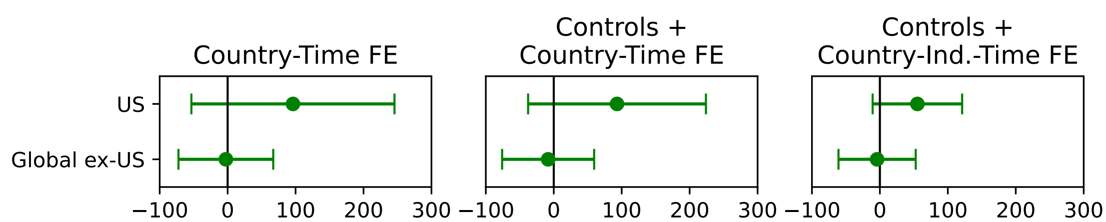
$$r_{t+1}^i = \alpha_{c,t} + g \times s_t^i + \text{controls} + \epsilon_{t+1}^i, \tag{4}$$

in which the dependent variable is the realized return, r_{t+1}^i, which is annualized (by multiplying by 12) and expressed in basis points. Here, $\alpha_{c,t}$ is a country (c) by time (t) fixed effect, s_t^i is the robust green score, and certain specifications include various controls as explained below. The coefficient of interest is the annual greenium, g.

Since most existing studies are focused on the US, we estimate this regression separately for the sample of US stocks (in which case the country-by-time-fixed effect is simply a time-fixed effect) and for the sample of global ex-US stocks. The first column in Figure 4 shows that the estimated greenium is positive, but not statistically different from zero for both US stocks and global ex-US stocks. The inclusion of a country-by-time-fixed effect implies that the greenium is identified from variation in returns across stocks with different robust green scores within a given country at a given point in time.[17]

Figure 4 also shows the results when we add an increasing number of control variables and fixed effects to the specification in Equation (4). Either way, we do not find evidence of a significant return difference between green and brown stocks. In particular, the second column estimates the greenium with the following control variables: market beta, the log of book equity, net debt-to-assets, and EBIT-to-assets, and the third column further adds country-by-industry-by-time fixed effects. In conclusion, we do not find significant evidence that green stocks realize higher returns than brown stocks and vice versa.

Figure 4: Regressions of realized returns on robust green score



The figure shows the annual greenium (in basis points) estimated by regressing (annualized) one-month-ahead stock returns on our robust green score and controls, see (4). The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. In the first row, the sample is US stocks; in the second row, the sample is global ex-US stocks. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

2.5 Why realized returns do not identify the greenium

The literature uses both realized out- and underperformance of green stocks to support the existence of a greenium. On one hand, realized underperformance can be seen as an estimate of the unconditional greenium (e.g., Bolton and Kacperczyk, 2021).

On the other hand, green stocks could be repriced and temporarily outperform brown stocks when environmental concerns strengthen unexpectedly, even when investors require

[17]We present most of our regression results in figures, but the exact estimates are in the appendix, tables A12-A16.

larger returns on brown stocks unconditionally. Pástor et al. (2022) therefore control for changes in the Media Climate Change Concerns Index of Ardia et al. (2022) as well as other variables. However, when making these adjustments, their estimated greenium from realized returns remains insignificant, consistent with our replication of their results in Table A11 (in which we actually do not even find a significant exposure to the Media Climate Change Concerns Index over our extended sample period).

At a more basic level, realized returns cannot identify the greenium because the signal-to-noise ratio is simply too small. To see this problem, consider a GMB factor that buys the green tercile of stocks and shorts the brown one, e.g., based on our robust green score. Empirically, this portfolio has a spread in the robust green score of around two standard deviations.[18] Using the baseline greenium estimate from Figure 1(b) of -25 bps per year per standard deviation increase in the green score, we predict an annual factor return of around $-25\text{bps} \times 2 = -50$ bps. The realized volatility of the GMB portfolio is 5.2%, so the predicted Sharpe ratio is $-0.50/5.2 = -0.10$. Given the sample length of $T = 13.33$ years, the expected t-statistic is

$$t = \frac{E[r]}{\sigma/\sqrt{T}} = \text{SR} \times \sqrt{T} = -0.37. \tag{5}$$

Thus, finding an insignificant realized greenium is not surprising, even if a small greenium really does exist. We can also consider how many years T it would take to get significance at the conventional 5% level (i.e., $t = 1.96$):

$$T = \left(\frac{1.96}{SR}\right)^2 = \left(\frac{1.96}{0.1}\right)^2 = 384 \text{ years}. \tag{6}$$

In summary, the noise in realized returns from repricing of the greenium, shocks to cashflows, and the short sample period mean that the greenium cannot be robustly identified from realized returns with the currently available data. Therefore, we next turn to estimating

[18] The statistics used in this section come from the US GMB factor that uses capped value weights, implemented from 2009-09 to 2022-12. The exact spread in the green score is 2.03, the annualized return volatility is 5.2%, and the sample length is 13 years and 4 months.

the greenium using forward-looking measures of expected returns.

3 Greenium based on forward-looking returns

In search of the true greenium, we next combine two ingredients: our robust green score and forward-looking expected returns. Using both ingredients leads to a more precisely estimated equity greenium, as we show in this section.

We consider the same monthly regression as (4), except that we replace realized returns with measures of each stock's forward-looking annualized expected return, $\tilde{E}_t[r^i_{t,t+h}]$, over some future period, h:

$$\tilde{E}_t[r^i_{t,t+h}] = \alpha_{c,t} + g \times s^i_t + \text{controls} + \epsilon^i_t. \tag{7}$$

To appreciate the distinction between forward-looking expected returns and realized returns, consider the simple example of a recently issued ten-year Treasury bond with a current 3% yield-to-maturity. Holding this bond until maturity guarantees an annual return of 3%, thus 3% is the forward-looking expected return. Suppose now that the yield-to-maturity rises to 4%. In this case, forward-looking expected returns are higher, but the realized return is negative at around −10%—realized returns in a short sample are extremely noisy measures of true expected returns.

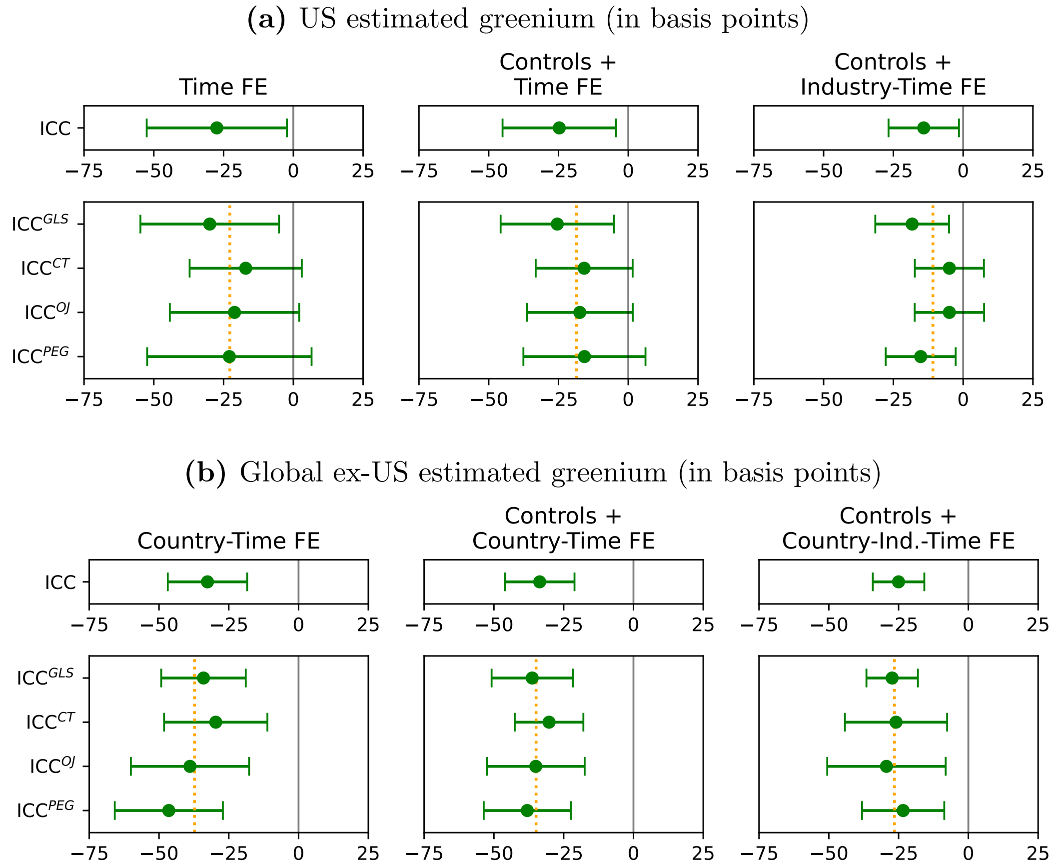
The same logic applies to equities, which are similar to long-duration bonds, except that the "coupon payments" (dividends) are uncertain. As opposed to Treasury bonds, expected equity returns are not directly observable, but the literature contains several proxies, which we consider in the next four subsections: ICCs, valuation ratios, option-implied expected returns, and subjective expected/required returns.

3.1 Greenium based on implied cost of capital

The first expected return proxy is the ICC, defined in Section 1.2. Recall that the baseline ICC is an average of four different versions, ICC^{GLS}, ICC^{CT}, ICC^{PEG}, ICC^{OJ}. Mohanram and

Gode (2013) show that the average ICC is less noisy than the individual methods, so our discussion focuses on the average while showing the individual methods as robustness.

Figure 5: Regressions of implied cost of capital on robust green score



The figure shows the annual greenium (in basis points) estimated by regressing implied costs of capital (ICCs) on our robust green score and controls, see (7). We consider ICCs from Gebhardt et al. (2001, ICC$^{\mathrm{GLS}}$), Claus and Thomas (2001, ICC$^{\mathrm{CT}}$), Ohlson and Juettner-Nauroth (2005, ICC$^{\mathrm{OJ}}$), and Easton (2004, ICC$^{\mathrm{PEG}}$), as well as their equal-weighted average, ICC. In Panel (a), the sample is US stocks; in Panel (b), the sample is global ex-US stocks. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

Figure 5(a) reports the estimated greenium, $\hat{g}$, from (7) with the ICC as the dependent variable for US stocks. Going from left to right, we consider more and more detailed controls and fixed effects, as in the analysis based on realized returns. In particular, we consider time-fixed effects, controls for risk characteristics and industry-by-time-fixed effects. In contrast to the results based on realized returns, most of the estimated greeniums are negative and significant. Further, the estimated standard errors are relatively small, measured in basis points per year, not percentage points per year.

Our baseline greenium estimate shown in Figure 1(b) is the second column with a time-fixed effect and risk controls. The control variables are market beta, size (log book equity), leverage (net debt-to-assets), and profitability (EBIT-to-assets). We measure size via the book equity instead of the market equity to avoid introducing a bias by having the endogenous market price on the right-hand side, and similarly for the other controls.

The baseline greenium estimate in the US sample is -25 bps, meaning that a one-standard-deviation increase in the robust green score is associated with a -25 bps drop in the annual ICC. The estimate is significant with a t-statistic of -2.4 and a 95% confidence interval of $(-45, -4)$ bps.

We note that the greenium estimated with an industry-by-time-fixed effects is also of interest as expected return differences across industries could be driven by unobserved industry-specific confounders. Industry adjusting eliminates such confounders, but also eliminates interesting variation in greenness. The estimated greenium tends to be smaller with industry-by-time-fixed effects, which could be because industry-by-time fixed effects eliminate a confounding bias or because they eliminate part of the actual effect of greenness on expected stock returns. In any event, the results with industry fixed effects show robustness.

Panel (b) reports the results in the global ex-US sample. The estimated greenium is -33 bps with a t-statistic of -5.3 and a 95% confidence interval of $(-46, -21)$ bps. These estimates are robust to using any of the individual ICC measures and to including the various controls.

3.2 Greenium based on valuation ratios

The estimated greenium in the previous subsection relies on forward-looking expected returns based on ICCs, which are a function of cash-flow forecasts of sell-side analysts and different ways of extrapolating these forecasts into the future. To check the robustness of these results with regard to potential biases in the cash flow forecasts or the extrapolation methods, we next estimate the greenium based on basic valuation ratios. In present value models, valuation ratios are simple measures of forward-looking expected returns.

In particular, we estimate the greenium using the regression framework (7) with each of four different valuation ratios as the dependent variable. For each valuation ratio, we use the market value in the denominator for two reasons. First, market values are always positive, so this procedure ensures that we do not divide by zero. Second, as a high price corresponds to a low forward-looking expected return, having market values in the denominator ensures that the sign of the estimated greenium has the same interpretation as in the previous subsection.

Figure 6 reports the results. In all 24 specifications (four different valuation ratios $\times$ three sets of controls $\times$ two regions), the greenium, $\hat{g}$ is negative, and the estimate is significant at the 95% level in most specifications.

In terms of magnitude, we note that earnings-to-price ratios are proxies for real (i.e., inflation-adjusted) expected returns under certain conditions (see, e.g., Pedersen, 2015, ch. 10.3). Hence, under these conditions, the magnitude of the estimated greeniums based on the earnings-to-price ratios can be directly compared to those in the previous section, and, indeed, the estimated magnitudes are similar.

The estimated magnitude for the log-book-to-market ratios is interesting. For example, the estimated US coefficient of -17% in the second column means that equity prices are about 17% higher for a one-standard-deviation increase in greenness.

While price levels are interesting in their own right, we can also try to convert them to returns. To do so in a simple way, we can use Gordon's growth formula:

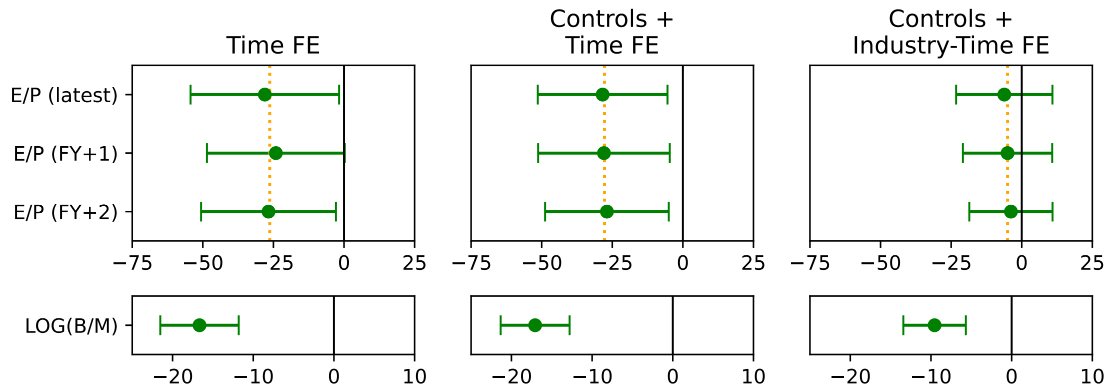
$$p = \frac{d}{r-g} \quad \text{i.e.,} \quad r = \frac{d}{p} + g\,, \tag{8}$$

where p is the stock price, d is the dividend next period, g is a constant growth rate, and r is the expected return. Since $\frac{\partial r}{\partial p} = -\frac{d}{p^2}$ and $\frac{\partial \log(b/p)}{\partial p} = -\frac{1}{p}$, where b is the book value, we can use the approximation

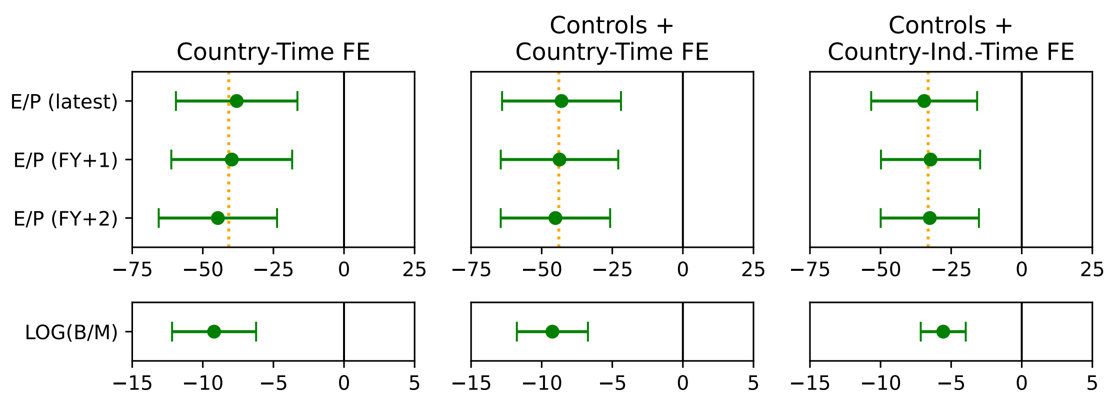
$$\partial r \cong -\frac{\partial p}{p}\frac{d}{p} \cong \partial \log(b/p)\frac{d}{p}. \tag{9}$$

Figure 6: Regressions of valuation ratios on robust green score

(a) US estimated greenium (in basis points)



(b) Global ex-US estimated greenium (in basis points)



The figure shows the annual greenium (in basis points) estimated by regressing valuation ratios on our robust green score and controls, see (7). The valuation ratios are the latest earnings-to-price ratio (E/P), the earnings-to-price ratio using one-year (E/P FY+1) and two-year ahead (E/P FY+2) consensus analyst earnings forecasts, and log book-to-market equity. Except for the forward-looking earnings-to-price ratios, we calculate all ratios using the current stock price and the accounting variables from the most recent financial statement. In Panel (a), the sample is US stocks; in Panel (b), the sample is global ex-US stocks. The greenium based on LOG(B/M) is expressed in percentage points. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

In other words, we can translate a greenium measured in terms of log-book-to-market into a greenium for expected returns by multiplying the coefficient by the dividend-to-price ratio. Using the estimated slope coefficient of -17% from Figure 6(a) multiplied by the value-weighted dividend-to-price ratio of 1.8%, the estimated "price greenium" corresponds to a "return greenium" of about -31 bps, again similar to our baseline estimate.[19]

3.3 Greenium based on option-implied expected returns

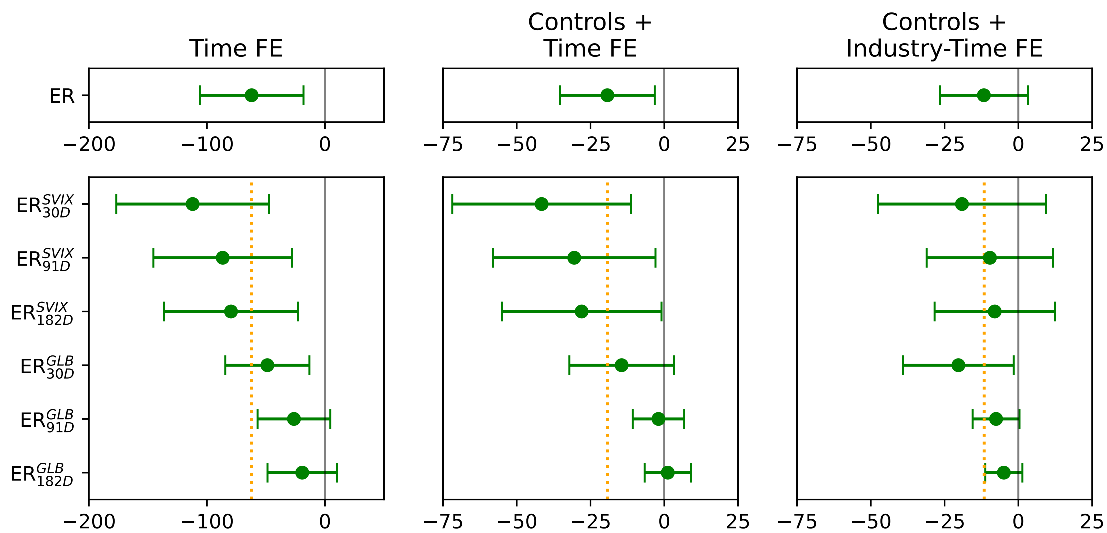
While implied costs of capital and valuation ratios are available globally, we have access to additional forward-looking measures of expected returns in the US. The first ones we consider are the option-implied expected returns of Martin and Wagner (2019) and Chabi-Yo et al. (2023). These measures, denoted SVIX and GLB, respectively, use option prices of optionable stocks coupled with assumptions about the representative investor to infer the expected return of each underlying stock—so we can use them as dependent variables in the regression (7).

Figure 7 reports the results for both measures over the next 30, 91, and 182 days (corresponding to options of 1-, 3-, and 6-month maturities) as well as the average of all these $2 \times 3 = 6$ measures (top row). The estimated annual greenium in the top row is negative in all specifications and ranges from -62 bps with only time-fixed effects to -12 bps with controls and time- and industry-fixed effects. As such, the option-implied expected returns suggest the same sign and magnitude for the greenium as those we inferred from ICCs and valuation ratios.

The average, however, conceals heterogeneity across the two measures. The SVIX-based greenium is consistently negative, whereas the GLB-based greenium is smaller in magnitude and sometimes switches sign. A stock's SVIX is proportional to its risk-neutral volatility, whereas the GLB measure is based on additional moments of the risk-neutral distribution, so the variation in results may indicate differences in higher-order risk-neutral moments across

[19] We compute the value-weighted dividend-to-price ratio each month over our sample from 2009-05 to 2022-12 and then take the average over time to arrive at 1.8%. If we replace the dividend yield with the net payout ratio (that also accounts for stock buybacks and issuance), the corresponding number is 3.1%, which translates into a greenium of -53 bps.

Figure 7: Regressions of option-implied expected returns on robust green score



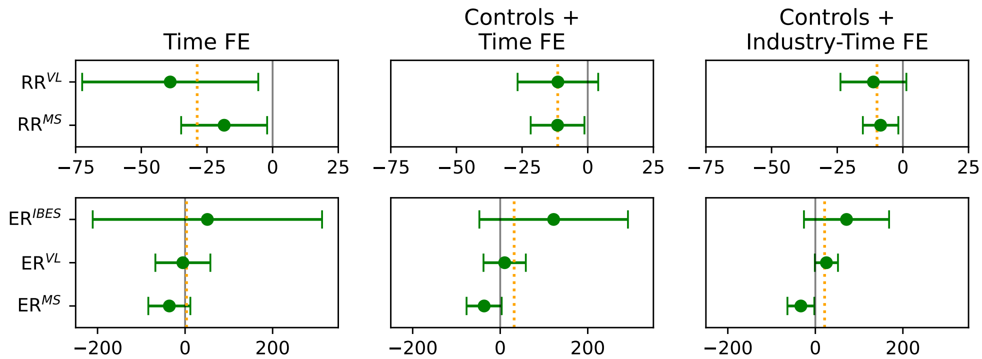
The figure shows the annual greenium (in basis points) estimated by regressing option-implied expected returns on our robust green score and controls, see (7). The option-implied expected returns are the SVIX measure from Martin and Wagner (2019) and the GLB measure from Chabi-Yo et al. (2023), each with horizons over 30, 91, and 182 days, as well as the average over all these six measures. The sample is US stocks. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

brown and green stocks.

3.4 Greenium based on subjective expected returns

We next estimate the regression (7) with dependent variables based on analysts' subjective required returns, available in the US. As explained in Section 1.2, these required returns are from Morningstar and Value Line (as in Jensen, 2023) and reflect how risky stocks are perceived to be. Figure 8 shows the resulting estimates of the greenium in the first two rows. The estimates are consistently negative, and significantly so in 4 out of 6 specifications. The magnitude of the effects ranges from around −30 bps with only time-fixed effects to around −10 bps with controls and time- and industry-fixed effects. In other words, the magnitudes are close to our baseline estimate of −25 bps. These results suggest that green stocks have lower required returns, perhaps because they are perceived as safer.

Figure 8: Greenium based on subjective expectations



The figure shows the annual greenium (in basis points) estimated by regressing subjective required returns (first two rows) or subjective expected returns (last three rows) on our robust green score and controls, see (7). The required returns are from Morningstar and Value Line. The Morningstar required return is their cost of equity estimate, which reflects a qualitative risk assessment and a constant risk premium. The Value Line required return is their risk assessment times a price of risk as in Jensen (2023). The subjective expected returns are computed based on a future price target divided by the current price, with data from Value Line, Morningstar, and I/B/E/S. All returns are annualized, and the sample is US stocks. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

In addition to these measures of required returns, we also have data on analysts' return expectations derived from dividing their future "price target" (plus expected dividends) by the current stock price. These data are available for Value Line, Morningstar, and I/B/E/S. Using these return expectations as dependent variables, Figure 8 reports the corresponding greenium in the last three rows. The estimates are generally noisier than the others we have considered and most of the greenium estimates are not statistically significant.

3.5 Further robustness and results

Using the regression specification in (7) with different dependent variables, different controls, and across US and global stocks we have considered a total of 102 different ways of estimating the forward-looking equity greenium. The estimated greenium is negative in 94% of the specifications, and most estimates are of the same order of magnitude. In this section, we test whether the results are robust to changes in the methodology (7).

Decile sorts. First, we relax the implicit assumption of linearity in (7). Specifically, instead of using a linear dependence on the robust green score, we construct ten dummy variables that indicate which decile each firm belongs to at a specific point in time. For example, a stock i is in decile 1 at time t (written as $i \in D_t^1$) if its green score is among those with the 10% lowest scores, it is in decile 2 if its score is in the $(10\%, 20\%]$ range, and so on. We then replace (7) by the following regression:

$$\tilde{E}_t[r_{i,t+1}] = \alpha_{c,t} + \sum_{d=1,\dots,4,6,\dots,10} g_d \, 1_{(i \in D_t^d)} + \text{controls} + \epsilon_t^i, \tag{10}$$

where g_d are dummy parameters and, to avoid multicollinearity, we leave out the dummy for decile five, g_5, so that the other dummies reflect the difference in expected returns relative to an "average stock" in group 5.

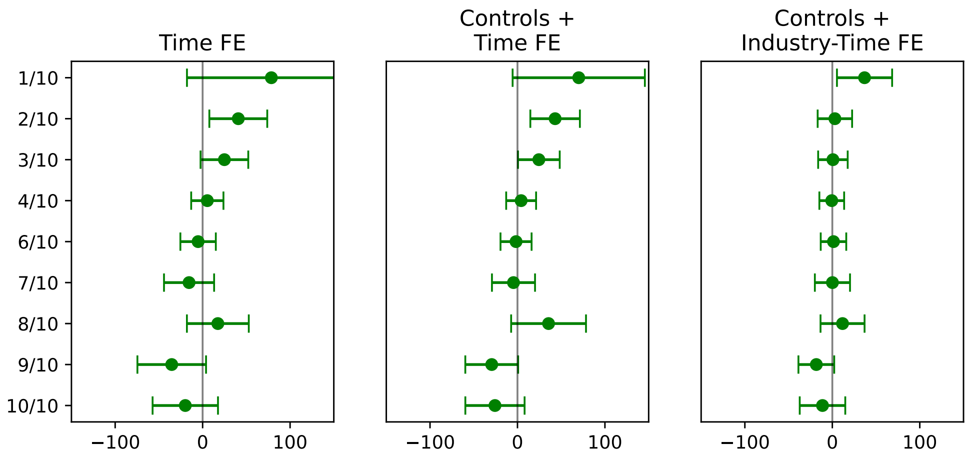
We run this regression with ICC as the dependent variable and report the results in Figure 9. Figure 9 shows that the relationship between greenness and expected returns is close to monotonic and the greenium appears to be driven by both ends of the green spectrum. In most specifications, the brownest stocks (decile 1) have the highest expected returns, and the greenest stocks (decile 10) have the lowest.

The most extreme portfolios 1 and 10 have very different average green scores — in fact, the greenest decile is about 3.5 standard deviations greener than the brownest one. Therefore, we expect that the corresponding difference in expected returns is approximatey 3.5 times the estimated greenium from Figure 5. The results in Figure 9 are consistent with this prediction. For example, the expected return spread from decile 10 to decile 1 is 96 bps with time-fixed effects and controls. So replacing the brownest stocks with the greenest leads to a meaningful loss in expected returns of nearly 1% per year. On the other hand, tilting the portfolio away from stocks of median greenness (decile 5) to the almost-greenest stocks from decile 9, only leads to a loss of around 0.3% per year.

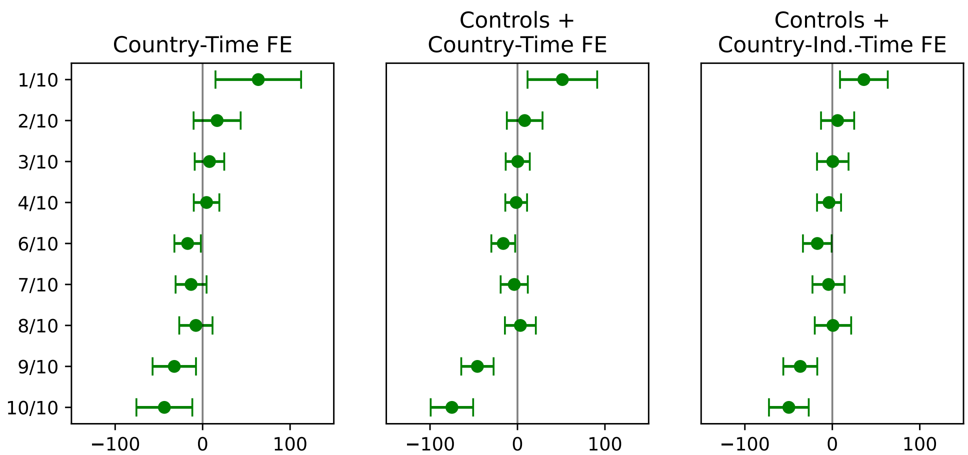
Text-based firm matching. Another potential issue with the regression in (7) is that we only control for observable firm characteristics. If green and brown firms differ on unobservable characteristics, that could bias our results. To investigate this possibility,

Figure 9: Expected return across ten bins sorted on the robust green score

(a) US estimated greenium (in basis points)



(b) Global ex-US estimated greenium (in basis points)



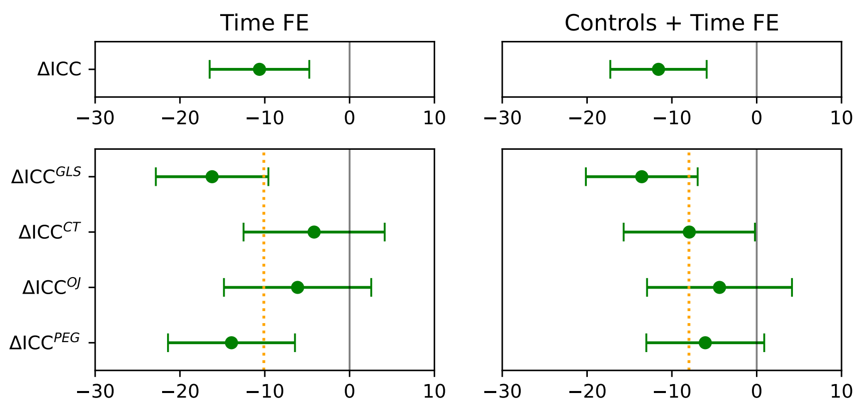
The figure shows the annual greenium (in basis points) estimated by regressing the average implied cost of capital from Figure 5 on decile dummy variables, see (10). In Panel (a), the sample is US stocks; in Panel (b), the sample is global ex-US stocks. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

we use the text-based industry classification from Hoberg and Phillips (2010, 2016).[20] The industry classification measures the similarity of a firm's 10-K business description to that of other firms. For each firm month, we find a control firm with the most similar business description. We then create the difference between the firm's ICC, their robust green score, and their controls and estimate the regression:

$$\Delta \text{ICC}_t^i = \alpha_{c,t} + g\,\Delta s_t^i + \Delta\text{controls} + \epsilon_t^i, \tag{11}$$

where the Δ indicates the difference between firm i and its closest match. We exclude the industry-fixed effect because the text-based matching already captures industry effects, and the firm effect we use is specific to each pairwise firm combination.

Figure 10: Greenium controlling for matched stocks



The figure shows the annual greenium (in basis points) estimated by regressing differences in implied costs of capital on differences in our robust green score and controls, see (11). We use the text-based similarity measure from Hoberg and Phillips (2010, 2016) to match firms to their closest competitor. The sample is US stocks. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

Figure 10 shows that the relationship between greenness and the implied cost of capital is still negative when controlling for matched firms. The magnitude is, however, smaller at around −10 bps when including a time-fixed effect and controls. As such, unobservable differences could drive part of the estimated greenium. Another possibility, however, is that

[20] The data are available at hobergphillips.tuck.dartmouth.edu/industryclass.htm.

we are absorbing too much variation in greenness by controlling for matched firms such that we cannot capture the part of the greenium arising from ESG investors shying away from either both stocks in a pair or neither stock.

4 The greenium across countries and time

The previous section established the existence of a robust equity greenium in the full sample of around -25 bps. In this section, we show that the equity greenium is getting more negative over time and that it is more negative in greener countries.

4.1 The equity greenium is getting more negative over time

To investigate whether the equity greenium is changing over time, we first estimate the regression from (7) separately each month in the global sample that pools the US and non-US data. Figure 11 shows the time series of the estimated greenium, $\hat{g}_t$, in each month. The estimated greenium is close to zero early in the sample and gets more and more negative over time. By December 2022, the estimated equity greenium is around -40 bps. The increasingly negative greenium suggests that the recent rise of impact investing has had a tangible effect on the discount rate of green versus brown stocks.

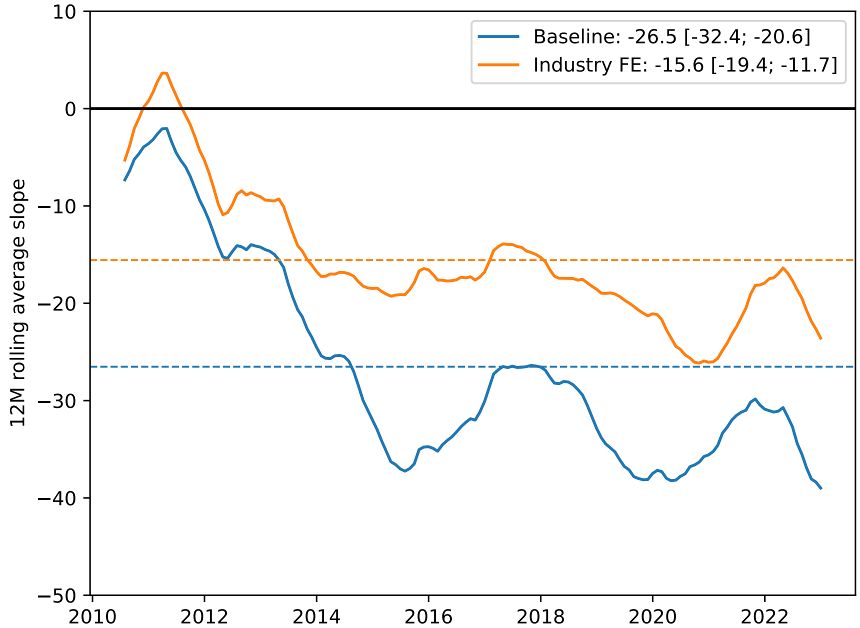
More formally, we test whether the greenium has become more negative via the following regression:

$$\mathrm{ICC}_t^i = \alpha_{c,t} + \left(g_1 + g_2 \times \frac{t - t_{\text{start}}}{t_{\text{end}} - t_{\text{start}}} \right) s_t^i + \text{controls} + \epsilon_t^i, \tag{12}$$

where ICC_t^i is one of the four ICC measures or their equal-weighted average at time t, t_{start} is the beginning of our sample in August 2009, and t_{end} is end of our sample in December 2022. Hence, g_1 is the greenium at the beginning of the sample period and $g_1 + g_2$ is the greenium at the end of the sample period.

Figure 12 shows the evolution of the estimated global greenium. The greenium was initially small, but significantly negative. Over time, the greenium became significantly more negative, a conclusion that holds for all ICC measures. The baseline greenium point

Figure 11: Global equity greenium over time



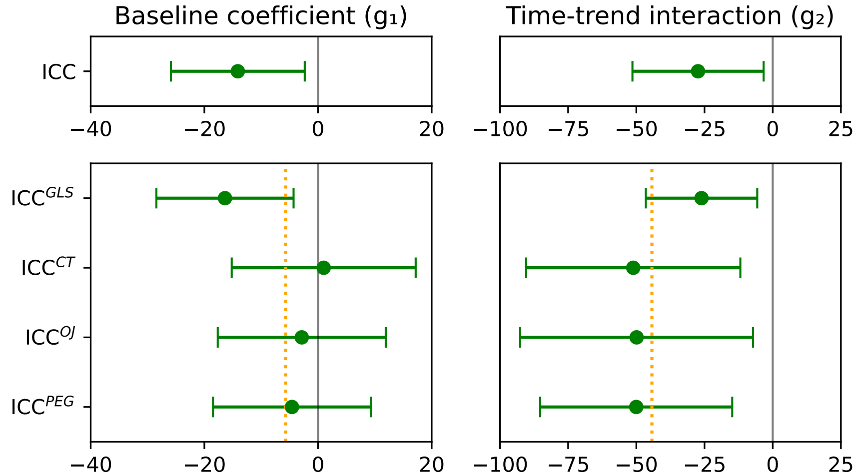
The figure shows the annual greenium (in basis points) over time, estimated by regressing the average cost of capital from Figure 5 on our robust green score and controls month-by-month in the global sample that pools the US and non-US data. The blue line shows the greenium estimated with country-fixed effects and control variables and the orange line shows the greenium when also controlling for GICS6 industry-fixed effects. Both lines show the rolling 12-month average greenium estimate. The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The green score is standardized to have zero mean and unit standard deviation within each country by month. The figure also shows the time-series averages of the greenium estimates.

estimate in the top line of the figure more than doubles over the sample period, going from -14 bps at the start of the sample period to $-14 - 27 = -41$ bps at the end of the sample period.

4.2 The equity greenium is more negative in greener countries

Next, we investigate whether the equity greenium is more negative in greener countries. We start by estimating the greenium within each country using the regression in (7) with the average ICC as the dependent variable (and the baseline specification with controls and time-fixed effects). Figure 13 shows that the estimated greenium is negative in most countries, but especially in the Nordics and Australasia.

Figure 12: Greenium over time



The figure shows the evolution of the global equity greenium, estimated by regressing ICC on our green score and the green score interacted with a time trend as in (12). The coefficient g_1 (left panel) is the annual greenium (in bps) at the start of the sample. The coefficient g_2 (right panel) is the linear time trend, indicating the increase in the annual greenium (in bps) from the start of teh sample to the end of the sample (2009-08 to 2022-12). The sample includes all stocks globally and the regressions include country-by-time fixed effects along with four controls: market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The robust green score is standardized to have zero mean and unit standard deviation within each country by month. Standard errors are clustered by industry and month.

To measure the greenness of a country, we use the Climate Change Performance Index (CCPI).[21] The CCPI measures the climate performance of up to 63 countries and has been published annually since 2005. In the 2024 ranking, Denmark is the best-performing country, and Saudi Arabia is the worst (Burck, Uhlich, Bals, Höhne, and Nascrimiento, 2024). Each year, the covered countries get a score between 0 and 100. We define green countries as those with an above-median CCPI.

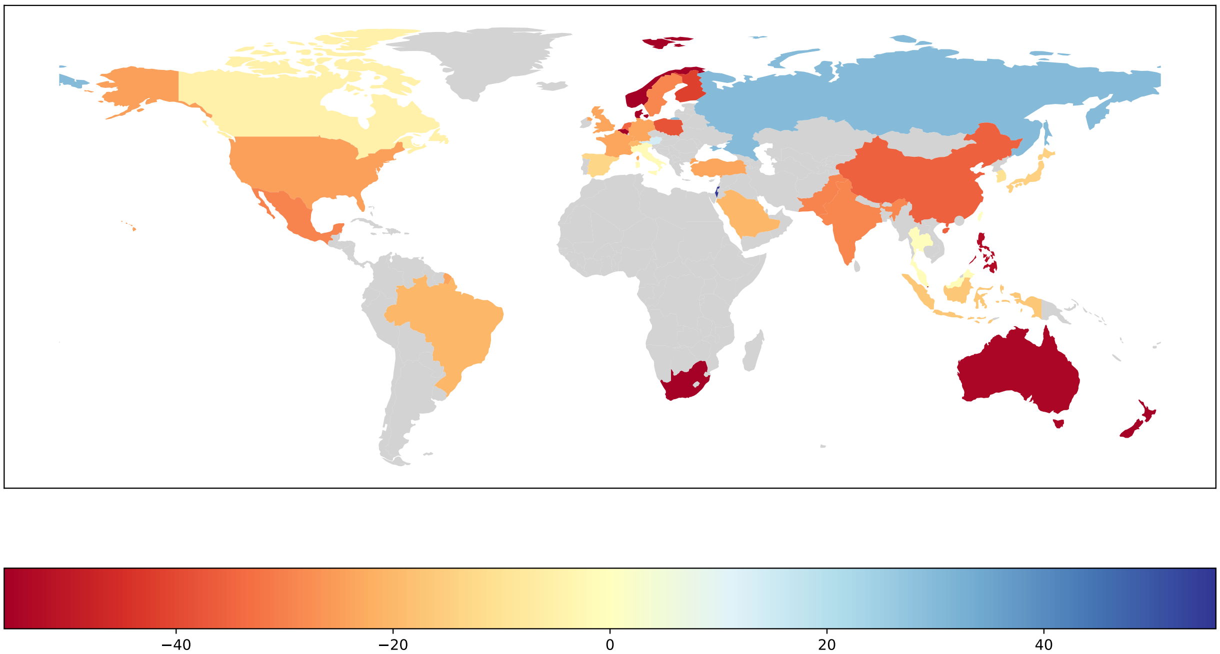
To estimate the greenium in green versus brown countries, we rely on the following regression:

$$\mathrm{ICC}_t^i = \alpha_{c,t} + (g_1 + g_2 \times 1_{(\mathrm{CCPI}_{c,t} > \mathrm{median})}) s_t^i + \mathrm{controls} + \epsilon_t^i, \qquad (13)$$

where ICC_t^i is stock i's average ICC and $1_{(\mathrm{CCPI}_{c,t} > \mathrm{median})}$ is equal to 1 if the country's CCPI is above the median in year t and zero otherwise. With this specification, g_1 is the greenium

[21]The CCPI data are available at ccpi.org. The CCPI has previously been used in other papers, such as Zhang (2023).

Figure 13: Global greenium map



The figure shows a world map in which countries are assigned colors according to their greenium estimates (i.e., the estimated expected return on green securities relative to brown securities). Red countries have lower greenium estimates, whereas blue countries have larger greenium estimates. We get these estimates by regressing the average implied cost of capital from Figure 5 on our robust green score, country-by-country. The regressions include a time fixed effects and four control variables: market beta, log book equity, net debt-to-assets, and EBIT-to-assets.

in brown countries, and $g_1 + g_2$ is the greenium in green countries.

Table 4 shows that greener countries tend to have more negative equity greeniums. Specifically, column (1) repeats the baseline regression of ICC on the robust green score with controls and time-fixed effects in the global sample. The column shows that the estimated global equity greenium is -31 bps. Column (2) estimates (13) and shows that the equity greenium in brown countries is $g_1 = -24$ basis points, whereas it is $g_1 + g_2 = -36$ basis points in green countries. This difference is statistically significant at the 5% level, meaning that the equity greenium is significantly more negative in greener countries.

Table 4: **Global cost of capital and Climate Change Performance Index**

Dep. Variable	(1) ICC	(2) ICC
GreenScore	-30.54	-24.39
	(-4.66)	(-3.45)
GreenScore × GreenCountry		-12.09
		(-2.02)
N	898,194	842,129
R2	50%	50%
Time FE	Yes	Yes
Controls	Yes	Yes

The table shows greenium estimates for green and brown countries by regressing the average ICC on control variables and a dummy that is equal to one if the country has an above-median Climate Change Performance Index (CCPI) score. Specifications (1) shows the baseline global greenium estimate and specifications (2) include interactions with the dummy variable. t-statistics (in parentheses) are based on standard errors clustered by industry and month. All specifications include time fixed effects. N refers to the number of observations.

5 The greenium across asset classes

It is interesting to compare the greenium across a firm's liabilities, equity and debt, and to aggregate these to the firm's weighted average cost of capital. It is also interesting to contrast these measures of the corporate greenium faced by firms to the greenium for sovereign bonds faced by governments. This section studies these greeniums in turn.

5.1 Corporate bond greenium

Comparing bonds issued by green versus brown firms, we can estimate a bond greenium. Figure 14 reports the estimated greenium using several different measures of forward-looking expected returns and several different sets of controls.

To estimate the expected return, we look at, respectively, each bond's (i) yield to maturity, (ii) yield spread over a maturity-matched risk-free bond, (iii) yield adjusted for expected default losses using the method of Campello et al. (2008), and (iv) yield spread adjusted for expected default losses. We regress each of these forward-looking expected returns on our robust green score as well as a set of controls, similar to the method used in our equity analysis. Since the green score is measured at the firm level, we aggregate all individual bond data to the firm level using value weights. As in the equity analysis, we avoid price-based measures to avoid biases, using book value as opposed to market value and time-to-maturity as opposed to duration.

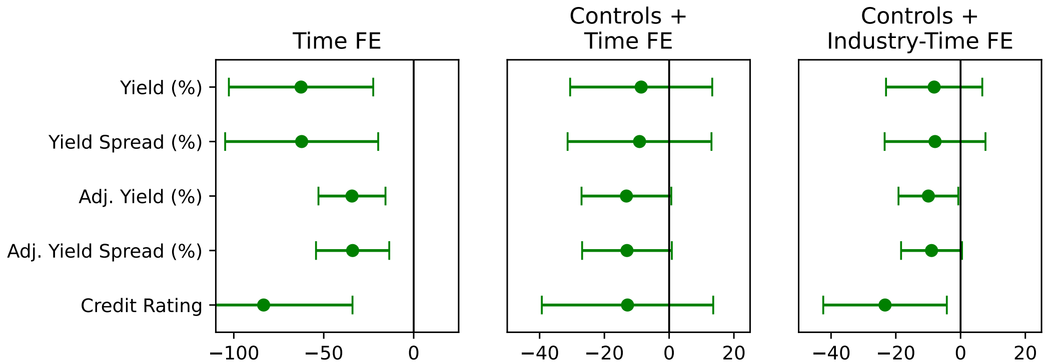
Panel (a) of Figure 14 shows estimated greeniums ranging from around -50 bps to near zero, depending on the specification. Our baseline specification is the regression of adjusted yields with risk controls and time-fixed effects. This specification yields a greenium of -13 bps with a 95% confidence interval of $(-27, 1)$ bps per year.

The last row in Panel (a) also shows that the credit rating tends to be stronger for green firms, controlling for other observables (note that a strong credit rating is coded as a small number). In other words, the rating agencies appear to view greener firms as safer, perhaps taking transition risk into account.

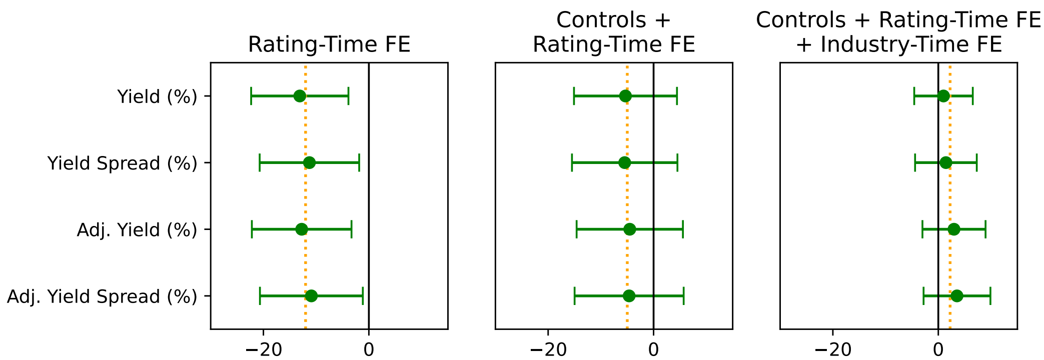
In Panel (b), all regressions include credit rating-by-time fixed effects. Analyzed in this way, the greenium becomes smaller and less statistically significant in most cases. While the differences are relatively small, an interpretation of this observation is as follows. The greenium can arise purely out of investor preferences or out of investor concerns with environmental risks. Only the latter part of the greenium should disappear when controlling for environmental risk, so the drop from Panel (a) to Panel (b) can be interpreted in this light. We should also note that controlling for risk factors, rating-time, and industry-time fixed effects might be over-differencing, because this specification controls for so much that there is little meaningful variation in greenness left.

Figure 14: Corporate bond greenium

(a) Greenium estimated (in basis points) without rating control



(b) Greenium estimated (in basis points) with rating-time fixed effects



The figure shows annual greenium estimates (in bps) by regressing corporate bond yields on our robust green score. Each regression is run at the firm level. Firm-level bond yields, credit ratings, and controls are value-weighted averages of bond-level yields, credit ratings, and controls using each bond's outstanding market value as weight. In Panel (a), the controls are log assets, net debt-to-assets, EBIT-to-assets, weighted bond time-to-maturity, and the log of the face value of debt. In Panel (b), all regressions include firm-weighted credit rating-by-time fixed effects. Yield spreads are calculated by deducting a maturity-matched risk-free bond. Adjusted yields capture expected returns as yields minus expected default losses using the method of Campello et al. (2008). The sample is US bonds. The robust green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

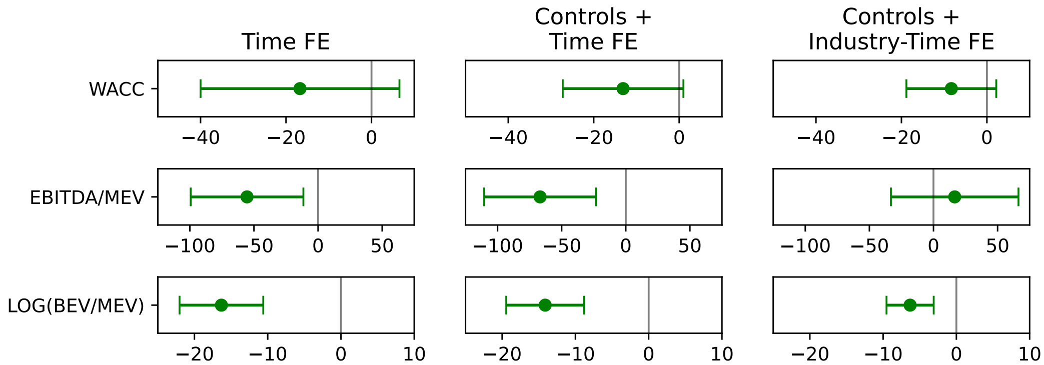
5.2 Firm-level cost of capital: WACC greenium

We next estimate the greenium at the overall firm level via the WACC. We compute the (pre-tax) WACC for each firm as the market value-weighted average of the equity's average ICC and corporate bonds' average adjusted yield. We regress the WACC on our robust green score and a set of controls.

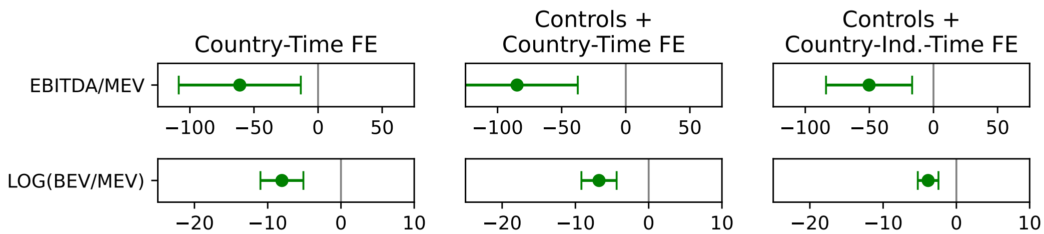
Figure 15 shows that the estimated WACC greenium is negative. The baseline estimate with controls and time-fixed effects yields a WACC greenium of -13 bps with a 95% confidence interval of $(-28, 1)$ bps per year.

Figure 15: WACC and the greenium at the overall firm level

(a) US estimated greenium (in basis points)



(b) Global ex-US estimated greenium (in basis points)



The figure shows annual greenium estimates (in basis points) by regressing each firm's overall cost of capital on its robust green score and a set of controls and fixed effects. A firm's cost of capital is measured as either its weighted average cost of capital (WACC), EBITDA to market enterprise value (EBITDA/MEV), or the log of book enterprise value to market enterprise value (LOG(BEV/MEV)). The greenium based on LOG(BEV/MEV) is expressed in percentage points. Controls are similar to those in Figure 5. The green score is standardized to have zero mean and unit standard deviation within each country and month. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

Figure 15 also reports two alternative measures of the WACC greenium based on valuation ratios (in parallel to Section 3.2). These are available both for US stocks (Panel (a)) and global stocks (Panel (b)). First, we use a dependent variable similar to earnings-to-price, but converted to the firm level, namely EBITDA-to-enterprise value. This measure leads to a negative greenium in all but one case in the US and global samples.

Second, we use a firm-level book-to-price, namely book enterprise value-to-market enterprise value. The figure shows that greener firms are more expensive than brown ones in all regressions, both in the US and globally.

5.3 Sovereign bond greenium

Finally, to see how the order of magnitude of the corporate greenium compares to an entirely different asset class, we estimate the greenium for sovereign bonds. While several countries have issued green sovereign bonds, we focus on the cases in which a country has issued so-called twin bonds, that is, paired green and standard bonds of exactly the same maturity, coupon, and seniority. Having such paired securities means that we can perfectly control for interest-rate risk and credit risk, meaning that the sovereign greenium can be crisply identified. Indeed, the greenium is simply the yield on the green bond minus that of the standard bond.

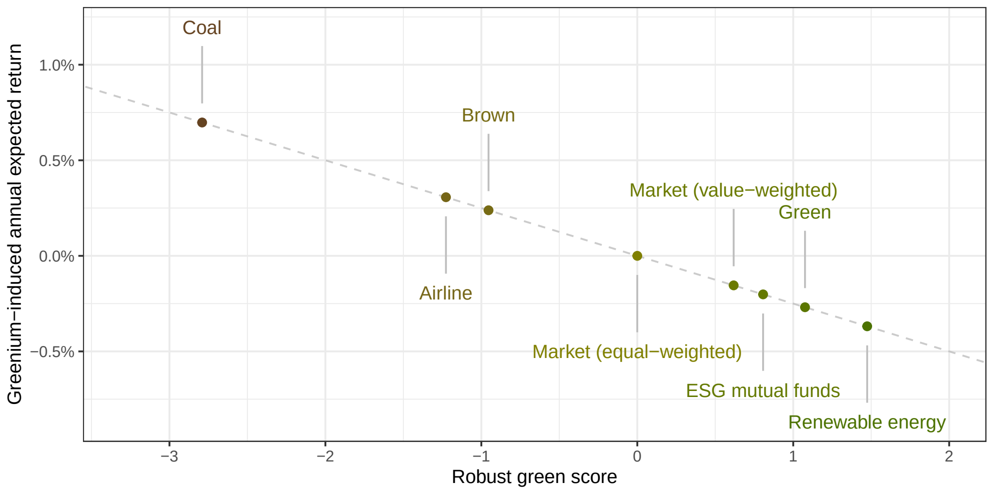
We use five twin-bond pairs from Feldhütter and Pedersen (2023), which consist of one Danish government bond pair with a time-to-maturity at issuance of 10 years, and four German government bond pairs with a time-to-maturity at issuance of 5, 10, 10, and 30 years. For each pair and day, we compute the difference in yields between the green and the standard bond. We then take the average of the yield difference across all five pairs each day and average the resulting number from January 20th, 2022 to August 10th, 2022 (when all five pairs have non-missing observations). The sovereign greenium estimated in this way is -3.2 bps with a 95% confidence interval of $(-4.5, -2.0)$ bps per year as seen in Figure 1(c).

6 Conclusion: Unveiling the global greenium

We find widespread robustness problems with the ESG literature that estimates the greenium based on realized returns combined with a variety of greenness measures. When we consider the evidence across greenness measures, time periods, and countries, we find that these estimates of the greenium are centered near zero globally and universally insignificant when taking multiple testing into account.

In search of the true greenium, we consider a robust green score, forward-looking returns, and a host of specifications. The estimated greenium is negative across countries and asset classes. In equities, the estimated annual greenium is −25 bps per standard deviation increase in the robust green score.

Figure 16: How big are the greenium effects?



The figure shows the cost of capital impact of the estimated greenium for different firms, industries, and investment portfolios. Specifically, for each firm, industry, or portfolio, we compute the average robust green score (the x-axis), and multiply this score by the estimated greenium of −25 bps, yielding the marginal greenium effect on their expected returns (the y-axis). The "Market (equal-weighted)" has a robust green score of zero because our green score is standardized to have a mean of zero across stocks; "Market (value-weighted)" uses the value-weighted average across stocks; "ESG mutual funds" is the value-weighted holding of ESG mutual funds as defined in Van der Beck (2023); "Green" is the tercile of stocks with the highest robust green score based on capped value-weights; "Brown" is the bottom tercile; "Renewable energy," "Coal," and "Airlines" are the equal-weighted averages of stocks with a GICS code of, respectively, 55105020, 10102050, and 20302010.

How large is the impact of a greenium of −25 bps for the expected return of real-world investors and firms? Figure 16 provides an answer by showing the average robust green score for different firms and investment portfolios (on the x-axis) and the corresponding expected return impact (on the y-axis). As a starting point, the equal-weighted market portfolio (or, equivalently, the average stock) has a marginal impact of zero, by construction. Next, the value-weighted market portfolio has a marginal greenium of −15 bps, which shows that, relative to the average firm, larger firms tend to be greener. This number also provides a natural benchmark for ESG mutual funds, which we identify using the classification from

Van der Beck (2023). Surprisingly, ESG mutual funds only tilt slightly towards green stocks, so the marginal effect on their expected return is only -5 bps lower than the value-weighted market portfolio. A green investor who switches from average stocks to the green portfolio faces a marginal reduction in expected returns of -27 bps while switching to brown stocks generates 24 bps.

Figure 16 further shows that renewable energy firms (the greenest industry based on 8-digit GICS) face a reduction in their cost of capital by -37 bps. In contrast, the average airline firm face an increased cost of capital by 31 bps, and the average coal firm (the brownest industry) faces an impact of 70 bps. Overall, these numbers suggest that the estimated greenium has a non-negligible effect on firms in certain industries and the portfolios of aggressive green investors but has a limited impact on the representative investors in ESG mutual funds.

Our findings have clear implications for ESG investors who trade off the greenium against the benefits of green investments in terms of risk and environmental effects. Likewise, the estimated greeniums are relevant for firms trading off the costs of a green transition against the reduction in their cost of capital, regulators who consider the interaction of carbon taxes and green finance, and for the finance theory of ESG investing.

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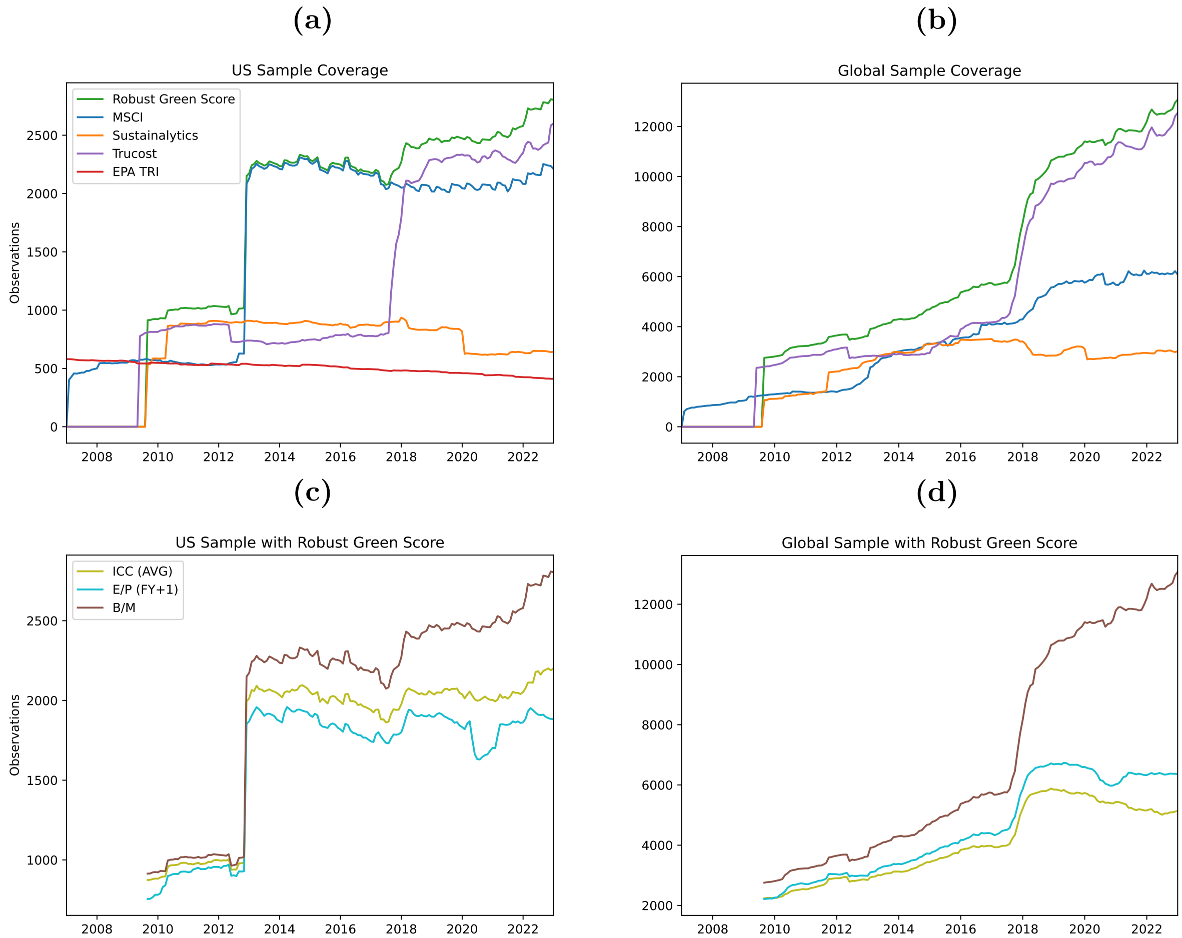
A Internet appendix

Table A1: Greenness measures

Name	Time period	Avg. N (US)	Avg. N (G)	Source
Robust Green Score	2009-08 to 2022-12	2042	6967	Several
S1INT (Sales)	2009-05 to 2022-12	1364	5939	Trucost
S1+2INT (Sales)	2009-05 to 2022-12	1364	5939	Trucost
S1+2+3INT (Sales)	2009-05 to 2022-12	1364	5939	Trucost
S1INT (Assets)	2009-05 to 2022-12	1364	5939	Trucost
S1+2INT (Assets)	2009-05 to 2022-12	1364	5939	Trucost
S1+2+3INT (Assets)	2009-05 to 2022-12	1364	5939	Trucost
Weighted ESG score	2007-01 to 2022-12	1558	3339	MSCI
Environment score	2007-01 to 2022-12	1558	3340	MSCI
Total ESG score	2009-08 to 2022-12	808	2722	Sustainalytics
Environmental score	2009-08 to 2022-12	808	2723	Sustainalytics
LOG(S1TOT)	2009-05 to 2022-12	1364	5939	Trucost
LOG(S1+2TOT)	2009-05 to 2022-12	1364	5939	Trucost
LOG(S1+2+3TOT)	2009-05 to 2022-12	1364	5939	Trucost
Ind.-adj. ESG score	2007-01 to 2022-12	1558	3341	MSCI
Greenness (PST)	2007-01 to 2022-12	1558	3340	MSCI
E climate score	2013-01 to 2022-12	2080	4391	MSCI
E nat. res. score	2013-01 to 2022-12	1479	3293	MSCI
E waste score	2013-01 to 2022-12	1397	2693	MSCI
E env. opps. score	2013-01 to 2022-12	725	1841	MSCI
TRINT (Sales)	1992-09 to 2022-12	586	0	EPA TRI
TPWINT (Sales)	1992-09 to 2022-12	586	0	EPA TRI
TRINT (Assets)	1992-09 to 2022-12	586	0	EPA TRI
TPWINT (Assets)	1992-09 to 2022-12	586	0	EPA TRI

The table shows, for our robust green score and the 23 individual greenness measures, the time period over which they are available, their stock-level observations (N) both in the US and globally (G), and their data sources. S1TOT, S1+2TOT, and S1+2+3TOT refer to the absolute amount of carbon emissions using scope 1, the sum of scope 1 and 2, and the sum of scope 1, 2, and 3 carbon emissions, respectively. S1INT, S1+2INT, and S1+2+3INT refer to the respective carbon intensities. Greenness (PST) refers to the measure of Pástor et al. (2022). Ind-adj. ESG score refers to MSCI's industry-adjusted ESG score. E nat. res. score and E env. opps. score refer to MSCI's natural resource and environmental opportunities scores. TRINT and TPWINT refer to toxic release intensity and toxic production waste intensity. We compute intensities by either scaling by sales or assets. EPA TRI refers to the Environmental Protection Agency's Toxics Release Inventory.

Figure A1: Sample coverage



The figure shows the number of firms covered by different data providers over time. Panels (a) and (b) show the number of covered firms in the US and globally. Panel (c) for US firms and Panel (d) for global ex-US firms show the number of firms that have at least one non-missing observation for the robust green score, and either the average ICC measure, the one-year forward earnings-to-price ratio, or the current book-to-market ratio.

A.1 Realized stock returns, firm characteristics, and equity factors

Realized stock returns and stock characteristics are from the data set in Jensen et al. (2023) available through WRDS. Realized returns are at a monthly frequency and sourced from CRSP for US stocks and Compustat for non-US stocks. Accounting data are quarterly if available and annual otherwise and are sourced from Compustat. Following Jensen et al. (2023), we restrict the sample to common stocks traded on the NYSE, NASDAQ, or AMEX

Table A2: Summary statistics for greenness measures (US stocks)

	N	Mean	Std	Min	25%	50%	75%	Max
S1INT (Sales)	221398	1.59	6.65	0.00	0.04	0.14	0.30	78.33
S1+2INT (Sales)	221398	1.92	6.88	0.01	0.12	0.36	0.74	79.11
S1+2+3INT (Sales)	221398	3.43	7.64	0.12	0.56	1.35	3.17	86.97
S1INT (Assets)	221398	0.86	3.08	0.00	0.01	0.10	0.34	39.37
S1+2INT (Assets)	221398	1.12	3.29	0.00	0.05	0.25	0.76	40.55
S1+2+3INT (Assets)	221398	2.50	4.51	0.00	0.25	1.05	2.78	45.94
Weighted ESG score	283075	4.50	1.02	0.00	3.90	4.50	5.10	9.45
Environment score	283058	4.56	2.18	0.00	3.00	4.50	6.02	10.00
Total ESG score	130070	52.67	11.81	7.22	47.00	52.83	60.00	91.00
Environmental score	130070	48.00	16.64	0.00	38.84	47.00	58.60	100.00
LOG(S1TOT)	221398	9.82	3.06	0.00	7.78	9.92	11.66	18.87
LOG(S1+2TOT)	221398	10.81	2.84	0.21	9.07	10.99	12.59	18.87
LOG(S1+2+3TOT)	221398	12.25	2.58	0.58	10.57	12.48	13.96	19.52
Ind.-adj. ESG score	283099	4.31	1.97	0.00	2.86	4.10	5.60	10.00
Greenness (PST)	283029	8.44	1.32	1.45	7.74	8.74	9.55	10.00
E climate score	249640	5.59	2.67	0.00	3.90	6.00	7.00	10.00
E nat. res. score	177463	4.38	2.25	0.00	2.80	4.30	5.50	10.00
E waste score	167636	5.22	2.42	0.00	3.50	5.30	6.90	10.00
E env. opps. score	87045	3.88	1.46	0.00	2.80	3.60	4.80	9.20
TRINT (Sales)	79768	3.38	11.02	0.00	0.01	0.19	1.56	186.37
TPWINT (Sales)	79768	27.53	82.35	0.00	0.26	2.12	14.87	1034.13
TRINT (Assets)	79768	2.64	8.63	0.00	0.01	0.17	1.50	193.54
TPWINT (Assets)	79768	25.52	76.79	0.00	0.22	1.74	12.27	1067.92

The table shows the number of observations, means, standard deviations, minimums, 25th percentiles, medians, 75th percentiles, and maximums for 23 individual greenness measures. The sample is US stocks.

in the US and on standard exchanges outside of the US. We retain all common stocks for a specific firm in the US but outside of the US we only retain the primary stock as identified by Compustat.

We use the following firm characteristics as risk controls (name in data set): market beta (`beta_252d`), the log of book equity (`book_equity`), net debt-to-assets (`debt_at - cash_at`), and ebit-to-assets (`ebit_at`).

We also use the following valuation ratios: The current earnings-to-price (`ni_me`), ebitda-to-market enterprise value (`ebitda_mev`), book-to-market equity value (`be_me`), and book-to-

Table A3: **Summary statistics for greenness measures (global ex-US stocks)**

	N	Mean	Std	Min	25%	50%	75%	Max
S1INT (Sales)	967988	2.46	8.79	0.00	0.07	0.18	0.55	78.33
S1+2INT (Sales)	967988	2.98	9.24	0.01	0.21	0.48	1.11	79.11
S1+2+3INT (Sales)	967988	4.92	10.21	0.12	0.85	1.96	4.31	86.97
S1INT (Assets)	967988	1.34	4.39	0.00	0.03	0.13	0.47	39.37
S1+2INT (Assets)	967988	1.67	4.65	0.00	0.09	0.32	0.99	40.55
S1+2+3INT (Assets)	967988	3.34	6.01	0.00	0.35	1.39	3.51	45.94
Weighted ESG score	613411	4.71	1.20	0.00	3.95	4.70	5.50	9.80
Environment score	613521	4.91	2.19	0.00	3.30	4.75	6.40	10.00
Total ESG score	439154	52.80	15.27	1.61	46.00	53.36	62.93	100.00
Environmental score	439154	50.57	18.53	0.00	39.65	50.50	63.14	100.00
LOG(S1TOT)	967988	9.79	2.88	0.00	7.91	9.62	11.48	20.19
LOG(S1+2TOT)	967988	10.75	2.54	0.00	9.08	10.62	12.30	20.19
LOG(S1+2+3TOT)	967988	12.07	2.31	0.20	10.53	12.02	13.58	20.21
Ind.-adj. ESG score	613619	4.88	2.39	0.00	3.09	4.90	6.70	10.00
Greenness (PST)	613494	8.39	1.22	0.67	7.62	8.62	9.35	10.00
E climate score	528424	6.22	2.75	0.00	4.40	6.60	8.30	10.00
E nat. res. score	396552	4.97	2.40	0.00	3.40	4.90	6.30	10.00
E waste score	324797	5.53	2.68	0.00	3.50	5.40	7.80	10.00
E env. opps. score	221775	4.41	1.62	0.00	3.20	4.20	5.50	10.00

The table shows the number of observations, means, standard deviations, minimums, 25th percentiles, medians, 75th percentiles, and maximums for 23 individual greenness measures. The sample is global ex-US stocks.

market enterprise value (`bev_mev`). We also consider the forward one- and two-year earnings-to-price ratio, which we define as the median consensus forecast from I/B/E/S divided by the current stock price.

US equity factor returns are from Kenneth French's data library and from global-q.org. Global ex-US equity factor returns are from Jensen et al. (2023).[22]

[22]The Jensen et al. (2023) factors are available at jkpfactors.com. We use the value-weighted market return and the capped value-weighted return of all non-market factors. The non-market factors are based on the following characteristics (with the factor name in parentheses): market equity (size), book-to-market equity (value), operating profit-to-book equity (profitability), asset growth (investment), and 12-1 month past returns (momentum).

A.2 Implied cost of capital measures

We use the implementation of Mohanram and Gode (2013) of ICC^{GLS}, ICC^{CT}, ICC^{PEG}, ICC^{OJ}, based on, respectively, Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). We also got inspiration from the description in the internet appendix of Dick-Nielsen et al. (2022). Note that while Mohanram and Gode (2013) adjusts cash flow forecasts for predictable errors, we follow Dick-Nielsen et al. (2022) and use the raw forecasts.

ICC methods based on the dividend discount model. The Ohlson and Juettner-Nauroth (2005) and Easton (2004) methods are based on the dividend discount model, which expresses the price of a stock as

$$p_t = \sum_{h=1}^{\infty} \frac{E_t[d_{t+h}]}{(1+r)^h}, \tag{14}$$

where p_t is the stock price, $E_t[d_{t+h}]$ is the expected dividend, and r is the cost of equity capital.

The Ohlson and Juettner-Nauroth (2005) method estimates the implied cost of capital as

$$\text{ICC}^{OJ} = A + \sqrt{A^2 + \frac{\tilde{E}_t[e_{t+1}]}{p_t} \times (\text{STG} - \lambda)}\,, \tag{15}$$

where

$$A = \frac{1}{2}\left(\lambda + \frac{\tilde{E}_t[d_{t+1}]}{p_t}\right) \quad \text{and} \quad \text{STG} = \max\left[\left(\frac{\tilde{E}_t[e_{t+2}] - \tilde{E}_t[e_{t+1}]}{\tilde{E}_t[e_{t+1}]} \times \text{LTG}\right)^{\frac{1}{2}}, \text{LTG}\right]. \tag{16}$$

Here, $\tilde{E}_t[e_{t+1}]$ and $\tilde{E}_t[e_{t+2}]$ are analyst forecasts of earnings per share (EPS) over the next two fiscal years, and LTG is the analyst forecast of long-term growth in EPS. All three forecasts are obtained from the I/B/E/S consensus file as the median forecast.[23] Further, $E_t[d_{t+1}]$ is a forecast of next year's dividend estimated using the payout ratio—dividend divided by earnings—from the last fiscal year times the analyst forecast of next fiscal year's EPS. For firms with negative earnings, we follow Mohanram and Gode (2013) and set the payout ratio to 6% of total assets. Finally, λ is the expected long-run growth of the economy, and we follow Mohanram and Gode (2013) and estimate it as the yield on a ten-year US treasury

[23] Ohlson and Juettner-Nauroth (2005) defines STG as the two-year growth in earnings, $\frac{\tilde{E}_t[e_{t+2}]-\tilde{E}_t[e_{t+1}]}{\tilde{E}_t[e_{t+1}]}$, but, to get a more stable estimate, we follow Mohanram and Gode (2013) and estimate STG as the geometric mean of short- and long-term growth.

bond minus 3%.

The Easton (2004) method is inspired by the price-earnings-growth (PEG) ratio. It is a simplification of (15) that sets $\lambda = 0$ and ignores dividends, leading to

$$\mathrm{ICC}^{PEG} = \sqrt{\frac{\tilde{E}_t[e_{t+1}]}{p_t} \times \mathrm{STG}}, \tag{17}$$

where the input are estimated as in (15).

ICC methods based on the residual income model. The Gebhardt et al. (2001) and Claus and Thomas (2001) methods are based on the residual income model, which expresses the price of a stock as:

$$p_t = b_t + \sum_{h=1}^{\infty} \left(\frac{E_t\left[(\mathrm{ROE}_{t+h} - r) b_{t+h-1}\right]}{(1+r)^h} \right), \tag{18}$$

where p_t is the stock's price, b_t the book equity per share (BPS), ROE_t the return on equity, and r the equity cost of capital.

Gebhardt et al. (2001) construct their ICC estimate by forecasting earnings from year $t+1$ to year $t+12$ (as described below) and then computing the terminal value as a constant perpetuity. Hence, the internal rate of return ICC^{GLS} is found by solving the following equation numerically:

$$p_t = b_t + \sum_{h=1}^{11} \left(\frac{\tilde{E}_t\left[(\mathrm{ROE}_{t+h} - \mathrm{ICC}^{GLS}) b_{t+h-1}\right]}{(1+\mathrm{ICC}^{GLS})^h} \right) + \frac{\tilde{E}_t\left[(\mathrm{ROE}_{t+12} - \mathrm{ICC}^{GLS}) b_{t+11}\right]}{\mathrm{ICC}^{GLS}(1+\mathrm{ICC}^{GLS})^{11}}. \tag{19}$$

Here, the return on equity is computed as

$$\tilde{E}_t[\mathrm{ROE}_{t+h}] = \frac{\tilde{E}_t[e_{t+h}]}{b_{t+h-1}}, \tag{20}$$

and the book value per share is imputed using clean surplus accounting:

$$b_t = b_{t-1} + e_t - d_t. \tag{21}$$

where $d_t = e_t \times$ payout-ratio and the payout-ratio is computed as in the OJ method.

To forecast earnings from year $t+1$ to year $t+12$, Mohanram and Gode (2013) use analyst forecasts for EPS over the first two fiscal years. For the remaining years, they assume that the ROE converges linearly to the median ROE of firms in the same industry over the past 10 years. We use the 49 industries from Fama and French (1997) and compute the median ROE expressed in US dollars across all global firms with valid data for all firms. We note that most ICC papers focus on stocks listed in the US and, as such, estimate the industry ROE on US firms only. We also have non-US firms, and we use the same convention for all firms for consistency.

Claus and Thomas (2001) construct their ICC estimate by forecasting earnings to year $t+5$ and then computing terminal value as a growing perpetuity:

$$p_t = b_t + \sum_{h=1}^{5} \left(\frac{\tilde{E}_t \left[(\text{ROE}_{t+h} - \text{ICC}^{CT}) b_{t+h-1} \right]}{(1+\text{ICC}^{CT})^h} \right) + \frac{\tilde{E}_t \left[(\text{ROE}_{t+5} - \text{ICC}^{CT}) b_{t+4}(1+g) \right]}{(\text{ICC}^{CT} - g)(1+\text{ICC}^{CT})^5}, \quad (22)$$

where g is the terminal growth rate. Similar to GLS, the CT method uses EPS forecasts from I/B/E/S for the first two years. For years three to five, the CT method increases the second-year forecast in each using the LTG forecast from I/B/E/S. Finally, the CT method uses a terminal growth, g, equal to the yield on a ten-year US treasury bond minus 3%.

A.3 Data choices: Screens, winsorization, lag conventions, and linking

In this section, we provide additional details on the data construction.

A.3.1 Screens

To ensure that our empirical results are created on a comparable set of firms, we require all firms to have:

- Non-missing values for all the controls (beta, EBIT-to-assets, net debt-to-assets, and book equity)
- A non-missing GICS industry code
- Positive sales, assets, book equity, and market equity

In addition, for the analysis with valuation ratios shown in Figure 6, we only include firms where the numerator (current earnings, one-year forward earnings, two-year forward earnings, and current book equity) is positive. Finally, for the analysis of bond yields shown in Figure 14, we exclude bonds that are in selective default (rating='SD') or full default (rating='D').

A.3.2 Winsorization

To handle outliers, we winsorize the following variables at the 1% and 99% level within each month across all firms with available data (i.e., we winsorize across the US and global ex-US sample):

- The emission intensity measures from Trucost and EPA TRI
- A subset of the controls used throughout the paper, namely beta, EBIT-to-assets, and net debt-to-assets.
- The individual implied cost of capital measures (ICC^{GLS}, ICC^{CT}, ICC^{PEG}, and ICC^{OJ})
- The valuation ratios used in Figure 6
- The options-implied expected returns used in Figure 7
- The subjective required and expected returns used in Figure 8

In addition, we follow Jensen et al. (2023) and winsorize realized returns from Compustat each month across all stocks at the 0.1% and 99.9% level.

A.3.3 Lag conventions

To ensure that the data we use is publicly available, we adopt the following lag conventions:

- Accounting data is assumed to be available four months after the fiscal end following Jensen et al. (2023).
- Trucost data is assumed to be available by the end of the month where the emissions estimate is made or when the emissions are disclosed following Pedersen et al. (2021) and Zhang (2023). For example, if Trucost estimated Apple's December 2009 emissions in April 2011, then we would use the estimated emissions from April 2011.
- EPA data is assumed to be available by September in the year after reporting following Hsu et al. (2023)

- When scaling total emissions by sales, we use the sales from the last accounting statement in the specific year. For example, 2009 emissions data from Trucost would be scaled with sales from the last accounting statement in the 2009 fiscal year (typically, the fiscal year that ends in December 2009)
- We use MSCI, Sustainalytics, and EPA TRI data for up to one year following the latest estimate. For example, if MSCI gave Apple a rating in December 2009 and no rating after, then we use the December 2009 rating until December 2010.
- We use Trucost data for up to 3 years following the latest estimate. For example, if Trucost estimated Apple's 2009 emissions in April 2011 and made no estimates after, then we would use the estimated emissions from April 2011 until April 2014. In order to include an estimate, we require no more than 5 years of lag between the estimation date and firm reporting date. For example, if Trucost' estimate for Apple's 2009 emissions were made in 2016, we would not include this estimate.

A.3.4 Linking

To link firms across different databases, we use the following resources:

- CRSP to I/B/E/S: Linking table from WRDS (called `wrdsapps.ibcrsphist` on WRDS's servers)
- CRSP to Compustat: Linking table from CRSP (`crsp.ccmxpf_lnkhist`)
- Trucost to Compustat: Trucost provides the Compustat GVKEY
- MSCI to Compustat: Linking table from Capital IQ between historical ISIN and GVKEY (`ciq.wrds_isin`)
- Sustainalytics to Compustat: Linking table from Capital IQ Company ID to GVKEY followed by linking table from ISIN to GVKEY for those not matched in the first step
- EPA to Compustat: Linking table provided in replication code from Hsu et al. (2023)

A.4 Descriptive statistics

This section provides descriptive statistics. Table A4 shows descriptive statistics for stock return and firm characteristics. Table A5 shows descriptive statistics for the implied cost of capital measures and valuation ratios. Table A6 shows descriptive statistics for the option-implied expected returns. Table A7 shows descriptive statistics for bond yields and characteristics.

Table A4: Descriptive statistics: Stock return and firm characteristics

(a) US

	count	mean	std	min	25%	50%	75%	max
ret_exc_lead1m	325934.00	0.96	14.58	-96.63	-5.36	0.76	6.66	1625.05
log_size	328737.00	7.72	1.73	0.70	6.51	7.65	8.80	14.88
log_assets	328737.00	7.86	1.82	1.37	6.60	7.79	9.00	15.19
log_be	328737.00	6.82	1.69	-4.51	5.70	6.74	7.85	13.30
debt_at	328737.00	0.24	0.20	0.00	0.07	0.22	0.37	0.77
cash_at	328737.00	0.18	0.21	0.00	0.03	0.09	0.23	0.89
netdebt_at	328737.00	0.06	0.32	-0.85	-0.10	0.09	0.29	0.72
ebit_at	328737.00	0.04	0.15	-1.05	0.02	0.06	0.11	0.37
ret_12_1	325361.00	0.14	0.51	-0.87	-0.13	0.08	0.31	7.78
beta_252d	327841.00	1.13	0.43	-0.32	0.84	1.10	1.39	2.52
rvol_252d	327841.00	0.03	0.01	0.01	0.02	0.02	0.03	0.15
div_me	328551.00	0.01	0.03	0.00	0.00	0.00	0.02	0.39

(b) Global ex-US

	count	mean	std	min	25%	50%	75%	max
ret_exc_lead1m	1108638.00	0.49	12.37	-78.97	-5.76	-0.02	5.89	295.56
log_size	1121714.00	7.11	1.66	-3.31	5.95	7.10	8.22	14.78
log_assets	1121714.00	7.63	1.92	-1.25	6.30	7.49	8.80	15.59
log_be	1121714.00	6.68	1.66	-8.18	5.56	6.64	7.75	13.17
debt_at	1114371.00	0.23	0.18	0.00	0.07	0.21	0.35	0.77
cash_at	1115002.00	0.16	0.15	0.00	0.05	0.11	0.21	0.89
netdebt_at	1107934.00	0.07	0.27	-0.85	-0.09	0.09	0.26	0.72
ebit_at	1120298.00	0.06	0.09	-1.05	0.02	0.05	0.09	0.37
ret_12_1	1115065.00	0.09	0.48	-0.87	-0.19	0.01	0.25	7.78
beta_252d	1102696.00	0.97	0.36	-0.32	0.72	0.95	1.19	2.52
rvol_252d	1102696.00	0.02	0.01	0.01	0.02	0.02	0.03	0.15
div_me	938157.00	0.03	0.04	0.00	0.01	0.02	0.04	0.39

A.5 Additional empirical results

Table A5: Descriptive statistics: Implied cost of capital and valuation ratios

(a) US

	count	mean	std	min	25%	50%	75%	max
icc_avg	285675.00	8.49	3.27	1.16	6.57	8.18	9.94	36.62
icc_gls	280568.00	8.30	3.30	1.35	6.25	8.09	9.96	31.67
icc_ct	173191.00	7.52	3.57	1.16	5.43	7.02	8.86	37.90
icc_oj	159220.00	9.82	3.63	2.69	7.75	9.20	10.99	44.98
icc_peg	159498.00	8.93	3.04	2.14	7.10	8.53	10.15	38.44
ep_fwd0	256865.00	6.27	4.90	0.14	3.64	5.30	7.47	69.72
ep_fwd1	261063.00	6.29	4.03	0.23	4.02	5.66	7.63	55.20
ep_fwd2	273934.00	7.01	4.11	0.36	4.67	6.46	8.50	64.06
ebitda_mev	284321.00	11.63	11.18	0.21	6.42	9.44	13.42	180.77
be_me	328737.00	0.63	0.76	0.02	0.24	0.46	0.79	15.50
bev_mev	313498.00	0.61	0.58	0.01	0.27	0.53	0.82	12.10

(b) Global ex-US

	count	mean	std	min	25%	50%	75%	max
icc_avg	653263.00	9.62	4.00	1.16	6.94	9.04	11.59	38.44
icc_gls	591693.00	9.13	3.76	1.35	6.52	8.86	11.33	31.67
icc_ct	283591.00	9.11	4.88	1.16	5.95	8.06	10.92	37.90
icc_oj	247494.00	11.63	5.03	2.69	8.36	10.52	13.50	44.98
icc_peg	300944.00	9.92	4.38	2.14	7.05	9.01	11.70	38.44
ep_fwd0	710282.00	7.50	6.00	0.14	3.88	6.10	9.20	69.72
ep_fwd1	736718.00	7.61	5.16	0.23	4.40	6.51	9.33	55.20
ep_fwd2	761691.00	8.63	5.46	0.36	5.23	7.46	10.47	64.06
ebitda_mev	1029714.00	13.47	13.72	0.21	6.21	10.17	15.94	180.77
be_me	1121714.00	1.00	1.18	0.02	0.36	0.69	1.18	15.50
bev_mev	1096681.00	0.87	0.83	0.01	0.39	0.74	1.10	12.10

Table A6: Descriptive statistics: Option implied expected returns

	count	mean	std	min	25%	50%	75%	max
mw30	94729.00	6.71	8.56	-0.84	2.23	4.35	8.06	163.66
mw91	94725.00	5.99	6.40	-0.25	2.40	4.11	7.22	104.59
mw182	94714.00	5.89	5.64	0.17	2.61	4.22	7.09	83.13
glb2_D30	94298.00	9.28	9.44	0.05	4.16	6.83	11.31	168.84
glb2_D91	94294.00	7.75	6.48	0.04	3.84	5.84	9.58	87.18
glb2_D182	94282.00	7.32	5.57	0.08	3.77	5.62	9.23	63.68

Table A7: Descriptive statistics: Bond yields and characteristics

	count	mean	std	min	25%	50%	75%	max
tmt	87283.00	8.53	4.80	1.00	5.21	7.09	11.13	87.64
coupon	87283.00	5.37	1.61	0.00	4.18	5.25	6.44	15.00
rating_num	87283.00	9.90	3.39	1.00	7.74	9.00	12.11	21.00
yield	86578.00	4.52	5.16	0.28	2.86	3.80	5.27	576.42
yield_spread	82489.00	2.84	5.29	0.02	1.10	1.82	3.46	576.31
yield_adj	86578.00	3.74	4.71	-17.48	2.69	3.56	4.61	559.25
yield_spread_adj	82489.00	2.02	4.80	-18.65	1.00	1.58	2.72	559.13
debt_mv	87283.00	5211.74	11074.46	1.15	599.62	1616.63	4695.59	126693.55
debt_fv	87283.00	4848.93	10241.18	1.20	600.00	1531.00	4414.37	122674.31
market_leverage	87283.00	38.41	98.61	0.05	10.71	20.64	40.64	8248.80

Table A8: Number of unique firms by country with robust green score

Exchange Country	N	Region/Area	Continent	Country
ARE	51	South West Asia	Asia	United Arab Emirates
ARG	29	CS America	Americas	Argentina
AUS	660	Pacific	Oceania	Australia
AUT	49	Western Europe	Europe	Austria
BEL	84	Western Europe	Europe	Belgium
BGD	11	South Asia	Asia	Bangladesh
BRA	214	CS America	Americas	Brazil
CAN	610	North America	Americas	Canada
CHE	226	Western Europe	Europe	Switzerland
CHL	72	CS America	Americas	Chile
CHN	2033	East Asia	Asia	China
CIV	16	Africa	Africa	Cote d'Ivoire
COL	33	CS America	Americas	Colombia
DEU	383	Western Europe	Europe	Germany
DNK	67	Northern Europe	Europe	Denmark
EGY	49	Africa	Africa	Egypt
ESP	125	Western Europe	Europe	Spain
FIN	91	Northern Europe	Europe	Finland
FRA	387	Western Europe	Europe	France
GBR	874	Western Europe	Europe	United Kingdom
GRC	41	CE Europe	Europe	Greece
HKG	1200	East Asia	Asia	Hong Kong (China)
IDN	239	South East Asia	Asia	Indonesia
IND	756	South Asia	Asia	India
IRL	28	Western Europe	Europe	Ireland
ISR	142	South West Asia	Asia	Israel
ITA	210	Western Europe	Europe	Italy
JPN	2484	East Asia	Asia	Japan
KEN	17	Africa	Africa	Kenya
KOR	1199	East Asia	Asia	Korea, South
KWT	42	South West Asia	Asia	Kuwait
LKA	18	South Asia	Asia	Sri Lanka
MAR	31	Africa	Africa	Morocco
MEX	93	CS America	Americas	Mexico
MYS	293	South East Asia	Asia	Malaysia
NGA	29	Africa	Africa	Nigeria
NLD	108	Western Europe	Europe	Netherlands
NOR	171	Northern Europe	Europe	Norway
NZL	79	Pacific	Oceania	New Zealand
OMN	10	South West Asia	Asia	Oman
PAK	70	South Asia	Asia	Pakistan
PER	41	CS America	Americas	Peru
PHL	97	South East Asia	Asia	Philippines
POL	99	CE Europe	Europe	Poland
PRT	25	Western Europe	Europe	Portugal
QAT	36	South West Asia	Asia	Qatar
ROU	10	CE Europe	Europe	Romania
RUS	94	CE Europe	Europe	Russia
SAU	171	South West Asia	Asia	Saudi Arabia
SGP	204	South East Asia	Asia	Singapore
SWE	352	Northern Europe	Europe	Sweden
THA	270	South East Asia	Asia	Thailand
TUR	139	South West Asia	Asia	Turkey
TWN	936	East Asia	Asia	Taiwan
USA	4356	North America	Americas	United States
VNM	28	South East Asia	Asia	Vietnam
ZAF	189	Africa	Africa	South Africa

The table shows the number of unique firms by IS3166-1 alpha-3 country codes. We require at least ten unique firms in a country.

Table A9: Alphas and t-statistics of industry-agnostic GMB equity factors

	SR	r	$t(r)$	α^{CAPM}	$t(\alpha^{CAPM})$	α^{FF3}	$t(\alpha^{FF3})$	α^{FF6}	$t(\alpha^{FF6})$	α^{q5}	$t(\alpha^{q5})$
Robust Green Score	0.47	0.20	1.53	0.27	1.79	0.19	2.09	0.16	1.75	0.14	1.30
S1INT (Sales)	0.24	0.13	0.84	0.11	0.66	0.09	0.66	0.28	2.22	0.13	0.97
S1+2INT (Sales)	0.24	0.13	0.85	0.09	0.57	0.08	0.59	0.28	2.42	0.14	1.00
S1+2+3INT (Sales)	0.14	0.08	0.49	0.07	0.43	0.07	0.46	0.30	2.47	0.17	1.25
S1INT (Assets)	0.19	0.11	0.68	0.06	0.37	0.06	0.37	0.27	2.26	0.13	0.89
S1+2INT (Assets)	0.17	0.10	0.62	0.05	0.27	0.04	0.28	0.30	2.90	0.15	1.13
S1+2+3INT (Assets)	-0.02	-0.01	-0.07	-0.07	-0.44	-0.07	-0.45	0.21	2.21	0.09	0.72
Weighted ESG score	0.37	0.16	1.44	0.23	2.19	0.19	2.03	0.13	1.33	0.00	0.03
Environment score	0.24	0.13	0.86	0.21	1.32	0.12	1.10	0.18	1.51	0.08	0.69
Total ESG score	-0.01	-0.00	-0.03	0.13	1.05	0.10	1.09	-0.02	-0.23	-0.09	-0.96
Environmental score	0.32	0.16	1.14	0.29	2.13	0.25	2.42	0.11	1.17	0.06	0.63
LOG(S1TOT)	0.12	0.08	0.39	-0.05	-0.24	-0.01	-0.04	0.30	2.91	0.18	1.42
LOG(S1+2TOT)	0.07	0.05	0.21	-0.06	-0.24	-0.00	-0.02	0.31	3.02	0.22	1.61
LOG(S1+2+3TOT)	-0.06	-0.05	-0.21	-0.14	-0.53	-0.08	-0.49	0.23	2.39	0.18	1.34
Ind.-adj. ESG score	0.42	0.15	1.60	0.23	2.77	0.20	2.90	0.16	2.24	0.08	1.11
Greenness (PST)	0.04	0.03	0.15	0.03	0.15	-0.01	-0.05	0.24	1.33	-0.00	-0.02
E climate score	0.50	0.32	1.37	0.41	1.58	0.30	2.73	0.26	2.16	0.23	1.50
E nat. res. score	0.41	0.23	1.28	0.35	1.84	0.26	1.85	0.26	1.91	0.19	1.40
E waste score	0.22	0.19	0.77	0.49	1.71	0.39	2.12	0.33	1.76	0.27	1.36
E env. opps. score	0.06	0.03	0.20	0.12	0.75	0.06	0.41	0.04	0.28	-0.03	-0.19
TRINT (Sales)	0.11	0.06	0.61	0.04	0.43	0.09	1.03	0.19	1.93	0.10	1.00
TPWINT (Sales)	0.01	0.00	0.05	0.09	1.20	0.12	1.60	0.14	1.64	0.10	1.22
TRINT (Assets)	0.15	0.08	0.75	0.09	0.80	0.14	1.56	0.23	2.29	0.11	1.12
TPWINT (Assets)	0.03	0.02	0.17	0.13	1.58	0.17	2.09	0.18	2.05	0.12	1.32

The table shows Sharpe ratios (SR) as well as alphas and their corresponding t-statistics for 24 green-minus-brown (GMB) equity factors. The 24 factors are constructed as the return difference of a portfolio that goes long the top tercile of stocks based on a greenness measure and short the bottom tercile. Portfolio returns are value-weighted capped stock returns with a cap on market capitalization at the NYSE 80th percentile. The 24 greenness measures are the 23 individual greenness measures from Table 1 and our robust green score. We compute alphas with respect to five models: i) no risk adjustment (excess returns r), ii) the CAPM, iii) the Fama-French three-factor model, iv) the Fama-French five-factor model augmented by momentum, and v) the q5-factor model. The sample is US stocks. Standard errors are heteroskedasticity robust.

Table A10: Alphas and t-statistics of industry-neutral GMB equity factors

	SR	r	$t(r)$	α^{CAPM}	$t(\alpha^{CAPM})$	α^{FF3}	$t(\alpha^{FF3})$	α^{FF6}	$t(\alpha^{FF6})$	α^{q5}	$t(\alpha^{q5})$
Robust Green Score	0.33	0.10	1.31	0.15	1.72	0.11	1.62	0.05	0.82	0.01	0.09
S1INT (Sales)	0.26	0.06	0.95	0.07	0.93	0.05	0.82	0.04	0.68	0.04	0.58
S1+2INT (Sales)	0.24	0.06	0.93	0.09	1.17	0.08	1.41	0.06	0.97	0.07	1.06
S1+2+3INT (Sales)	0.14	0.04	0.54	0.05	0.62	0.05	0.86	0.05	0.99	0.07	1.10
S1INT (Assets)	0.05	0.01	0.16	-0.03	-0.38	-0.05	-0.65	-0.01	-0.07	-0.01	-0.18
S1+2INT (Assets)	-0.03	-0.01	-0.11	-0.05	-0.63	-0.06	-1.02	-0.03	-0.49	-0.01	-0.09
S1+2+3INT (Assets)	-0.09	-0.03	-0.37	-0.08	-1.20	-0.08	-1.43	-0.03	-0.45	-0.00	-0.05
Weighted ESG score	0.47	0.16	1.66	0.24	3.03	0.22	3.19	0.17	2.42	0.12	1.65
Environment score	0.27	0.09	1.02	0.15	1.60	0.12	1.54	0.08	1.08	0.05	0.71
Total ESG score	0.08	0.03	0.32	0.06	0.71	0.05	0.75	0.01	0.10	-0.08	-1.16
Environmental score	0.18	0.06	0.71	0.09	1.01	0.06	0.93	0.02	0.32	-0.04	-0.70
LOG(S1TOT)	0.01	0.01	0.04	0.00	0.02	0.02	0.30	0.05	0.66	0.11	1.30
LOG(S1+2TOT)	-0.10	-0.05	-0.35	-0.06	-0.36	-0.03	-0.36	0.01	0.13	0.08	0.87
LOG(S1+2+3TOT)	-0.20	-0.11	-0.64	-0.09	-0.48	-0.05	-0.59	-0.02	-0.18	0.08	0.73
Ind.-adj. ESG score	0.32	0.09	1.09	0.15	2.05	0.14	2.22	0.10	1.59	0.04	0.59
Greenness (PST)	0.21	0.07	0.87	0.11	1.38	0.09	1.30	0.08	1.27	0.06	0.96
E climate score	0.55	0.22	1.57	0.31	2.20	0.21	2.60	0.17	2.40	0.10	1.43
E nat. res. score	0.12	0.05	0.36	0.21	1.68	0.13	1.41	0.10	1.02	0.04	0.43
E waste score	0.24	0.09	0.88	0.19	1.63	0.14	1.37	0.08	0.79	0.06	0.55
E env. opps. score	0.14	0.05	0.52	0.04	0.41	0.01	0.06	0.05	0.61	0.03	0.32
TRINT (Sales)	0.00	0.00	0.01	0.09	1.21	0.11	1.58	0.12	1.57	0.10	1.30
TPWINT (Sales)	-0.14	-0.05	-0.74	0.02	0.32	0.03	0.45	0.05	0.70	0.05	0.69
TRINT (Assets)	0.02	0.01	0.08	0.08	1.01	0.10	1.40	0.12	1.55	0.10	1.25
TPWINT (Assets)	-0.19	-0.07	-1.10	-0.01	-0.15	0.00	0.02	0.06	0.86	0.06	0.82

The table is similar to Table A9, but shows results for industry-neutral GMB equity factors.

Table A11: PST's GMB alphas, changes in climate concerns, and cash-flow news

	(1)	(2)	(3)	(4)
Constant	0.11	0.08	-0.03	-0.01
	(0.25)	(0.25)	(0.19)	(0.18)
Δ Climate concerns (same month)	2.52***	2.53***	0.59	0.76
	(0.90)	(0.90)	(0.58)	(0.57)
Δ Climate concerns (prev. month)	1.79**	1.69**	-0.01	0.09
	(0.84)	(0.85)	(0.60)	(0.61)
Earnings announcement returns		0.19		0.17*
		(0.17)		(0.10)
Δ Earnings forecasts		-0.15		-0.32***
		(0.13)		(0.09)
Adj. R-squared	0.15	0.16	-0.01	0.10
N	68	68	187	187

The table shows regressions of a green-minus-brown (GMB) factor's Fama-French three-factor alpha on a constant, contemporaneous and lagged changes in climate concerns, and two earnings measures. The GMB factor is constructed using the greenness measure from Pástor et al. (2022), and the earnings announcement return and Δ earnings forecast factors come from Chen and Zimmermann (2020). Changes in climate concerns are constructed as in Pástor et al. (2022). Specifications (1) and (2) use a sample period from 2012–2018 and reproduce specifications (3) and (4) in Table 4 of Pástor et al. (2022). Specifications (3) and (4) extend their sample period backward and forward. Standard errors (in parentheses) are heteroskedasticity robust. *, **, and *** denote 10%, 5%, and 1% significance levels, respectively, for the null hypothesis of a zero coefficient. *N* refers to the total number of observations.

Table A12: Country-Time FE without Controls

(a) US

	Greenium	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	96.2	76.3	325016	0.0	15.9
ICC	-27.4	12.8	285370	0.7	4.9
ICC (GLS)	-30.0	12.7	280504	0.9	6.0
ICC (CT)	-17.1	10.3	173187	0.2	6.2
ICC (OJ)	-21.1	11.8	159008	0.3	4.6
ICC (PEG)	-22.9	15.0	159255	0.6	4.4
E/P (latest)	-28.0	13.4	256718	0.4	7.2
E/P (FY+1)	-24.1	12.5	260453	0.4	6.8
E/P (FY+2)	-26.7	12.2	273291	0.5	7.3
LOG(B/M)	-16.7	2.5	327817	3.2	5.2
LOG(BEV/MEV)	-16.3	2.9	312613	2.7	4.2
EBITDA/MEV (latest)	-55.4	22.4	283523	0.3	2.4
Exp. Ret. (options)	-62.1	22.4	94525	2.0	56.5
Exp. Ret. (SVIX 30D)	-112.1	33.0	94525	2.4	35.3
Exp. Ret. (SVIX 91D)	-86.6	30.0	94521	2.4	31.9
Exp. Ret. (SVIX 182D)	-79.6	29.0	94510	2.5	27.7
Exp. Ret. (GLB 30D)	-48.8	18.2	94298	0.7	66.9
Exp. Ret. (GLB 91D)	-26.3	15.7	94294	0.5	71.9
Exp. Ret. (GLB 182D)	-19.3	15.0	94282	0.4	72.5
Req. Ret. (ValueLine)	-39.0	17.1	172531	2.1	3.3
Req. Ret. (Morningstar)	-18.5	8.4	77841	3.2	58.1
Exp. Ret. (IBES)	51.0	133.7	278481	0.0	8.8
Exp. Ret. (ValueLine)	-5.0	32.1	172249	0.0	11.3
Exp. Ret. (Morningstar)	-36.0	24.5	77797	0.2	10.8
WACC	-16.7	11.9	84595	0.3	4.4

(b) Global ex-US

	Greenium	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	-2.6	35.6	1074523	0.0	28.6
ICC	-32.3	7.2	641896	0.8	17.7
ICC (GLS)	-33.7	7.7	581053	1.0	20.0
ICC (CT)	-29.7	9.4	279721	0.4	14.9
ICC (OJ)	-38.8	10.8	244066	0.6	13.8
ICC (PEG)	-46.5	9.9	296908	1.1	16.0
E/P (latest)	-37.2	11.0	697142	0.4	18.1
E/P (FY+1)	-39.2	11.0	722832	0.7	19.9
E/P (FY+2)	-44.1	10.7	747479	0.8	21.7
LOG(B/M)	-9.2	1.5	1087118	1.1	15.1
LOG(BEV/MEV)	-8.0	1.5	1070100	0.8	11.5
EBITDA/MEV (latest)	-59.1	24.3	1007008	0.2	9.8

Table A13: Country-Time FE and Controls

(a) US

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	93.1	66.8	-556.6	462.7	-20.2	57.8	284.5	1045.8	131.2	428.3	325016	0.0	15.9
ICC	-24.7	10.4	129.8	27.4	13.3	5.1	184.9	92.9	243.1	31.8	285370	8.6	12.4
ICC (GLS)	-25.4	10.4	113.3	31.2	6.8	6.0	69.3	112.2	251.1	34.7	280504	7.8	12.5
ICC (CT)	-15.8	8.9	167.9	23.3	26.4	5.2	21.3	96.1	216.3	34.4	173187	6.7	12.3
ICC (OJ)	-17.4	9.7	198.5	22.2	15.2	5.0	12.7	105.2	204.1	33.8	159008	6.5	10.5
ICC (PEG)	-15.7	11.2	256.7	26.4	-1.9	4.9	24.6	104.5	127.3	31.5	159255	11.4	14.8
E/P (latest)	-28.4	11.7	142.3	33.4	19.0	6.8	238.7	194.5	270.0	49.2	256718	4.3	10.9
E/P (FY+1)	-28.0	11.9	94.1	28.9	24.6	7.0	409.5	174.4	260.5	47.3	260453	5.8	11.9
E/P (FY+2)	-26.9	11.2	118.9	29.7	17.7	7.3	278.6	122.0	295.7	48.0	273291	6.7	13.1
LOG(B/M)	-17.1	2.2	-1.2	7.3	15.5	1.2	-126.4	43.9	38.6	7.5	327817	13.0	14.9
LOG(BEV/MEV)	-14.1	2.7	-4.9	6.3	10.1	1.2	-95.1	56.0	161.5	14.0	312613	29.7	30.8
EBITDA/MEV (latest)	-66.8	22.2	49.7	93.4	17.7	19.1	779.9	732.7	-409.3	220.1	283523	1.7	3.8
Exp. Ret. (options)	-19.3	8.2	469.8	31.3	-76.8	6.4	-975.4	118.4	-4.9	30.1	94525	34.9	71.1
Exp. Ret. (SVIX 30D)	-41.6	15.4	531.3	46.2	-143.9	12.4	-1941.0	213.3	18.5	60.8	94525	27.5	51.9
Exp. Ret. (SVIX 91D)	-30.5	14.0	536.3	38.9	-103.2	9.5	-1454.0	143.5	0.4	54.5	94521	34.2	54.0
Exp. Ret. (SVIX 182D)	-28.0	13.8	532.3	35.8	-90.5	8.7	-1303.0	128.8	-2.0	53.1	94510	37.1	53.4
Exp. Ret. (GLB 30D)	-14.5	9.0	391.8	43.1	-66.4	7.2	-627.7	173.1	-3.7	40.3	94298	14.2	71.4
Exp. Ret. (GLB 91D)	-2.0	4.5	418.3	29.6	-33.5	4.1	-313.9	87.3	-19.2	20.3	94294	28.2	79.7
Exp. Ret. (GLB 182D)	1.2	4.0	411.5	25.3	-22.5	3.3	-200.9	63.5	-21.6	16.3	94282	34.5	81.9
Req. Ret. (ValueLine)	-11.4	7.8	291.6	15.9	-77.9	3.5	-901.0	87.7	77.7	22.2	172531	53.8	54.4
Req. Ret. (Morningstar)	-11.5	5.2	110.5	12.2	-6.1	2.6	-151.5	31.4	35.3	12.0	77841	26.3	68.1
Exp. Ret. (IBES)	122.1	86.6	692.4	201.2	-389.9	60.2	-10430.1	1351.0	-367.6	377.1	278481	21.8	28.7
Exp. Ret. (ValueLine)	10.2	24.7	434.5	71.9	-9.9	11.0	-459.0	192.0	292.7	72.7	172249	5.2	15.9
Exp. Ret. (Morningstar)	-36.7	20.5	291.0	71.8	85.1	15.1	-699.6	234.3	148.4	106.5	77797	4.6	14.7
WACC	-13.1	7.2	147.5	21.4	5.7	5.0	-124.4	120.6	-120.8	40.0	84595	4.3	8.2

(b) Global ex-US

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	-8.3	34.6	-146.8	395.1	-3.1	46.7	1245.3	723.3	-187.6	206.3	1074523	0.0	28.6
ICC	-33.3	6.3	132.2	17.9	27.8	5.4	-998.6	91.4	105.7	24.3	641896	9.5	24.9
ICC (GLS)	-36.0	7.4	72.2	22.3	37.3	4.9	-1165.7	97.9	79.2	24.9	581053	12.3	29.1
ICC (CT)	-30.3	6.3	228.2	25.8	15.5	10.9	-1206.2	144.9	181.3	47.0	279721	9.1	22.4
ICC (OJ)	-35.0	8.9	275.0	26.0	-5.0	7.6	-1241.8	153.0	167.0	41.2	244066	8.6	20.7
ICC (PEG)	-38.1	7.9	322.7	22.6	-24.7	5.7	-1177.2	110.4	98.3	31.9	296908	11.6	24.9
E/P (latest)	-42.2	10.7	74.6	28.3	51.1	10.1	192.4	190.9	164.2	40.9	697142	3.2	20.4
E/P (FY+1)	-43.2	10.6	56.8	24.0	47.7	10.4	257.3	173.9	192.3	43.4	722832	4.3	22.8
E/P (FY+2)	-44.6	9.9	106.2	23.6	31.5	12.0	-129.1	155.2	228.8	49.5	747479	4.2	24.4
LOG(B/M)	-9.2	1.3	-13.2	4.1	19.4	0.9	-309.8	41.1	40.2	7.4	1087118	22.7	33.7
LOG(BEV/MEV)	-6.8	1.2	-16.1	3.3	16.5	0.9	-298.8	44.5	110.7	10.7	1070100	29.5	37.1
EBITDA/MEV (latest)	-82.7	24.1	3.7	46.3	89.9	12.9	1579.8	439.2	-962.5	108.9	1007008	5.2	14.4

Table A14: Country-Industry-Time FE with Controls

(a) US

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	55.2	33.6	-507.0	415.3	13.0	57.9	830.9	1068.5	347.5	349.9	325016	0.0	25.9
ICC	-14.1	6.4	80.6	17.3	5.2	3.5	220.1	75.0	283.0	18.8	285370	6.9	29.8
ICC (GLS)	-18.3	6.7	76.4	18.9	-2.5	4.3	186.0	91.6	309.8	21.7	280504	7.6	31.7
ICC (CT)	-4.9	6.3	127.3	21.1	17.1	4.1	18.4	65.1	263.0	24.8	173187	5.5	32.6
ICC (OJ)	-4.9	6.3	133.0	18.5	5.3	4.3	-58.6	78.2	218.5	24.9	159008	4.0	29.6
ICC (PEG)	-15.2	6.4	179.7	16.0	-6.3	3.5	-126.9	76.0	161.7	21.8	159255	7.4	37.5
E/P (latest)	-6.2	8.7	134.3	29.5	7.5	5.6	431.1	157.2	323.4	30.3	256718	4.0	29.0
E/P (FY+1)	-5.0	8.1	101.3	24.3	15.1	5.2	548.2	113.7	323.7	25.9	260453	6.3	33.0
E/P (FY+2)	-3.8	7.5	111.4	24.7	7.7	5.6	319.6	80.8	349.8	26.9	273291	6.7	34.3
LOG(B/M)	-9.6	2.0	-1.0	4.8	12.0	1.1	-154.1	39.4	8.0	7.7	327817	8.0	35.9
LOG(BEV/MEV)	-6.3	1.6	-8.9	4.2	7.1	0.9	-132.9	43.2	140.7	7.9	312613	21.2	49.0
EBITDA/MEV (latest)	16.6	25.4	125.6	54.2	-7.0	14.7	1731.9	351.6	-444.8	135.6	283523	2.6	22.2
Exp. Ret. (options)	-11.7	7.6	523.6	35.2	-78.1	6.5	-915.4	146.9	-43.8	31.8	94525	34.8	80.9
Exp. Ret. (SVIX 30D)	-19.1	14.6	660.4	52.3	-150.2	12.7	-1816.1	289.4	-97.0	63.6	94525	29.3	66.6
Exp. Ret. (SVIX 91D)	-9.6	10.9	644.1	43.4	-107.6	9.5	-1424.6	205.8	-87.6	51.9	94521	35.8	68.6
Exp. Ret. (SVIX 182D)	-8.0	10.4	634.6	39.8	-93.9	8.6	-1293.8	184.8	-83.0	49.7	94510	38.7	68.6
Exp. Ret. (GLB 30D)	-20.3	9.6	392.8	46.8	-66.1	8.2	-459.7	133.8	5.8	33.5	94298	12.5	81.0
Exp. Ret. (GLB 91D)	-7.6	4.1	412.3	31.7	-31.0	4.2	-283.8	71.0	0.7	17.4	94294	23.5	87.1
Exp. Ret. (GLB 182D)	-4.9	3.2	399.2	26.5	-18.9	3.1	-204.4	52.6	-1.1	13.4	94282	28.2	88.7
Req. Ret. (ValueLine)	-11.2	6.4	290.8	17.5	-76.3	3.8	-870.8	104.5	102.0	18.8	172531	52.2	64.6
Req. Ret. (Morningstar)	-8.5	3.4	100.6	11.5	-6.4	2.5	-177.5	35.0	24.0	14.5	77841	20.6	78.6
Exp. Ret. (IBES)	71.2	49.6	442.4	184.4	-389.0	68.3	-8687.0	989.9	-22.0	171.2	278481	13.2	38.5
Exp. Ret. (ValueLine)	25.3	13.5	328.2	50.0	-19.8	9.5	-584.5	190.7	364.5	69.9	172249	3.9	33.8
Exp. Ret. (Morningstar)	-33.1	15.7	105.1	72.4	80.3	14.0	-789.9	220.9	159.4	91.1	77797	2.7	37.2
WACC	-8.3	5.4	72.8	25.2	3.6	5.0	-114.4	112.5	-37.8	41.7	84595	0.6	22.5

(b) Global ex-US

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	-4.1	29.0	36.8	417.9	6.5	42.9	1315.4	706.0	-206.2	193.1	1074523	0.0	48.4
ICC	-25.0	4.7	86.2	16.0	0.3	5.0	-804.2	105.4	171.1	21.9	641896	5.1	56.5
ICC (GLS)	-27.3	4.7	41.7	19.2	5.1	3.9	-996.5	112.5	122.0	24.7	581053	6.6	62.3
ICC (CT)	-26.1	9.4	190.8	35.7	-27.8	9.1	-986.1	164.8	298.8	45.9	279721	6.4	60.9
ICC (OJ)	-29.4	10.8	234.1	34.5	-41.6	9.3	-1057.7	223.2	291.8	52.2	244066	6.9	60.9
ICC (PEG)	-23.4	7.5	233.0	24.5	-50.7	6.5	-991.9	143.8	238.6	37.8	296908	9.0	63.2
E/P (latest)	-34.6	9.6	51.7	24.0	4.2	5.4	554.5	166.7	200.0	29.4	697142	1.2	54.2
E/P (FY+1)	-32.4	9.0	36.5	19.1	0.3	5.0	544.9	130.1	241.6	26.5	722832	2.0	57.8
E/P (FY+2)	-32.6	8.9	60.4	21.1	-19.3	5.5	180.8	93.7	308.6	29.1	747479	2.9	58.6
LOG(B/M)	-5.5	0.8	-22.4	3.7	14.0	1.0	-278.4	31.0	22.1	4.7	1087118	13.9	58.6
LOG(BEV/MEV)	-3.8	0.7	-25.6	3.6	11.4	0.8	-280.6	33.0	93.9	8.6	1070100	20.1	59.0
EBITDA/MEV (latest)	-49.8	17.2	-138.1	48.5	44.6	13.4	1917.3	448.9	-1076.5	110.9	1007008	5.3	41.1

Table A15: Bonds: without rating-time FE

(a) Time FE without controls

	Greenium	S.E.	N	R2	R2 (Total)
Yield	-62.5	20.4	86578	1.8	4.9
Yield Spread	-62.2	21.7	82489	1.7	4.7
Adj. Yield	-34.3	9.5	86578	0.7	3.9
Adj. Yield Spread	-33.9	10.4	82489	0.6	3.8
Credit Rating	-83.3	25.1	87283	7.4	8.5

(b) Time FE and Controls

	Greenium	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	LOG(FV)	S.E.	TMT	S.E.	N	R2	R2 (Total)
Yield	-8.6	11.2	-83.3	11.7	-1544.2	182.1	248.5	51.8	11.1	8.4	-0.1	2.4	86578	13.1	15.8
Yield Spread	-9.1	11.3	-84.3	11.9	-1552.1	187.6	254.7	52.3	12.8	8.5	-7.7	2.5	82489	14.0	16.6
Adj. Yield	-13.2	7.1	-38.5	9.5	-658.6	132.6	52.8	33.7	4.9	8.2	4.5	1.6	86578	2.8	5.9
Adj. Yield Spread	-13.0	7.1	-38.1	9.7	-656.0	133.2	51.5	34.1	6.9	8.3	-3.1	1.5	82489	3.0	6.1
Credit Rating	-12.8	13.4	-106.7	14.0	-1242.5	328.2	425.3	63.9	2.3	12.1	-15.5	2.7	87283	56.1	56.6

(c) Industry-Time FE and Controls

	Greenium	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	LOG(FV)	S.E.	TMT	S.E.	N	R2	R2 (Total)
Yield	-8.2	7.6	-70.2	9.9	-1299.6	188.9	372.2	73.4	-5.4	7.9	3.2	2.2	86578	10.2	29.0
Yield Spread	-7.9	7.9	-71.4	10.4	-1300.6	191.3	376.2	76.4	-3.9	8.2	-4.7	2.3	82489	11.1	29.7
Adj. Yield	-9.9	4.7	-32.1	10.5	-409.5	128.4	92.9	47.7	-1.7	8.9	5.8	1.5	86578	1.6	18.9
Adj. Yield Spread	-8.9	4.8	-32.3	10.8	-404.5	127.6	88.7	50.1	0.5	9.2	-2.0	1.5	82489	1.7	19.1
Credit Rating	-23.4	9.6	-104.4	16.2	-1192.5	409.8	529.8	49.4	-2.9	12.9	-9.7	1.6	87283	55.6	69.3

Table A16: Bonds: with rating-time FE

(a) Rating-Time FE without controls

	Greenium	S.E.	N	R2	R2 (Total)
Yield	-13.1	4.7	86578	0.2	70.2
Yield Spread	-11.3	4.8	82489	0.2	71.0
Adj. Yield	-12.7	4.8	86578	0.2	62.7
Adj. Yield Spread	-10.9	5.0	82489	0.2	63.3

(b) Rating-Time FE and Controls

	Greenium	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	LOG(FV)	S.E.	TMT	S.E.	N	R2	R2 (Total)
Yield	-5.3	5.0	-16.5	6.8	-432.6	81.9	-9.0	14.6	0.3	5.0	8.2	1.2	86578	2.9	71.0
Yield Spread	-5.5	5.1	-17.4	7.0	-446.3	85.0	-3.8	14.5	2.1	5.0	0.2	1.1	82489	1.4	71.3
Adj. Yield	-4.5	5.1	-14.3	6.8	-421.8	80.9	-9.2	15.1	-3.6	4.9	8.4	1.2	86578	2.8	63.7
Adj. Yield Spread	-4.6	5.3	-15.2	7.0	-435.2	83.7	-4.2	15.1	-2.0	4.9	0.5	1.1	82489	1.3	63.8

(c) Rating-Time FE, Industry-Time FE and Controls

	Greenium	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	LOG(FV)	S.E.	TMT	S.E.	N	R2	R2 (Total)
Yield	1.0	2.8	-20.3	6.5	-285.6	72.7	42.1	25.7	0.0	4.9	8.0	1.4	86578	1.8	74.4
Yield Spread	1.4	3.0	-20.9	7.0	-294.1	75.3	45.0	26.9	1.8	5.1	-0.1	1.4	82489	0.7	74.7
Adj. Yield	3.0	3.1	-16.7	6.7	-254.3	72.4	37.3	27.2	-4.9	4.9	8.2	1.4	86578	1.7	67.9
Adj. Yield Spread	3.5	3.2	-17.3	7.1	-262.3	74.9	39.6	28.8	-3.4	5.2	0.2	1.3	82489	0.6	68.1