

In Search of the True Greenium

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Abstract

The greenium—the expected return differential between green and brown securities—is central to climate finance. Based on an asset pricing model in which investors hold heterogeneous views about each firm’s greenness, we show how an “aggregate green score” can be inferred from green investors’ portfolios. The aggregate green score is the green score with the most negative greenium and exact pricing, while any other greenium is determined by the correlation between its corresponding green score and the aggregate one. Consistent with the theory, the greenium corresponding to the aggregate green score is more negative in greener countries and over time.

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

JEL Codes: G11, G12, H23, Q5

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Environmental investors and sustainable finance regulators seek to improve the climate 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 paramount in a rapidly growing literature. However, greenium estimates—and even its sign—vary tremendously across papers and among practitioners. These varying views arise because of the differences in empirical methodologies and in the definition of what it means to be green. Indeed, the large difference between green scores is termed “aggregate confusion” by [Berg, Kölbel, and Rigobon \(2022\)](#).¹

How should the greenium be measured and how large is it? We address these questions with theory and evidence. The theory shows that investors’ heterogeneous green scores are aggregated in the market into an aggregate green score, and we show how to identify this aggregate green score from environmental investors’ portfolio holdings. Consistent with the theory, the empirical analysis shows that the aggregate green score implies a more negative greenium than any individual one and drives out each individual one in a horse race. The global equity greenium is -39 basis points (bps) per standard deviation increase in the aggregate green score, on average over time. The greenium based on any individual green score is -39 bps times its correlation with the aggregate green score. Further, consistent with the theory, the greenium is more negative in greener countries and over time.

Theory. In an asset pricing model in which investors have different views of how to measure an asset’s greenness and how much they care about greenness, risk-adjusted expected returns depend on an average of the greenness measures used by investors, weighted by their green preferences, risk tolerances, and wealth. We denote this weighted average as the “aggregate green score.” Specifically, the expected return of any asset n , controlling for

¹Some academic papers estimate a negative greenium based on negative realized returns of green stocks relative to brown ones (see, e.g., [Bolton and Kacperczyk, 2023](#); [Hsu, Li, and Tsou, 2023](#)). In contrast, others report positive returns of green stocks relative to brown ones (see, e.g., [Pástor, Stambaugh, and Taylor, 2022](#); [Zhang, 2025](#)). While the evidence is opposite, the latter papers also conclude that the greenium is negative as the realized returns are taken to be evidence of repricing rather than a proxy for expected returns. As an example of practitioner views, [Edmans, Gosling, and Jenter \(2024\)](#) reports that 73% of sustainable fund managers expect good ES performers to deliver positive alphas, and 45% of traditional fund managers agree.

its risk compensation, $\lambda\beta_n$, is driven by its aggregate green score, s_n ,

$$E(r_n) = \lambda\beta_n + gs_n, \quad (1)$$

where $g < 0$ is the greenium corresponding to the aggregate green score.

Equation (1) may seem daunting to identify, as we cannot observe each investor’s perception of greenness, wealth, risk aversion, and green preference, which enter the definition of the aggregate green score. However, we show that the aggregate green score can be identified from the portfolio holdings of green investors, under certain assumptions. Specifically, the aggregate green score can be estimated as the total dollar ownership by green investors in a given stock relative to the stock’s market capitalization, standardized across stocks. Intuitively, a stock is considered greener if green investors hold a larger fraction of its shares, and such stocks have lower expected returns.

Estimating the greenium. To estimate the aggregate green score, we use Morningstar data to identify global sustainable investment funds and their stock holdings. We also consider measures of greenness from the literature, including emissions measures from Trucost, and environmental scores from MSCI and Sustainalytics. In total, we consider 19 green scores from three data providers.

The greenium is typically estimated by using realized returns as a proxy for expected returns in Equation (1). However, replicating this literature, we show that all greenium estimates are insignificant due to the short sample period, noise in realized returns, and potential repricing of green and brown stocks over the sample period.²

Instead, we proxy expected returns by a stock’s implied cost of capital (ICC), following [Mohanram and Gode \(2013\)](#), which has several advantages: First, it is less noisy than realized returns as it is based on prices, just like bond yields are less noisy than bond returns. Second, it is a forward-looking measure of expected returns, so repricing does not create a bias.

²When studying all greenness measures across a host of specifications, we do find statistically significant estimates in single-hypothesis testing, but these become insignificant when we account for multiple testing. The existence of such significant estimates in single-hypothesis testing can help explain why the literature contains many significant estimates, which may also reflect a publication bias and other biases.

Greenium magnitude. Using forward-looking expected returns of global stocks and the aggregate green score, we estimate a statistically significant equity greenium of -39 bps annualized per standard deviation increase in the aggregate green score, as seen in Figure 1. This greenium corresponds to an expected return of -82 bps per year for a green-minus-brown (GMB) tercile portfolio due to the portfolio having a just over two standard deviations spread in greenness. This greenium is economically meaningful but smaller than prominent estimates in the literature and a modest part of the overall equity premium.

The global greenium estimate is highly statistically significant and negative, as predicted by the theory. The 95% confidence interval is $(-47 \text{ bps}, -30 \text{ bps})$, which identifies the magnitude more precisely than estimates from the literature for which the width of the confidence interval is typically in the hundreds of bps, due to our use of an aggregate green score, forward-looking returns, and global data.³

Greenium with aggregate vs. individual green scores. The theory predicts that the aggregate green score explains risk-adjusted returns. We present several empirical findings consistent with this prediction.

First, we find that the greenium with respect to the aggregate green score is larger in absolute magnitude than the greenium corresponding to any of the individual green scores.

Second, the aggregate green score has more explanatory power for expected returns—it has a larger absolute t -statistic and larger R^2 .

Third, the aggregate green score remains statistically significant in a regression of ICC on the aggregate green score and any individual green score, whereas each individual green score becomes insignificant in this horse race.

Fourth, the aggregate green score helps explain any individual greenium. In particular, the theory predicts that any individual green score i has a greenium,

$$\tilde{g}_i = \rho_i g \tag{2}$$

³E.g., our confidence interval is much narrower than the 511 bps width of the confidence interval in Hsu et al. (2023), Table II.A.

given by the product of the aggregate greenium, g , and the correlation, ρ_i , between the individual green score and the aggregate green one. Said differently, if an individual green score tends to rate the same stocks as green as the aggregate green score (i.e., if most investors consider such stocks green), then this green score should have a large absolute greenium. Figure 1(a) shows the empirical connection between the correlations and the corresponding greeniums, and we find a statistically significant relation consistent with the theoretical predictions.

The greenium is more negative in greener countries. The greenium is not just negative overall globally, it is in fact negative in most countries, and significantly negative in two non-overlapping samples, the US and outside the US. Further, we uncover interesting global variation in the greenium, as predicted by our theory. We find that the greenium is more negative in greener countries as seen in Figure 1(b). This finding is consistent with the theoretical idea that, if investors overweight local stocks, greener local investors accept a more negative local greenium.

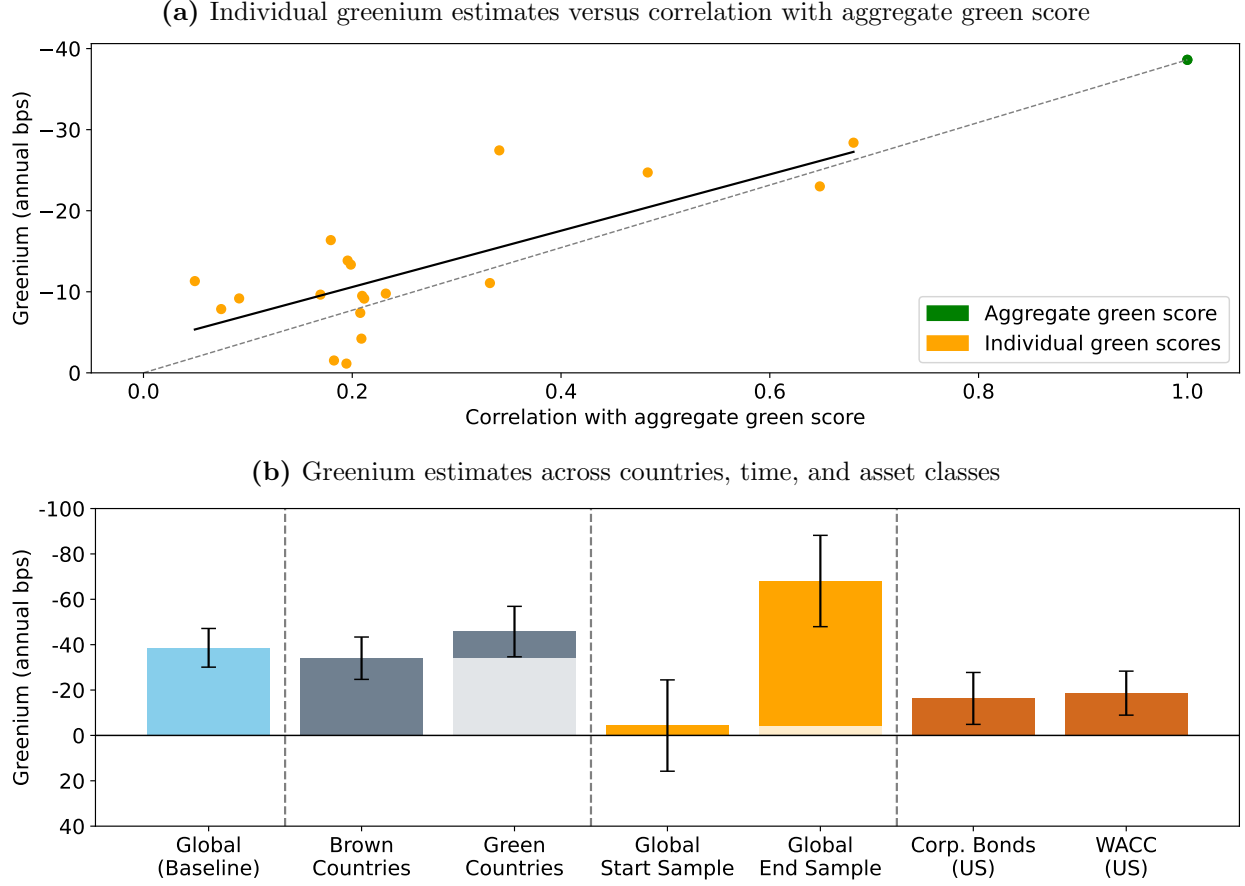
The greenium has become more negative over time. Given that the importance of ESG investors has increased over time as perceived environmental risks have increased, our theory predicts a decreasing greenium. Indeed, we find that the global equity greenium has become more negative over time as illustrated in the fourth and fifth bars in Figure 1(b).

Robustness of the greenium. We find that our greenium estimate is robust to a host of different specification choices. We consider different (a) definitions of the aggregate green score; (b) risk controls; and (c) measures of forward-looking expected returns.⁴

The greenium beyond equities. Finally, we consider the greenium in other asset

⁴Regarding (a), we consider for example projections of the holdings-based measure on the individual greenness measures from the literature. Regarding (b), we present specifications with only time-fixed effects, adding standard risk controls, and further adding industry-by-time-fixed effects. These correspond to comparing, respectively, raw returns, risk-adjusted returns, and industry-relative returns. 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. Regarding (c), we include valuation ratios, option-implied expected returns based on [Martin and Wagner \(2019\)](#) and [Chabi-Yo, Dim, and Vilkov \(2023\)](#) across three different horizons, and analysts’ required returns from Morningstar and ValueLine.

Figure 1: Greenium estimates



Panel (a) plots annualized greenium estimates in basis points corresponding to 19 individual green scores from the literature against their correlations with the aggregate green score (yellow dots). The figure also shows the greenium for the aggregate green score, which is constructed based on the equity portfolio holdings of global sustainable investment funds. Greeniums are estimated as the slope coefficients in 20 separate regressions of forward-looking expected equity returns (implied equity costs of capital) on each green score, see Equation (1). The panel also shows a fitted regression line (solid line) and the theory-implied relation given in Equation (2), which is the dashed line through (0,0) and (1,−39). Panel (b) shows annualized greenium estimates and 95% confidence bands corresponding to the aggregate green score for, respectively, global stocks; brown and green countries; the sample period’s start (August 2009) and end (December 2022); corporate bonds and firms’ weighted-average costs of capital. For green countries (third bar), the confidence interval shows the uncertainty of the additional greenium for green countries over and above the greenium for brown countries. Similarly, the confidence interval for the end-sample greenium (fifth bar) shows the significance of the increase in greenium over the sample period. Standard errors are clustered by industry and month.

classes. We find a meaningful greenium of -18 bps for corporate bonds as seen in Figure 1(b). Aggregating each firm’s equity and bonds, we find a greenium for the weighted average cost of capital (WACC) of -19 bps as seen in Figure 1(b). We also find a significant greenium among sovereign bonds, consistent with [Pástor et al. \(2022\)](#), [Feldhütter and Pedersen \(2023\)](#), and [D’Amico, Klausmann, and Pancost \(2023\)](#).

Related literature. Our model builds on existing ESG theories ([Pástor, Stambaugh, and Taylor, 2021](#); [Pedersen, Fitzgibbons, and Pomorski, 2021](#); [Zerbib, 2022](#)), which focus on investors with the same greenness measure. [Pástor et al. \(2021\)](#) also consider investors who differ in their greenness views in their footnote 4, but do not consider empirical evidence. We complement this literature by showing—theoretically and empirically—how the aggregate green score can be identified from investors’ portfolios, how the corresponding greenium is the largest among all and explains other greeniums, and how it varies when investors have home bias or time-varying greenness preferences.

[Berk and van Binsbergen \(2025, p. 6\)](#) and [Pedersen et al. \(2021, p. 583\)](#) provide calibrations in which they predict equity greeniums of, respectively, 0.44 and 23 bps per year. The difference arises because the former paper assumes a smaller fraction of sustainable investors and a larger correlation between green and brown stocks. While our greenium estimate is smaller in absolute magnitude than most estimates in the literature, it is nevertheless significantly larger in magnitude than the calibration of [Berk and van Binsbergen \(2025\)](#).

[Pedersen \(2023\)](#) shows how to “translate” sustainable finance to a corresponding carbon tax. He shows that the corresponding carbon tax is the sensitivity of expected returns to firms’ carbon emission-to-value ratios. Regressing ICC on firms’ emission ratios as well as controls, we find a slope coefficient of 4.2. Hence, we estimate that sustainable finance has a similar effect as a carbon tax of $4.2\$/\text{tCO}_2$. This magnitude is non trivial, but significantly less than the recommended carbon tax of [Nordhaus \(2019\)](#) of at least $43\$/\text{tCO}_2$ and, over time, upwards of $200\$/\text{tCO}_2$. We can reject that the carbon-intensity greenium is that high, suggesting that ESG investing in its current form cannot replace a carbon tax.

A large literature examines the realized returns of green-versus-brown stocks using dif-

ferent green scores. This literature includes papers that find green outperformance,⁵ brown outperformance,⁶ and no significant difference.⁷ We contribute to this literature by conducting a comprehensive robustness analysis accounting for multiple testing, showing that all these green-versus-brown realized returns are statistically insignificant when adjusting for multiple testing.

The idea of using ICC as a measure of forward-looking expected returns comes from the accounting literature (e.g., Gebhardt, Lee, and Swaminathan, 2001). ICC has been used to estimate different return premiums, e.g., related to corporate social responsibility (El Ghouli, Guedhami, Kwok, and Mishra, 2011) and the greenium (Chava, 2014; Pástor et al., 2022). Our contribution relative to these papers is to estimate the greenium using the aggregate green score and show how it explains all other greeniums and varies over time, geographies, and asset classes. Further, we consider a range of forward-looking expected return proxies (several ICCs, valuation ratios, and option-implied expected returns) and emphasize that standard errors should take into account the serial correlation in ICCs.⁸

Several papers make use of institutional investors’ portfolio holdings in connection with environmental investing (see, e.g., Bolton and Kacperczyk, 2021; Gibson Brandon, Krueger, and Mitali, 2021; Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022; Berg, Heeb, and Kölbel, 2024; Pástor, Stambaugh, and Taylor, 2025; Starks, Venkat, and Zhu, 2025). We complement this literature by showing how green portfolios can be used to identify the

⁵See, e.g., Garvey, Iyer, and Nash (2018); In, Park, and Monk (2019); Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang (2021a,b); Giese, Nagy, and Rauis (2021); Huij, Dries, Stork, and Zwinkels (2021); Ardia, Bluteau, Boudt, and Inghelbrecht (2022); Bauer, Huber, Rudebusch, and Wilms (2022); Pástor et al. (2022); Zhang (2025); Berg, Lo, Rigobon, Singh, and Zhang (2023); Karolyi, Wu, and Xiong (2023).

⁶See, e.g., Alessi, Ossola, and Panzica (2020); Bolton and Kacperczyk (2021, 2023); Hsu et al. (2023); Lioui and Misra (2024); Crosignani, Osambela, and Pritsker (2024).

⁷See, e.g., Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2020); Pedersen et al. (2021); Aswani, Raghunandan, and Rajgopal (2024); Alves, Krüger, and van Dijk (2025); Lindsey, Pruitt, and Schiller (2023).

⁸In terms of other forward-looking expected returns, Giglio, Maggiori, Stroebel, Tan, Utkus, and Xu (2023) find that Vanguard investors expect ESG investments to underperform the overall stock market by −1.4% annually over a ten-year horizon and 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, but controlling for emissions their finding is difficult to interpret as a greenium, which is also not their stated intention.

aggregate pricing of green preferences. We study portfolio holdings of global investors, which is helpful since the majority of environmentally designated funds are domiciled in Europe.

Beyond equities, 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 complement this literature by studying regular corporate bonds and the WACC.

In summary, we complement the literature by providing (i) a theory of green pricing with multiple green scores, (ii) an aggregate green score based on environmental investors’ portfolios (to be made public), (iii) a replication analysis of the ESG literature that uses realized returns, highlighting a lack of robustness, (iv) evidence that the aggregate green score has the largest absolute greenium, largest R^2 , drives out other scores, and explains other greeniums via correlations, (v) estimates of the greenium across countries, time, and asset classes, and (vi) evidence that the greenium is more negative in greener countries and over time.

1 Asset pricing with multiple green scores

Motivated by the “aggregate confusion” literature (see, e.g., [Berg et al., 2022](#); [Berg, Kölbel, Pavlova, and Rigobon, 2023](#); [Berg et al., 2023](#)), and the various green scores considered in the literature and by real-world investors, we consider a theory that allows investors to disagree about how to measure greenness. For instance, one investor may consider carbon emissions as the relevant measure of greenness, whereas another investor may consider the MSCI environmental score as the relevant measure of greenness.

The economy has $i = 1, \dots, I$ investors, $n = 1, \dots, N$ risky securities, and a risk-free rate, r^f . Each security n has a future cashflow, v_n , shares outstanding normalized to one, an endogenous price, p_n , and an endogenous excess return of $r_n = v_n/p_n - 1 - r^f$.

Investor i has a wealth of W_i and chooses her portfolio $x_i \in \mathbb{R}^N$, measuring the fractions of wealth invested in each risky security. The investor's portfolio choice determines her future wealth, $\hat{W}_i = W_i(1 + r_f + x_i' r)$, where $r = (r_1, r_2, \dots, r_N)'$ is the vector of excess returns. Investor i assigns a green score to all assets, collected in the vector $\tilde{s}_i \in \mathbb{R}^N$. In other words, a higher $\tilde{s}_{i,n}$ means that investor i perceives asset n to be greener. Further, investor i has a relative risk aversion, $\gamma_i > 0$, and a green preference, $\eta_i \geq 0$, in the sense that she maximizes the following expected utility:

$$\mathbb{E}(\hat{W}_i) - \frac{\gamma_i}{2W_i} \text{Var}(\hat{W}_i) + \eta_i W_i x_i' \tilde{s}_i = W_i \left(1 + r_f + x_i' \mathbb{E}(r) - \frac{\gamma_i}{2} x_i' \Sigma x_i + \eta_i x_i' \tilde{s}_i \right), \quad (3)$$

where $\Sigma = \text{Var}(r)$. The first order condition yields the optimal portfolio:

$$x_i = \frac{1}{\gamma_i} \Sigma^{-1} (\mathbb{E}(r) + \eta_i \tilde{s}_i). \quad (4)$$

In equilibrium, the total demand for each stock must equal its supply. The demand measured in dollars is the sum of all investors' allocations, $W_i x_i$, and the supply is the product of the unit number of shares and the price per share, leading to the following market-clearing condition:

$$p = \sum_i W_i x_i = \sum_i \frac{W_i}{\gamma_i} \Sigma^{-1} (\mathbb{E}(r) + \eta_i \tilde{s}_i). \quad (5)$$

To determine equilibrium prices and expected returns, we need the following definitions. First, W is the *aggregate wealth* defined as $W = \sum_i W_i$. Second, γ is the *aggregate risk aversion* defined by $\frac{1}{\gamma} = \sum_i \frac{W_i}{W} \frac{1}{\gamma_i}$, Third, η is the *aggregate green preference* defined by

$$\eta = \sum_i \frac{W_i / \gamma_i}{W / \gamma} \eta_i. \quad (6)$$

Fourth, $s \in \mathbb{R}^N$ is the *aggregate green score* defined by

$$s = \sum_i \frac{\eta_i W_i / \gamma_i}{\eta W / \gamma} \tilde{s}_i. \quad (7)$$

Fifth, m is the *market portfolio* with payoff $v_m = \vec{1}'v$, price $p_m = \vec{1}'p$, excess return $r_m = \frac{\vec{1}'v}{\vec{1}'p} - 1 - r^f$, and aggregate green score $s_m = s'p/(\vec{1}'p)$. Sixth, each asset's *market beta* is $\beta_n = \frac{\text{Cov}(r_n, r_m)}{\text{Var}(r_m)}$.

Based on these definitions, we are ready to state the first result, showing how assets are priced in light of heterogeneous green scores. All proofs are in Internet Appendix A.

Proposition 1 (Green CAPM with Aggregate Green Score). *The aggregate green score, s_n , of any asset n determines its equilibrium price*

$$p_n = \frac{E(v_n) - \frac{\gamma}{W} \text{Cov}(v_n, v_m)}{1 + r^f - \eta s_n} \quad (8)$$

and its expected excess return

$$E(r_n) = \lambda \beta_n + g s_n = \lambda \beta_n - \eta s_n \quad (9)$$

where $\lambda = E(r_m) + \eta s_m$ is the risk premium and g is the greenium, which equals minus the aggregate green preference (6), that is, $g = -\eta$.

The aggregate green score is a weighted-average of investors' green scores (7), where the weights sum to one, and an investor's green score has a larger weight if the investor has more wealth, W_i , more risk tolerance, $1/\gamma_i$, and a stronger green preference, η_i .

The proposition shows that, even if investors have a multitude of views on greenness, $\tilde{s}_i$, the market aggregates these views into a single aggregate green score, which explains all risk-adjusted returns, $E(r_n) - \lambda \beta_n$, as these are given by $g s_n$ from (9).⁹ For example, there is only one price of Exxon Mobil, so this one price must reflect how investors perceive it on average.

⁹Pástor et al. (2021) present a version of (9) in their footnote 4.

Nonetheless, individual investors and researchers might still be interested in the greenium with respect to their own favorite measure of greenness. For example, how sensitive are expected returns with respect to carbon emissions? This question has relevance even if carbon emissions are only a part of the aggregate green score. The next result shows how to answer this question.

Proposition 2 (Greenium with Individual Green Scores). *The greenium with respect to green score i , $\tilde{s}_i$, is*

$$\tilde{g}_i = \rho_i g, \quad (10)$$

where g is the greenium for the aggregate green score, s , and $\rho_i = \text{Cor}(\tilde{s}_i, s) \in (-1, 1)$ is the cross-sectional correlation between $\tilde{s}_i$ and s , assuming that all green scores are cross-sectionally standardized. The individual green score i has a greenium, which is smaller in magnitude than that of the aggregate green score, $|\tilde{g}_i| < |g|$, and a lower explanatory power of expected returns:

$$E(r_n) = \lambda\beta_n + \tilde{g}_i \tilde{s}_{i,n} + \tilde{\varepsilon}_{i,n} \quad (11)$$

where $\tilde{\varepsilon}_{i,n}$ has mean zero and is uncorrelated with $\tilde{s}_{i,n}$ across n .

This proposition has several implications that we study empirically.

First, the aggregate green score is the only green score with an exact pricing relation. In other words, individual green scores should have lower explanatory power for risk-adjusted returns, as seen in Equation (11).

Second, controlling for the aggregate green score should drive out the effect of any individual green score, as seen in Equation (9).

Third, the aggregate green score should have the largest absolute greenium.

Fourth, each greenium based on an individual green score should equal the product of the aggregate greenium and the correlation between the individual green score and the aggregate one as seen in Equation (10).

Interestingly, as we show next, the aggregate green score gives the portfolio that brown investors (those with $\eta_i = 0$) want to bet against. At the same time, the aggregate green score gives the portfolio that green investors (those with $\eta_i > 0$) want to tilt toward, in aggregate.

Proposition 3 (Green and Brown Portfolios). *Brown investors tilt their portfolios away from stocks with high aggregate green scores due their lower expected returns (9). Green investors hold different portfolios depending on their individual green scores, but the wealth-weighted average green portfolio is tilted toward the aggregate green score in the sense that it is chosen as if expected returns are $\lambda\beta_n + \delta\eta s_n$ where $\delta > 0$.*

It is also interesting to consider how to identify the aggregate green score from green investors' portfolios. In this connection, let $W_g = \sum_{i:\eta_i>0} W_i$ be the total capital controlled by green investors, that is, those with $\eta_i > 0$. Further, consider for each stock n , the aggregate market value owned by green investors as a fraction of the total market capitalization (which equals p_n given that the shares outstanding is normalized to one):

$$\theta_n = \frac{\sum_{i:\eta_i>0} W_i x_{i,n}}{p_n} \quad (12)$$

The following results shows that θ can be used to identify the aggregate green score, s . The proposition relies on symmetric assets, but the proof discusses why the result may hold more broadly.¹⁰

Proposition 4 (Aggregate Green Score via Portfolios). *Under symmetric assets, the fraction of stocks held by green investors, θ , can be written based on a first-order Taylor-approximation in W_g at $W_g = 0$ as*

$$\theta \cong W_g c(d\vec{1} + s) \quad (13)$$

¹⁰Symmetric assets means that all the assets have fundamentals, v_n , with equal means, variances, $\text{Var}(v_n) = \sigma^2$, and correlations, $\text{Cor}(v_n, v_k) = \rho \in [0, 1)$, but different green scores.

where $c > 0$ and $d \in \mathbb{R}$. Standardizing θ and s in the cross section of stocks, we have

$$\frac{\theta - \text{mean}(\theta)}{\text{std}(\theta)} \cong \frac{s - \text{mean}(s)}{\text{std}(s)} \quad (14)$$

This proposition yields two intuitive results. First, Equation (13) shows that the aggregate green holdings are a linear combination of the vector of ones, $\vec{1}$, and the vector of aggregate green scores, s . The vector of ones arises because green investors partly hold the market portfolio, so, when we normalize their holdings by each stock's total market capitalization in Equation (12), this part of the ownership shares is the same across stocks. The second component, s , reflects that green investors tilt toward their green preferences.

Second, Equation (14) states that, once we standardize in the cross section of stocks, the vector of green holdings equals the aggregate green score. Mathematically, this result arises because the vector of ones from Equation (13) is “averaged away” since standardizing removes anything that affects all stocks equally. Likewise, any multiplicative constants do not matter when we standardize.

Practically, the result in Equation (14) means that we can identify the aggregate green score as follows. First, we aggregate all green investors' dollar holdings for a given stock. Second, we normalize the aggregate dollar holdings by the stock's market capitalization. Third, we standardize. Then, we have the standardized aggregate green score! This result might seem surprising since the aggregate green score in Equation (7) seems daunting to identify: It depends on all green investors' individual green scores, their wealth, risk aversion, and green preferences. However, all these features are captured by their investments. In other words, the vector of aggregate green investment shares is a sufficient statistic that reveals the aggregate green score. This result is very useful in our empirical analysis.

The model also has implications for how the greenium varies over time. To study this in a simple way, suppose that, just after prices equilibrate, preferences unexpectedly change, and prices move to a new equilibrium.

Proposition 5 (Time-Varying Greenium). *If investor preferences unexpectedly become greener, then green stocks with higher aggregate scores outperform brown stocks contemporaneously,*

but the forward-looking greenium becomes more negative.

Lastly, to consider how the greenium varies globally, suppose that assets and investors are divided across several countries, $c = 1, 2, \dots, C$. We use the notation that investor i belongs to country c_i and asset n is the same country if $n \in c_i$ and in another country if $n \notin c_i$. To capture the idea that investors can have a home bias (or, equivalently, face costs associated with investing abroad), we assume that the investor's objective function (3) is modified to

$$W_i \left(1 + r_f + x'_i E(r) - \frac{\gamma_i}{2} x'_i \Sigma x_i + \eta_i x'_i \tilde{s}_i - \frac{h}{1-h} \sum_{n \notin c_i} \frac{x_{i,n}^2}{p_n^2} \right) \quad (15)$$

where $h \in [0, 1)$ captures the degree of home bias. We see that $h = 0$ is the same model as before, while a larger h implies larger costs of investing abroad.

Proposition 6 (Green and Brown Countries). *In a fully integrated global market, $h = 0$, the greenium is the same in all countries. As home bias increases, $h \rightarrow 1$, the greenium becomes more negative in countries in which investors have a larger green preference, η_c .*

2 Data

2.1 Equity data

Realized stock returns and stock characteristics are from the data set in [Jensen, Kelly, and Pedersen \(2023\)](#) 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 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 use book equity instead of the market equity to avoid introducing a bias by having the endogenous market price on the right-hand side in our regressions, and similarly we use the book value of assets for the other controls. We also use firms' GICS8 industry codes. Internet Appendix B5 contains additional details about data screens, winsorization, lag conventions (see [Zhang, 2025](#)), and data linking.

2.2 Green scores

Table 1: Green scores

Name	Time period	Avg. N (US)	Avg. N (Global ex-US)	Source
Aggregate Green Score	2009-08 to 2022-12	1966	6002	Several
LOG(S1TOT)	2009-05 to 2022-12	1337	5933	Trucost
LOG(S1+2TOT)	2009-05 to 2022-12	1337	5933	Trucost
LOG(S1+2+3TOT)	2009-05 to 2022-12	1337	5933	Trucost
S1INT (Sales)	2009-05 to 2022-12	1337	5932	Trucost
S1+2INT (Sales)	2009-05 to 2022-12	1337	5932	Trucost
S1+2+3INT (Sales)	2009-05 to 2022-12	1337	5932	Trucost
S1INT (Assets)	2009-05 to 2022-12	1337	5933	Trucost
S1+2INT (Assets)	2009-05 to 2022-12	1337	5933	Trucost
S1+2+3INT (Assets)	2009-05 to 2022-12	1337	5933	Trucost
Ind.-adj. ESG score	2007-01 to 2022-12	1529	3333	MSCI
Weighted ESG score	2007-01 to 2022-12	1529	3332	MSCI
Environment score	2007-01 to 2022-12	1529	3333	MSCI
Greenness (PST)	2007-01 to 2022-12	1528	3333	MSCI
E climate score	2013-01 to 2022-12	2043	4384	MSCI
E nat. res. score	2013-01 to 2022-12	1449	3285	MSCI
E waste score	2013-01 to 2022-12	1374	2685	MSCI
E env. opps. score	2013-01 to 2022-12	718	1840	MSCI
Total ESG score	2009-08 to 2022-12	788	2717	Sustainalytics
Environmental score	2009-08 to 2022-12	788	2718	Sustainalytics

The table shows, for the aggregate green score and the 19 individual green scores, the time period over which they are available, their stock-level observations (N) both in the US and globally ex-US, 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. Scope 3 refers only to upstream emissions as downstream emissions are only available from 2017. 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.

We consider 19 individual green scores from three different data providers. The green

scores are based on data from Trucost, MSCI, and Sustainalytics as shown in Table 1.¹¹ Table 1 shows the time period, the number of stocks covered on average in the US and globally ex-US, and the underlying data sources.

We sign each green scores such that a higher value means being greener. We include MSCI’s and Sustainalytics ESG scores as green scores as many green investors may use these as catch-all sustainability metrics. As an example, in BlackRock’s 2020 Global Sustainable Investing Survey, 88% of respondents rank Environment as their top priority among the ESG factors.

Internet Appendix B.2 contains additional information on the greenness data. The 19 green scores cover green scores considered in the literature and Internet Appendix Table D1 shows the corresponding references.

2.3 Green investment funds’ portfolio holdings

We identify green investment funds using Morningstar Direct’s “Sustainable Investment Overall” variable. According to Morningstar, a fund is classified as a sustainable investment product if it is described as focusing on sustainability, impact, or environmental, social, and governance, or ESG factors in its prospectus or other regulatory filings.¹² Morningstar’s classification comes with a variable that indicates when a fund started being sustainable, suggesting that this classification is time-varying. The earliest start date for this variable is October 2018, so before this date it is unknown whether a fund is sustainable or not.¹³

We consider global equity funds, that is, open-end investment funds and ETFs. Here,

¹¹The 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.

¹²Moreover, funds must claim to have a sustainability objective, and/or use binding ESG criteria for their investment selection. Funds that employ only limited exclusions or only consider ESG factors in a non-binding way are not considered to be a sustainable investment product.

¹³One could try to identify sustainable funds based on their names as opposed to Morningstar’s classification, but to the best of our knowledge no database stores time-varying names for global investment funds. Focusing on global investment funds is important, as many sustainable funds are domiciled in Europe and not in the US.

“global” means that these funds can be domiciled anywhere in the world, e.g., in the United States, Europe, or elsewhere, and these funds can make local or global investments. We obtain a fund’s portfolio holdings also from Morningstar. These holdings are often available at a monthly frequency, but sometimes they are only available at a quarterly frequency. Finally, we match the stock-level holdings to our other stock-level data by ISIN in order to construct the green ownership measure.

2.4 Forward-looking expected return measures

Equities: Implied costs of capital and beyond. A stock’s implied cost of capital, ICC, is the equal-weighted average of four individual ICC measures from the accounting literature, following [Mohanram and Gode \(2013\)](#). The four individual measures, ICC^{GLS} , ICC^{CT} , ICC^{PEG} , and ICC^{OJ} , are based on [Gebhardt et al. \(2001\)](#), [Claus and Thomas \(2001\)](#), [Easton \(2004\)](#) and [Ohlson and Juettner-Nauroth \(2005\)](#). [Mohanram and Gode \(2013\)](#) show that the average ICC is less noisy than the individual measures, so our discussion focuses on the average while showing the results with the individual measures as robustness in the Internet Appendix.

Each ICC measure computes the implied cost of capital as the internal rate of return that equates the discounted value of future expected cash flows 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 use as similar methods as possible outside the US. We describe each of the ICCs in detail in Internet Appendix [B.3](#).

We also use several other forward-looking expected equity return measures to ensure the robustness of our main results (Internet Appendix [B.4](#) provides details). We consider four different equity valuation ratios: the current earnings-to-price (`ni_me`) ratio and book-to-

market equity value (`be_me`) as well as forward one- and two-year earnings-to-price ratios. We define the latter as the median consensus forecasts from I/B/E/S for the respective forecast horizon divided by the current stock price. We also use two option-implied expected returns: The SVIX from [Martin and Wagner \(2019\)](#) and the generalized lower bound (GLB) from [Chabi-Yo et al. \(2023\)](#). The option-implied expected returns are available in the US, but not globally.¹⁴ Finally, we consider analysts’ subjective required and expected returns, relying on the measures in [Jensen \(2023\)](#). The subjective required and expected returns are available in the US, but not globally.

Corporate bonds. 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). To estimate the expected return, we consider 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, Chen, and Zhang \(2008\)](#), and (iv) yield spread adjusted for expected default losses.¹⁵

WACC. Equipped with both equity costs of capital and bond yields, we compute the (pre-tax) WACC for each firm as the market value-weighted average of its equity ICC and its corporate bond yield adjusted for expected default losses, averaged across the firm’s

¹⁴The data are provided by Grigory Vilkov at doi.org/10.17605/OSF.IO/Z2486.

¹⁵Specifically, for the yield adjusted for expected default losses using the method of [Campello et al. \(2008\)](#), 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:

$$\hat{E}[r_{t+1}^b] = \text{yield}_t^b - \text{prob. of default}_t^b \times (1 - \text{recovery rate}_t^b), \quad (16)$$

where $\hat{E}[r_{t+1}^b]$ proxies for the expected return of bond b over the next year. Following [Campello et al. \(2008\)](#), 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 \(1998\)](#). 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%.

outstanding bonds. As robustness checks for this firm-level expected return, we also consider two measures based on valuation ratios. Specifically, we consider ebitda-to-market enterprise value (`ebitda_mev`) and the enterprise value’s book-to-market (`bev_mev`).

3 Aggregate green score

Motivated by Proposition 4, we construct an aggregate green score based on green investors’ portfolio holdings. For each stock, we compute the aggregate dollar value of shares owned by green investment funds using the data presented in Section 2.3. We normalize this green ownership by the firm’s total equity market capitalization, and denote this variable as “green share.” Further, we standardize this measure, denoted “ $z(\text{green share})$,” where the z -score means subtracting the cross-sectional mean and dividing by the cross-sectional standard deviation as in Equation (14).

It is interesting to see how $z(\text{green share})$ relates to the individual green scores from the literature. Therefore, we regress $z(\text{green share})$ on all of the 19 individual green scores from the literature simultaneously using the sample of global stocks. We impose a non-negativity constraint on the parameter estimates, and we rescale the non-negative coefficient estimates such that they sum to one. To increase coverage, we also impute missing observations for the individual green scores using the mean of the non-missing observations within the same country and month.

The left panel of Figure 2 shows the parameter estimates from the regression. The figure suggests that green investors tilt their holdings towards MSCI’s weighted and industry-adjusted ESG scores, scope 1 carbon intensities (scaled by sales), and the environmental opportunities score.¹⁶

We show that our main results hold with this theory-based aggregate green score, $z(\text{green share})$, in Section 5.1, but we believe that the score can nevertheless be improved based on two practical considerations.

¹⁶Similarly, Berg et al. (2024) find that green funds in the US tilt their holdings towards stocks with high MSCI ESG scores.

First, $z(\text{green share})$ is positively skewed, reflecting large outliers (see Table B2 in the Internet Appendix). A standard way to limit the effect of outliers and noise in the data is to use a log- or rank-transformation (see, e.g., Moskowitz, Ooi, and Pedersen, 2012). Therefore, we also consider $z(\log(\text{green share}))$ and $z(\text{rank}(\text{green share}))$, which result in more balanced green scores with skewness near zero.

The middle and right panels of Figure 2 show that the $\log(\text{green share})$ and $\text{rank}(\text{green share})$ relate to the green scores from the literature in a similar way as the untransformed green share variable. In fact, the log- and rank-transformations load the most on those individual green scores from the literature that are most typically considered. For instance, MSCI is a market leader in providing ESG information, and the log- and rank-transformations have the largest loadings associated with MSCI’s weighted ESG score.

Another reason to use one of these transformations is that individual green scores from the literature have skewnesses that are close to zero or negative (see Table B1). Indeed, many commercial ESG providers have scores with a skewness close to zero by construction. Other measures such as carbon emissions intensity are concentrated among a minority of firms. Thus, carbon emissions are positively skewed, but become negatively skewed once signed such that larger numbers mean greener stocks.

In contrast, green investors’ portfolio shares are positively skewed because these investors can express strong positive opinions by buying large positions, but they cannot express strong negative views if they cannot sell short. Hence, a benefit of the log- and rank-transformations is that they give more weight to values close to the zero, making left-censoring less impactful.

A second practical consideration is that $z(\text{green share})$ is only available from 2018 onwards as we can only identify sustainable funds from 2018 onwards using the Morningstar data. At the same time, many of the individual green scores from the literature are available much earlier (e.g., going back to 2009). To construct the aggregate green score for a given stock before 2018, we compute a weighted-average of its individual green scores with weights given by Figure 2. In other words, we use the data post 2018 to learn which individual green scores green investors tilt their portfolio holdings towards. We then impute the aggregate green

score before 2018. Internet Appendix C contains further details on the projection.

We can construct an aggregate green score extended back to 2009 based on $z(\text{green share})$, $z(\log(\text{green share}))$, or $z(\text{rank}(\text{green share}))$, each based on the corresponding weights in Figure 2. In fact, we find that all these methods yield similar results (see Section 5.1).

That said, since we also consider many other variations of the data, we choose a “baseline” measure for the aggregate green score. We use $z(\text{rank}(\text{green share}))$ as the baseline, since this measure provides a simple and outlier-robust way to capture the relative ranking of stocks in terms of their green ownership.

To sum up, after 2018 the aggregate green score is $s = z(\text{rank}(\text{green share}))$. Before 2018, the aggregate green score is a weighted-average of the individual green scores for a given stock, standardized to mean zero and unit standard deviation within each country and month, with weights given by the right panel in Figure 2.

4 Equity greenium

4.1 Greenium with the aggregate green score

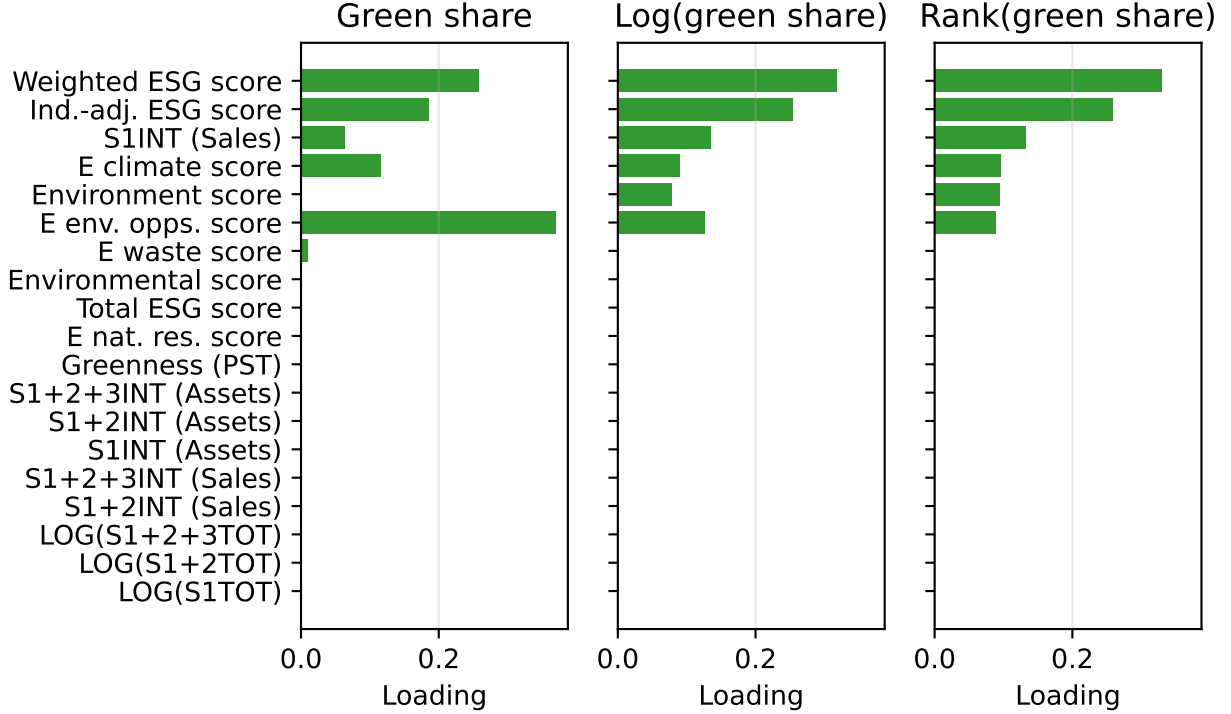
To measure the greenium as in Proposition 1, we run a cross-sectional regression of expected returns on the aggregate green score while controlling for risk:

$$\hat{E}_t[r_{t+1}^n] = \alpha_{c,t} + g \times s_t^n + \text{controls} + \epsilon_{t+1}^n. \quad (17)$$

Here, $\alpha_{c,t}$ is a country(c)-by-time(t)-fixed effect, s_t^n is the aggregate green score, and the control variables are listed below. The coefficient of interest is the annual greenium, g . The dependent variable are ICC, a forward-looking proxy for expected returns. We later show that the results are robust to several other forward-looking measures of expected returns (Section 5), while realized returns are too noisy to identify the greenium, both for the aggregate green score and all the green scores in the literature (Internet Appendix D).

Figure 3(a) reports the estimated greenium, $\hat{g}$, from Equation (17) for global stocks.

Figure 2: Greenium loadings



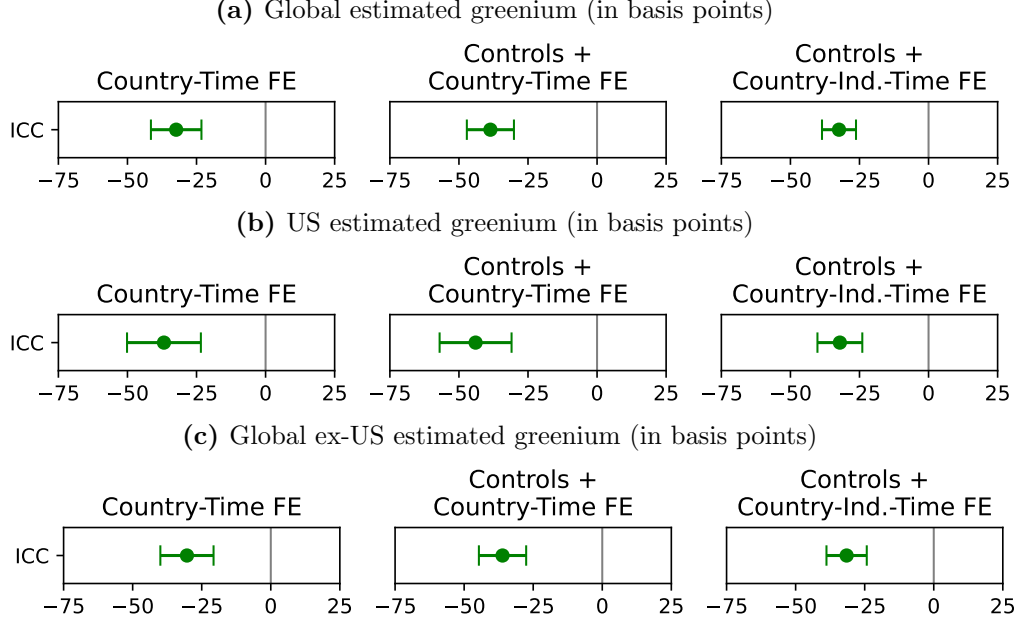
The figure shows rescaled regression coefficients from a regression of standardized (within country and month) green ownership shares, log green ownership shares, and rank-transformed green ownership shares of global sustainable investment funds on 19 individual green scores. The regression imposes a non-negativity constraint and rescales the coefficient estimates such that they sum to one. The regression includes country-by-time-fixed effects and control variables (market beta, log book equity, net debt-to-assets, and ebit-to-assets).

Since most existing studies are focused on the US, we also estimate this regression for the sample of US stocks in Figure 3(b), and the sample of global ex-US stocks in Figure 3(c).

Going from left to right, we consider more and more detailed controls and fixed effects. Specifically, we consider country-by-time-fixed effects, controls for risk characteristics, and country-by-industry-by-time-fixed effects. The risk control variables are market beta, the log of book equity, net debt-to-assets, and EBIT-to-assets. While Figure 3 shows the estimated greenium and its confidence interval graphically, we report the precise numerical values of all regressions in Internet Appendix Tables E1-E17.

Across all nine specifications, the estimated greeniums are negative, significant, and of similar magnitude. This is a striking consistency, including across non-overlapping samples

Figure 3: Regressions of implied cost of capital on aggregate green score



The figure shows the annual greenium (in basis points) estimated by regressing implied equity costs of capital (ICC) on the aggregate green score and control variables, see Equation (17). The ICC is an equal-weighted average of four individual ICC methods from Gebhardt et al. (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005, ICC^{OJ}), and Easton (2004). In Panel (a), the sample is global stocks; in Panel (b), the sample is US stocks; in Panel (c), 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 aggregate 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.

and controls.

The baseline global greenium estimate is -39 bps, seen in the middle panel of Figure 3(a) and also highlighted in the introduction (Figure 1). This greenium means that a one-standard-deviation increase in the aggregate green score is associated with a -39 bps drop in the annual ICC. The corresponding greenium estimate in the sample of US stocks is -44 bps (middle panel in Figure 3(b)). Similarly, the corresponding greenium for global ex-US stocks is -36 bps (middle panel in Figure 3(c)).

Just as the magnitude of the greenium is important, so is its standard error. To compute standard errors, we cluster by month and industry. Thus, we allow the errors to be correlated across stocks within a given month as well as to be correlated within a given industry over

time. Internet Appendix F shows that the choice of clustering matters for the analysis with ICCs due to auto-correlation in ICCs, and that our standard errors are the most conservative standard errors.

Even with these conservative standard errors, our baseline global greenium estimate of -39 bps is highly statistically significant with a t -statistic of 8.9. Further, the estimated standard errors are relatively small—measured in basis points per year, not percentage points per year—in contrast to the results in the literature with realized returns.

Interestingly, the estimates are relatively similar across the different controls, going from left to right in Figure 3. The right panels are of interest if one worries that expected return differences across industries could be driven by unobserved industry-specific confounders. Industry adjusting eliminates such confounders, but could also eliminate interesting variation in greenness. In any case, the results in the right panels focusing on within-industry variation show robustness.

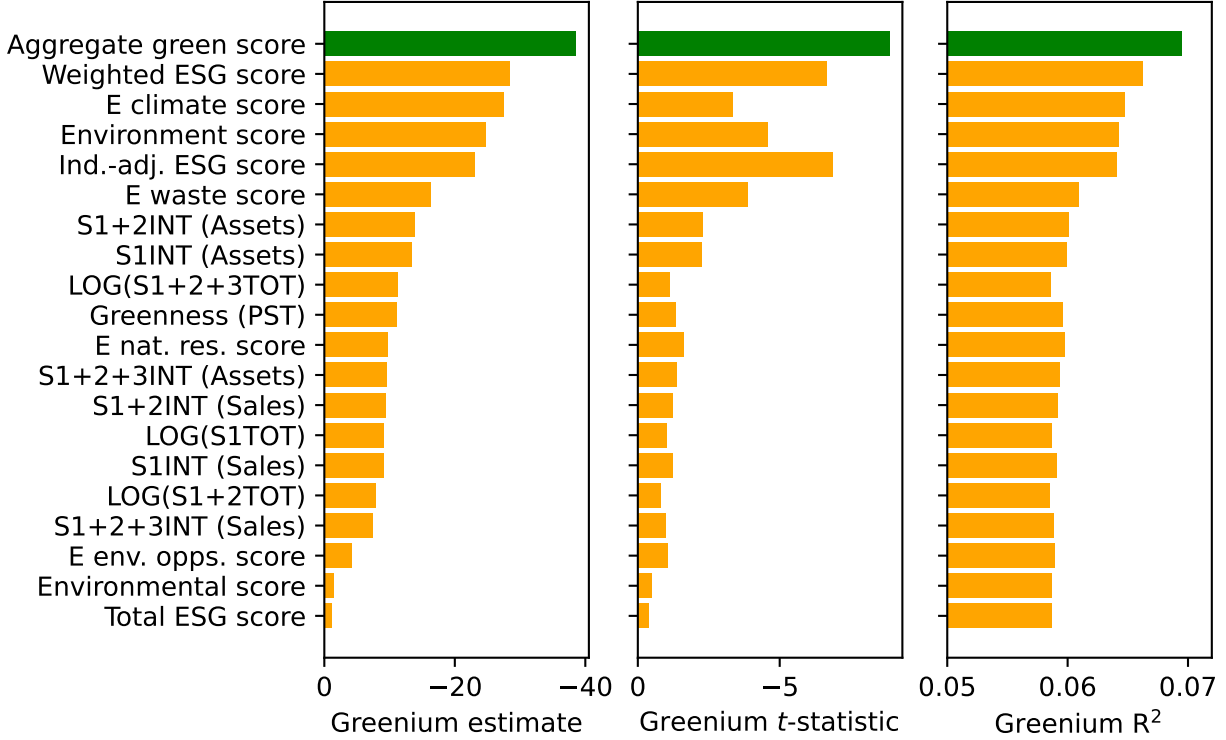
4.2 Aggregate green score versus individual green scores

We next study the greeniums of individual green scores and test further implications of the theory in Section 1. In particular, Proposition 2 implies that the aggregate green score has the largest associated absolute greenium, that any greenium corresponding to an individual green score is determined by its correlation with the aggregate green score, and that the aggregate green scores drives out each individual green score in a horse race.

First, Figure 4 illustrates the greenium estimate associated with the aggregate green score and each of the individual green scores from the literature. We see that the greenium corresponding to the aggregate green score is larger in absolute magnitude than any of the 19 greenium estimates associated with the individual green scores. The figure also shows that the aggregate green score has the largest absolute t -statistic and R -squared. These results are consistent with the prediction from Proposition 2 that the aggregate green score should have the strongest explanatory power for expected returns.

Each individual greenium in Figure 4 is also interesting in its own right. For example,

Figure 4: Greeniums based on aggregate green score vs. individual green scores



The figure shows greenium estimates in basis points per year corresponding to 20 different green scores, their t -statistics for the null hypothesis that the greenium is zero, as well as R^2 s from 20 separate regressions of implied equity costs of capital (ICC) on one of the 20 green scores at a time. All scores are standardized to have a cross-sectional standard deviation of one. We require that at least one of the individual green scores are non-missing, and impute missing green scores with the country-month mean to ensure all regressions use the same sample. The greenium corresponding to each green score is the slope coefficient estimate in a regression of ICCs on the green score, see Equation (17). The regressions include country-by-time-fixed effects and four control variables (market beta, log book equity, net debt-to-assets, and ebit-to-assets). The green bar refers to the aggregate green score from Section 3 and the orange bars refer to the 19 individual green scores from Table 1.

investors interested in the ratio of scope-1 carbon emission to assets learn that the associated greenium is -13 bps per standard deviation (the numbers behind the figure are in Table E16). Pedersen (2023) shows that this greenium can be interpreted as a carbon tax, but only when the emission ratio is measured in tCO_2 per dollars (rather than being cross-sectionally standardized). Measured in this way, we find a greenium of $4.2\$/\text{tCO}_2$.¹⁷

¹⁷See Table E18. Note that the left-hand side is scaled by 10^4 since it is measured in bps. Also, the right-hand side is scaled by 10^4 since assets are measured in millions of dollars, corresponding to scaling by 10^6 , and the ratio is then divided by 100. Since the left- and right-hand sides are scaled by the same

Second, Equation (10) in Proposition 2 predicts that the individual greeniums line up with their correlations to the aggregate green score. More specifically, a regression of the greeniums based on individual green scores on their correlations with the aggregate green score should have an intercept of zero and a slope equal to the aggregate green score greenium, -39 bps.

Figure 1(a) in the introduction shows the scatter plot associated with this regression. The x -coordinate is the correlation between the residuals from regressions of the individual and aggregate green scores on the same controls used to estimate the greenium (we use residuals instead of raw values to ensure that the correlations and greenium estimates are comparable). We require that at least one of the individual green scores is non-missing, and impute missing green scores with the country-month mean to ensure all regressions use the same sample.

As Proposition 2 predicts, the greenium estimates based on the individual green scores are positively related to their correlations with the aggregate green score. In fact, Figure 1(a) shows that the theoretical relation is close to the fitted relation in a regression of greeniums on the correlations.

Table 2 reports the results of the regression of the 19 individual greenium estimates on their correlations with the aggregate green score. The intercept estimate is -4 bps and the slope estimate is -34 bps, both economically close to 0 bps and -39 bps, respectively. Statistically, too, we cannot reject the null hypothesis that the intercept is zero and that the slope is -39 bps based on OLS standard errors.

The non-rejection is not due to excessively wide standard errors. Using OLS standard errors, we can reject the null hypothesis that the slope coefficient is zero. As OLS standard errors may understate the true standard errors since both the dependent and independent variables are estimated rather than known, Table 2 also shows standard errors based on a bootstrap. The conclusion remains the same: we cannot reject the null of a zero intercept and a slope of -39 bps, and these conclusions are not due to excessively wide standard errors since we have enough power to reject a slope of zero.

number, the slope coefficient is unaffected.

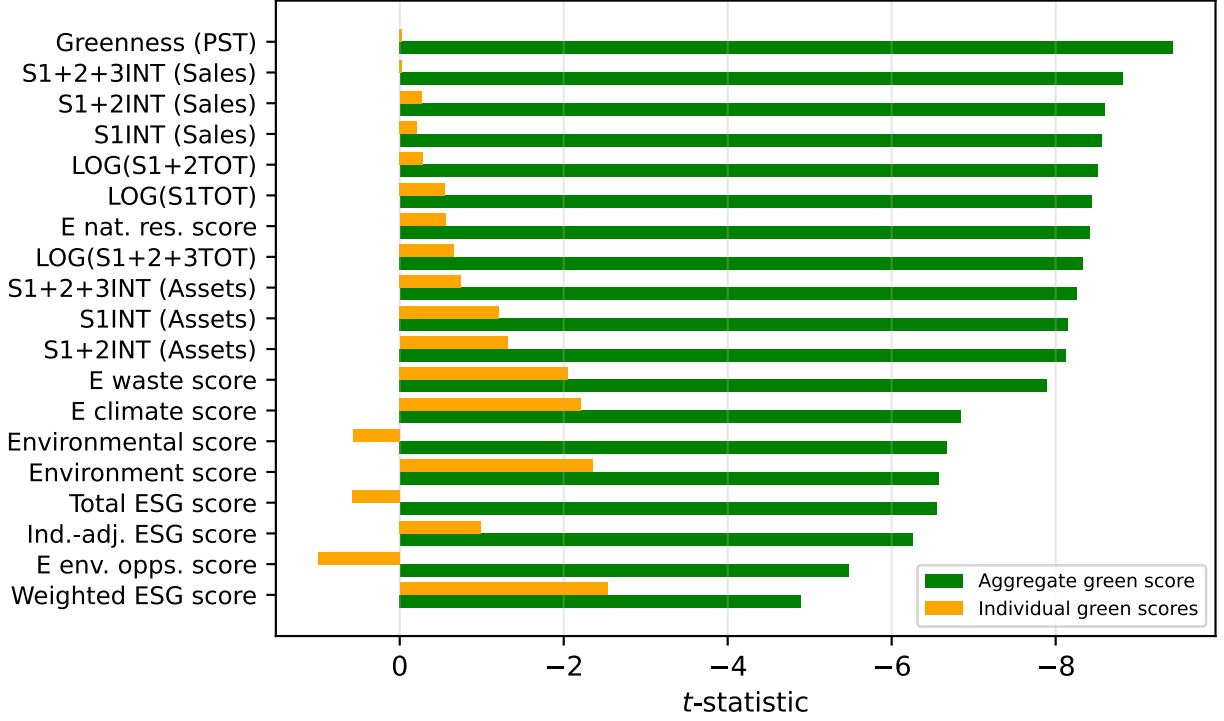
Third, Figure 5 summarizes the results of 19 horse-race regressions of ICCs on both the aggregate green score and one individual green score at a time. As before, these regressions include country-by-time-fixed effects as well as control variables. The aggregate green score drives out any individual green score in these horse-race regressions, i.e., it remains significant while the individual green scores do not. Four of the individual green scores have an absolute t -statistic slightly larger than two and are, thus, statistically different from zero in single-hypothesis testing. These scores tend to have larger correlations with the aggregate green score (see Internet Appendix Table E16 for their correlations). However, we find that the method of Benjamini and Hochberg (1995) classifies all the coefficients on the individual green scores as false discoveries, i.e., none of them is statistically different from zero when accounting for multiple testing.

Table 2: Correlations with aggregate green score explain individual greeniums

Parameter	Estimate	SE (OLS)	SE (BS)	t -stat ($H_0: 0$)	t -stat ($H_0: -39$)
Intercept	-3.64	2.31	5.19	-0.70	
Slope	-34.73	7.51	11.89	-2.92	0.33

The table reports the intercept and slope coefficient estimates from regressing greenium estimates based on each of the 19 individual green scores on the correlations between each score and the aggregate green score. Greenium estimates are obtained from regressions of implied equity costs of capital on the corresponding green score, see Equation (17), where the controls are country-by-time-fixed effects, market beta, log book equity, net debt-to-assets, and ebit-to-assets. The column “SE (OLS)” shows standard OLS standard errors and “SE (BS)” shows the standard errors based on 100 bootstrap replications, in which observations are randomly resampled by country with replacement. The table also shows t -statistics for the null hypothesis of a zero intercept and slope coefficient as well as for the null hypothesis that the slope coefficient equals -39 basis points. The bootstrapped standard errors are used to compute the t -statistics since the bootstrapped standard errors take into account that the regression variables are estimated rather than known. The regression has 19 observations and the adjusted R^2 is 0.53.

Figure 5: Aggregate green score drives out individual green scores



Each pair of green/orange bars shows the t -statistics of a separate bi-variate regression. The figure shows 19 such pairs, each representing a regression of the implied equity costs of capital on the aggregate green score (green bar) and one of the 19 individual green scores from the literature (orange bar). Each regression includes country-by-time-fixed effects and four control variables (market beta, log book equity, net debt-to-assets, and ebit-to-assets). The standard errors to compute the t -statistics are clustered by industry and month. All 19 individual green scores are insignificant when controlling for multiple testing.

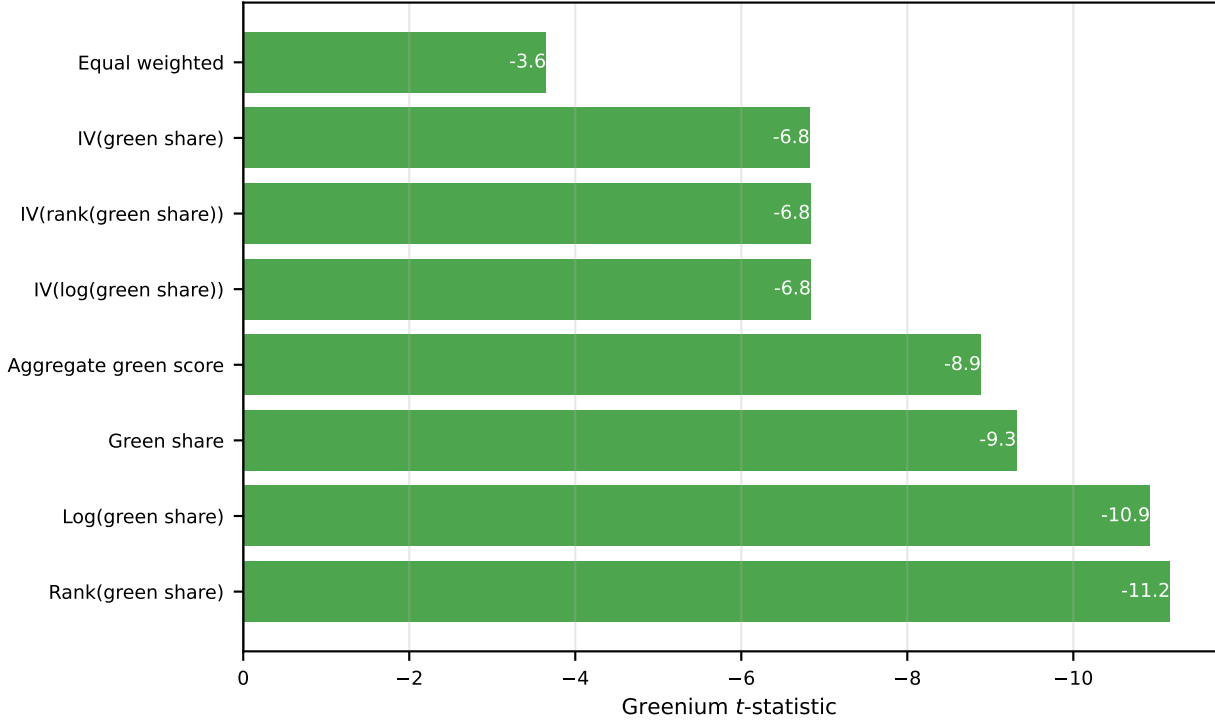
5 Robustness of equity greenium

5.1 Alternative definitions of the aggregate green score

As explained in Section 3, the baseline aggregate green score is the ranked green ownership share after October 2018 (when ownership data is available), and the IV version earlier, which uses the projection on the individual green scores. To test the robustness of our results, we also consider alternative ways to construct the aggregate green score.

Figure 6 shows the t -statistics from the main regression of ICCs on the aggregate green score, along with a country-time fixed effect and the standard control variables, using the

Figure 6: Greenium t -statistics with different aggregate green scores



The figure shows the t -statistics for the null hypothesis of a zero coefficient corresponding to different ways to construct an aggregate green score for a given stock. t -statistics are obtained from a regression of implied equity costs of capital on an aggregate green score version. The regressions include a country-by-time fixed effect and four control variables (market beta, log book equity, net debt-to-assets, and ebit-to-assets). The versions of the aggregate green score considered are (in order of absolute magnitude): equal-weighted average across 19 individual green scores for a given stock; IV(green share); IV(log(green share)); IV(rank(green share)); (baseline) aggregate green score; green share; log(green share); rank(green share). IV refers to a projection of green ownership shares (or their log and rank transformations, respectively) by global sustainable investment funds on the 19 individual green scores. The projection imposes a non-negativity constraint and uses the rescaled coefficients as fixed weights over time to construct an aggregate green score for a given stock. The baseline aggregate green score is IV(rank(green share)) before 2018/10 and rank(green share) after. The standard errors to compute the t -statistics are clustered by industry and month.

baseline aggregate green score as well as seven alternative definitions of the aggregate green score. The first alternative takes an equal-weighted average of the 19 individual green scores with global coverage (“Equal weighted”). The six other alternatives are either the raw green ownership share (“Green share”), its log transformation (“Log(green share)”), or its rank-based transformation (“Rank(green share)”), using either the observable value (which restricts the sample to after October 2018) or its projected counterpart over the full sample.

With the equal-weighted green score, the greenium is still significantly negative, but the t -statistic is less than half of the t -statistic based on the baseline aggregate green score. In fact, using any of the other approaches leads to a larger t -statistic in absolute magnitude than with the equal-weighted score. Overall, we find that the greenium is significantly negative across specifications, and the use of holdings data increases its significance.

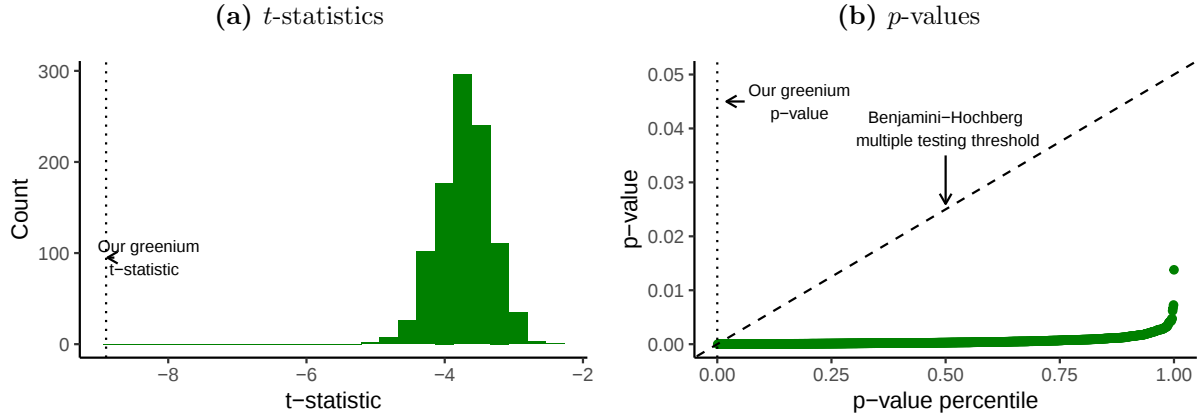
As additional robustness, we estimate greeniums based on random weighted averages of the 19 individual greenness scores. Again, our theory predicts that these random averages should not work as well as our theory-motivated aggregate green score. We generate a random aggregate green score by first drawing a random standard uniformly distributed weight for each of the 19 individual green scores from Table 1. If a stock does not have a specific green score, we set the corresponding weight to zero. We normalize the weights such that they sum to one. The random green score is the product of the weights and the individual green scores. We then get a new estimate of the greenium by regressing ICCs on this random aggregate green score, using Equation (17). We repeat this procedure 1,000 times.

Figure 7(a) shows the distribution of t -statistics of the resulting 1,000 greenium estimates. All of the t -statistics are large in magnitude, far above standard thresholds for statistical significance—there does seem to be a greenium, regardless of how the aggregate green score is constructed. However, the absolute t -statistic based on our baseline aggregate green score is well above any of the t -statistics associated with the random averages of the individual green scores. Further, Figure 7(b) shows that all these results survive a Benjamini and Hochberg (1995) multiple testing adjustment, as the solid line of p -values is always below the dashed threshold implied by their method.

5.2 Greenium based on valuation ratios

The estimated greenium in the previous section 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

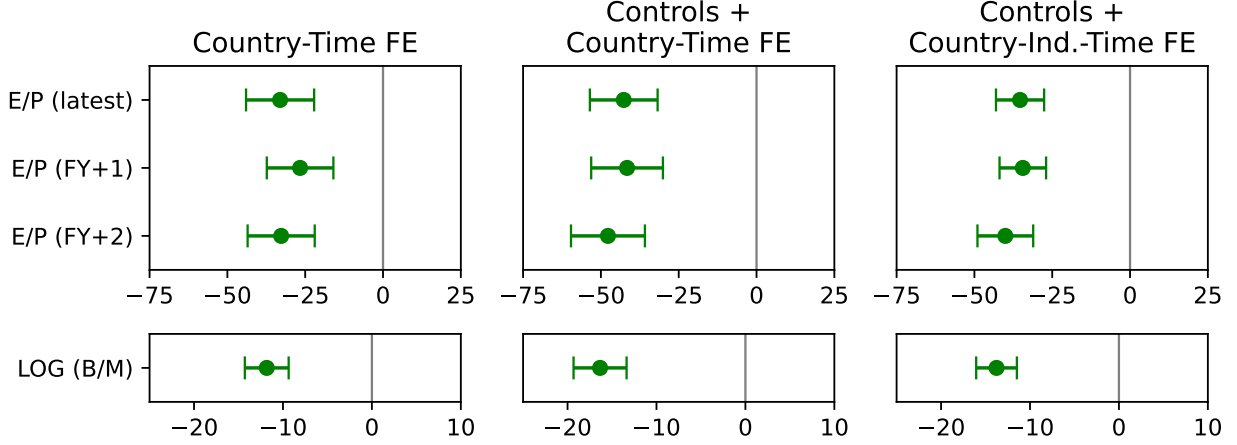
Figure 7: Random green scores and multiple testing



The figure shows the distribution of t -statistics and p -values when the main regression in Equation (17) is estimated with 1000 random averages of the individual green scores. Specifically, we regress the average implied cost of capital on a country-by-time-fixed effect, firm-specific controls (market beta, log book equity, net debt-to-assets, and EBIT-to-assets), and a random green score in the global sample of stocks. The random green score is created by first drawing a random standard uniformly distributed weight for each of the 19 individual green scores from Table 1 and then normalizing the weights such that they sum to one. The random green score is the product of the weights and the individual green scores, standardized to have a cross-sectional mean of zero and a variance of one within each country and month. This procedure is repeated 1000 times. Panel (a) shows the distribution of the t -statistics of the resulting greenium estimates, and the vertical dotted line shows the t -statistic based on our aggregate green score. Panel (b) shows the p -values ranked from low to high, and the x coordinate shows their percentile rank. The dashed line shows the multiple testing threshold from [Benjamini and Hochberg \(1995\)](#) that controls the false discovery rate at a 5% level. All of the estimates are statistically significant after adjusting for multiple testing, as the solid line is uniformly below the dashed one. The vertical dotted line shows the p -value based on the aggregate green score.

with regards 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.

Figure 8: Regressions of valuation ratios on aggregate green score



The figure shows greeniums estimated by regressing valuation ratios on the aggregate green score and control variables, see Equation (17). The sample is global stocks. 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 (LOG(B/M)). The greenium estimates are expressed in basis points per year, except for log book-to-market equity. The greenium based on log book-to-market equity is expressed in percent increase in book-to-market equity for a one-standard-deviation increase in the aggregate green score. The control variables are market beta, log book equity, net debt-to-assets, and ebit-to-assets. The aggregate 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 particular, we estimate the greenium using the specification in Equation (17) 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 or a negative number. 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 8 reports the results using the sample of global stocks. In all 12 specifications (four different valuation ratios $\times$ three sets of controls and fixed effects), the greenium estimates,

$\hat{g}$, are significantly negative. 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 compared to the results with ICCs.

The interpretation of the estimated magnitudes for the log-book-to-market ratios are as follows: The estimated coefficient of -16 the second column means that equity prices are about 16% higher for a one-standard-deviation increase in greenness.

While price levels are interesting in their own right, we can convert them to returns. To do so, we can use the Gordon growth model:

$$p = \frac{d}{r - g} \quad \text{i.e.,} \quad r = \frac{d}{p} + g, \quad (18)$$

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

$$\partial r \cong -\frac{\partial p}{p} \frac{d}{p} \cong \partial \log(b/p) \frac{d}{p}. \quad (19)$$

That is, 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 -16 from Figure 8 multiplied by the capped value-weighted dividend-to-price ratio of 2.52%, the estimated “price greenium” corresponds to a “return greenium” of about -40 bps, again similar to our baseline estimate.¹⁸

¹⁸We compute the capped 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 2.52%. If we replace the dividend yield with the net payout ratio (that also accounts for stock buybacks and issuance), the corresponding number is 1.75%, which translates into a greenium of -28 bps.

5.3 Greenium based on option-implied expected returns

We consider two option-implied expected returns: The SVIX from [Martin and Wagner \(2019\)](#) and the generalized lower bound (GLB) from [Chabi-Yo et al. \(2023\)](#). 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. However, in contrast to ICCs and valuation ratios, option-implied expected returns are only available for US stocks. The data are at a daily frequency, but we convert them to the monthly frequency by taking the average of daily expected returns within each month, following [Chabi-Yo et al. \(2023\)](#).

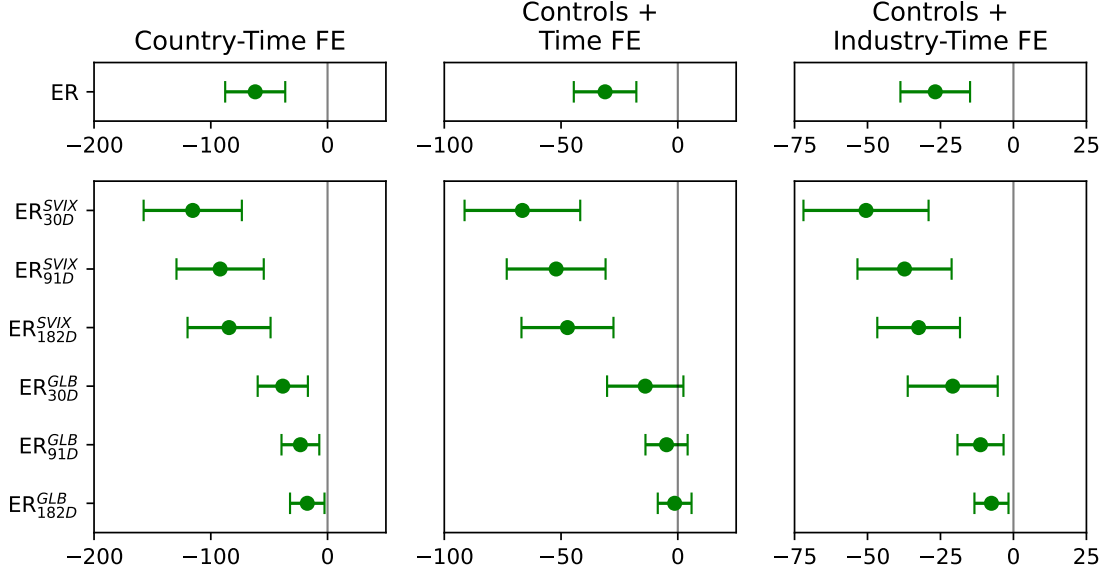
Figure 9 reports the results for both measures over the next 30, 91, and 182 days (corresponding to options of 1-, 3-, and 6-month maturities) as well as for the average of all these $2 \times 3 = 6$ measures (top row). The estimated annual greenium in the top row is negative in all specifications and ranges from -62 bps with only time-fixed effects to -27 bps with control variables and country-by-time-by-industry-fixed effects. As such, the option-implied expected returns suggest the same sign and magnitude for the greenium as those that we have 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. 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. Thus, the variation in results may indicate differences in higher-order risk-neutral moments across brown and green stocks.

5.4 Greenium based on subjective expected returns

As final measures of forward-looking expected equity returns, we consider analysts’ subjective required and expected returns, relying on the measures in [Jensen \(2023\)](#). Subjective required and expected returns are available in the US, but not globally. We consider two

Figure 9: Regressions of option-implied expected returns on aggregate green score



The figure shows the annual greenium (in basis points) estimated by regressing option-implied expected returns on the aggregate green score and control variables, see Equation (17). 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 aggregate 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.

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.¹⁹ 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.

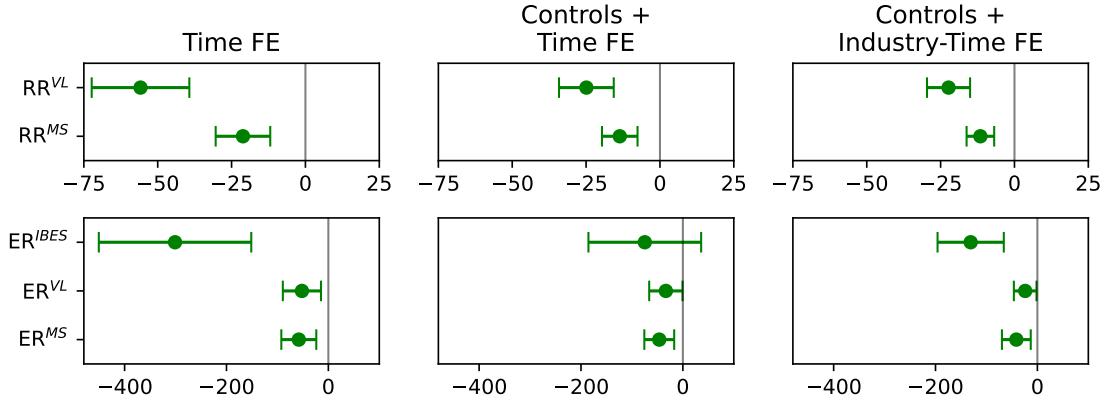
We obtain subjective expected returns from three different providers: Four-year expected

¹⁹The 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.

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. These expected returns are then annualized using geometric compounding.²⁰

Figure 10 shows the estimates of the greenium using required returns in the first two rows. The estimates are consistently negative, and significantly so in all specifications at the 5% level. The magnitude of the effects ranges from around -56 bps with only time-fixed effects to around -21 bps with control variables and time-by-industry-fixed effects.

Figure 10: 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 the aggregate green score and control variables, see Equation (17). 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 aggregate 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 also reports the greenium estimates using subjective expected returns in the last three rows and shows broadly similar results. The greenium estimated based on subjective expected returns from IBES is an order of magnitude of larger, ranging from -301 bps to

²⁰For a detailed description of how the subjective expected returns are constructed, see Jensen (2023, Section A.2.2).

−75 bps. However, the associated 95% confidence bands are also significantly wider.

6 The greenium across countries, time, and asset classes

The previous sections establish the existence of a negative equity greenium (consistent with Proposition 1), especially relative to the aggregate green score (consistent with Proposition 2), which is identified from portfolios (as in Propositions 3–4). This section considers further implications of the theory, showing that the equity greenium has been declining over time (Proposition 5) and that it is more negative in greener countries (Proposition 6). Finally, we also search for the greenium in corporate and sovereign bonds.

6.1 The equity greenium is getting more negative over time

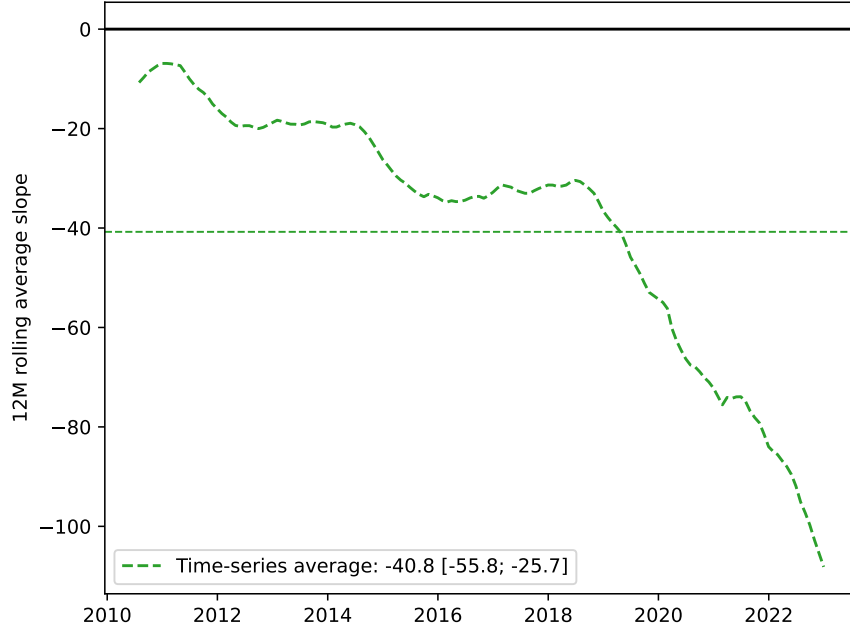
To investigate whether the equity greenium is changing over time, we first estimate the specification in Equation (17) separately each month in the global sample that pools US and non-US stocks. Figure 11 shows the time series of the estimated greenium, $\hat{g}_t$, in each month. The estimated greenium is close to zero early in the sample and gets more and more negative over time. By December 2022, the estimated equity greenium is more than 100 bps in absolute magnitude. 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.

To formally test whether the greenium has become more negative, we run the following regression:

$$ICC_t^n = \alpha_{c,t} + \left(g_1 + g_2 \times \frac{t - t_{\text{start}}}{t_{\text{end}} - t_{\text{start}}} \right) s_t^n + \text{controls} + \epsilon_t^n, \quad (20)$$

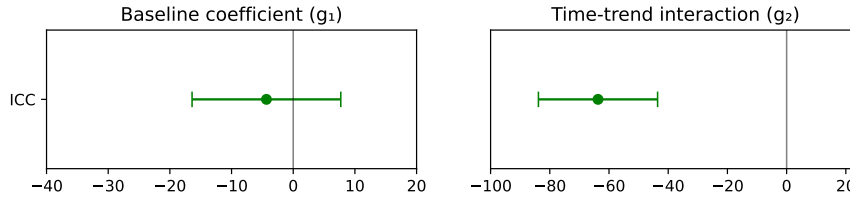
where ICC_t^n is stock n 's forward-looking expected return at time t , t_{start} is the beginning of our sample in August 2009, and t_{end} is the end of our sample in December 2022. Hence, g_1 is the greenium at the beginning of the sample period, and $g_1 + g_2$ is the greenium at the end of the sample period. Figure 12 shows the regression results and shows that the interaction term is statistically negative.

Figure 11: Global equity greenium over time



The figure shows the annual greenium (in basis points) over time, derived from regressing implied equity costs of capital (ICCs) on the aggregate green score, control variables, and a country-fixed effect month-by-month in the global sample that pools the US and non-US data. The ICC is an equal-weighted average of four individual ICC methods from Gebhardt et al. (2001), Claus and Thomas (2001), Ohlson and Juettner-Nauroth (2005, ICC^{OJ}), and Easton (2004). The four control variables are market beta, log book equity, net debt-to-assets, and ebit-to-assets. The solid line shows the rolling 12-month average greenium estimate. The aggregate green score is standardized to have zero mean and unit standard deviation within each country by month. The figure also shows the time-series average of the greenium estimates (dashed line).

Figure 12: Greenium over time

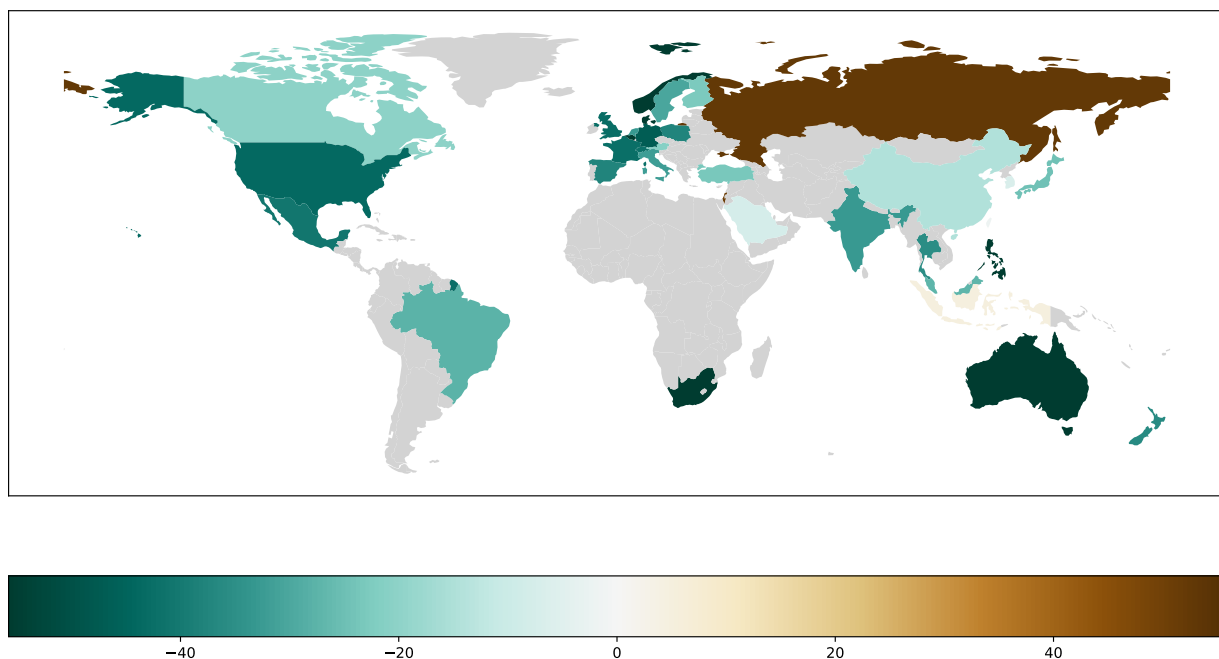


The figure shows the evolution of the global equity greenium, estimated by regressing implied equity costs of capital on the green score and the aggregate green score interacted with a time trend as in Equation (20). The coefficient g_1 (left panel) is the annual greenium (in basis points) at the start of the sample. The coefficient g_2 (right panel) is the linear time trend, indicating the increase in the annual greenium (in basis points) from the start of the 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 control variables: market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The aggregate 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.

6.2 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 Equation (17) with the ICC as the dependent variable, using the baseline specification with control variables and time-fixed effects. Figure 13 shows that the estimated greenium is negative in most countries, but especially in the Nordics and Australasia.

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). Green countries have lower greenium estimates, whereas brown countries have larger greenium estimates. We get these estimates by regressing the average implied cost of capital from Figure 3 on our aggregate 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.

To measure the greenness of a country, we use the Climate Change Performance Index (CCPI). The CCPI data are available at ccpi.org. The CCPI has previously been used in

other papers (see, e.g., [Zhang, 2025](#)). 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 Nascimento, 2024](#)). Each year, the covered countries get a score between 0 and 100. We define green countries as those with an above-median CCPI in a given year.

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

$$ICC_t^n = \alpha_{c,t} + (g_1 + g_2 \times 1_{(CCPI_{c,t} > \text{median}_t)})s_t^n + \text{controls} + \epsilon_t^n, \quad (21)$$

where ICC_t^n is stock n 's average ICC and $1_{(CCPI_{c,t} > \text{median}_t)}$ is equal to 1 if the country's CCPI is above the median in the given year and zero otherwise. With this specification, g_1 is the greenium in brown countries, and $g_1 + g_2$ is the greenium in green countries. Note that the baseline dummy $1_{(CCPI_{c,t} > \text{median}_t)}$ is absorbed by the country-by-time-fixed effects $\alpha_{c,t}$, but that its interaction with the aggregate green score is not.

Table 3 shows that greener countries tend to have more negative equity greeniums. Specifically, Column (1) repeats the baseline regression of ICCs on the aggregate green score with control variables and time-fixed effects in the global sample. Column (2) estimates the specification in Equation (21) and shows that the equity greenium in brown countries is $\hat{g}_1 = -34$ bps, whereas it is $\hat{g}_1 + \hat{g}_2 = -46$ basis points in green countries. This difference, $\hat{g}_2$, is statistically significant at the 5% level, meaning that the equity greenium is significantly more negative in greener countries.

6.3 Corporate bond greenium

Comparing bonds issued by green versus brown firms, we next estimate a US bond greenium. Figure 14 reports the estimated greeniums using several different measures of forward-looking expected returns and several different sets of control variables, similar to our equity analysis. As the aggregate green score is constructed at the firm level, we aggregate all individual bond data to the firm level using value weights in case a firm has multiple bonds outstanding. As in the equity analysis, we avoid price-based controls to avoid biases,

Table 3: Greenium in green versus brown countries

	ICC _t ⁿ	
	(1)	(2)
s_t^n	-38.62 (-8.88)	-34.03 (-7.14)
$s_t^n \times 1_{(\text{CCPI}_{c,t} > \text{median}_t)}$		-11.74 (-2.07)
N	875,596	811,993
R^2	54%	54%
Country-Time FE	Yes	Yes
Controls	Yes	Yes

The table shows greenium estimates for green and brown countries by regressing implied equity costs of capital 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 specification (2) includes an interaction with the dummy variable. t -statistics (in parentheses) are based on standard errors clustered by industry and month. All specifications include country-by-time-fixed effects. N refers to the number of observations, and R^2 to the total R-squared.

using book values as opposed to market values and time-to-maturity as opposed to duration.

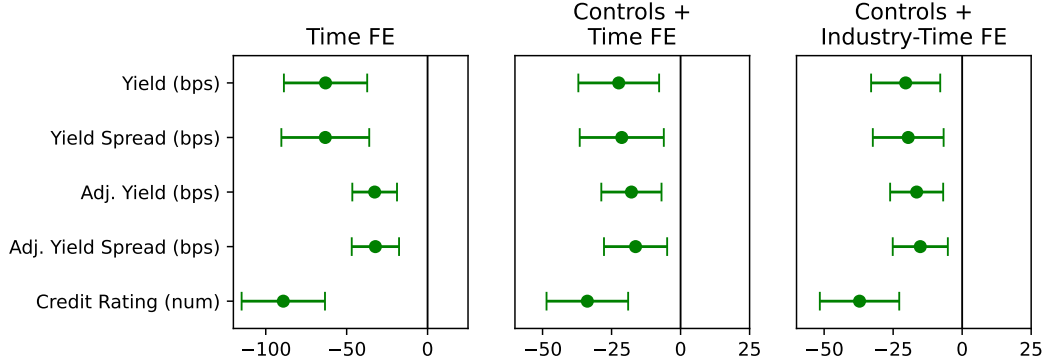
Panel (a) of Figure 14 shows estimated greeniums ranging from around -63 bps to -15 bps, depending on the specification. Our baseline specification is the regression of default-adjusted yields with control variables and time-fixed effects. This specification yields a greenium estimate of -18 bps with a 95% confidence interval of $(-29, -7)$ bps per year.

The last row in Panel (a) also shows that credit ratings tend to be stronger for greener firms. We construct numerical credit ratings on a scale from 1 to 21 following [Dick-Nielsen et al. \(2023\)](#) and note that a strong credit rating is coded as a small number. In sum, rating agencies appear to view greener firms as safer, perhaps taking transition risk into account.

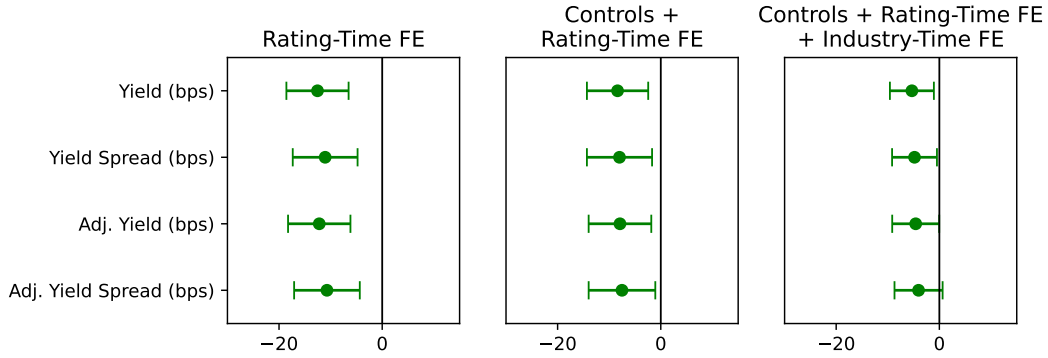
Panel (b) shows greenium estimates when we include credit-rating-by-time-fixed effects in the specifications. The panel shows broadly similar results. However, naturally, the greenium estimates tends to be smaller compared with Panel (a), presumably because credit-rating-by-time-fixed effects absorb a lot of the variation in greenness.

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 basis points) by regressing corporate bond yields on the aggregate 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 a 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 aggregate 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.

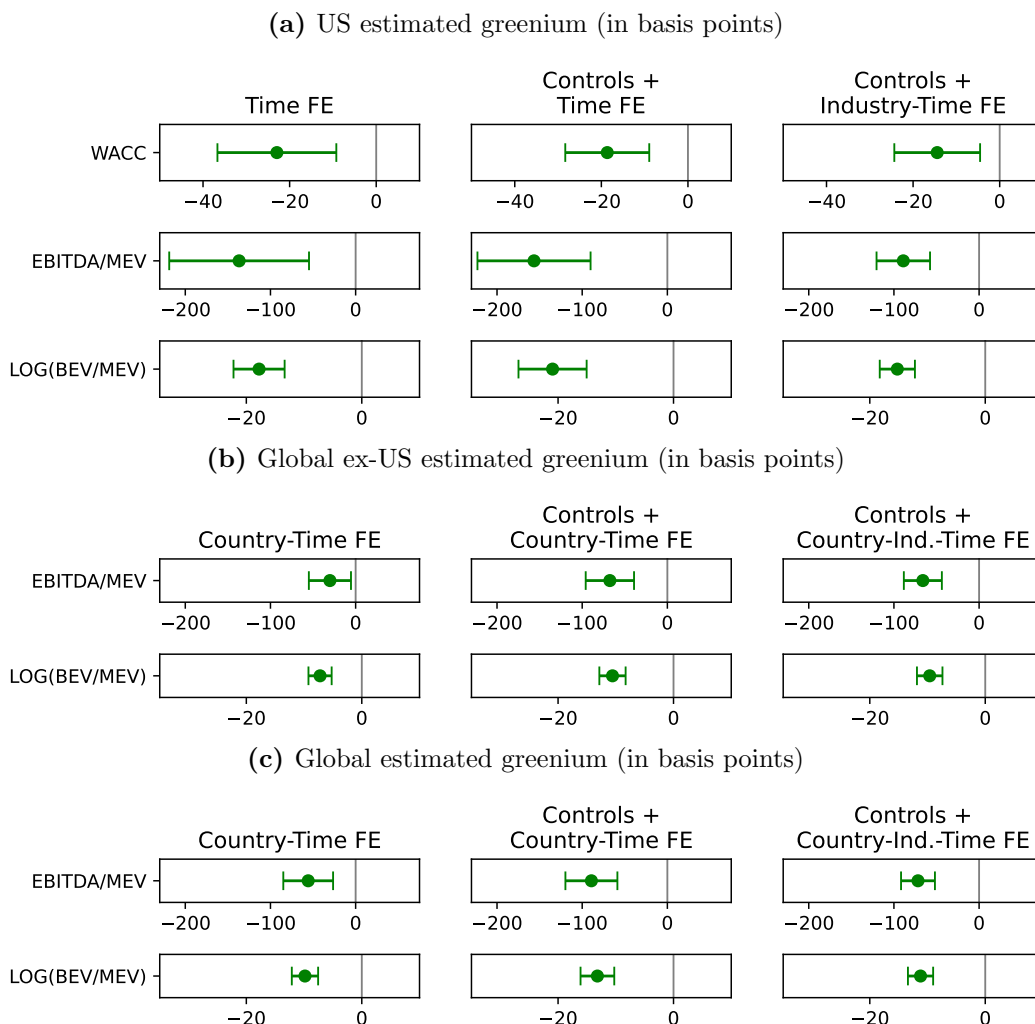
6.4 Firm-level cost of capital: WACC greenium

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 ICC and the corporate bonds' average adjusted yield.

Panel (a) Figure 15 shows that the estimated WACC greenium is negative, too. The

baseline estimate with control variables and time-fixed effects yields a WACC greenium of -19 bps with a 95% confidence interval of $(-28, -9)$ bps per year for the sample of US firms.

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



The figure shows annual greenium estimates (in basis points) by regressing each firm's overall cost of capital on its aggregate 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 3. 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. These are available both for US firms (Panel (a)) and global firms (Panel (b)).

First, we use a dependent variable similar to earnings-to-price, but converted to the firm level, namely EBITDA-to-enterprise value. Second, we use a firm-level book-to-price ratio, namely book enterprise value relative to market enterprise value. In sum, the results based on valuation ratios show that greener firms are more expensive than brown ones in all regressions, both in the US and globally.

6.5 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 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 neatly identified. Indeed, the greenium is simply the yield difference between the green bond minus and 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).

We note that the magnitude of this sovereign greenium is not directly comparable to that of the corporate greeniums, since the sovereign bonds do not have an aggregate green score. In other words, the difference between twin bonds does not compare directly to a one standard deviation change in the aggregate green score.

In any case, the sign and significance of the sovereign greenium is of interest. 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).

7 Conclusion: Unveiling the global greenium

The greenium is important for investors, firms, policymakers, and the environment. For investors, it represents a trade-off between the potential costs of concentrating portfolios in green assets and the benefits of aligning capital with sustainability preferences. For firms, it creates both an incentive to lower their costs of capital through greener policies and a risk of facing higher financing costs if perceived as brown. For policymakers, the greenium offers a potential market-based complement to environmental regulation. For environmental outcomes, the key question is whether the greenium is large enough to meaningfully shift investment and innovation toward a green economy.

Yet investors, firms, and policymakers hold diverse views about what it means to be green, whether green firms earn higher or lower expected returns, and how large the greenium truly is. We show theoretically that market prices aggregate this disagreement into an aggregate green score, which can be inferred from the portfolio holdings of green investors. Intuitively, the firms most heavily bought by green investors enjoy higher valuations and lower costs of capital.

To estimate the aggregate green score and the magnitude of the greenium, we bring the theory to the data by combining global holdings of sustainable investors with forward-looking measures of expected returns. We find that greener firms have a 39 bps lower cost of capital per standard deviation in the aggregate green score. Figure 16 illustrates the economic magnitude by plotting the average aggregate green score of firms and portfolios against the corresponding expected return effects. For example, coal firms face an elevated cost of capital of about 30 bps, while renewables enjoy a reduction of similar magnitude. This represents a meaningful but modest cost for green investors and, in turn, a modest incentive for firms.

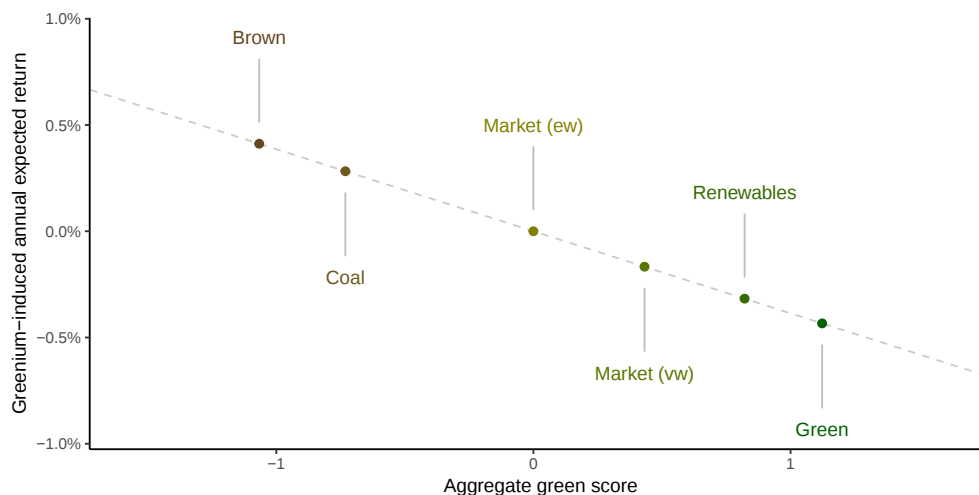
Each investor may care only about her own definition of greenness, but in equilibrium, the aggregate green score determines the cost of pursuing that strategy. We show that the greenium associated with any individual green score is simply the correlation of that score with the aggregate green score multiplied by the greenium corresponding to the aggregate

green score. In other words, an investor experiences a stronger greenium when their notion of greenness aligns with how other investors perceive greenness.

From a firm’s perspective, the cost of capital declines if it caters to the aspects of greenness valued by most investors. If investors’ preferred scores average together factors that are costly and meaningful (such as carbon emissions) with others that are cheaper to adjust, firms may face incentives to emphasize the latter.

From a policy perspective, the challenge is to ensure that the market’s aggregate view of greenness aligns with meaningful environmental goals. If markets reward superficial greenness rather than substantive environmental improvement, then the greenium may misallocate capital relative to policymakers’ objectives.

Figure 16: How big are the greenium effects?



The figure shows the equity cost of capital impact of the estimated greenium for different industries and investment portfolios. Specifically, for each industry or portfolio, we compute the average aggregate green score (the x -axis), and multiply this score by the estimated greenium of -39 bps, yielding the marginal greenium effect on their expected returns (the y -axis). The “Market (equal-weighted)” has an aggregate green score of zero as the aggregate green score is standardized to have a mean of zero across stocks; “Market (value-weighted)” uses the value-weighted average across stocks; “Green” is the tercile of stocks with the highest aggregate green score based on capped value-weights; “Brown” is the bottom tercile; “Coal” and “Renewables,” are the equal-weighted averages of stocks with a GICS code of, respectively, 10102050 and 55105020. Everything is based on global stocks.

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Internet Appendix: In Search of the True Greenium

Internet Appendix [A](#) provides the proofs of Propositions 1–6 in the main text. Internet Appendix [B](#) provides details about the data, including descriptive statistics and data conventions such as the lagging of carbon emissions data. Internet Appendix [C](#) contains details about the projection of green ownership shares on the 19 individual green scores. Internet Appendix [D](#) estimates greeniums based on realized returns, both using our aggregate green score and using green scores from the literature, performing a wide-ranging scientific replication of the literature. Internet Appendix [E](#) provides detailed results for the regressions shown in Figures in the main text. Internet Appendix [F](#) discusses the choice of standard errors. Internet Appendix [G](#) discusses further robustness tests.

A Proofs

Proof of Proposition 1. Given that $\Sigma = \text{Var}(r) = \text{Var}(\text{diag}(p)^{-1}v) = \text{diag}(p)^{-1}\bar{\Sigma}\text{diag}(p)^{-1}$, where $\bar{\Sigma} = \text{Var}(v)$, the equilibrium condition [\(5\)](#) can be written as

$$\text{diag}(p)1 = \sum_i \frac{W_i}{\gamma_i} \text{diag}(p)\bar{\Sigma}^{-1} \text{diag}(p) (\text{diag}(p)^{-1}\text{E}(v) - 1 - r^f + \eta_i \tilde{s}_i) \quad (\text{A22})$$

which can be reduced to:

$$1 = \sum_i \frac{W_i}{\gamma_i} \bar{\Sigma}^{-1} (\text{E}(v) - \text{diag}(1 + r^f - \eta_i \tilde{s}_i)p) \quad (\text{A23})$$

This equation can be simplified as

$$\bar{\Sigma}1 = \frac{W}{\gamma} (\text{E}(v) - \text{diag}(1 + r^f - \eta s)p) \quad (\text{A24})$$

using the definitions in the main text of aggregate wealth and so on.

The equilibrium price of any asset n can now be solved from [\(A24\)](#) as

$$p_n = \frac{\text{E}(v_n) - \frac{\gamma}{W} \text{Cov}(v_n, v_m)}{1 + r^f - \eta s_n} \quad (\text{A25})$$

where $v_m = 1'v$ is the payoff of the market portfolio, m . This expression solves the model by showing how each endogenous price depends on the exogenous parameters that capture

preferences and production.

To determine each security's expected excess return, $E(r_n) = \frac{E(v_n)}{p_n} - 1 - r^f$, we can rearrange (A25) as

$$E(r_n) = \frac{\gamma}{W} p_m \text{Cov}\left(\frac{v_n}{p_n}, \frac{v_m}{p_m}\right) - \eta s_n = \frac{\gamma}{W} p_m \text{Cov}(r_n, r_m) - \eta s_n \quad (\text{A26})$$

where we recall that $p_m = 1/p$ price of the market portfolio and $r_m = \frac{1'v}{1'p} - 1 - r^f$ is the market excess return. Applying this expression for the market yields a green CAPM (9). $\square$

Proof of Proposition 2. The regression of s on $\tilde{s}_i$ is

$$s = a_0 + a_1 \tilde{s}_i + \tilde{\varepsilon}_i = \rho_i \tilde{s}_i + \tilde{\varepsilon}_i \quad (\text{A27})$$

where $\tilde{\varepsilon}_i$ has mean zero and is uncorrelated with $\tilde{s}_i$ across n . Since s and $\tilde{s}_i$ are standardized to have means of zero and units variances, we have that $a_0 = E(s) - E(\tilde{s}_i) = 0$ and $a_1 = \frac{\text{Cov}(\tilde{s}_i, s)}{\text{Var}(\tilde{s}_i)} = \frac{\text{Cor}(\tilde{s}_i, s)}{1} = \rho_i$.

Hence, risk-adjusted returns can be written as

$$E(r_n) - \lambda \beta_n = g s_n = \rho_i g \tilde{s}_{i,n} + g \tilde{\varepsilon}_{i,n} = \tilde{g}_i \tilde{s}_{i,n} + g \tilde{\varepsilon}_{i,n} \quad (\text{A28})$$

The greenium with respect to green score i , $\tilde{s}_i$, is smaller in magnitude than that of the aggregate green score because $|\tilde{g}_i| = |\rho_i g| = |\rho_i| |g| < |g|$. $\square$

Proof of Proposition 3. Let $W_g = \sum_{i:\eta_i > 0} W_i$ be the aggregate wealth of the green investors and γ_g be their risk aversion, $\frac{1}{\gamma_g} = \sum_{i:\eta_i > 0} \frac{W_i}{\gamma_i W_g}$. Then with $\beta = (\beta_1, \dots, \beta_N)'$ denoting the vector of betas,

$$\begin{aligned} \sum_{i:\eta_i > 0} \frac{W_i}{W_g} x_i &= \sum_{i:\eta_i > 0} \frac{W_i}{\gamma_i W_g} \Sigma^{-1} (\lambda \beta - \eta s + \eta_i \tilde{s}_i) \\ &= \frac{1}{\gamma_g} \Sigma^{-1} (\lambda \beta - \eta s + (1 + \delta) \eta s) \\ &= \frac{1}{\gamma_g} \Sigma^{-1} (\lambda \beta + \delta \eta s) \end{aligned} \quad (\text{A29})$$

where $\delta := \frac{W/\gamma}{W_g/\gamma_g} - 1 > 0$ since $\frac{W}{\gamma} = \sum_i \frac{W_i}{\gamma_i} > \sum_{i:\eta_i > 0} \frac{W_i}{\gamma_i} = \frac{W_g}{\gamma_g}$ and we have used that $\sum_{i:\eta_i > 0} \frac{W_i}{\gamma_i W_g} \eta_i \tilde{s}_i = \frac{\eta W}{\gamma W_g} \sum_{i:\eta_i > 0} \frac{\gamma W_i}{\eta \gamma_i W} \eta_i \tilde{s}_i = \frac{\gamma_g W}{\gamma W_g} \frac{1}{\gamma_g} \eta s = \delta \eta s$. Conversely, the brown investors

with $\eta_i = 0$ tilt their portfolios away from stocks with high aggregate green score

$$\begin{aligned} \sum_{i:\eta_i=0} \frac{W_i}{W_b} x_i &= \sum_{i:\eta_i=0} \frac{W_i}{\gamma_i W_b} \Sigma^{-1} (\lambda \beta - \eta s) \\ &= \frac{1}{\gamma_b} \Sigma^{-1} (\lambda \beta - \eta s) \end{aligned} \quad (\text{A30})$$

□

Proof of Proposition 4. Using (A29) and $\beta = \Sigma m$ with $m = \frac{1}{p_m} p$, the vector of normalized green portfolio weights is

$$\begin{aligned} \theta &= \text{diag}(p)^{-1} \sum_{i:\eta_i>0} W_i x_i \\ &= \frac{W_g}{\gamma_g} \text{diag}(p)^{-1} \Sigma^{-1} (\lambda \beta + \delta \eta s) \\ &= \frac{W_g}{\gamma_g} \text{diag}(p)^{-1} \Sigma^{-1} \left(\frac{\lambda}{p_m} \Sigma p + \delta \eta s \right) \\ &= \frac{W_g}{\gamma_g} \left(\frac{\lambda}{p_m} \vec{1} + \delta \eta \text{diag}(p)^{-1} \Sigma^{-1} s \right) \end{aligned} \quad (\text{A31})$$

Next, consider the Taylor approximation

$$\theta \cong \theta(W_g = 0) + W_g \frac{\partial \theta}{\partial W_g} \Big|_{W_g=0} = W_g \frac{\partial \theta}{\partial W_g} \Big|_{W_g=0} \quad (\text{A32})$$

using that clearly $\theta = 0$ when $W_g = 0$ from (A35). We next compute the derivative in (A32) with symmetric assets at $W_0 = 0$. In this connection, note that with $W_0 = 0$ (no green investors) and symmetric assets, Σ has the form $\Sigma = a I + b \vec{1} \vec{1}'$, where $a > 0$ and $b \geq 0$ and p is of the form $p = \bar{p} \vec{1}$. Hence, $\Sigma^{-1} = \frac{1}{a} I - z \vec{1} \vec{1}'$ where $z = \frac{b}{a^2 + abN}$ using the Woodbury matrix identity. Therefore,

$$\begin{aligned} \frac{\partial \theta}{\partial W_g} \Big|_{W_g=0} &= \frac{1}{\gamma_g} \left(\frac{\lambda}{p_m} \vec{1} + \frac{\delta \eta}{\bar{p}} \left(\frac{1}{a} I - z \vec{1} \vec{1}' \right) s \right) \\ &= \frac{1}{\gamma_g} \left(\frac{\lambda}{p_m} \vec{1} + \frac{\delta \eta}{\bar{p}} \left(\frac{1}{a} s - z \vec{1} s. \right) \right) \\ &= \frac{1}{\gamma_g} \left(\left[\frac{\lambda}{p_m} - \frac{\delta \eta z s.}{\bar{p}} \right] \vec{1} + \frac{\delta \eta}{a \bar{p}} s \right) \end{aligned} \quad (\text{A33})$$

where $s = \vec{1}'s$. Standardizing θ in the cross section of stocks, yields

$$\frac{\theta - \text{mean}(\theta)}{\text{std}(\theta)} \cong \frac{s - \text{mean}(s)}{\text{std}(s)} \quad (\text{A34})$$

since the vector of ones disappears when subtracting the mean, and, further, any strictly positive multiplicative constants disappear when dividing by the cross-sectional standard deviation.

Suppose that the economy does not consist of symmetric firms, but instead has firms of different sizes. Specifically, suppose that the economy has a set of firms, which we think of as holding companies, with ownership in different plants. The set of plants is a set of symmetric assets, but the firms are not necessarily symmetric as some firms own many plants and others own few. Specifically, there N firms and N plants. The $N \times N$ matrix A of full rank summarizes the ownership structure, where A_{ij} says what fraction firm i owns of plant j . We let x_i be portfolio weights measured at the level of plants (given by the equations above), $\tilde{x}_i$ be portfolio weights measured in terms of firms, and similarly other firm-level variables indicated with tilde. Then we have $\tilde{p} = Ap$, so a large firm i with many large entries in the i 'th row of A also has a large price. Further,

$$\begin{aligned} \tilde{\theta} &= \text{diag}(\tilde{p})^{-1} \sum_{i:\eta_i>0} W_i \tilde{x}_i \\ &= \text{diag}(Ap)^{-1} \sum_{i:\eta_i>0} W_i A x_i \\ &\cong \text{diag}(\bar{p}A\vec{1})^{-1} A \sum_{i:\eta_i>0} W_i x_i \\ &\cong \text{diag}(A\vec{1})^{-1} A \frac{1}{\gamma_g} \left(\left[\frac{\lambda}{p_m} - \frac{\delta\eta z s}{\bar{p}} \right] \vec{1} + \frac{\delta\eta}{a\bar{p}} s \right) \\ &= \frac{1}{\gamma_g} \left(\left[\frac{\lambda}{p_m} - \frac{\delta\eta z s}{\bar{p}} \right] \vec{1} + \frac{\delta\eta}{a\bar{p}} \tilde{s} \right) \end{aligned} \quad (\text{A35})$$

where we use that $\text{diag}(A\vec{1})^{-1} A\vec{1} = \vec{1}$ and $\tilde{s} = \text{diag}(A\vec{1})^{-1} As$ is the vector of firm-level green scores (the weighted average of the green scores of the underlying plants). Hence, even in this more general case, we still have

$$\frac{\tilde{\theta} - \text{mean}(\tilde{\theta})}{\text{std}(\tilde{\theta})} \cong \frac{\tilde{s} - \text{mean}(\tilde{s})}{\text{std}(\tilde{s})} \quad (\text{A36})$$

□

Proof of Proposition 5. Prices are set based on (A25), but suddenly some agents' green preferences rise such that the overall green preference, η rises. As seen from (A25), this shock increases prices of green stocks with $s_i > 0$ and decreases prices of brown stocks with $s_i < 0$. The forward-looking greenium, g , becomes more negative since $g = -\eta$. □

Proof of Proposition 6.

$$x_i = \Sigma_i^{-1} (E(r) + \eta_i \tilde{s}_i). \quad (\text{A37})$$

where $\Sigma_i = \gamma_i \Sigma + \text{diag}(p)^{-2} H_i$, where $H_i \in \mathbb{R}^{N \times N}$ is the diagonal matrix with $\frac{2h}{1-h}$ in the n 'th diagonal if $n \in c_i$ and 0 if $n \notin c_i$. The market-clearing condition becomes:

$$p = \sum_i W_i x_i = \sum_i W_i \Sigma_i^{-1} (E(r) + \eta_i \tilde{s}_i) \quad (\text{A38})$$

Given that $\Sigma_i = \text{diag}(p)^{-1} (\gamma_i \bar{\Sigma} + H_i) \text{diag}(p)^{-1}$, where $\bar{\Sigma} = \text{Var}(v)$, the equilibrium can be written as

$$\text{diag}(p)1 = \sum_i W_i \text{diag}(p) (\gamma_i \bar{\Sigma} + H_i)^{-1} \text{diag}(p) (\text{diag}(p)^{-1} E(v) - 1 - r^f + \eta_i \tilde{s}_i) \quad (\text{A39})$$

This expression reduces to:

$$1 = \sum_i W_i (\gamma_i \bar{\Sigma} + H_i)^{-1} (E(v) - \text{diag}(1 + r^f - \eta_i \tilde{s}_i)p) \quad (\text{A40})$$

which can be used to derive the equilibrium prices as before.

Clearly, when $h = 0$, the global version of the green CAPM (9) holds, implying the same greenium in all countries.

As $h \rightarrow 1$, the cost of investing abroad becomes so large that portfolios are narrowed to the home country. To see this mathematically, we rename the assets such that the first ones are investor i 's home assets and the last ones are foreign ones. Then, using block inversion, we can show that Σ_i^{-1} converges to a 2-by-2 block matrix, where the top-left block is the inverse of the local assets' variance-covariance matrix and the other blocks are zero. Hence, (A37) shows that the portfolio converges to the optimal portfolio of local assets. Similarly, we

see from the equilibrium condition (A40) that an asset’s equilibrium price is only determined by the local investors in the limit. Hence, in the limit, the local version of the green CAPM holds for asset n in country c

$$E(r_n) = \lambda^c \beta_n^c + g^c s_n^c = \lambda^c \beta_n - \eta^c s_n^c \quad (\text{A41})$$

where λ^c is the risk premium in country c , $\beta_n^c = \frac{\text{Cov}(r_n, r_m^c)}{\text{Var}(r_m^c)}$ is the beta to the local market r_m^c , η^c aggregate green preference in country c , and s_n^c is the aggregate green score for asset n in country c .

□

B Data

B.1 Screens, winsorization, lag conventions, and linking

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 8, we only include firms for which the numerator (current earnings, one-year forward earnings, two-year forward earnings, or 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”).

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 share of a stock held by sustainable funds
- 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 8
- The option-implied expected returns used in Figure 9
- The subjective required and expected returns used in Figure 10

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.

Lag conventions

To ensure that the data we use is publicly available to investors and does not have look-ahead bias, we adopt the following lag conventions:

- Accounting data are assumed to be available four months after the fiscal end following [Jensen et al. \(2023\)](#).
- Trucost data are 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 \(2025\)](#). 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 are 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 are 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 would use the December 2009 rating until December 2010.
- We use Trucost data for up to three 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 five years of lag between the estimation date and firm reporting date. For example, if Trucost’s estimate for Apple’s 2009 emissions were made in 2016, we would not include this estimate.

Linking

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

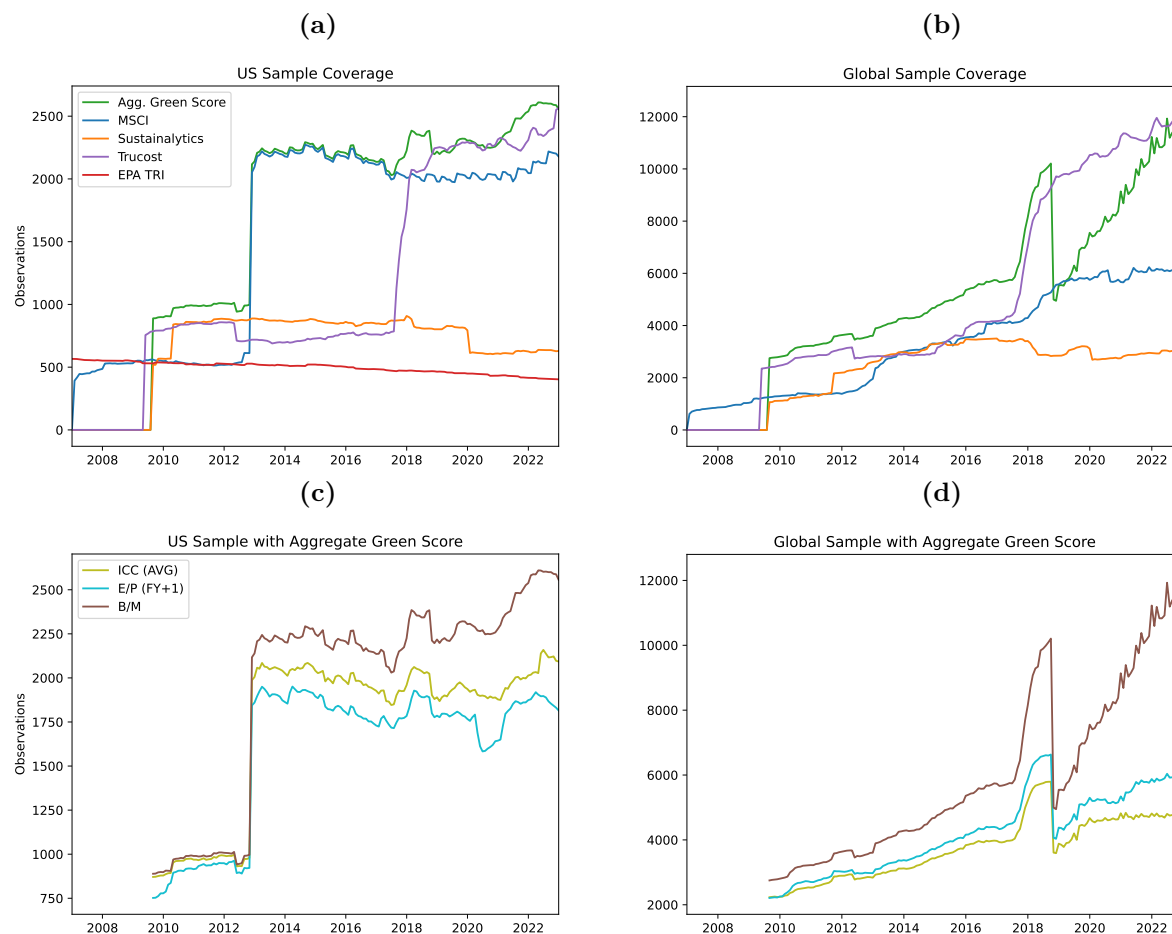
- CRSP to I/B/E/S: Linking table from WRDS (called `wrdsapps.ibcrsphist` on WRDS’s servers)
- CRSP to Compustat: Linking table from CRSP (`crsp.ccmxpf_lnkhist`)
- Trucost to Compustat: Trucost provides the Compustat GVKEY
- Morningstar/MSCI to Compustat: Linking table from Capital IQ between historical 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. \(2023\)](#)

B.2 Green scores

This subsection provides additional information about the 19 green scores that we consider in the main text, four additional measures that we use for our replication study in Internet Appendix D that are based on data from the Environmental Protection Agency (EPA and only available in the US), and the aggregate green score. Figure B1 shows how the number of stocks covered changes over time. Table B1 shows additional summary statistics for the 23 green scores. Table B2 shows summary statistics for different versions of the

aggregate green score, our baseline version being the “aggregate green score” as explained in the main text. Table B3 shows the number of unique firms with an aggregate green score in each country.

Figure B1: 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 ex-US. 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 aggregate green score, and either the average ICC measure, the one-year forward earnings-to-price ratio, or the current book-to-market ratio.

Table B1: Summary statistics for individual green scores

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%	Skewness
LOG(S1TOT)	1,183,892	9.79	2.92	5.14	7.88	9.67	11.52	15.10	0.20
LOG(S1+2TOT)	1,183,892	10.76	2.60	6.59	9.08	10.68	12.36	15.33	0.11
LOG(S1+2+3TOT)	1,183,892	12.10	2.36	8.27	10.53	12.09	13.65	16.03	-0.11
S1INT (Sales)	1,183,892	2.30	8.46	0.01	0.06	0.17	0.50	11.49	5.62
S1+2INT (Sales)	1,183,892	2.79	8.87	0.02	0.19	0.44	1.04	12.65	5.44
S1+2+3INT (Sales)	1,183,892	4.65	9.81	0.26	0.77	1.83	4.09	16.65	4.95
S1INT (Assets)	1,183,892	1.25	4.19	0.00	0.02	0.13	0.44	6.28	5.38
S1+2INT (Assets)	1,183,892	1.58	4.44	0.00	0.08	0.31	0.93	7.25	5.16
S1+2+3INT (Assets)	1,183,892	3.19	5.78	0.01	0.33	1.32	3.39	12.78	3.94
Ind.-adj. ESG score	890,220	4.70	2.28	1.40	2.93	4.60	6.40	8.40	0.10
Weighted ESG score	889,988	4.65	1.15	2.80	3.90	4.60	5.40	6.60	0.08
Environment score	890,081	4.80	2.19	1.40	3.20	4.70	6.30	8.80	0.27
Greenness (PST)	890,025	8.41	1.25	6.02	7.66	8.66	9.42	9.91	-0.93
E climate score	772,726	6.02	2.74	0.90	4.20	6.40	8.00	10.00	-0.40
E nat. res. score	569,512	4.79	2.37	1.10	3.20	4.70	6.00	9.70	0.33
E waste score	488,733	5.43	2.60	1.00	3.50	5.40	7.40	9.60	-0.05
E env. opps. score	307,738	4.26	1.60	2.00	3.10	4.00	5.30	7.20	0.56
Total ESG score	565,138	52.78	14.57	22.41	46.00	53.00	62.00	75.00	-0.65
Environmental score	565,138	49.99	18.16	14.45	39.00	50.00	62.04	79.06	-0.25
TRI (Sales)	78,149	3.43	11.12	0.00	0.02	0.20	1.58	15.91	5.97
TPWINT (Sales)	78,149	27.80	83.07	0.00	0.26	2.14	15.00	140.27	5.34
TRI (Assets)	78,149	2.67	8.71	0.00	0.01	0.17	1.51	12.84	7.18
TPWINT (Assets)	78,149	25.70	77.39	0.00	0.23	1.77	12.49	136.45	5.32

The table shows the number of observations, means, standard deviations, 5th, 25th, 50th, 75th, and 95th percentiles for 23 individual green scores. The table presents “raw scores”, meaning that they are signed as originally signed by the data providers, not as in the remaining analysis in which we sign greenness measures such that a larger score means a greener stock. This distinction matters for the first 9 greenness measures (based on Trucost carbon emissions) and the last 4 ones (based on toxic emissions data from the Environmental Protection Agency). In case a variable is winsorized, summary stats are shown using the winsorized variable. See Section B5 for a list of variables that are winsorized at the 1st and 99th percentiles. Total emissions are measured in tCO₂, then we take the natural logarithm. The emissions intensities are measured in tCO₂ per millions of dollars, divided by a factor of 100. Environmental scores are measured in the units used by MSCI and Sustainalytics. Toxic emissions are measured in pounds of emissions from all factories of a firm divided by assets or sales in millions of dollars, divided by a factor of 100. The sample is all stocks globally.

Table B2: Summary statistics for candidate aggregate green scores

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%	Skewness
Green share (%)	562,090	0.40	0.84	0.00	0.01	0.06	0.34	2.10	3.57
Green share	561,829	-0.00	1.00	-0.68	-0.42	-0.28	-0.01	1.74	4.72
Log(green share)	561,829	0.00	1.00	-1.57	-0.70	-0.04	0.74	1.59	-0.05
Rank(green share)	561,829	0.00	1.00	-1.55	-0.86	0.00	0.86	1.55	-0.00
IV(green share)	1,442,832	-0.00	1.00	-1.64	-0.39	0.03	0.25	1.74	0.21
IV(log(green share))	1,442,832	0.00	1.00	-1.69	-0.40	0.06	0.29	1.73	-0.13
IV(rank(green share))	1,442,832	0.00	1.00	-1.70	-0.40	0.06	0.29	1.73	-0.12
Aggregate green score	1,282,728	0.00	1.00	-1.59	-0.66	0.05	0.63	1.60	-0.04

The table shows the number of observations, means, standard deviations, 5th, 25th, 50th, 75th, and 95th percentiles for green ownership and the six candidate aggregate green scores. *green share (%)*, henceforth, GS, is the share of a stock's market cap owned by funds that have been designated as "sustainable" by Morningstar. The remaining measures are candidate proxies for the aggregate green score. They are all based on some transformation of GS, after trimming it at 1% and 99%, and they are all standardized to have a mean of zero and a variance of one within each country and date. *green share* is based on the raw value of GS; *log(green share)* is the log of GS; *rank(green share)* is the rank of GS within each country and date; The variables starting with IV is the projection of the three before mentioned measures on individual greenness measures, as explained in Section 3. The aggregate green score is based on *rank(green share)* before October 2018, and *IV(rank(green share))* after. The green shares variable is winsorized at the 1st and 99th percentiles. The sample is all stocks globally.

Table B3: Number of unique firms by country with aggregate green score

Exchange Country	N	Region/Area	Continent	Country
ARE	70	South West Asia	Asia	United Arab Emirates
ARG	27	CS America	Americas	Argentina
AUS	827	Pacific	Oceania	Australia
AUT	50	Western Europe	Europe	Austria
BEL	96	Western Europe	Europe	Belgium
BGD	15	South Asia	Asia	Bangladesh
BRA	222	CS America	Americas	Brazil
CAN	591	North America	Americas	Canada
CHE	234	Western Europe	Europe	Switzerland
CHL	71	CS America	Americas	Chile
CHN	3087	East Asia	Asia	China
CIV	16	Africa	Africa	Cote d'Ivoire
COL	34	CS America	Americas	Colombia
DEU	437	Western Europe	Europe	Germany
DNK	84	Northern Europe	Europe	Denmark
EGY	46	Africa	Africa	Egypt
ESP	136	Western Europe	Europe	Spain
FIN	127	Northern Europe	Europe	Finland
FRA	444	Western Europe	Europe	France
GBR	1017	Western Europe	Europe	United Kingdom
GRC	50	CE Europe	Europe	Greece
HKG	1179	East Asia	Asia	Hong Kong (China)
IDN	247	South East Asia	Asia	Indonesia
IND	978	South Asia	Asia	India
IRL	30	Western Europe	Europe	Ireland
ISL	12	Northern Europe	Europe	Iceland
ISR	164	South West Asia	Asia	Israel
ITA	305	Western Europe	Europe	Italy
JPN	2413	East Asia	Asia	Japan
KEN	17	Africa	Africa	Kenya
KOR	1403	East Asia	Asia	Korea, South
KWT	30	South West Asia	Asia	Kuwait
LKA	23	South Asia	Asia	Sri Lanka
MAR	32	Africa	Africa	Morocco
MEX	92	CS America	Americas	Mexico
MYS	356	South East Asia	Asia	Malaysia
NGA	27	Africa	Africa	Nigeria
NLD	116	Western Europe	Europe	Netherlands
NOR	251	Northern Europe	Europe	Norway
NZL	90	Pacific	Oceania	New Zealand
OMN	10	South West Asia	Asia	Oman
PAK	72	South Asia	Asia	Pakistan
PER	37	CS America	Americas	Peru
PHL	102	South East Asia	Asia	Philippines
POL	118	CE Europe	Europe	Poland
PRT	29	Western Europe	Europe	Portugal
QAT	39	South West Asia	Asia	Qatar
ROU	13	CE Europe	Europe	Romania
RUS	90	CE Europe	Europe	Russia
SAU	146	South West Asia	Asia	Saudi Arabia
SGP	194	South East Asia	Asia	Singapore
SWE	479	Northern Europe	Europe	Sweden
THA	332	South East Asia	Asia	Thailand
TUR	160	South West Asia	Asia	Turkey
TWN	1150	East Asia	Asia	Taiwan
USA	4468	North America	Americas	United States
VNM	37	South East Asia	Asia	Vietnam
ZAF	193	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.

B.3 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, Gyntelberg, and Thimsen \(2022\)](#). Note that while [Mohanram and Gode \(2013\)](#) adjust 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

$$p_t = \sum_{h=1}^{\infty} \frac{E_t[d_{t+h}]}{(1+r)^h}, \quad (B42)$$

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

$$ICC^{OJ} = A + \sqrt{A^2 + \frac{\hat{E}_t[e_{t+1}]}{p_t}} \times (STG - \lambda), \quad (B43)$$

where

$$A = \frac{1}{2} \left(\lambda + \frac{\hat{E}_t[d_{t+1}]}{p_t} \right) \quad \text{and} \quad STG = \max \left[\left(\frac{\hat{E}_t[e_{t+2}] - \hat{E}_t[e_{t+1}]}{\hat{E}_t[e_{t+1}]} \times LTG \right)^{\frac{1}{2}}, LTG \right]. \quad (B44)$$

Here, $\hat{E}_t[e_{t+1}]$ and $\hat{E}_t[e_{t+2}]$ 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.²¹ 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

²¹[Ohlson and Juettner-Nauroth \(2005\)](#) define STG as the two-year growth in earnings, $\frac{\hat{E}_t[e_{t+2}] - \hat{E}_t[e_{t+1}]}{\hat{E}_t[e_{t+1}]}$, 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.

follow [Mohanram and Gode \(2013\)](#) and estimate it as the yield on a ten-year US treasury bond minus 3%.

The [Easton \(2004\)](#) method is inspired by the price-earnings-growth (PEG) ratio. It is a simplification of [\(B43\)](#) that sets $\lambda = 0$ and ignores dividends, leading to

$$ICC^{PEG} = \sqrt{\frac{\hat{E}_t[e_{t+1}]}{p_t}} \times STG, \quad (B45)$$

where the input are estimated as in [\(B43\)](#).

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:

$$p_t = b_t + \sum_{h=1}^{\infty} \left(\frac{E_t[(ROE_{t+h} - r)b_{t+h-1}]}{(1+r)^h} \right), \quad (B46)$$

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:

$$p_t = b_t + \sum_{h=1}^{11} \left(\frac{\hat{E}_t[(ROE_{t+h} - ICC^{GLS})b_{t+h-1}]}{(1 + ICC^{GLS})^h} \right) + \frac{\hat{E}_t[(ROE_{t+12} - ICC^{GLS})b_{t+11}]}{ICC^{GLS}(1 + ICC^{GLS})^{11}}. \quad (B47)$$

Here, the return on equity is computed as

$$\hat{E}_t[ROE_{t+h}] = \frac{\hat{E}_t[e_{t+h}]}{b_{t+h-1}}, \quad (B48)$$

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

$$b_t = b_{t-1} + e_t - d_t. \quad (B49)$$

where $d_t = e_t \times \text{payout-ratio}$ 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:

$$p_t = b_t + \sum_{h=1}^5 \left(\frac{\hat{E}_t [(ROE_{t+h} - ICC^{CT})b_{t+h-1}]}{(1 + ICC^{CT})^h} \right) + \frac{\hat{E}_t [(ROE_{t+5} - ICC^{CT})b_{t+4}(1 + g)]}{(ICC^{CT} - g)(1 + ICC^{CT})^5}, \quad (B50)$$

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%.

B.4 Valuation ratios, option-implied expected returns, subjective expected/required returns

Valuation ratios. In present-value models, valuation ratios are simple measures of forward-looking expected returns. We consider four different 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-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.

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 or a negative number. 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.

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. \(2023\)](#).²² 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. However, in contrast to ICCs and valuation ratios, option-implied expected returns are only available for US stocks. The data are at a daily frequency, but we convert them to the monthly frequency by taking the average of daily expected returns within each month, following [Chabi-Yo et al. \(2023\)](#).

Subjective expected/required returns. As final measures of forward-looking expected returns, we consider analysts’ subjective required and expected returns, relying on the measures in [Jensen \(2023\)](#). Subjective required and expected returns are available in the US, but not globally. 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.²³ 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. These expected returns are then annualized using geometric compounding.²⁴

²²The data are provided by Grigory Vilkov at doi.org/10.17605/OSF.IO/Z2486.

²³The 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.

²⁴For a detailed description of how the subjective expected returns are constructed, see [Jensen \(2023, Section A.2.2\)](#).

B.5 Descriptive statistics

This subsection provides descriptive statistics. Table B4 shows descriptive statistics for stock return and firm characteristics. Table B5 shows descriptive statistics for the implied cost of capital measures and valuation ratios. Table B6 shows descriptive statistics for the option-implied expected returns. Table B7 shows descriptive statistics for bond yields and characteristics.

Table B4: Summary statistics stock return and firm characteristics

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%
Exc. Ret. (leading)	1,267,874	0.54	12.26	-17.14	-5.62	0.21	6.08	18.98
LOG(ME)	1,282,728	7.40	1.65	4.80	6.25	7.37	8.48	10.22
LOG(Assets)	1,282,728	7.78	1.92	4.87	6.45	7.67	8.97	11.14
LOG(BE)	1,282,728	6.80	1.67	4.18	5.67	6.77	7.88	9.63
Debt/Assets	1,276,432	0.23	0.18	0.00	0.07	0.21	0.35	0.57
Cash/Assets	1,276,758	0.16	0.16	0.01	0.05	0.11	0.21	0.51
NetDebt/Assets	1,270,656	0.07	0.28	-0.44	-0.09	0.09	0.26	0.49
EBIT/Assets	1,281,518	0.06	0.10	-0.06	0.02	0.06	0.10	0.21
Beta (252D)	1,267,095	1.01	0.38	0.43	0.75	0.98	1.24	1.70

The table shows summary statistics for realized returns and various control variables, for the sample with a non-missing aggregate green score. In case a variable is winsorized, summary stats are shown using the winsorized variable. See Section for a list of variables that are winsorized at the 1st and 99th percentiles.

Table B5: Summary statistics ICCs and valuation ratios

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%
ICC	886,227	9.26	3.79	4.12	6.82	8.70	11.02	16.34
ICC (GLS)	820,958	8.82	3.59	3.38	6.42	8.54	10.83	15.17
ICC (CT)	448,763	8.51	4.48	3.21	5.74	7.60	10.07	17.11
ICC (OJ)	399,943	10.92	4.60	5.75	8.09	9.89	12.44	19.79
ICC (PEG)	452,339	9.58	3.97	4.81	7.09	8.81	11.06	17.25
E/P (latest)	909,541	7.10	5.56	1.40	3.83	5.83	8.64	16.90
E/P (FY+1)	937,318	7.20	4.77	1.82	4.31	6.24	8.80	15.66
E/P (FY+2)	971,180	8.13	4.99	2.42	5.09	7.14	9.85	16.98
EBITDA/MEV	1,176,481	12.90	12.82	2.33	6.36	9.97	15.13	31.45
B/M	1,282,728	0.85	0.99	0.10	0.31	0.59	1.02	2.33
BEV/MEV	1,247,669	0.77	0.73	0.08	0.34	0.65	1.00	1.73

The table shows summary statistics for various implied cost of capital measures and valuation ratios that we use to study the equity and firm greenium, for the sample with a non-missing aggregate green score. In case a variable is winsorized, summary stats are shown using the winsorized variable. See Section for a list of variables that are winsorized at the 1st and 99th percentiles.

Table B6: Summary statistics option-implied expected returns

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%
SVIX (30D)	93,303	6.67	8.47	0.56	2.22	4.34	8.02	20.11
SVIX (91D)	93,299	5.96	6.36	1.03	2.39	4.10	7.19	16.98
SVIX (182D)	93,287	5.87	5.61	1.32	2.60	4.21	7.07	15.87
GLB (30D)	92,870	9.22	9.33	1.95	4.14	6.80	11.25	23.25
GLB (91D)	92,866	7.71	6.43	1.87	3.83	5.82	9.53	19.30
GLB (182D)	92,854	7.29	5.54	1.83	3.76	5.60	9.19	17.82

The table shows summary statistics for various option-implied expected return measures that we use to study the equity greenium, for the sample with a non-missing aggregate green score. SVIX refers to the measure from [Martin and Wagner \(2019\)](#) and GLB to the generalized lower bound measure from [Chabi-Yo et al. \(2023\)](#).

Table B7: Summary statistics bond yields and characteristics

	<i>N</i>	Mean	Std. Dev.	5%	25%	50%	75%	95%
Time to maturity	98,820	8.62	4.86	3.00	5.18	7.19	11.42	17.64
Coupon rate	98,820	5.32	1.62	2.95	4.15	5.20	6.38	8.06
Rating (numeric)	98,820	9.66	3.39	5.00	7.10	9.00	12.00	16.00
Yield	98,029	4.39	4.10	1.71	2.82	3.74	5.15	8.03
Yield spread	93,445	2.70	4.19	0.60	1.08	1.76	3.32	6.61
Yield (adj.)	98,029	3.67	3.69	1.36	2.66	3.53	4.56	6.60
Yield spread (adj.)	93,445	1.95	3.75	0.46	0.99	1.55	2.65	5.03
Market leverage	98,820	36.14	90.86	3.40	10.18	19.64	39.05	107.03

The table shows summary statistics for various bond characteristics that we use to study the corporate bond greenium, for the sample with a non-missing aggregate green score.

C Projection of green ownership on 19 green scores

To create the aggregate green score before October 2018, we project green ownership share (and its log and rank-based transformation) on 19 individual green scores and controls. Specifically, we estimate the following regression:

$$g(\text{green share}_t^n) = \alpha_{c,t} + \sum_{j=1}^{19} g_j s_t^{n,j} + \text{controls} + \epsilon_t^n, \quad (\text{B51})$$

where $g(x)$ is either the identity function, the natural logarithm, or the rank within each country and time, $\alpha_{c,t}$ is a country-time fixed effect, $s_t^{n,j}$ is one of 19 individual green scores, standardized to have a mean of zero and a variance of one within each country and time, and the controls are market beta, log of book equity, net debt-to-assets, and EBIT-to-assets. We impose a non-negativity constraint on the parameters associated with the individual green scores to reflect our prior that a stock's perceived greenness is positively (or at least not negatively) related to individual green scores. We also experimented with adding a ridge penalty to the objective function but found, using five-fold cross-validation, that the optimal ridge penalty was zero. We estimate this projection using green ownership data from 2018 to 2022.

We require the green ownership share, the control variables, and at least one of the individual green scores to be non-missing. To handle outliers in the green ownership share, we also exclude observations below the 1st percentile and above the 99th percentile. To increase our coverage, we impute missing observations for the individual green scores using the mean within the same country and time. Finally, we standardize the dependent variable to a mean of zero and a variance of one within each country and time.

We create the projected aggregate green score as a weighted average of the 19 individual green scores, where the weights are given by the (rescaled) parameter estimates from Equation (B51). The weights are shown in Figure 2.

D Greenium estimates via realized returns

D.1 Realized returns and the aggregate green score

To measure the greenium based on realized returns, we use realized returns in Equation (17). The standard errors 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 returns, this makes little difference.

Figure D1 shows the results from estimating these regressions. While this figure shows the estimated greenium and its confidence interval graphically, we report their precise numerical values of all regressions in Internet Appendix Tables E1-E17.

The left panel in Figure D1 shows that the estimated greenium is positive, but not statistically different from zero in all samples. The middle and right panels show the results when we add an increasing number of control variables and fixed effects to the specification in Equation (17). 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. Either way, we do not find evidence of a significant return difference in realized returns between green and brown stocks.

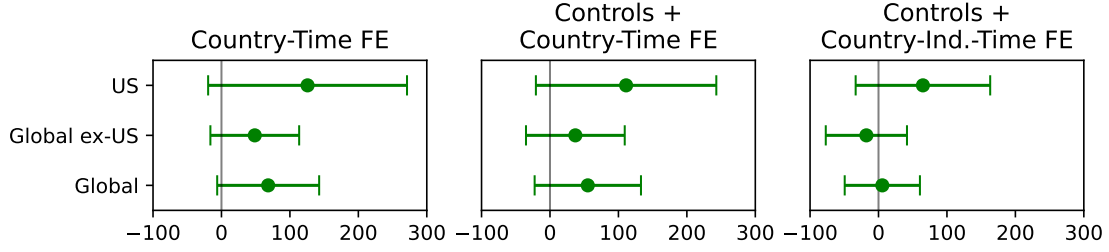
We argue that the time series of realized returns is too short to identify the greenium. In fact, our baseline greenium estimate of -39 bps based on forward-looking expected returns implies that one needs 167 years of data to find a t -statistic that is larger than 1.96 for a portfolio that is long the top tercile of green stocks and short the bottom tercile of green stocks. For details regarding this calculation and a replication study of the green finance literature that uses realized returns, see Internet Appendix D.3.

D.2 Scientific replication of the literature

The literature contains a wide range of greenium estimates. In fact, the various papers even disagree on whether green stocks have under- or outperformed.²⁵

²⁵A 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 et al., 2018; In et al., 2019; Cheema-Fox et al., 2021a,b; Giese et al., 2021; Huij et al., 2021; Ardia et al., 2022; Bauer et al.,

Figure D1: Regressions of realized returns on aggregate green score



The figure shows the annual greenium (in basis points) estimated by regressing (annualized) one-month-ahead stock returns on the aggregate green score and control variables, see Equation (17). The control variables are market beta, log book equity, net debt-to-assets, and EBIT-to-assets. The aggregate 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; in the third row, the sample is all stocks globally. The figure also shows 95% confidence bands based on standard errors clustered by industry and month.

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 large economically, but when we construct a similar factor using their greenness measure in an updated sample, we find an insignificant effect.

[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 \(2025\)](#) 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 \(2025\)](#) 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 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. \(2022\)](#)

2022; [Pástor et al., 2022](#); [Zhang, 2025](#); [Berg et al., 2023](#); [Karolyi et al., 2023](#)), papers that find the opposite (see, e.g., [Alessi et al., 2020](#); [Bolton and Kacperczyk, 2021, 2023](#); [Hsu et al., 2023](#)), and papers that find no significant difference (see, e.g., [Görgen et al., 2020](#); [Pedersen et al., 2021](#); [Aswani et al., 2024](#); [Alves et al., 2025](#); [Lindsey et al., 2023](#)).

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. 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). To further account for the variation across papers, we test the significance of the corresponding risk-adjusted returns using five common risk controls (average 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.

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.

Figure D2 shows the distribution of our replicated global t -statistics as well as the distribution of t -statistics reported in the literature. The distribution of replicated global t -statistics is bell-shaped with a center near zero, consistent with these t -statistics all being insignificant when accounting for multiple testing. The literature’s distribution is over-sampled in the left and right tail (consistent with publication bias) and contains a particularly extreme left tail that does not overlap with our replication distribution (consistent with the literature using ESG measures with look-ahead bias).

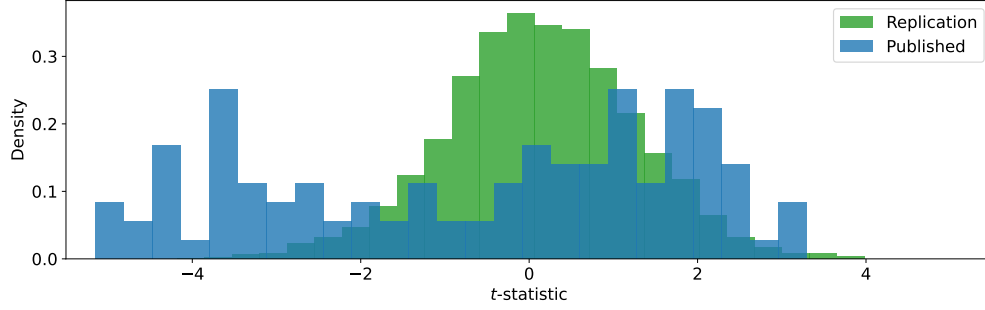
To shed light on the source of these widespread robustness issues, we show that a GMB factor based on the aggregate green score has a low predicted annual Sharpe ratio of -0.10 , computed as the ratio of the modest greenium (estimated using forward-looking returns, defined below) to the high realized GMB volatility. This low Sharpe ratio implies that one needs around 400 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.

D.2.1 Greenness measures

We consider 23 greenness measures. The 23 greenness measures cover greenness measures considered in the literature and Table 1 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. The idea is to construct a

Figure D2: Distribution of t -statistics of green-minus-brown portfolios globally



The figure plots the distribution of our replicated t -statistics for the alphas of global green-minus-brown portfolios, and the distribution of published t -statistics. See Table D6 for the list of published t -statistics.

comprehensive set of greenness measures that researchers could have plausibly considered ex ante to mitigate the effects of publication bias (i.e., the tendency of statistically significant results to be more likely to be published than insignificant results). For each measure, we seek to only use the data when they are available to investors and lag the data appropriately.

D.2.2 Replication problems: portfolio sorts

For each of the 23 greenness measures, we construct an industry-neutral and an industry-agnostic green-minus-brown portfolio. This process yields $2 \times 23 = 46$ GMB factors.

We use this method to encompass both the papers in the literature that focus on industry-agnostic portfolios (e.g., [Pástor et al., 2022](#); [Zhang, 2025](#)) and those that focus on within-industry variation (e.g., [Bolton and Kacperczyk, 2021, 2023](#); [Hsu et al., 2023](#)). Both approaches are reasonable ex ante—the decision of whether to adjust for industry reflects the usual trade-off between mitigating omitted variable bias at the cost of eliminating potentially interesting variation.

Starting with the US, to construct each industry-agnostic 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

Table D1: Greenness measures

Name	Source	References
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 (2025)
S1+2INT (Sales)	Trucost	Griffin, Lont, and Sun (2017), Garvey et al. (2018) ^a , Grgen et al. (2020) ^a , Cheema-Fox et al. (2021a), Cheema-Fox et al. (2021b), 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. (2021b), 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), Grgen et al. (2020), Berg et al. (2023), Lindsey et al. (2023)
Total ESG score	Sustainalytics	Alves et al. (2025), Lindsey et al. (2023)
Environmental score	Sustainalytics	Engle et al. (2020), Grgen et al. (2020), Seltzer, Starks, and Zhu (2022), Alves et al. (2025), Lindsey et al. (2023)
LOG(S1TOT)	Trucost	Bolton and Kacperczyk (2021, 2023), Aswani et al. (2024), Atilgan et al. (2023), Zhang (2025)
LOG(S1+2TOT)	Trucost	Huij et al. (2021), Bauer et al. (2022) ^a
LOG(S1+2+3TOT)	Trucost	Matsumura, Prakash, and Vera-Muoz (2014) ^{a,b} , Delmas, Nairn-Birch, and Lim (2015) ^c , Busch et al. (2022) ^c
Ind.-adj. ESG score	MSCI	Grgen et al. (2020), Pedersen et al. (2021), Alves et al. (2025), Ang et al. (2023), Berg et al. (2023), Berg et al. (2023), Lindsey et al. (2023)
Greenness (PST)	MSCI	Pstor et al. (2022), Karolyi et al. (2023)
E climate score	MSCI	Cheema-Fox et al. (2021b), Kacperczyk and Peydr (2022) ^c
E nat. res. score	MSCI	Kacperczyk and Peydr (2022) ^c
E waste score	MSCI	Kacperczyk and Peydr (2022) ^c
E env. opps. score	MSCI	Cheema-Fox et al. (2021b), Kacperczyk and Peydr (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

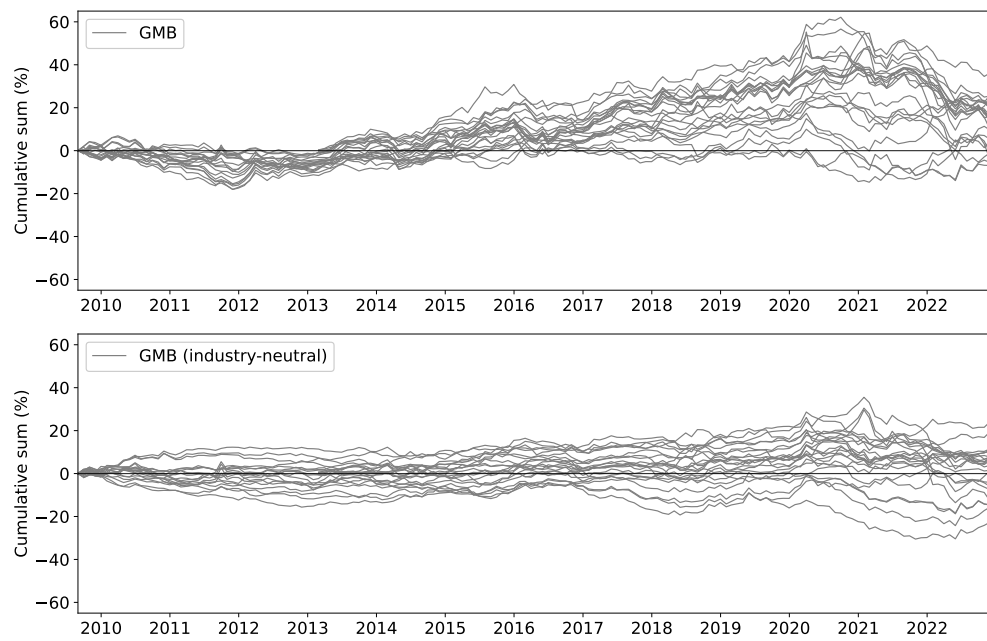
The table shows data sources for 23 individual greenness measures. The table also shows the academic papers which use a particular greenness measure when studying realized financial performance, in particular realized stock returns. S1TOT, S1+2TOT, and S1+2+3TOT refer to the absolute amount of carbon 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. Scope 3 refers only to upstream emissions as downstream emissions are only available from 2017. Greenness (PST) refers to the measure of Pstor 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 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 using toxic releases (which are arguably more relevant for pollution than the toxic production waste used in Hsu et al. (2023)) and which we then scale as in Hsu et al. (2023).

bottom tercile (the brown portfolio return).

Figure D3 shows the cumulative returns of the 46 GMB portfolios that we construct based on the 23 greenness measures in the US sample. As seen in the figure, the returns are noisy over a short sample period and vary across the greenness measures.

For each of the 46 factors, we compute the alpha in five different ways to account for risk

Figure D3: Replicated Green-Minus-Brown Portfolios in the US



The figure plots the cumulative sum of realized returns of 46 green-minus-brown (GMB) US equity factors constructed using 23 different greenness measures with either an industry-agnostic (top panel) or industry-neutral (bottom panel) approach.

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).

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).²⁶

Tables D2 and D3 show the t -statistics of the 46 US GMB factors’ returns, constructed both industry-neutral and industry-agnostic, corresponding to each greenness measure with respect to the different factor models. The tables show that the vast majority of t -statistics are close to zero. Further, for the small minority of significant greeniums, the greenium for the same greenness measure is insignificant when using another risk model or another industry adjustment. This low degree of significant results is consistent with the mixed picture of cumulative GMB returns in Figure D3.

D.2.3 Pure vs. scientific replication: Relation to literature

Our results in Tables D2 and D3 present our “scientific replication” of the literature, meaning that we examine the results from the literature using a common framework for all greenness measures, rather than following each paper’s specific steps using exactly the same sample as in “pure replication” or “reproduction.”

The advantage of scientific replication is that it shows the robustness of the literature’s results to (a) extending the sample over time and countries; (b) considering different risk models; and (c) a standard framework (not tailored to finding a significant effect for a specific measure); and (d) a unified framework, which makes the various greenium estimates comparable.

That said, it is interesting to relate our results to those in the literature. To be clear, we are not saying that the literature’s results cannot be reproduced if following each paper’s exact method. To the contrary, we now show that several results from the literature can be reproduced. Our point is that these results are rather special, relying on a specific greenness measure, time period, and methodology.

We first consider a reproduction of Pástor et al. (2022) (henceforth “PST”). Columns (1)–

²⁶The 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).

Table D2: 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}	$t(\alpha^{q5})$
LOG(S1TOT)	0.11	0.07	0.37	-0.05	-0.27	-0.01	-0.07	0.29	2.87	0.17	1.36
LOG(S1+2TOT)	0.06	0.05	0.21	-0.06	-0.25	-0.00	-0.03	0.31	2.97	0.22	1.59
LOG(S1+2+3TOT)	-0.06	-0.05	-0.21	-0.13	-0.51	-0.08	-0.47	0.24	2.45	0.18	1.34
S1INT (Sales)	0.24	0.13	0.84	0.11	0.67	0.10	0.66	0.28	2.22	0.13	0.97
S1+2INT (Sales)	0.25	0.13	0.90	0.10	0.63	0.09	0.65	0.29	2.48	0.14	1.04
S1+2+3INT (Sales)	0.15	0.09	0.52	0.08	0.46	0.07	0.50	0.30	2.53	0.18	1.31
S1INT (Assets)	0.20	0.11	0.69	0.07	0.39	0.06	0.39	0.28	2.32	0.13	0.90
S1+2INT (Assets)	0.17	0.09	0.59	0.04	0.24	0.04	0.25	0.29	2.80	0.15	1.05
S1+2+3INT (Assets)	-0.02	-0.01	-0.05	-0.07	-0.43	-0.06	-0.44	0.22	2.22	0.09	0.72
Ind.-adj. ESG score	0.43	0.16	1.66	0.23	2.78	0.20	2.94	0.17	2.29	0.08	1.14
Weighted ESG score	0.38	0.16	1.46	0.23	2.18	0.19	2.03	0.13	1.32	0.00	0.05
Environment score	0.25	0.13	0.87	0.21	1.29	0.12	1.09	0.18	1.53	0.08	0.69
Greenness (PST)	0.03	0.02	0.10	0.02	0.12	-0.02	-0.08	0.24	1.28	-0.02	-0.10
E climate score	0.49	0.32	1.36	0.41	1.57	0.30	2.73	0.27	2.15	0.23	1.48
E nat. res. score	0.40	0.22	1.25	0.35	1.82	0.26	1.82	0.25	1.86	0.19	1.36
E waste score	0.22	0.19	0.75	0.49	1.71	0.40	2.13	0.34	1.77	0.27	1.37
E env. opps. score	0.07	0.04	0.23	0.13	0.77	0.07	0.45	0.04	0.31	-0.02	-0.16
Total ESG score	-0.01	-0.00	-0.02	0.12	1.03	0.10	1.06	-0.02	-0.24	-0.09	-0.94
Environmental score	0.31	0.15	1.09	0.27	2.02	0.24	2.29	0.10	1.03	0.05	0.52
TRI (Sales)	0.12	0.06	0.67	0.05	0.47	0.10	1.08	0.19	1.96	0.10	1.02
TPWINT (Sales)	-0.01	-0.00	-0.04	0.08	1.10	0.11	1.50	0.13	1.57	0.09	1.13
TRI (Assets)	0.13	0.07	0.66	0.07	0.70	0.13	1.44	0.22	2.17	0.10	1.02
TPWINT (Assets)	0.02	0.01	0.13	0.13	1.53	0.16	2.05	0.18	2.04	0.12	1.31

The table shows Sharpe ratios (SR) as well as alphas and their corresponding t -statistics for 23 green-minus-brown (GMB) equity factors. The 23 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 23 greenness measures are the 23 individual greenness measures from Table 1. 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. Standard errors are Newey and West (1987) adjusted with three lags.

(3) of Table D4 reproduce Columns (1)–(3) of Table 3 in PST, who form a GMB factor based on a transformation of MSCI’s ESG scores. Column (4) considers alphas with respect to the Fama-French five-factor model augmented with momentum, which we consider throughout our paper, but they do not. We can reproduce the results in PST. For instance, they find a 65 basis points monthly mean excess return of their green-minus-brown (GMB) factor, whereas we find a 71 basis points monthly excess return.

However, Columns (5)–(8) of Table D4 show that the GMB factor has insignificant excess returns and alphas when we extend the sample period forward by two years until December 2022. We also extend their sample backward until February 2007 and Columns (9)–(12) show that, once again, the GMB factor has insignificant excess returns and alphas. The number of firms covered when backward extending is smaller than the number of firms covered after

Table D3: 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}	$t(\alpha^{q5})$
LOG(S1TOT)	0.00	0.00	0.02	0.00	0.01	0.02	0.24	0.05	0.69	0.11	1.32
LOG(S1+2TOT)	-0.12	-0.06	-0.41	-0.07	-0.40	-0.04	-0.45	0.00	0.01	0.07	0.70
LOG(S1+2+3TOT)	-0.18	-0.10	-0.60	-0.08	-0.43	-0.04	-0.47	-0.01	-0.06	0.09	0.83
S1INT (Sales)	0.23	0.06	0.85	0.07	0.89	0.05	0.78	0.04	0.64	0.04	0.54
S1+2INT (Sales)	0.20	0.05	0.76	0.08	1.06	0.07	1.27	0.04	0.81	0.06	0.93
S1+2+3INT (Sales)	0.15	0.04	0.62	0.06	0.71	0.05	1.01	0.06	1.18	0.07	1.28
S1INT (Assets)	0.06	0.02	0.20	-0.02	-0.25	-0.04	-0.52	0.00	0.03	-0.00	-0.05
S1+2INT (Assets)	-0.07	-0.02	-0.26	-0.06	-0.73	-0.08	-1.21	-0.05	-0.69	-0.02	-0.29
S1+2+3INT (Assets)	-0.12	-0.03	-0.48	-0.09	-1.32	-0.10	-1.62	-0.04	-0.68	-0.02	-0.28
Ind.-adj. ESG score	0.29	0.09	1.02	0.15	2.00	0.14	2.19	0.09	1.55	0.04	0.58
Weighted ESG score	0.45	0.15	1.60	0.22	2.82	0.20	3.01	0.16	2.29	0.10	1.48
Environment score	0.27	0.09	1.03	0.14	1.55	0.11	1.50	0.09	1.09	0.05	0.68
Greenness (PST)	0.20	0.07	0.84	0.11	1.30	0.08	1.19	0.08	1.25	0.06	0.92
E climate score	0.54	0.22	1.55	0.31	2.18	0.21	2.57	0.17	2.33	0.10	1.43
E nat. res. score	0.15	0.07	0.48	0.23	1.90	0.15	1.70	0.11	1.26	0.07	0.73
E waste score	0.22	0.09	0.80	0.19	1.60	0.14	1.34	0.08	0.79	0.06	0.58
E env. opps. score	0.11	0.04	0.44	0.04	0.40	0.00	0.01	0.04	0.49	0.02	0.22
Total ESG score	0.04	0.01	0.17	0.05	0.61	0.04	0.64	-0.00	-0.05	-0.08	-1.23
Environmental score	0.15	0.05	0.61	0.08	0.97	0.06	0.91	0.02	0.27	-0.05	-0.85
TRI (Sales)	0.00	0.00	0.01	0.09	1.19	0.11	1.59	0.13	1.67	0.11	1.37
TPWINT (Sales)	-0.13	-0.05	-0.72	0.02	0.35	0.03	0.51	0.06	0.85	0.07	0.90
TRI (Assets)	0.01	0.00	0.06	0.07	0.97	0.10	1.37	0.12	1.57	0.10	1.24
TPWINT (Assets)	-0.20	-0.08	-1.13	-0.01	-0.17	0.00	0.03	0.06	0.96	0.07	0.98

The table is similar to Table D2, but shows results for industry-neutral GMB equity factors.

2012, but still at around 500, see Figure B1.

Since our main analysis uses a common sample period until December 2022 for all greenness measures, it is not surprising that our scientific replication in Table D2 shows insignificant excess returns and alphas for industry-agnostic factors based on their greenness measure. It is also not surprising that Table D3, which uses industry-neutral factors, shows insignificant excess returns and alphas throughout, as PST’s own results show insignificant results for an industry-neutral factor (see their Figure 8).

Further, PST emphasize that realized returns of the GMB factor need to be purged from unexpected shocks to climate concerns and cash-flow news. Once purged, the constant in a regression of the GMB factor’s return on climate change concern shocks and cash-flow news is an estimate of the greenium.

Columns (1) and (2) of Table D5 replicate Columns (1) and (2) of Table 4 in PST. As in the original paper, we find a significant effect of changes in climate concerns on the GMB factor. However, this effect largely turns insignificant when we extend the sample forward by two years in Columns (3) and (4), and backward until February 2007. Columns (7)–

(12) show similar results with Fama-French three-factor alphas as opposed to excess returns of the GMB factor as the dependent variables. In any case the key quantity of interest—the greenium as measured by the constant—is not statistically different from zero in all specifications, even in PST’s original results.

Finally, Figure D4 shows the performance of the original GMB factor that is not industry-adjusted over time and compares with PST’s Figure 8. The figure also shows the climate change concerns index of Ardia et al. (2022) (used by PST). Climate change concerns continued to increase until 2022, yet the GMB factor return reversed.

The second paper we reproduce is Zhang (2025). Zhang (2025) focuses on industry-agnostic GMB portfolios sorted on carbon intensity (appropriately lagged scope 1 or scope 2 carbon emissions scaled by year-end sales) from June 2009 to December 2021. Figure D5 reproduces Zhang (2025)’s GMB factor’s return based on scope 1 carbon emissions scaled by sales as in her Figure 2. Once again, we can reproduce her results, but when we extend the sample forward by one year, the GMB factor’s returns partially reverse. Thus, it is not surprising that our scientific replication in Table D2 shows no evidence of significant excess returns for a GMB factor formed based on scope 1 carbon emissions scaled by sales (S1INT (Sales)). The monthly mean excess return for this factor is only 13 basis points.

There is evidence of significant Fama-French six-factor alphas in our Table D2—the factor model considered by Zhang (2025)—for portfolios formed based on scope 1 carbon emissions scaled by sales. However, these are not robust to the factor model (i.e., there are no significant CAPM, Fama-French three-factor, or $q5$ -factor alphas). Moreover, these alphas, which are significant using conventional significance tests, do not survive a multiple testing adjustment as we show below. Finally, there is no evidence of significant excess returns or alphas of industry-neutral factors based on carbon emissions scaled by scales as shown in our Table D3, which is a result to be expected from Zhang (2025)’s own results (see her Table 6).

As another example, Hsu et al. (2023) find that an industry-neutral GMB portfolio based on toxic emission intensity generates a significant annual return of -4.42% from 1991 to 2016. Our scientific replication shows that a long-short portfolio sorted on toxic emission intensity (TPWINT (Assets)) has an insignificant excess return. There are several methodological differences, including that this paper uses quintile as opposed to tercile sorts for portfolio construction and that their industry-adjustment is based on SIC codes only from CRSP while we use the standard Fama-French approach.²⁷ In any case, the EPA metric used by

²⁷We follow Fama and French and use SIC codes from Compustat and only supplement with CRSP when-

Table D4: PST’s GMB performance

	Exc. Ret. (1)	CAPM (2)	FF3 (3)	FF6 (4)	Exc. Ret. (5)	CAPM (6)	FF3 (7)	FF6 (8)
Constant	0.71*** (0.23)	0.81*** (0.29)	0.56** (0.26)	0.54** (0.25)	0.24 (0.24)	0.27 (0.28)	0.22 (0.21)	0.31 (0.21)
Mkt-RF		-0.08 (0.08)	0.01 (0.06)	0.06 (0.07)		-0.02 (0.08)	0.02 (0.05)	0.04 (0.06)
SMB			-0.18* (0.11)	-0.27** (0.13)			-0.14 (0.09)	-0.29** (0.12)
HML			-0.25** (0.10)	-0.14 (0.15)			-0.39*** (0.06)	-0.22** (0.09)
RMW				-0.36** (0.17)				-0.33** (0.14)
CMA				-0.03 (0.23)				-0.26* (0.14)
MOM				0.12 (0.08)				0.03 (0.07)
Adj. R-squared	-0.00	0.01	0.18	0.23	-0.00	-0.01	0.32	0.38
<i>N</i>	98	98	98	98	122	122	122	122

The table shows returns of a green-minus-brown factor regressed on different factor models. Columns (1)–(3) (purely) reproduce Columns (1)–(3) of Table 3 in [Pástor et al. \(2022\)](#). Column (4) uses the Fama-French five-factor model augmented with momentum over the same sample period. Columns (5)–(8) extend the sample period from December 2020 until December 2022. Columns (9)–(12) further extend the sample period backward until February 2007. 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.

[Hsu et al. \(2023\)](#) does not distinguish between more or less dangerous chemicals and does not even distinguish between whether they have been recycled versus released (into the air, water, or ground) even though these data exist. For instance, our TRINT variable only considers released toxic waste, while their TPWINT variable does not distinguish one pound of cyanide released into the water versus one pound of paint waste that is recycled.²⁸

Finally, the level of carbon emissions—as opposed to carbon intensity (i.e., emissions scaled by sales or assets)—has received significant attention in the literature (see, e.g., [Bolton and Kacperczyk, 2021, 2023](#)). However, once again, Tables [D2](#) and [D3](#) show that

ever these are not available, see https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_49_ind_port.html. [Kahle and Walkling \(1996\)](#) find substantial divergence between SIC codes from CRSP and Compustat with more than 80% disagreement at the 4-digit level used to generate FF49 industry classifications.

²⁸For completeness, [Hsu et al. \(2023\)](#) consider toxicity in their Internet Appendix using a county-level mortality model (as opposed to simply scaling by EPA’s toxicity estimates).

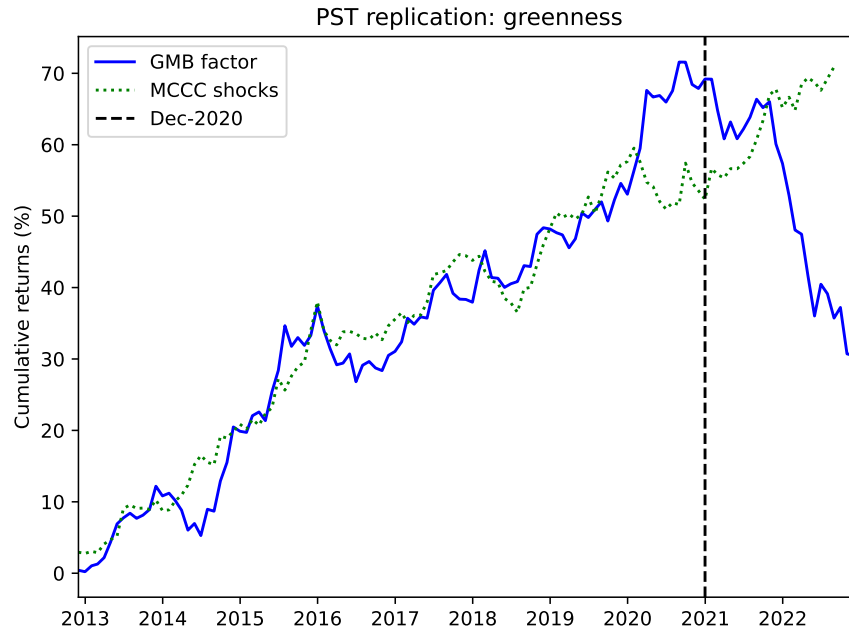
Table D5: PST’s GMB returns, changes in climate concerns, and cash-flow news

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	0.19 (0.28)	0.06 (0.28)	0.23 (0.29)	0.04 (0.25)	0.09 (0.21)	0.05 (0.20)	0.01 (0.25)	-0.08 (0.25)	0.06 (0.21)	0.00 (0.20)	0.01 (0.20)	0.00 (0.19)
Δ Climate concerns (same month)	2.16* (1.14)	2.14* (1.12)	1.11 (0.90)	1.44* (0.77)	0.54 (0.67)	0.76 (0.65)	2.40** (0.96)	2.40** (0.94)	1.37** (0.66)	1.50** (0.63)	0.59 (0.62)	0.79 (0.62)
Δ Climate concerns (prev. month)	2.21* (1.13)	1.82* (1.02)	-0.37 (1.00)	-0.54 (0.92)	-0.41 (0.75)	-0.31 (0.74)	1.95** (0.89)	1.68** (0.83)	0.35 (0.69)	0.31 (0.68)	-0.21 (0.66)	-0.11 (0.67)
Earnings announcement returns		0.35* (0.21)		0.43*** (0.14)		0.25** (0.11)		0.29 (0.18)		0.23** (0.10)		0.21* (0.11)
Δ Earnings forecasts		0.04 (0.14)		-0.07 (0.13)		-0.27*** (0.10)		-0.04 (0.13)		-0.13 (0.10)		-0.30*** (0.10)
R^2	0.15	0.23	0.02	0.14	0.01	0.08	0.17	0.22	0.04	0.09	0.00	0.09
Adj. R^2	0.12	0.18	0.00	0.11	-0.01	0.06	0.14	0.17	0.02	0.06	-0.01	0.07
N	68	68	118	118	187	187	68	68	118	118	187	187

The table shows regressions of a green-minus-brown (GMB) factor’s excess returns or Fama-French three-factor alpha on a constant, contemporaneous and lagged changes in climate concerns, and two earnings measures. Columns (1)–(6) have excess return as the dependent variable, whereas Columns (7)–(12) have alphas as the dependent variable. 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 \(2022\)](#). Changes in climate concerns are constructed as in [Pástor et al. \(2022\)](#). Specifications (1), (2), (7), and (8) use a sample period from 2012–2018 and reproduce specifications (1)–(4) in Table 4 of [Pástor et al. \(2022\)](#). Specifications (3), (4), (9), and (10) extend their sample period forward until December 2022. Specifications (5), (6), (11), and (12) further extend their sample backward until February 2007. 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.

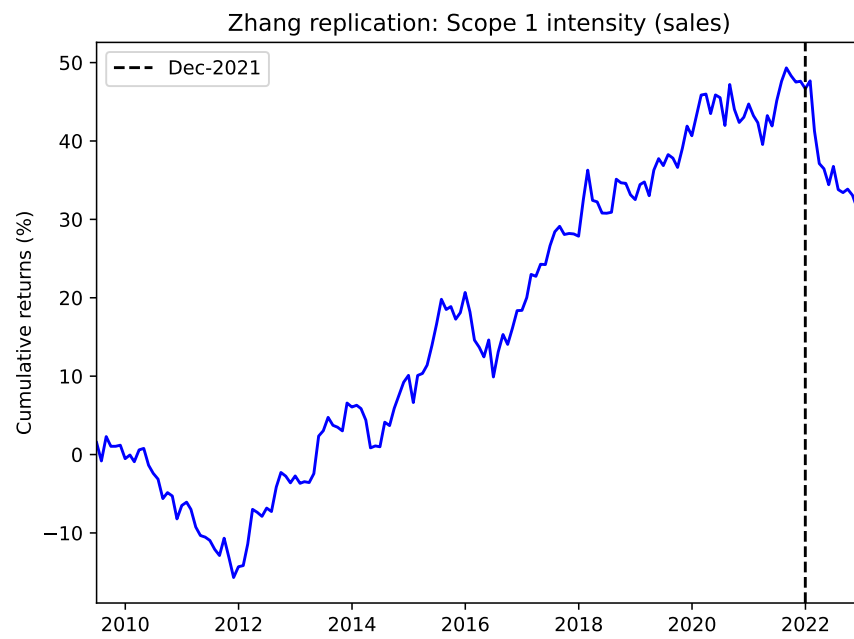
there is little evidence for significant mean excess returns or alphas of portfolios sorted on the level of carbon emissions (e.g., sorted on LOG(S1TOT)). The exception is the alphas of industry-agnostic portfolios with respect to the Fama-French five-factor model augmented with momentum, but these alphas are positive, which is the opposite of what [Bolton and Kacperczyk \(2021\)](#) find. However, Tables D2 and D3 conduct so many tests that conventional significance tests may be misleading as we need to take multiple testing into account. We turn to this next.

Figure D4: [Pástor et al. \(2022\)](#) pure replication



The figure shows cumulative excess returns of a green-minus-brown factor based on [Pástor et al. \(2022\)](#) and replicates their Figure 8, extending the sample period by two years until 2022. The vertically dashed line indicates the end of their sample period. The green dotted line indicates cumulative media climate change concern ("MCCC") shocks, defined as surprises to a 36 month AR(1) process, following [Pástor et al. \(2022\)](#) using the Media Climate Change Concerns Index from [Ardia et al. \(2022\)](#). The index is available until August 2022. The MCCC time series is scaled by a factor of six for visual purposes.

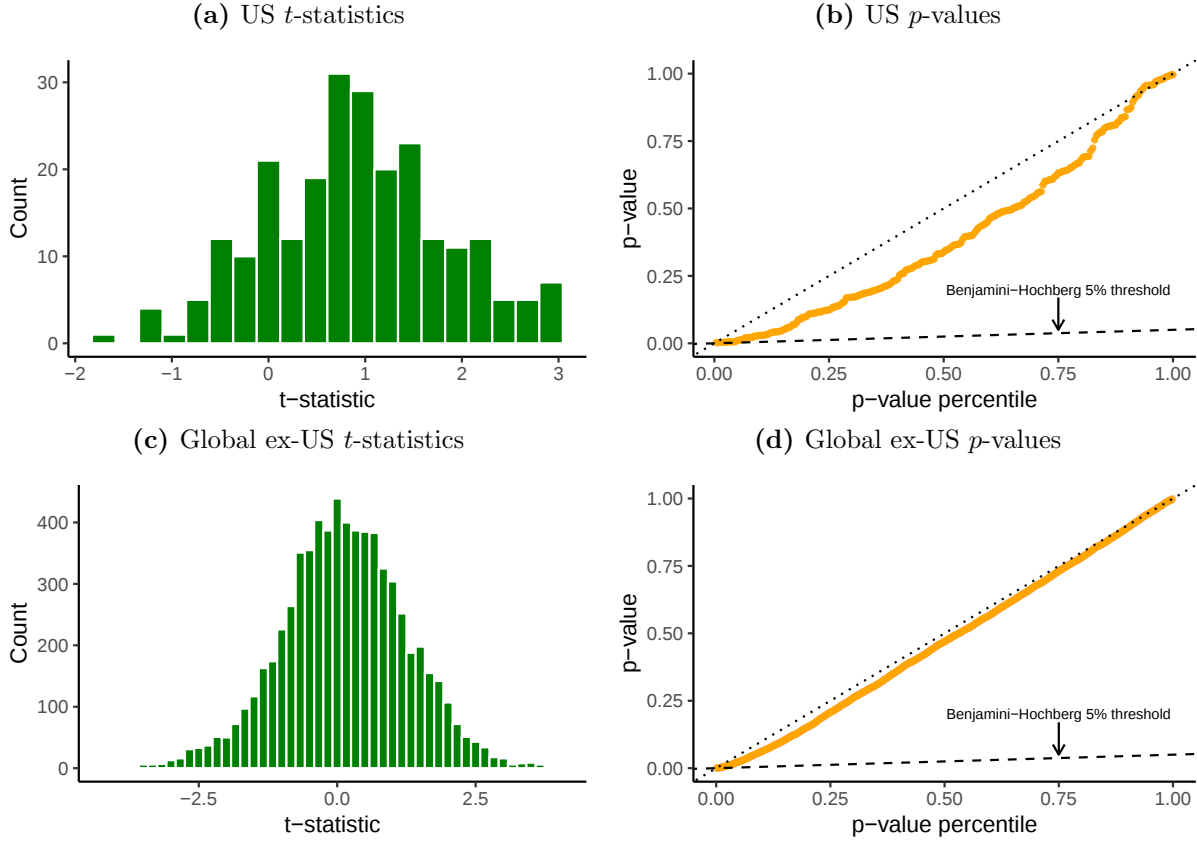
Figure D5: Zhang (2025) pure replication



The figure shows cumulative excess returns of a green-minus-brown factor based on scope 1 carbon intensity as in [Zhang \(2025\)](#) and replicates her Figure 2, extending the sample period by one year from December 2021 until December 2022. The vertically dashed line indicates the end of her sample period.

D.2.4 No significance with multiple-testing adjustment

Figure D6: Distributions of t -statistics and p -values



Panels (a) and (c) show the distributions of t -statistics of all GMB alphas. Panels (b) and (d) show the corresponding p -values ranked from low to high, plotted against their percentile rank on the x -axis. The dotted line is the 45-degree line and the dashed line shows the multiple testing threshold from [Benjamini and Hochberg \(1995\)](#) that controls the false discovery rate at a 5% level. Since the p -values in the solid line is above the dashed line, all of the estimates are statistically insignificant after adjusting for multiple testing. To compute these results, GMB factors are constructed using 23 (US) and 19 (Global ex-US) individual greenness measures, separately for the US and 48 other countries, 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 $23 \times 2 \times 5 = 230$ t -statistics. Standard errors are [Newey and West \(1987\)](#) adjusted with three lags.

Figure [D6\(a\)](#) plots a histogram of all the t -statistics in [Tables D2 and D3](#), corresponding to the $23 \times 5 \times 2$ alphas of the US GMB portfolios. The figure shows that most of the t -statistics are less than 1.96 in absolute value, meaning that the corresponding alphas are insignificant at the conventional 5% significance level. However, there are a number of larger

t -statistics, which helps explain why the literature sometimes finds a significant greenium. We show in this subsection that none of these larger t -statistics survive a multiple testing adjustment. Conceptually, our approach is similar to research in asset pricing that algorithmically generates a universe of factors to control for publication bias and that then controls for multiple testing (see, e.g., [Yan and Zheng, 2017](#); [Chordia, Goyal, and Saretto, 2020](#)).

We compute the multiple-testing adjustment of [Benjamini and Hochberg \(1995\)](#), which is one of the most commonly used methods. The Benjamini-Hochberg (BH) method considers the p -values from all tests and classifies them as significant or not such that the false discovery rate (FDR) is controlled at a 5% given level.

The BH method first ranks the p -values from low to high as seen in the solid line in [Figure D6\(b\)](#). This cumulative distribution of p -values is then compared to the threshold $m/M \times 0.05$ (dashed line), where m/M is the percentile rank of a given p -value (i.e., the rank, m , divided by the total number of tests, M). The BH method then finds the highest value of m for which the actual p -value is below this threshold and rejects the null hypothesis for all tests that have a lower rank. For a textbook treatment of these issues, see [Efron \(2012\)](#).

As seen in [Figure D6\(b\)](#), the ranked p -values (solid line) are always above the BH threshold (dashed line), so none of the alphas is significant when accounting for multiple testing. This finding is all the more notable given that the BH method is not as conservative as other multiple-testing adjustments (e.g., the Bonferroni correction or the Benjamini-Yekutieli method), meaning that the BH method is more prone to find significant greeniums.

Some readers might be concerned that our procedure does not detect any significant GMB factors because we inflate the number of tests by having many greenness measures and many ways of computing alphas. This concern would be justified if we used a method like Bonferroni, which indiscriminately lowers the p -value cutoff based on the number of tests. However, this concern need not apply to the BH method for the following reason: As seen in [Figure D6\(b\)](#), the BH method depends on the distribution of p -values given by the dashed line. If we made ten copies of each p -value, the dashed line would be unchanged, so the conclusions regarding significance would be unchanged. More broadly, considering many similar ways of computing alphas does not lead BH to find a lower fraction of significant greeniums if the distribution of p -values remains similar. Given that all our greenium estimates are *ex ante* about equally reasonable, their p -values should come from the same distribution, implying that our BH method does not become more stringent because of the large number of tests.

Finally, the reader might wonder why our multiple-testing correction makes all greeniums insignificant when the asset-pricing literature finds that most equity factors survive multiple-testing corrections (see, e.g., [Jensen et al., 2023](#)). In other words, why do we find a replication crisis when the literature on equity factors did not have one? To see why, simply consider the magnitude of the t -statistics. In asset pricing, most of the replicated t -statistics are above 2, frequently exceed 4, and are sometimes as high as 6 (see, e.g., [Chen, 2021](#)). In contrast, most replicated greenium t -statistics are close to zero and the largest is 3.02 (arising for the industry-agnostic GMB factor based on scope 1 and 2 carbon emissions). This difference in magnitude arises because the asset pricing factors use many decades of data on potentially high-turnover strategies designed to deliver high returns, whereas the GMB factors use short samples for low-turnover strategies motivated by environmental rather than financial concerns.

D.2.5 Out-of-sample evidence: global replication problems

So far, we have focused on US stocks, but it is also interesting to consider out-of-sample evidence in other countries. We next study realized return differences of global green and brown stocks outside the US. Figure [D6\(c\)](#) shows the distribution of alpha t -statistics for global ex-US GMB factors. Specifically, we compute a GMB factor for each country, greenness measure, and industry adjustment 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.

As seen in Figure [D6\(c\)](#), the distribution of the global alphas' t -statistics is centered near zero and close to Normal. In other words, the distribution of the global greenium t -statistics almost looks the way it would look if all the greenium were near zero plus random noise.

Figure [D6\(d\)](#) shows the cumulative distribution of the corresponding p -values. As seen in the figure, the ranked p -values (solid line) are always above the BH threshold (dashed line), so, as in the US, none of the alphas is significant when accounting for multiple testing. In fact, the ranked p -values are close to the 45-degree line, which indicates pure uncorrelated noise, echoing the nearly mean-zero Normal distribution of t -statistics.

In sum, looking in the US (as the literature) or abroad (out of sample), we do not find

evidence of a significant greenium, as also seen in the merged US and ex-US global sample in Figure 1(a).

Figure 1(a) also shows a distribution of published t -statistics from the literature. We detail the collection of these t -statistics in Internet Appendix D.4. To be consistent with our scientific replication, we sign t -statistics such that a positive t -statistic indicates green outperformance over brown, whereas a negative t -statistic indicates brown outperformance over green. Relative to our scientific replication experiment, the distribution of published t -statistics is bimodal, with published t -statistics clustering at around +2 and -4. Such a bimodal distribution of published t -statistics is indicative of publication bias. Our scientific replication experiment attempts to correct for any such bias by seeking to include the full set of ex ante plausible GMB factors, countries, and risk adjustments.

D.3 Why realized returns do not identify the greenium

Realized returns cannot identify the greenium with data from little more than a single decade because this sample simply has a too low signal-to-noise ratio. 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 aggregate green score. Empirically, this portfolio implemented in the U.S. has a spread in the aggregate green score of around two standard deviations.²⁹ Using the baseline greenium estimate from Figure 1(b) of -39 bps per year per standard deviation increase in the green score, we predict an annual factor return of around $-39\text{bps} \times 2 = -78$ bps. The realized volatility of the GMB portfolio is 5.4%, so the predicted Sharpe ratio is $-0.78/5.4 = -0.15$. Given the sample length of $T = 13.33$ years, the expected t -statistic is

$$t = \frac{E(r)}{\sigma/\sqrt{T}} = \text{SR} \times \sqrt{T} = -0.55. \quad (\text{D52})$$

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 a t -statistic of 1.96 (the typical cut-off for significance at the 5% level):

$$T = \left(\frac{1.96}{\text{SR}} \right)^2 = 167 \text{ years}. \quad (\text{D53})$$

²⁹The 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 2.12, the annualized return volatility is 5.42%, and the sample length is 13 years and 4 months.

Naturally, since estimating the overall equity premium is known to require a long sample (Merton, 1980), estimating its green component requires an even longer sample.

Estimating the greenium is made even more difficult by the fact that the sample period is a time of rising green investor concerns. Such rising concerns may lead to a repricing, where green stocks temporarily outperform as the forward-looking expected returns fall. In other words, during a time of repricing, expected returns and realized returns can move in opposite directions.

As a case in point, the literature uses both realized out- and underperformance of green stocks to support the existence of a negative greenium. Some argue that realized underperformance can be seen as an estimate of the unconditional greenium (e.g., Bolton and Kacperczyk, 2021), while others argue that the realized outperformance is a sign of repricing Pástor et al. (2022).³⁰

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 turn to a theory-based estimation of the greenium using forward-looking measures of expected returns.

D.4 Published t -statistics

Table D6 shows the t -statistics used to construct the histogram of published t -statistics in Panel a) of Figure D2. We collect t -statistics for papers published in the literature on the realized performance of green versus brown stocks. For each paper, we collect the t -statistics from (what we consider) the main tables of the paper and sign them such that a positive t -statistic indicates green outperformance over brown and a negative t -statistic indicates brown outperformance over green. The papers under consideration are published in the Journal of Financial Economics (JFE), Journal of Finance (JF), Review of Financial Studies (RFS), and the Review of Finance (RoF).

³⁰Pástor et al. (2022) seek to account for the repricing by controlling 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 D5 (in which we actually do not find a significant exposure to the Media Climate Change Concerns Index over our extended sample period).

E Further details on greenium regressions

Throughout the paper, we report estimates and 95% confidence intervals for estimates of the greenium under various regression specifications. In this section, we provide additional details on these regressions. The first three tables show details on regressions used to estimate the equity- and firm-level greeniums: Table E1 for the regressions with country-time-fixed effects but without controls; Table E2 for the regressions with country-time-fixed effect and additional controls; and Table E3 for the regressions with country-industry-time-fixed effect and additional controls. The remaining tables show the detailed results for estimating bond greeniums, as well as further robustness tests.

Table D6: t -statistics published in the literature

Paper	Sample	t -stat.	Measure	Industry adj.	Risk model	Reference	Journal
Bolton and Kacperczyk (2021)	US	-2.33	LOG(S2TOT)	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-2.93	LOG(S3TOT)	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-4.56	LOG(S1TOT)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-3.48	LOG(S2TOT)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-4.39	LOG(S3TOT)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-4.19	Delta S1TOT	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-2.76	Delta S2TOT	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-3.78	Delta S3TOT	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-4.35	Delta S1TOT	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-2.68	Delta S2TOT	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-3.78	Delta S3TOT	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	0.83	S1INT (Sales)	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-1.20	S2INT (Sales)	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-1.67	S3INT (Sales)	No	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-0.83	S1INT (Sales)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-1.09	S2INT (Sales)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2021)	US	-0.64	S3INT (Sales)	Yes	Excess returns	Table 8	JFE
Bolton and Kacperczyk (2023)	US	-3.38	LOG(S1TOT)	No	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	US	-2.08	LOG(S2TOT)	Yes	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	US	-2.86	LOG(S3TOT)	Yes	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	US	-4.27	Delta S1TOT	Yes	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	US	-2.15	Delta S2TOT	Yes	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	US	-2.69	Delta S3TOT	Yes	Excess returns	Table 5	JF
Bolton and Kacperczyk (2023)	Global	-1.29	LOG(S1TOT)	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-3.21	LOG(S2TOT)	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-3.61	LOG(S3TOT)	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-4.20	LOG(S1TOT)	Yes	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-4.93	LOG(S2TOT)	Yes	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-4.69	LOG(S3TOT)	Yes	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-5.08	Delta S1TOT	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-3.73	Delta S2TOT	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-4.16	Delta S3TOT	No	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-5.15	Delta S1TOT	Yes	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-3.70	Delta S2TOT	Yes	Excess returns	Table 6	JF
Bolton and Kacperczyk (2023)	Global	-4.08	Delta S3TOT	Yes	Excess returns	Table 6	JF
Zhang (2025)	US	2.47	S1INT (Sales)	No	Excess returns	Table 4	JF
Zhang (2025)	US	1.87	S2INT (Sales)	No	Excess returns	Table 4	JF
Zhang (2025)	US	2.51	S1INT (Sales)	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	US	2.40	S2INT (Sales)	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	US	-1.37	Delta S1TOT	No	Excess returns	Table 4	JF
Zhang (2025)	US	0.17	Delta S2TOT	No	Excess returns	Table 4	JF
Zhang (2025)	US	-0.68	Delta S3TOT	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	US	0.57	Delta S2TOT	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	US	1.77	LOG(S1TOT)	No	Excess returns	Table 4	JF
Zhang (2025)	US	0.42	LOG(S2TOT)	No	Excess returns	Table 4	JF
Zhang (2025)	US	3.30	LOG(S1TOT)	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	US	2.17	LOG(S2TOT)	No	FF5 + MOM alphas	Table 4	JF
Zhang (2025)	Global	0.20	S1INT (Sales)	No	Excess returns	Table 7	JF
Zhang (2025)	Global	-0.08	S2INT (Sales)	No	Excess returns	Table 7	JF
Zhang (2025)	Global	0.74	S1INT (Sales)	No	FF5 + MOM alphas	Table 7	JF
Zhang (2025)	Global	0.43	S2INT (Sales)	No	FF5 + MOM alphas	Table 7	JF
Zhang (2025)	Global	1.13	Delta S1TOT	No	Excess returns	Table 7	JF
Zhang (2025)	Global	-0.25	Delta S2TOT	No	Excess returns	Table 7	JF
Zhang (2025)	Global	1.22	Delta S1TOT	No	FF5 + MOM alphas	Table 7	JF
Zhang (2025)	Global	0.00	Delta S2TOT	No	FF5 + MOM alphas	Table 7	JF
Zhang (2025)	Global	1.77	LOG(S1TOT)	No	Excess returns	Table 7	JF
Zhang (2025)	Global	3.06	LOG(S2TOT)	No	Excess returns	Table 7	JF
Zhang (2025)	Global	1.44	LOG(S1TOT)	No	FF5 + MOM alphas	Table 7	JF
Zhang (2025)	Global	2.07	LOG(S2TOT)	No	FF5 + MOM alphas	Table 7	JF
Aswani et al. (2024)	US	1.17	LOG(S1TOT)	No	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	1.15	LOG(S2TOT)	No	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	1.00	LOG(S3TOT)	No	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	1.23	LOG(S1TOT)	Yes	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	1.15	LOG(S2TOT)	Yes	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	0.86	LOG(S3TOT)	Yes	Excess returns	Table 5	RoF
Aswani et al. (2024)	US	2.60	S1INT (Sales)	Yes	Excess returns	Table 8	RoF
Aswani et al. (2024)	US	1.29	S2INT (Sales)	Yes	Excess returns	Table 8	RoF
Aswani et al. (2024)	US	-0.94	S3INT (Sales)	Yes	Excess returns	Table 8	RoF
Pástor et al. (2022)	US	3.23	Greenness (PST)	No	Excess returns	Table 3	JFE
Pástor et al. (2022)	US	2.91	Greenness (PST)	No	CAPM alphas	Table 3	JFE
Pástor et al. (2022)	US	2.23	Greenness (PST)	No	FF3 alphas	Table 3	JFE
Pástor et al. (2022)	US	2.14	Greenness (PST)	No	FF4 alphas	Table 3	JFE
Pástor et al. (2022)	US	2.25	Greenness (PST)	No	FF3 + LIQ	Table 3	JFE
Pástor et al. (2022)	US	2.38	Greenness (PST)	No	FF5 alphas	Table 3	JFE
Pástor et al. (2022)	US	2.28	Greenness (PST)	No	CAPM + controls	Table 3	JFE
Pástor et al. (2022)	US	1.99	Greenness (PST)	No	CAPM + controls	Table 3	JFE
Hsu et al. (2023)	US	-1.73	TPWINT (Sales)	Yes	Excess returns	Table 2	JF
Hsu et al. (2023)	US	-3.46	TPWINT (Assets)	Yes	Excess returns	Table 2	JF
Hsu et al. (2023)	US	-2.00	TPWINT (PPENT)	Yes	Excess returns	Table 2	JF
Hsu et al. (2023)	US	-2.63	TPWINT (ME)	Yes	Excess returns	Table 2	JF
Hsu et al. (2023)	US	-3.41	TPWINT (Assets)	Yes	CAPM alphas	Table 4	JF
Hsu et al. (2023)	US	-3.73	TPWINT (Assets)	Yes	FF3 alphas	Table 4	JF
Hsu et al. (2023)	US	-3.33	TPWINT (Assets)	Yes	FF4 alphas	Table 4	JF
Hsu et al. (2023)	US	-2.98	TPWINT (Assets)	Yes	FF5 alphas	Table 4	JF
Hsu et al. (2023)	US	-3.70	TPWINT (Assets)	Yes	q-factor alphas	Table 4	JF
Pedersen et al. (2021)	US	0.28	Ind-adj. ESG score	Yes	Excess returns	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	1.59	S1+S2INT (Sales)	No	Excess returns	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	0.01	Ind-adj. ESG score	Yes	Excess returns	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.89	S1+S2INT (Sales)	No	Excess returns	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.00	Ind-adj. ESG score	Yes	CAPM alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	2.09	S1+S2INT (Sales)	No	CAPM alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	0.80	Ind-adj. ESG score	Yes	CAPM alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.52	S1+S2INT (Sales)	No	CAPM alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	0.60	Ind-adj. ESG score	Yes	FF3 alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	1.63	S1+S2INT (Sales)	No	FF3 alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	0.45	Ind-adj. ESG score	Yes	FF3 alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.14	S1+S2INT (Sales)	No	FF3 alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	0.22	Ind-adj. ESG score	Yes	FF5 alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	1.92	S1+S2INT (Sales)	No	FF5 alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	-0.31	Ind-adj. ESG score	Yes	FF5 alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.85	S1+S2INT (Sales)	No	FF5 alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	0.22	Ind-adj. ESG score	Yes	FF5 + MOM alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	1.73	S1+S2INT (Sales)	No	FF5 + MOM alphas	Table 4 Panel A	JFE
Pedersen et al. (2021)	US	-0.32	Ind-adj. ESG score	Yes	FF5 + MOM alphas	Table 4 Panel B	JFE
Pedersen et al. (2021)	US	1.72	S1+S2INT (Sales)	No	FF5 + MOM alphas	Table 4 Panel B	JFE

Table E1: Global stocks: country-time-fixed effects without controls

	Greenium	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	68.24	38.01	1238817	0.00	26.60
ICC	-32.36	4.67	875596	0.88	16.74
ICC (GLS)	-39.76	5.07	811373	1.49	17.75
ICC (CT)	-29.47	4.86	444984	0.54	15.52
ICC (OJ)	-35.31	5.45	396278	0.72	14.95
ICC (PEG)	-38.31	5.57	448058	1.12	14.97
E/P (latest)	-32.72	5.50	897765	0.41	16.09
E/P (FY+1)	-26.64	5.46	924281	0.38	17.64
E/P (FY+2)	-33.06	5.58	957814	0.55	19.73
LOG(B/M)	-11.82	1.26	1253190	1.80	15.55
LOG(BEV/MEV)	-9.84	1.16	1225034	1.16	11.50
EBITDA/MEV (latest)	-55.69	14.91	1156747	0.21	8.20
Exp. Ret. (options)	-61.96	13.12	93092	2.38	56.63
Exp. Ret. (SVIX 30D)	-115.47	21.46	93092	3.09	35.59
Exp. Ret. (SVIX 91D)	-92.01	19.07	93088	3.31	32.34
Exp. Ret. (SVIX 182D)	-84.36	18.14	93077	3.36	28.15
Exp. Ret. (GLB 30D)	-38.34	10.97	92870	0.56	66.95
Exp. Ret. (GLB 91D)	-23.26	8.26	92866	0.51	71.90
Exp. Ret. (GLB 182D)	-17.37	7.53	92854	0.39	72.47
Req. Ret. (VL and MS)	-50.40	7.73	175939	3.99	4.99
Req. Ret. (ValueLine)	-55.82	8.43	170048	4.26	5.44
Req. Ret. (Morningstar)	-21.15	4.71	76873	4.59	59.07
Exp. Ret. (IBES)	-300.99	76.36	270624	0.80	10.03
Exp. Ret. (ValueLine)	-51.90	19.11	169770	0.38	11.52
Exp. Ret. (Morningstar)	-57.99	17.51	76829	0.50	10.91
WACC	-22.94	7.01	95272	0.77	13.03

The table shows key statistics from regressions of various dependent variables on the aggregate green score and a country-time fixed effect (but without any further controls). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the first column of several figures throughout the paper, starting with Figure D1. “S.E.” refers to the standard errors of this estimate, “ N ” to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is all stocks globally.

Table E2: Global stocks: country-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	55.26	39.64	-306.90	384.29	10.52	43.17	1255.97	690.61	-106.16	245.47	1238817	0.02	26.61
ICC	-38.62	4.35	129.35	18.73	31.88	5.10	-314.36	100.95	189.05	25.16	875596	8.07	22.78
ICC (GLS)	-46.83	5.13	89.79	22.42	36.07	5.07	-437.36	114.94	176.37	26.27	811373	9.61	24.53
ICC (CT)	-28.04	4.06	194.76	20.96	26.84	7.34	-537.28	121.23	213.68	33.58	444984	7.62	21.53
ICC (OJ)	-31.05	4.65	230.03	20.41	10.94	5.46	-539.16	121.65	204.62	31.24	396278	7.10	20.42
ICC (PEG)	-29.90	4.54	284.95	21.08	-9.77	4.72	-577.02	105.91	128.84	27.39	448058	10.32	22.88
E/P (latest)	-47.73	6.06	98.37	25.11	47.60	7.96	267.32	166.64	200.66	35.12	897765	3.82	18.96
E/P (FY+1)	-41.60	5.88	68.32	21.68	45.21	8.12	357.45	160.24	215.81	37.36	924281	4.75	21.26
E/P (FY+2)	-42.66	5.55	106.73	22.11	33.20	9.42	78.51	131.07	251.57	40.90	957814	4.80	23.16
LOG(B/M)	-16.34	1.52	-10.36	4.43	20.04	0.98	-232.75	52.39	45.57	7.70	1253190	21.89	32.83
LOG(BEV/MEV)	-13.18	1.49	-13.32	3.76	16.42	1.04	-217.41	58.93	135.03	13.35	1225034	30.89	38.12
EBITDA/MEV (latest)	-89.19	15.57	8.05	50.56	82.79	12.98	1304.29	398.54	-766.20	117.85	1156747	4.00	11.69
Exp. Ret. (options)	-31.14	6.83	463.83	30.30	-78.38	6.18	-955.71	113.03	-13.30	27.40	93092	35.81	71.48
Exp. Ret. (SVIX 30D)	-66.55	12.64	521.20	44.57	-146.59	12.09	-1890.85	200.98	4.84	55.83	93092	28.60	52.55
Exp. Ret. (SVIX 91D)	-52.09	10.80	525.98	37.13	-104.96	9.24	-1422.23	136.43	-15.16	50.84	93088	35.13	54.60
Exp. Ret. (SVIX 182D)	-47.25	10.05	522.61	34.38	-91.92	8.50	-1275.93	122.90	-16.55	49.98	93077	37.89	53.82
Exp. Ret. (GLB 30D)	-13.94	8.34	390.39	42.93	-68.34	7.06	-618.99	170.22	-3.09	39.64	92870	14.59	71.61
Exp. Ret. (GLB 91D)	-4.82	4.61	416.13	29.25	-34.27	4.03	-307.07	85.40	-21.04	19.46	92866	28.55	79.82
Exp. Ret. (GLB 182D)	-1.34	3.69	409.84	25.15	-22.93	3.27	-194.41	61.72	-23.12	15.80	92854	34.81	81.98
Req. Ret. (VL and MS)	-23.17	4.60	241.21	14.49	-74.35	3.55	-643.00	101.49	85.07	21.46	175939	48.83	49.36
Req. Ret. (ValueLine)	-24.90	4.73	291.32	15.76	-76.74	3.41	-879.05	85.22	75.03	22.03	170048	54.60	55.16
Req. Ret. (Morningstar)	-13.60	3.07	108.03	11.51	-6.85	2.40	-146.68	31.64	36.55	12.10	76873	27.01	68.68
Exp. Ret. (IBES)	-74.74	56.44	819.81	161.10	-290.21	30.77	-7957.33	1022.51	-356.63	355.54	270624	18.57	26.14
Exp. Ret. (ValueLine)	-33.40	16.69	426.76	71.40	-6.82	10.59	-400.53	191.33	275.06	72.27	169770	5.24	15.84
Exp. Ret. (Morningstar)	-46.34	14.95	284.96	70.16	83.07	14.76	-656.76	239.93	148.91	107.58	76829	4.68	14.66
WACC	-18.64	4.95	150.83	19.23	8.84	4.54	-55.45	107.35	-134.30	39.92	95272	6.73	18.25

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard errors of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is all stocks globally.

Table E3: Global stocks: country-industry-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	5.57	28.04	-220.44	381.42	39.70	36.03	1542.07	742.66	3.32	224.19	1238817	0.02	45.19
ICC	-32.42	3.14	75.21	14.27	10.32	3.57	-104.78	101.59	251.17	17.69	875596	4.98	51.30
ICC (GLS)	-39.04	3.60	52.04	16.59	10.03	3.37	-172.32	122.47	241.77	22.31	811373	5.93	54.33
ICC (CT)	-29.73	4.43	136.08	21.44	5.17	4.71	-284.80	94.25	285.97	24.93	444984	5.15	55.07
ICC (OJ)	-29.71	4.70	155.93	20.48	-6.39	4.89	-346.23	115.94	254.82	26.47	396278	4.81	54.52
ICC (PEG)	-25.56	3.72	187.37	16.56	-21.55	3.94	-444.37	95.93	201.76	21.38	448058	7.36	58.16
E/P (latest)	-40.06	4.57	81.13	22.57	13.89	4.22	578.48	138.45	251.15	22.56	897765	2.38	49.71
E/P (FY+1)	-34.45	3.82	54.78	17.55	12.14	3.72	620.01	104.17	271.79	19.43	924281	3.50	54.09
E/P (FY+2)	-35.33	3.95	71.19	18.64	-1.13	4.35	309.48	72.05	320.98	20.47	957814	3.99	55.37
LOG(B/M)	-13.76	1.17	-14.70	3.37	14.79	0.90	-228.12	41.99	21.18	3.57	1253190	14.37	57.19
LOG(BEV/MEV)	-11.21	1.11	-20.48	3.24	11.55	0.76	-217.55	44.58	120.15	8.57	1225034	22.88	59.78
EBITDA/MEV (latest)	-71.75	10.15	-44.28	41.09	38.63	11.02	1802.22	367.24	-805.51	103.72	1156747	4.07	38.41
Exp. Ret. (options)	-26.79	6.09	516.95	33.95	-77.42	6.07	-900.14	140.50	-45.34	30.34	93092	35.48	80.95
Exp. Ret. (SVIX 30D)	-50.51	10.94	650.10	50.42	-148.17	11.78	-1775.22	276.35	-96.61	61.47	93092	30.08	66.65
Exp. Ret. (SVIX 91D)	-37.31	8.23	635.20	41.99	-104.95	8.77	-1405.30	198.58	-96.20	50.45	93088	36.48	68.78
Exp. Ret. (SVIX 182D)	-32.48	7.23	626.83	38.85	-91.45	8.00	-1279.18	178.63	-92.71	48.28	93077	39.21	68.59
Exp. Ret. (GLB 30D)	-20.81	7.87	387.73	46.26	-67.97	7.85	-437.39	128.95	15.11	31.60	92870	12.70	80.96
Exp. Ret. (GLB 91D)	-11.28	4.03	407.94	31.13	-31.48	4.02	-275.45	68.25	2.98	16.51	92866	23.80	87.16
Exp. Ret. (GLB 182D)	-7.53	2.98	395.93	26.21	-19.24	2.97	-199.23	51.00	0.03	12.90	92854	28.31	88.67
Req. Ret. (VL and MS)	-21.37	3.77	237.36	15.01	-72.23	3.91	-670.81	111.84	96.08	21.17	175939	46.42	58.85
Req. Ret. (ValueLine)	-22.31	3.72	289.89	17.46	-75.12	4.00	-852.58	100.66	102.14	18.90	170048	52.84	65.19
Req. Ret. (Morningstar)	-11.53	2.38	98.43	11.37	-6.91	2.45	-167.77	35.86	25.20	14.64	76873	21.73	79.08
Exp. Ret. (IBES)	-130.97	33.18	607.93	123.71	-283.19	36.31	-6881.67	760.88	-74.88	199.55	270624	11.89	35.57
Exp. Ret. (ValueLine)	-23.98	11.34	319.81	49.69	-12.33	9.43	-562.56	182.23	369.29	70.23	169770	3.92	33.38
Exp. Ret. (Morningstar)	-41.33	14.43	102.24	71.02	78.50	13.97	-735.13	218.23	169.52	91.59	76829	2.81	37.02
WACC	-14.43	5.05	82.46	23.90	7.99	4.64	-21.62	107.63	-32.45	42.25	95272	1.22	38.18

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is all stocks globally.

Table E4: US stocks: country-time-fixed effects without controls

	Greenium	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	125.81	74.13	312621	0.01	17.80
ICC	-36.79	6.82	279279	1.37	5.64
ICC (GLS)	-45.11	7.19	274461	2.05	7.21
ICC (CT)	-28.10	5.85	170796	0.66	6.57
ICC (OJ)	-32.29	6.20	156927	0.83	5.01
ICC (PEG)	-30.77	7.40	157175	1.06	4.79
E/P (latest)	-45.06	7.44	252439	0.98	7.54
E/P (FY+1)	-35.21	8.09	256381	0.85	7.34
E/P (FY+2)	-38.98	7.48	268436	1.02	8.08
LOG(B/M)	-20.18	2.26	315171	4.77	6.74
LOG(BEV/MEV)	-17.79	2.26	301137	3.24	4.75
EBITDA/MEV (latest)	-136.80	41.87	275843	1.47	3.59
Exp. Ret. (options)	-61.96	13.12	93092	2.38	56.63
Exp. Ret. (SVIX 30D)	-115.47	21.46	93092	3.09	35.59
Exp. Ret. (SVIX 91D)	-92.01	19.07	93088	3.31	32.34
Exp. Ret. (SVIX 182D)	-84.36	18.14	93077	3.36	28.15
Exp. Ret. (GLB 30D)	-38.34	10.97	92870	0.56	66.95
Exp. Ret. (GLB 91D)	-23.26	8.26	92866	0.51	71.90
Exp. Ret. (GLB 182D)	-17.37	7.53	92854	0.39	72.47
Req. Ret. (VL and MS)	-50.40	7.73	175939	3.99	4.99
Req. Ret. (ValueLine)	-55.82	8.43	170048	4.26	5.44
Req. Ret. (Morningstar)	-21.15	4.71	76873	4.59	59.07
Exp. Ret. (IBES)	-300.99	76.36	270624	0.80	10.03
Exp. Ret. (ValueLine)	-51.90	19.11	169770	0.38	11.52
Exp. Ret. (Morningstar)	-57.99	17.51	76829	0.50	10.91
WACC	-22.94	7.01	95272	0.77	13.03

The table shows key statistics from regressions of various dependent variables on the aggregate green score and a country-time fixed effect (but without any further controls). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the first column of several figures throughout the paper, starting with Figure D1. “S.E.” refers to the standard errors of this estimate, “ N ” to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is US stocks.

Table E5: US stocks: country-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	111.22	67.25	-423.09	460.05	-1.67	47.26	961.34	940.83	-54.73	410.77	312621	0.04	17.82
ICC	-43.97	6.65	126.90	25.01	17.44	5.18	251.33	86.88	233.89	30.30	279279	9.70	13.61
ICC (GLS)	-48.80	7.20	110.19	28.28	11.29	6.15	137.12	109.73	240.81	32.93	274461	9.15	13.94
ICC (CT)	-27.67	5.59	165.96	23.06	27.56	5.20	32.94	97.34	210.68	34.64	170796	7.12	12.65
ICC (OJ)	-29.52	5.49	196.81	21.63	16.60	4.83	33.50	104.37	200.89	34.02	156927	6.92	10.85
ICC (PEG)	-23.00	6.14	255.45	25.59	-1.40	4.70	36.64	104.28	126.58	31.83	157175	11.82	15.14
E/P (latest)	-57.40	10.08	128.14	30.53	28.22	6.47	352.93	188.05	261.23	45.81	252439	5.51	11.78
E/P (FY+1)	-51.07	10.10	84.08	28.80	31.17	6.59	486.24	171.47	253.76	45.54	256381	7.04	13.13
E/P (FY+2)	-50.55	9.62	111.14	29.71	24.38	7.05	358.22	127.78	284.01	46.62	268436	7.79	14.37
LOG(B/M)	-25.24	2.69	-4.16	7.17	17.32	1.25	-119.34	48.69	38.03	7.59	315171	16.36	18.09
LOG(BEV/MEV)	-20.95	3.01	-8.33	6.32	11.41	1.32	-94.20	60.90	161.66	14.56	301137	31.66	32.72
EBITDA/MEV (latest)	-156.57	33.88	-13.17	97.91	32.49	17.84	725.70	718.83	-444.50	228.89	275843	3.01	5.10
Exp. Ret. (options)	-31.14	6.83	463.83	30.30	-78.38	6.18	-955.71	113.03	-13.30	27.40	93092	35.81	71.48
Exp. Ret. (SVIX 30D)	-66.55	12.64	521.20	44.57	-146.59	12.09	-1890.85	200.98	4.84	55.83	93092	28.60	52.55
Exp. Ret. (SVIX 91D)	-52.09	10.80	525.98	37.13	-104.96	9.24	-1422.23	136.43	-15.16	50.84	93088	35.13	54.60
Exp. Ret. (SVIX 182D)	-47.25	10.05	522.61	34.38	-91.92	8.50	-1275.93	122.90	-16.55	49.98	93077	37.89	53.82
Exp. Ret. (GLB 30D)	-13.94	8.34	390.39	42.93	-68.34	7.06	-618.99	170.22	-3.09	39.64	92870	14.59	71.61
Exp. Ret. (GLB 91D)	-4.82	4.61	416.13	29.25	-34.27	4.03	-307.07	85.40	-21.04	19.46	92866	28.55	79.82
Exp. Ret. (GLB 182D)	-1.34	3.69	409.84	25.15	-22.93	3.27	-194.41	61.72	-23.12	15.80	92854	34.81	81.98
Req. Ret. (VL and MS)	-23.17	4.60	241.21	14.49	-74.35	3.55	-643.00	101.49	85.07	21.46	175939	48.83	49.36
Req. Ret. (ValueLine)	-24.90	4.73	291.32	15.76	-76.74	3.41	-879.05	85.22	75.03	22.03	170048	54.60	55.16
Req. Ret. (Morningstar)	-13.60	3.07	108.03	11.51	-6.85	2.40	-146.68	31.64	36.55	12.10	76873	27.01	68.68
Exp. Ret. (IBES)	-74.74	56.44	819.81	161.10	-290.21	30.77	-7957.33	1022.51	-356.63	355.54	270624	18.57	26.14
Exp. Ret. (ValueLine)	-33.40	16.69	426.76	71.40	-6.82	10.59	-400.53	191.33	275.06	72.27	169770	5.24	15.84
Exp. Ret. (Morningstar)	-46.34	14.95	284.96	70.16	83.07	14.76	-656.76	239.93	148.91	107.58	76829	4.68	14.66
WACC	-18.64	4.95	150.83	19.23	8.84	4.54	-55.45	107.35	-134.30	39.92	95272	6.73	18.25

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard errors of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is US stocks.

Table E6: US stocks: country-industry-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	64.90	50.15	-371.01	421.48	29.67	48.50	1380.48	996.05	164.94	335.90	312621	0.04	28.77
ICC	-32.10	4.14	83.99	16.40	9.65	3.59	259.87	79.37	278.10	18.51	279279	7.84	29.98
ICC (GLS)	-37.67	4.53	80.21	17.97	2.37	4.61	226.89	98.20	304.95	21.78	274461	8.85	32.04
ICC (CT)	-24.02	4.72	125.56	21.09	19.63	3.94	23.93	65.74	258.90	24.40	170796	5.95	33.10
ICC (OJ)	-23.29	4.65	132.13	18.28	7.71	4.12	-40.99	77.34	216.93	24.34	156927	4.45	30.01
ICC (PEG)	-22.32	3.96	179.43	15.85	-5.73	3.32	-110.96	75.86	160.91	21.40	157175	7.88	37.74
E/P (latest)	-38.13	6.25	129.75	28.57	18.36	4.92	504.08	159.77	319.60	28.77	252439	5.00	29.04
E/P (FY+1)	-33.48	5.18	96.84	24.07	22.95	4.66	607.61	107.24	321.97	24.65	256381	7.46	33.83
E/P (FY+2)	-34.34	5.25	110.43	23.99	16.03	4.92	373.98	80.07	343.93	26.16	268436	7.79	35.17
LOG(B/M)	-19.69	1.66	-1.39	4.66	14.12	1.04	-150.61	41.41	7.93	6.97	315171	11.70	39.37
LOG(BEV/MEV)	-15.23	1.55	-10.46	4.25	8.82	0.83	-131.58	45.49	141.73	7.83	301137	24.00	51.20
EBITDA/MEV (latest)	-89.01	16.02	84.91	54.66	10.93	13.38	1686.75	326.77	-462.98	143.37	275843	2.92	22.73
Exp. Ret. (options)	-26.79	6.09	516.95	33.95	-77.42	6.07	-900.14	140.50	-45.34	30.34	93092	35.48	80.95
Exp. Ret. (SVIX 30D)	-50.51	10.94	650.10	50.42	-148.17	11.78	-1775.22	276.35	-96.61	61.47	93092	30.08	66.65
Exp. Ret. (SVIX 91D)	-37.31	8.23	635.20	41.99	-104.95	8.77	-1405.30	198.58	-96.20	50.45	93088	36.48	68.78
Exp. Ret. (SVIX 182D)	-32.48	7.23	626.83	38.85	-91.45	8.00	-1279.18	178.63	-92.71	48.28	93077	39.21	68.59
Exp. Ret. (GLB 30D)	-20.81	7.87	387.73	46.26	-67.97	7.85	-437.39	128.95	15.11	31.60	92870	12.70	80.96
Exp. Ret. (GLB 91D)	-11.28	4.03	407.94	31.13	-31.48	4.02	-275.45	68.25	2.98	16.51	92866	23.80	87.16
Exp. Ret. (GLB 182D)	-7.53	2.98	395.93	26.21	-19.24	2.97	-199.23	51.00	0.03	12.90	92854	28.31	88.67
Req. Ret. (VL and MS)	-21.37	3.77	237.36	15.01	-72.23	3.91	-670.81	111.84	96.08	21.17	175939	46.42	58.85
Req. Ret. (ValueLine)	-22.31	3.72	289.89	17.46	-75.12	4.00	-852.58	100.66	102.14	18.90	170048	52.84	65.19
Req. Ret. (Morningstar)	-11.53	2.38	98.43	11.37	-6.91	2.45	-167.77	35.86	25.20	14.64	76873	21.73	79.08
Exp. Ret. (IBES)	-130.97	33.18	607.93	123.71	-283.19	36.31	-6881.67	760.88	-74.88	199.55	270624	11.89	35.57
Exp. Ret. (ValueLine)	-23.98	11.34	319.81	49.69	-12.33	9.43	-562.56	182.23	369.29	70.23	169770	3.92	33.38
Exp. Ret. (Morningstar)	-41.33	14.43	102.24	71.02	78.50	13.97	-735.13	218.23	169.52	91.59	76829	2.81	37.02
WACC	-14.43	5.05	82.46	23.90	7.99	4.64	-21.62	107.63	-32.45	42.25	95272	1.22	38.18

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is US stocks.

Table E7: Global ex-US stocks: country-time-fixed effects without controls

	Greenium	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	48.67	33.08	926196	0.00	30.25
ICC	-30.34	4.91	596317	0.72	17.91
ICC (GLS)	-37.09	5.48	536912	1.26	20.46
ICC (CT)	-30.25	6.10	274188	0.49	15.02
ICC (OJ)	-37.13	6.83	239351	0.68	13.91
ICC (PEG)	-42.11	6.41	290883	1.17	16.07
E/P (latest)	-28.04	6.11	645326	0.28	17.25
E/P (FY+1)	-23.43	6.16	667900	0.27	18.61
E/P (FY+2)	-30.81	6.50	689378	0.43	20.37
LOG(B/M)	-9.00	1.06	938019	1.07	15.18
LOG(BEV/MEV)	-7.23	1.02	923897	0.66	11.69
EBITDA/MEV (latest)	-30.19	12.62	880904	0.06	9.15

The table shows key statistics from regressions of various dependent variables on the aggregate green score and a country-time fixed effect (but without any further controls). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the first column of several figures throughout the paper, starting with Figure D1. “S.E.” refers to the standard errors of this estimate, “N” to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is global ex-US stocks.

Table E8: Global ex-US stocks: country-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	37.08	36.80	-257.84	386.77	13.44	49.24	1436.53	701.26	-111.47	198.92	926196	0.02	30.26
ICC	-36.10	4.37	134.35	18.21	31.96	5.58	-963.59	95.30	104.89	24.13	596317	10.01	25.60
ICC (GLS)	-46.18	5.40	71.59	22.75	43.65	4.99	-1114.96	100.95	74.78	24.31	536912	13.62	30.42
ICC (CT)	-28.88	4.83	228.14	25.90	16.47	10.60	-1184.45	143.68	183.83	47.51	274188	9.29	22.54
ICC (OJ)	-32.80	5.90	274.58	25.84	-4.31	7.33	-1219.85	151.13	170.47	41.91	239351	8.71	20.86
ICC (PEG)	-34.26	5.28	323.17	22.69	-23.88	5.36	-1158.55	109.88	101.67	32.72	290883	11.70	25.01
E/P (latest)	-44.53	5.97	71.67	28.06	57.88	10.11	251.28	193.95	168.15	40.00	645326	3.65	20.05
E/P (FY+1)	-38.46	5.69	53.05	24.53	52.00	10.50	304.68	183.27	193.90	44.04	667900	4.36	21.94
E/P (FY+2)	-40.07	5.58	102.07	23.85	36.23	12.08	-88.12	160.34	224.60	50.15	689378	4.23	23.41
LOG(B/M)	-13.22	1.23	-11.87	3.94	20.63	1.06	-316.29	41.11	40.86	7.18	938019	26.02	36.56
LOG(BEV/MEV)	-10.57	1.16	-15.02	3.20	17.86	1.03	-305.31	43.07	116.11	10.32	923897	33.02	40.46
EBITDA/MEV (latest)	-67.50	14.48	-5.08	45.21	104.25	13.89	1586.96	451.43	-879.05	109.44	880904	4.87	13.52

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard errors of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is global ex-US stocks.

Table E9: Global ex-US stocks: country-industry-time-fixed effects with controls

	Greenium	S.E.	Beta	S.E.	Size	S.E.	Profitability	S.E.	Leverage	S.E.	N	R2	R2 (Total)
Exc. Ret. (leading)	-17.72	30.27	-129.46	409.97	39.73	42.91	1541.85	735.45	-97.36	188.12	926196	0.02	52.05
ICC	-31.54	3.72	85.01	16.56	4.89	5.41	-748.41	108.63	171.05	21.83	596317	5.41	57.31
ICC (GLS)	-39.06	4.36	38.18	19.47	12.03	4.26	-929.26	115.80	116.40	24.90	536912	7.39	63.56
ICC (CT)	-33.98	6.60	190.35	35.23	-25.99	9.54	-945.14	164.43	299.67	45.94	274188	6.74	61.36
ICC (OJ)	-35.61	7.65	233.46	33.78	-39.80	9.78	-1019.04	223.04	290.33	52.49	239351	7.19	61.38
ICC (PEG)	-27.96	5.38	233.63	24.46	-49.12	6.54	-960.80	142.39	237.15	38.08	290883	9.24	63.54
E/P (latest)	-41.08	5.14	49.14	25.46	12.60	5.88	630.94	171.48	204.08	28.10	645326	1.55	54.41
E/P (FY+1)	-34.81	4.23	34.21	20.38	5.19	5.24	607.92	138.06	236.36	26.09	667900	2.26	58.17
E/P (FY+2)	-35.53	4.44	58.11	22.13	-13.75	5.92	223.11	97.61	299.55	27.73	689378	3.03	59.00
LOG(B/M)	-11.33	1.15	-21.06	3.68	15.30	1.10	-287.49	34.23	24.42	4.67	938019	17.17	61.98
LOG(BEV/MEV)	-9.62	1.13	-25.03	3.54	13.06	1.02	-288.09	36.57	103.02	8.73	923897	23.94	62.54
EBITDA/MEV (latest)	-66.04	11.39	-130.60	49.49	58.95	15.40	1870.49	453.86	-978.71	114.02	880904	4.90	42.21

The table shows key statistics from regressions of various dependent variables on the aggregate green score, a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The column “Greenium” refers to the regression estimate on the aggregate green score, which we also visualize in the second column of several figures throughout the paper, starting with Figure D1. The first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimates and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression. *Exp. Ret. (options)* and *Req. Ret. (VL and MS)* refer to results with equal-weighted averages of the underlying measures. The sample is global ex-US stocks.

Table E10: Bonds: time-fixed effects without controls

	Greenium	S.E.	N	R2	R2 (Total)
Yield	-63.04	13.13	98006	3.01	11.35
Yield Spread	-63.20	13.85	93435	2.86	10.74
Adj. Yield	-32.69	7.05	98006	1.00	9.50
Adj. Yield Spread	-32.24	7.46	93435	0.93	9.15
Credit Rating	-89.15	13.14	98797	8.65	14.99

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (a). The regressions include a time-fixed effect. The column “Greenium” refers to the regression estimate on the aggregate green score and “S.E.” refers to the standard errors of this estimate. “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E11: Bonds: time-fixed effects with 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	-22.40	7.46	-71.28	9.97	-1372.12	145.48	234.48	50.65	1.91	7.53	1.62	2.05	98006	17.73	24.80
Yield Spread	-21.31	7.77	-71.73	10.06	-1382.82	150.28	243.71	50.89	3.05	7.55	-5.97	2.11	93435	18.71	25.31
Adj. Yield	-17.81	5.56	-30.95	7.06	-535.19	109.55	59.94	30.26	-1.29	6.84	5.79	1.24	98006	3.95	12.20
Adj. Yield Spread	-16.30	5.84	-30.04	7.17	-532.56	110.31	62.26	30.68	0.24	6.98	-1.70	1.17	93435	3.74	11.72
Credit Rating	-33.78	7.54	-106.79	12.27	-1220.09	317.26	392.22	63.87	-0.42	11.82	-13.40	2.72	98797	55.27	58.37

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (a). The regression include a time-fixed effect and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability), log face value, and the time-to-maturity. The column “Greenium” refers to the regression estimate on the aggregate green score and the first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimate and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E12: Bonds: industry-time-fixed effects with 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	-20.46	6.39	-56.32	8.54	-1129.02	147.13	361.00	66.65	-13.31	6.48	3.89	1.71	98006	14.41	32.94
Yield Spread	-19.54	6.54	-55.85	8.86	-1127.68	149.63	368.05	69.35	-12.44	6.83	-4.02	1.84	93435	15.42	33.32
Adj. Yield	-16.48	4.90	-26.80	6.89	-312.83	94.73	99.74	40.79	-6.65	6.95	6.97	1.14	98006	2.71	20.23
Adj. Yield Spread	-15.17	5.09	-25.82	7.10	-305.79	96.03	98.00	42.81	-5.24	7.17	-0.77	1.08	93435	2.51	19.73
Credit Rating	-37.17	7.34	-102.27	11.51	-1192.50	370.49	515.13	44.52	-7.83	8.87	-8.30	1.64	98797	55.28	67.57

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (a). The regressions include an industry-by-time-fixed effect and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability), log face value, and the time-to-maturity. The column “Greenium” refers to the regression estimate on the aggregate green score and the first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimate and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E13: Bonds: rating-time-fixed effects without controls

	Greenium	S.E.	N	R2	R2 (Total)
Yield	-12.54	3.08	98006	0.34	70.73
Yield Spread	-11.06	3.21	93435	0.26	71.86
Adj. Yield	-12.20	3.09	98006	0.31	61.96
Adj. Yield Spread	-10.71	3.25	93435	0.23	62.85

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (b). The regressions include a credit rating-by-time-fixed effect. The column “Greenium” refers to the regression estimate on the aggregate green score and “S.E.” refers to the standard errors of this estimate. “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E14: Bonds: rating-time-fixed effects with 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	-8.38	3.03	-4.82	4.80	-313.26	65.02	3.93	13.75	-7.63	3.72	9.11	0.78	98006	4.45	71.93
Yield Spread	-8.00	3.22	-4.58	4.92	-326.56	67.80	13.21	13.63	-6.44	3.74	1.31	0.64	93435	1.44	72.19
Adj. Yield	-7.91	3.10	-3.42	4.74	-304.63	64.41	2.84	14.23	-10.68	3.74	9.34	0.77	98006	4.34	63.50
Adj. Yield Spread	-7.52	3.30	-3.18	4.86	-317.68	66.97	12.01	14.21	-9.69	3.79	1.56	0.63	93435	1.42	63.29

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (b). The regression include a credit rating-by-time-fixed effect and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability), log face value, and the time-to-maturity. The column “Greenium” refers to the regression estimate on the aggregate green score and the first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimate and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E15: Bonds: industry-time-fixed and rating-time-fixed effects with 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	-5.32	2.17	-7.40	4.78	-171.96	55.85	48.08	24.59	-8.44	3.66	8.89	0.84	98006	3.16	75.84
Yield Spread	-4.82	2.22	-7.29	4.90	-179.08	57.63	53.49	25.79	-7.15	3.75	0.98	0.73	93435	0.68	76.09
Adj. Yield	-4.59	2.32	-5.80	4.70	-150.06	55.69	42.17	25.72	-11.61	3.63	9.06	0.84	98006	3.07	68.53
Adj. Yield Spread	-4.03	2.38	-5.69	4.84	-156.79	57.40	46.99	27.26	-10.56	3.78	1.17	0.72	93435	0.67	68.40

The table shows key statistics from regressions of various dependent variables on the aggregate green score for corporate bonds, as also visualized in Figure 14, panel (b). The regression include a credit rating-by-time-fixed effect, an industry-by-time-fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability), log face value, and the time-to-maturity. The column “Greenium” refers to the regression estimate on the aggregate green score and the first “S.E.” refers to the standard errors of this estimate. The next columns show the regression estimate and standard error of the controls. Finally, “N” refers to the number of observations used in the regression, while “R2” and “R2 (Total)” refer, respectively, to the within and total R^2 of the regression.

Table E16: Individual greenium estimates - balanced samples

Variable	Estimate	t-stat	R^2	ρ	N
LOG(S1TOT)	-9.18	-1.01	0.06	0.09	875596
LOG(S1+2TOT)	-7.87	-0.80	0.06	0.07	875596
LOG(S1+2+3TOT)	-11.32	-1.11	0.06	0.05	875596
S1INT (Sales)	-9.16	-1.22	0.06	0.21	875596
S1+2INT (Sales)	-9.50	-1.22	0.06	0.21	875596
S1+2+3INT (Sales)	-7.40	-0.98	0.06	0.21	875596
S1INT (Assets)	-13.35	-2.25	0.06	0.20	875596
S1+2INT (Assets)	-13.85	-2.27	0.06	0.20	875596
S1+2+3INT (Assets)	-9.65	-1.37	0.06	0.17	875596
Ind.-adj. ESG score	-23.00	-6.88	0.06	0.65	875596
Weighted ESG score	-28.39	-6.66	0.07	0.68	875596
Environment score	-24.72	-4.58	0.06	0.48	875596
Greenness (PST)	-11.08	-1.33	0.06	0.33	875596
E climate score	-27.44	-3.35	0.06	0.34	875596
E nat. res. score	-9.78	-1.62	0.06	0.23	875596
E waste score	-16.37	-3.88	0.06	0.18	875596
E env. opps. score	-4.22	-1.07	0.06	0.21	875596
Total ESG score	-1.14	-0.37	0.06	0.19	875596
Environmental score	-1.52	-0.50	0.06	0.18	875596
Aggregate green score	-38.62	-8.88	0.07	1.00	875596

The table shows the greenium estimates corresponding to the 19 individual green scores on a balanced sample. We create a balanced sample by imputing non-missing green score observations with the cross-sectional mean within the same country and time. If the green score is missing for all firms within a country-time, we set all observations to zero (zero is the expected cross-sectional mean, as all green scores are cross-sectionally standardized). The individual greeniums are estimated based on our preferred specification with a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The associated t -statistics and R^2 are in the “ t -stat” and “ R^2 ” columns, respectively. The “ ρ ” and “ N ” columns show the number of observations used to estimate the regression parameters and the correlation between the individual green score and the aggregate one. All columns are also shown for the aggregate green score for easy reference.

Table E17: Individual greenium estimates - unbalanced samples

Variable	Estimate	t-stat	R^2	ρ	N
LOG(S1TOT)	-10.90	-0.95	0.06	0.11	692253
LOG(S1+2TOT)	-8.18	-0.62	0.06	0.10	692253
LOG(S1+2+3TOT)	-12.53	-0.89	0.06	0.07	692253
S1INT (Sales)	-10.69	-1.25	0.06	0.24	692253
S1+2INT (Sales)	-11.21	-1.25	0.06	0.24	692253
S1+2+3INT (Sales)	-9.25	-1.04	0.06	0.24	692253
S1INT (Assets)	-16.57	-2.48	0.06	0.23	692253
S1+2INT (Assets)	-17.42	-2.52	0.06	0.22	692253
S1+2+3INT (Assets)	-13.11	-1.59	0.06	0.19	692253
Ind.-adj. ESG score	-31.66	-7.47	0.09	0.69	648794
Weighted ESG score	-38.21	-7.34	0.09	0.72	648574
Environment score	-33.30	-5.27	0.09	0.51	648678
Greenness (PST)	-14.84	-1.51	0.08	0.35	648663
E climate score	-37.34	-3.94	0.09	0.41	548774
E nat. res. score	-19.36	-2.48	0.08	0.33	419983
E waste score	-24.27	-3.49	0.08	0.27	358925
E env. opps. score	-8.37	-1.48	0.07	0.40	220230
Total ESG score	-8.35	-1.77	0.09	0.29	461102
Environmental score	-7.71	-1.70	0.09	0.27	461121
Aggregate green score	-38.62	-8.88	0.07	1.00	875596

The table shows the greenium estimates corresponding to the 19 individual green scores on an unbalanced sample, that is, using the sample where the individual green score is non-missing. The individual greeniums are estimated based on our preferred specification with a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). The greenium based on the aggregate green score is included for easy reference.

Table E18: Non-standardized individual greenium estimates - unbalanced samples

Variable	Estimate	t-stat	R^2	N
LOG(S1TOT)	-5.36	-1.19	0.06	752741
LOG(S1+2TOT)	-4.85	-0.84	0.06	752741
LOG(S1+2+3TOT)	-7.51	-1.11	0.06	752741
S1INT (Sales)	-1.55	-1.44	0.06	752741
S1+2INT (Sales)	-1.56	-1.47	0.06	752741
S1+2+3INT (Sales)	-1.24	-1.30	0.06	752741
S1INT (Assets)	-4.16	-2.13	0.06	752741
S1+2INT (Assets)	-4.06	-2.17	0.06	752741
S1+2+3INT (Assets)	-2.40	-1.59	0.06	752741
Ind.-adj. ESG score	-16.24	-7.50	0.08	675521
Weighted ESG score	-38.29	-6.90	0.08	675313
Environment score	-16.95	-5.32	0.08	675423
Greenness (PST)	-13.51	-1.61	0.08	675390
E climate score	-15.40	-3.99	0.09	575438
E nat. res. score	-10.27	-2.71	0.08	436520
E waste score	-11.52	-3.54	0.08	374147
E env. opps. score	-9.14	-2.29	0.07	234651
Total ESG score	-0.49	-1.08	0.09	469221
Environmental score	-0.27	-0.85	0.09	469221

The table shows the greenium estimates when using either of the 19 individual green scores on an unbalanced sample, that is, using the sample where the individual green score is non-missing. The individual greeniums are estimated based on our preferred specification with a country-time fixed effect, and controls for market beta, log book equity (size), net debt-to-assets (leverage), and ebit-to-assets (profitability). In contrast to Table E17, the green scores have not been standardized.

Table E19: Individual greenium estimates by correlation to aggregate green score: unbalanced samples

Parameter	Estimate	SE (OLS)	SE (BS)	t -stat ($H_0: 0$)	t -stat ($H_0: -39$)
Intercept	-3.72	3.24	7.01	-0.53	
Slope	-44.61	9.15	13.63	-3.27	-0.44

The table reports the intercept and slope parameter estimates from regressing greenium estimates based on each of the 19 individual greenness measures on the correlation between each measure and the aggregate green score. In contrast to Table 2, we use an unbalanced sample to estimate the greenium, meaning that we only use the sample where the individual green score is non-missing. The column “SE (OLS)” shows the normal OLS standard errors and “SE (BS)” shows the standard errors based on 100 bootstrap replications, in which we randomly sample observations by country with replacement. We use the bootstrap standard errors for the t -statistics because they account from the variability coming from the fact that the regression variables are estimated rather than known. The next column shows the t -statistics under the null hypothesis that the true parameter is zero. Similarly, the following column shows t -statistics under the null hypothesis that the slope is -39 bps, that is, the column tests the model-implied condition that the slope equals the greenium based on the aggregate green score. The regression has 19 observations and the adjusted R^2 is 0.56.

F 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 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.³¹ In contrast, we cluster standard errors by industry and time in all our analyses.

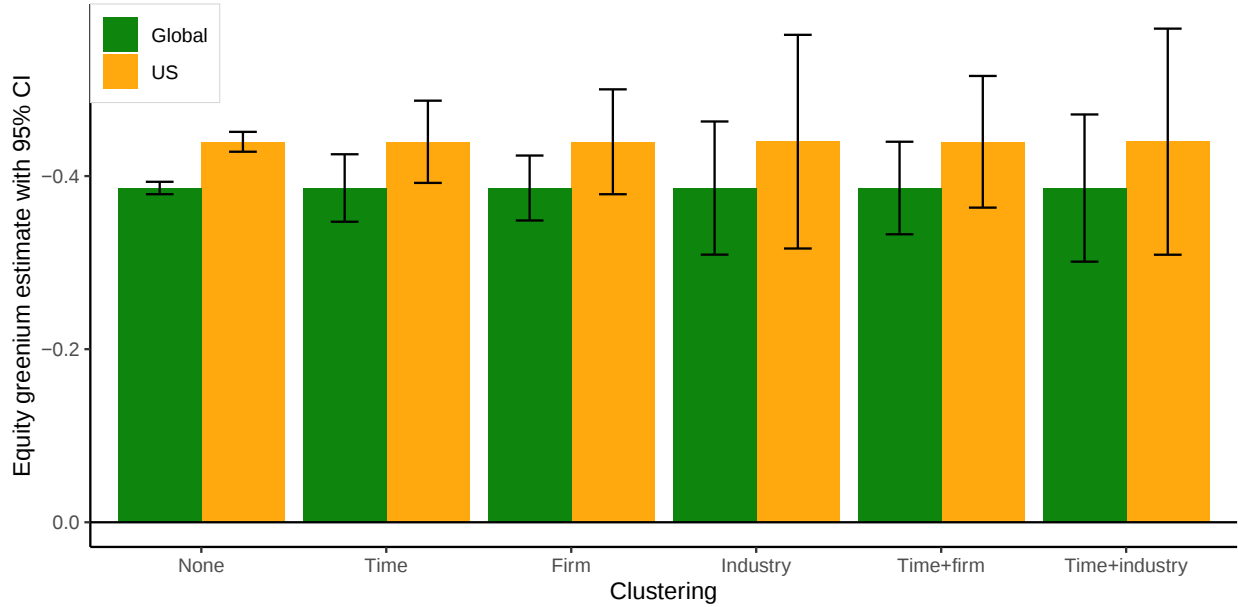
The clustering method matters for the analysis using ICCs. Figure [E1](#) shows the estimated equity greenium in the US and global ex-US samples using ICCs along with the 95% confidence intervals based on six different methods to compute standard errors: i) OLS standard errors, ii) clustering by time (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

³¹For 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 et al. \(2022, Table 3\)](#). 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 E1: Estimating correct standard errors and 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 aggregate 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 aggregate 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.

“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, represent sufficiently many clusters.³² 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](#)).

³²With 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).

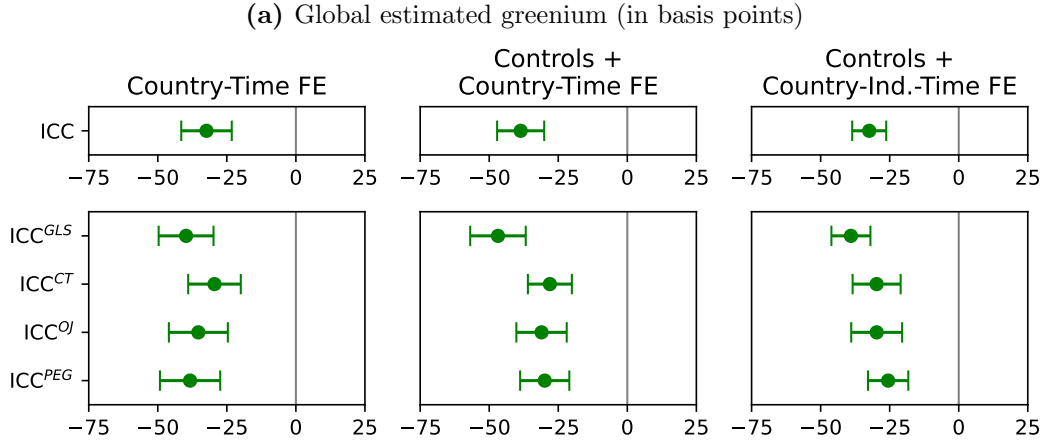
In summary, we compute standard errors that result in wider confidence intervals than prevailing methods in the ICC literature, but we believe that computing standard errors this way is most appropriate.

G Further robustness

G.1 Greenium estimates based on individual ICC methods

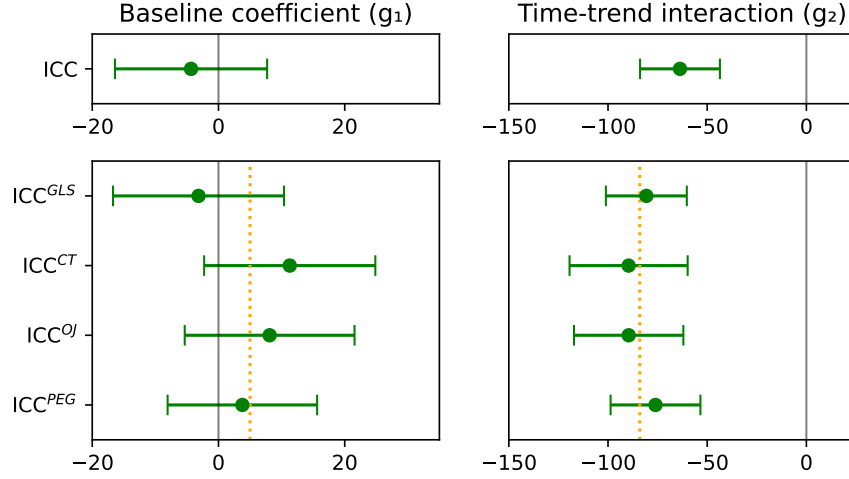
The ICC used to estimate our headline greenium estimate is based on an average of four individual ICC methods. Figure E2 shows the greenium estimate based on each of the individual methods. Similarly, the statement that the greenium has decreased over time is based on the average ICC. Figure ?? shows corresponding estimates based on each of the individual methods.

Figure E2: Regressions of implied cost of capital on aggregate green score



The figure shows the annual greenium (in basis points) estimated by regressing implied costs of capital (ICCs) on our aggregate green score and controls, see (17). We consider ICCs from Gebhardt et al. (2001, ICC^{GLS}), Claus and Thomas (2001, ICC^{CT}), Ohlson and Juettner-Nauroth (2005, ICC^{OJ}), and Easton (2004, ICC^{PEG}), as well as their equal-weighted average, ICC. The estimate based on the equal-weighted average is the same as in Figure 3, and is included here for easy reference. The sample is global stocks. The control variables are market beta, log book equity, net debt-to-assets, and ebit-to-assets. The aggregate 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 E3: 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 (20). 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 the sample to the end of the sample (2009-08 to 2022-12). We consider ICCs from Gebhardt et al. (2001, ICC^{GLS}), Claus and Thomas (2001, ICC^{CT}), Ohlson and Juettner-Nauroth (2005, ICC^{OJ}), and Easton (2004, ICC^{PEG}), as well as their equal-weighted average, ICC. The estimate based on the equal-weighted average is the same as in Figure 3, and is included here for easy reference. 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 aggregate 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.

G.2 Decile sorts

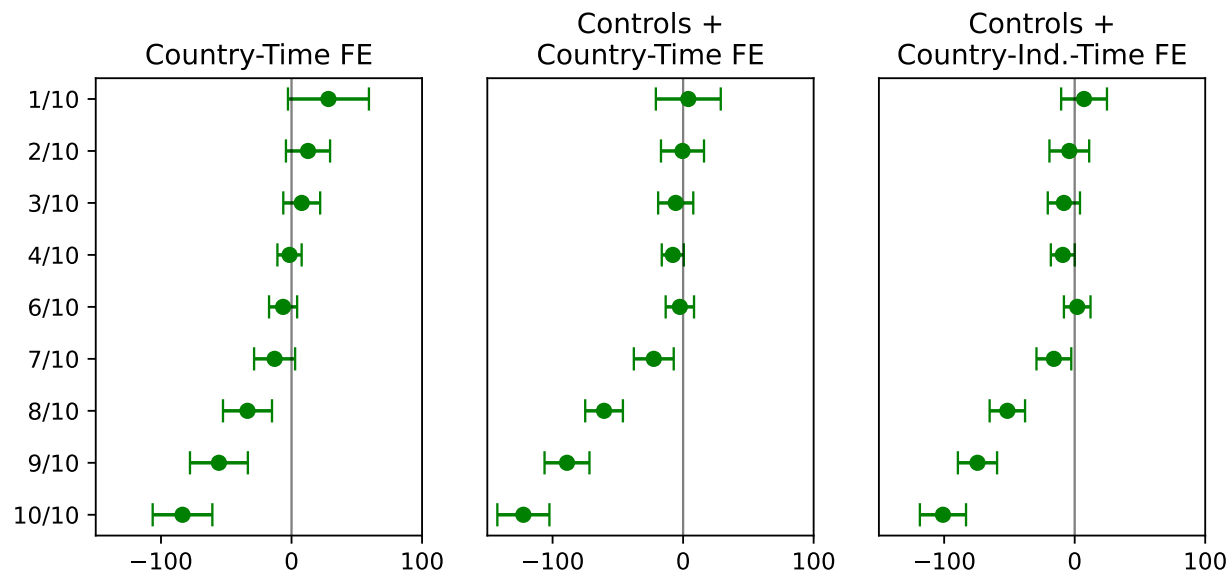
First, we relax the implicit assumption of linearity in Equation (17). Specifically, instead of using a linear dependence on the aggregate green score, we construct ten dummy variables that indicate which decile each firm belongs to at a specific point in time. For example, a stock i is in decile 1 at 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 (17) by the following regression:

$$\hat{E}_t[r_{t+1}^n] = \alpha_{c,t} + \sum_{d=1,\dots,4,6,\dots,10} g_d 1_{(n \in D_t^d)} + \text{controls} + \epsilon_{t+1}^n, \quad (\text{E54})$$

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.

Figure E4: Expected return across ten bins sorted on the aggregate green score



The figure shows the annual greenium (in basis points) estimated by regressing the average implied cost of capital from Figure 3 on decile dummy variables, see (E54). The sample is global stocks. The control variables are market beta, log book equity, net debt-to-assets, and ebit-to-assets. The aggregate 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 run this regression with ICC as the dependent variable and report the results in Figure E4. Figure E4 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 approximately 3.2 times the estimated greenium from Figure 3. The results in Figure E4 are consistent with this prediction. For example, the expected return spread from decile 10 to decile 1 is 116 bps with time-fixed effects and controls. So replacing the brownest stocks with the greenest leads to a meaningful loss in expected returns of more than 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 0.4% per year.

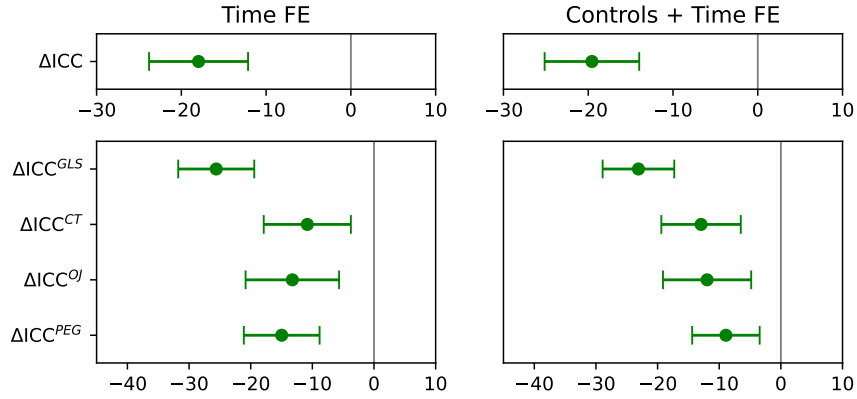
G.3 Text-based firm matching

Another potential issue with the regression in Equation (17) 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, we use the text-based industry classification from [Hoberg and Phillips \(2010, 2016\)](#).³³ 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 aggregate green score, and their controls and estimate the regression:

$$\Delta ICC_t^n = \alpha_{c,t} + g \Delta s_t^n + \Delta \text{controls} + \epsilon_t^n, \quad (\text{E55})$$

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 E5: 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 aggregate green score and controls, see (E55). 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 aggregate 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 E5 shows that the relationship between greenness and the implied cost of capital

³³The data are available at hobergphillips.tuck.dartmouth.edu/industryclass.htm.

is still negative when controlling for matched firms. The magnitude is, however, smaller at around -13 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 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.

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