Scoring in the Transition: A Signaling Model of Corporate Decarbonization

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Abstract

We assess a novel methodology to assign scores in a model in which: (i) a firm has a valuable transition growth option whose payoff is realized at the end of a transition period, (ii) the firm's CEO has private information on the growth option quality; and (iii) a fund manager must decide how much to invest in this firm under limited information. In this setting, a progress-oriented score improves the allocation of capital. In an empirical application to the economics of climate, we show that an investment strategy that uses progress-based scores delivers a superior performance.

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1 Introduction

Regardless of our prior on climate change, the following question has a first-order relevance: how do we think of ESG-based scores and their implications for investment? Given the recent growth of this segment of the industry, a deeper analysis of the industry practices is required. In this manuscript, we study alternative ways to assign ESG scores to firms in the transition, and show that some methodologies can be superior both in theory and in practice.

More in general, we think of firms going over a transition phase. Some of them are ready to transition and represent a 'safe' outside option for fund managers. Other firms, instead, are behind, meaning that they have a greater distance from target and an unrealized transition growth option. The transition growth option refers to the potential of ending the transition phase with great results. In such an environment, fund managers can obtain a higher performance by investing in 'currently-behind' firms which are underpriced despite their transition growth option. In what follows, we study how scores can be designed in order to help investors to identify firms with high-quality transition growth options.

In order to make our general model easier to explain, we apply our framework to the green transition. We think of a strategic game between a fund manager and a CEO. The fund manager is the first mover and decides (i) which kind of score to use for her investment decisions, and then (ii) how much to invest in the CEO's company. The fund manager must allocate her fund across (i) a 'good' firm which is modeled as an exogenous safe investment vehicle, and (ii) a firm with a transition-related growth opportunity with an unknown potential. At time zero, the fund manager can choose whether to use a 'backward looking' score based on the emissions realized by the CEO's company, or a 'forward looking score' based on distance-to-target, where the target is influenced by the disclosure of the CEO. In what follows, we first explain what happens under a traditional, i.e., backward looking, ESG score, and then we illustrate what happens under a 'forward looking' score.

We think of a game with three dates. At time 2, the transition is over and all

payoffs are realized. If the CEO has a high decarbonization potential, the final value of its company is high. Unfortunately, the fund manager does not know the CEO's type. At time 1, the fund manager observes a noisy signal about the CEO's decarbonization potential and can adjust her allocation of capital subject to a reallocation cost. At time zero, the fund manager anticipates what could happen at time 1 and invests an optimal amount in the firm, given her prior on whether the CEO of the firm is good/green or bad/brown.

Under the 'backward looking' setting, the fund manager trusts an ESG score based on realized emissions. At time 1, the fund manager observes the firm's time-1 decarbonization level, which is the result of (i) the true decarbonization growth opportunity to be realized at time $t = 2$, known to the CEO; and (ii) a pure noise shock. In this setting, three scenarios can occur. If the signal is very positive (negative), the fund manager identifies whether the CEO has a good/green (bad/brown) transition potential. In an intermediate region of values, the signal is not informative. At time zero, the fund manager anticipates these scenarios and knows that at time $t = 1$ capital reallocation is possible but costly. As a result, at time $t = 0$, the optimal amount invested in the CEO's firm is based on the expected, i.e., average decarbonization potential of the CEO. Ex-ante, this investment strategy minimizes the expected reallocation costs. Ex-post, however, this allocation is not efficient because it is either excessive if the CEO's type is brown, or limited if the CEO's type is green. When the ESG score obtained at time $t = 1$ is informative, the fund manager can change portfolio allocation, but the reallocation is still inefficient because of reallocation costs.

In a 'forward looking' score setting, the fund manager commits to use a score based on distance-to-target. At time $t = 0$, the fund manager asks the CEO to disclose a decarbonization target for time $t = 1$. This target is then compared with the noisy signal realized at time $t = 1$. Importantly, we assume that missing a disclosed target produces stigma, reducing the CEO's company value. In this setting, the good/green CEO can signal its type to the fund manager by announcing a sufficiently high decarbonization target. Because of stigma, if the target disclosed by the green CEO is high enough,

the bad/brown type finds it optimal not to mimic the green type, as the stigma cost dominates the benefit of receiving more capital. This mechanism delivers a separating equilibrium at time zero and an efficient allocation. Indeed, at the equilibrium, no stigma is realized and no reallocation cost is paid. Both ex-ante and ex-post, the fund manager expects a higher fund value under this score system. We think of this higher expected portfolio performance as an 'alpha' generated by a more informative score.

In the second part of this paper, we look at the data and study investment strategies based on different ESG indicators. A standard index to evaluate the 'greenness' of firms is the MSCI ESG index, see MSCI ESG Research LLC (2024). Most of the contributors to the index are related to current environmental data. Only a small portion reflects green opportunities. We think of this popular index as 'backward looking', meaning that it reflects primarily current environmental impact.

In addition, we use scores produced by ConsciESG (https://www.consciesg.com/). Their methodology differs in at least two key dimensions. First they use AI to extract and analyze numerical data from company reports, as the model is based solely on quantitative information. Second, they explicitly use these data to assess the 'progress to target' of each company. The resulting scores belong to three groups: 'Egressus', i.e., negative progress to target (0-10); 'Ante', i.e., positive progress to target (10-27); and 'Nova', i.e., met or surpassed targets (27+). We refer to this scoring approach as 'forward looking'.

Unfortunately, due to limited availability of ESG disclosure, the cross section of companies analyzed by both ConsciESG and MSCI is limited. Our dataset comprises 1,329 international companies which we track from 2019 to 2023. On the positive side, our sample involves a total of 30 countries with a good coverage of both the US, and the EU-Core+UK economic areas.

We consider one ESG score at a time and construct a zero-dollar investment strategy that is long in the top 20% and short in the bottom 20% of firms ranked by their ESG score for ConsciESG and by improvements in the ESG score for MSCI. In order to have an implementable strategy, we use pre-determined scores and we form the portfolios once a year. We run standard no arbitrage-based time series regressions controlling for both

the FF5 international factors (Fama and French 2017) and the traditional ESG factor. The traditional ESG factor is constructed by considering the excess return of a zero-dollar investment strategy long (short) in the top-20% (bottom-20%) of firms ranked according to their industry-adjusted MSCI ESG score in levels.

Across several specifications, a portfolio based on the improvement of the MSCI ESG score produces no significant additional alpha. In contrast, the investment strategy that uses the forward looking signal of ConsciESG produces a weekly alpha of about 0.18. In annualized terms, the alpha is in the order of 9%. Importantly, the alpha is never significant when we use the improvement in the MSCI score. When we control for both the ESG and FF5 factors, the annualized point estimate is slightly negative and not statistically significant. We show that these results apply also when we consider alternative indices such as the FTSE Russell (2025) and the LSEG Data & Analytics (2024) (previously called Refinitiv).

Interestingly, we also show that the results are stronger when we focus on continental EU and the UK, i.e., regions in which disclosure practices are stronger. In addition, when examining industry-level alphas, we find that abnormal returns are concentrated in a subset of industries, most notably Business Equipment, Non-Durables, and Chemicals. These sectors are characterized by relatively high abatement potential (see, for example, Walker et al. 2025a and Walker et al. 2025b).

Related literature. Measuring firms' ESG performance is a well-known challenge. Berg et al. (2022) shows that divergences across rating agencies arise from differences in scope, measurement, and weighting schemes, resulting in noisy and often contradictory signals for investors. In the context of the low-carbon transition, this problem becomes even more acute. Empirically, Ilhan et al. (2023) show that institutional investors express strong demand for improved climate-risk disclosure and that greater ownership by climate-conscious institutions is associated with higher-quality firm-level reporting. We take these facts seriously and study how ESG information and transition metrics shape capital allocation under asymmetric information. We propose a novel model to think of disclosure, ESG scoring, and fund managers' performance.

Serafeim (2022) uses an ESG *momentum* measure computed by TruValue Labs data (Truvalue Labs, A FactSet Company 2020), capturing the rate of change in public sustainability sentiment. We differ for our attention toward 'forward looking' ESG scores based on progress-to-target. Since the launch of the Task Force on Climate-related Financial Disclosures (Task Force on Climate-related Financial Disclosures, 2017) and, more recently, the IFRS/ISSB S2 standard (International Sustainability Standards Board, 2023), regulators and investors have increasingly called for the disclosure of transition plans, scenario analyses, and capital expenditure data to assess firms' alignment with net-zero pathways. Our evidence shows that scores based on progress-to-target could be optimal. Loumioti and Serafeim (2024) analyze the emergence and rapid expansion of sustainability-linked loans (SLLs). They highlight the relevance of their unregulated covenant structure. We differ for our focus on equity financing and ESG-score design.

Announced targets are useful only if paired with credible and verifiable actions. Lyon and Maxwell (2011) develops a model of strategic environmental disclosure in which firms may selectively highlight positive environmental actions under the threat of NGO audits. Our framework addresses this issue by emphasizing conditional verification: forward-looking scores are formed by assessing progress-to-target. Hence, our work contributes to the literature on credible signaling and reputation building under asymmetric information (e.g., Bénabou and Tirole, 2010; Board and Meyer-ter Vehn, 2013).

Bolton and Kacperczyk (2021) find that markets already price carbon risk. Heinkel et al. (2001) and Pastor et al. (2022) show that investor preferences for sustainability affect firms' financing costs. Specifically, exclusionary screening raises the cost of capital for brown firms, while preference-driven investing lowers it for green firms. When firm types are unobservable, these effects depend critically on the informativeness of ESG scores. Our model builds on this intuition by showing that a forward-looking scoring system allows investors to form more accurate beliefs about firm type, thereby improving capital allocation efficiency.

Goldstein et al. (2024) analyzes how ESG information affects asset prices. We examine the implications of such information for fund managers' capital allocation decisions. We

do so, by looking at a scoring strategy that focuses on 'progress-to-target'. In this sense, our approach is in the spirit of Green and Taylor (2016). Differently from us, these authors study the optimal contract for a dynamic screening problem in which the principal must infer the agent's private progress. We focus on optimal scoring design to better identify progress-to-target.

2 The Model

In this section, we present our stylized model in order to study the interaction between a CEO with financing needs and a fund manager that must allocate investments across firms. The fund manager can choose between a safe outside investment option and investing in the CEO's corporation. Ex-ante, this investment is risky because the fund manager does not know the growth option potential of the corporation and hence she does not know whether this investment will outperform the outside investment option. The CEO knows her type, i.e., the true potential of the growth option. In an environment in which companies are assigned a score which assesses the potential of the growth option, the CEO can disclose information that delivers a separating equilibrium and helps the fund manager to optimize investment. When looking at returns in the data, optimized investment manifests as an 'alpha'.

2.1 Environment and Timeline

The economy is populated by the **CEO** of a corporation, and a fund manager (**FM** henceforth). The corporation has a growth option whose quality is unknown to the **FM**. In what follows, we use an application to climate finance and think of the growth option in terms of decarbonization potential. As a result, a firm with a good growth option is denoted as G (which also stands for green), whereas a firm with a bad-quality growth option is denoted as B (which also stands for brown).

We study a transition that unfolds over three dates, $t \in \{0, 1, 2\}$. The timeline is depicted in figure 1 and it evolves as follows. At $t = 0$, the **FM** decides which kind of

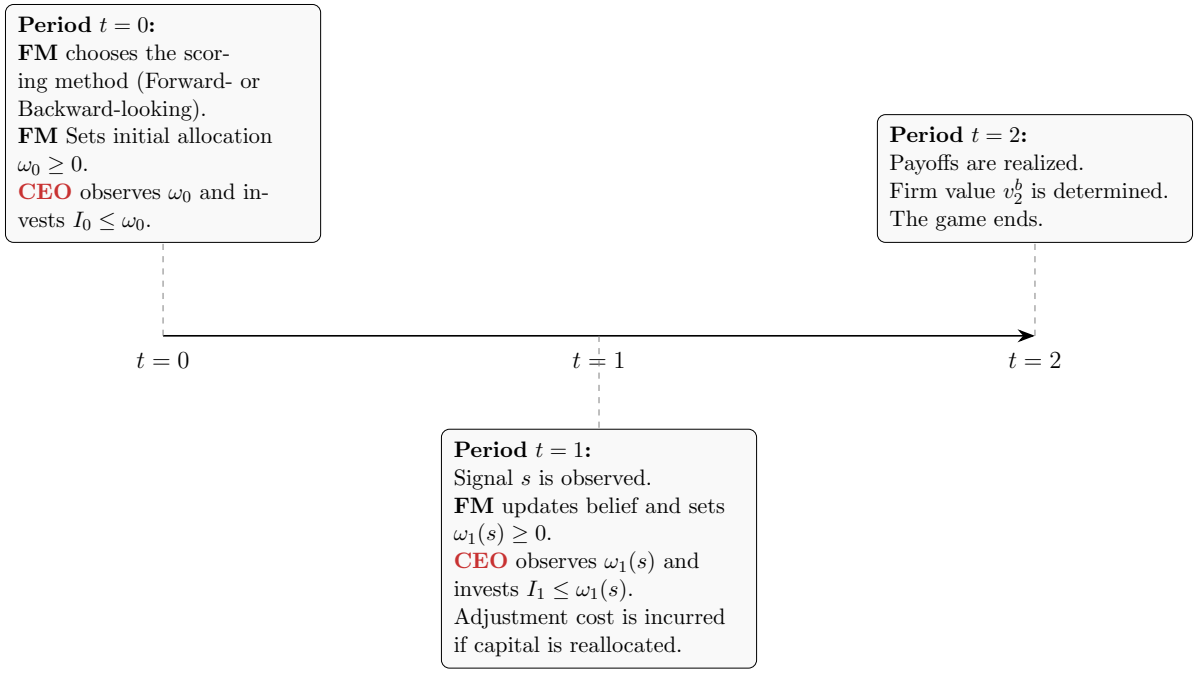


Fig. 1. **Timeline.** This figure shows the timeline of the game between the Fund Manager (**FM**) and the **CEO**.

score to adopt and sets the initial capital allocation $\omega_0 \in \mathbb{R}_{\geq 0}$. The **CEO** observes ω_0 and chooses the initial investment $I_0 \leq \omega_0$. At time $t = 1$, after observing a signal s, the **FM** updates her belief about the firm's type and selects a new allocation $\omega_1(s) \in \mathbb{R}_{\geq 0}$. Since the reallocation is subject to an adjustment cost, the **FM** has an incentive to optimize capital allocation at time $t = 0$. Simultaneously, the **CEO** observes $\omega_1(s)$ and chooses the follow-up investment $I_1 \leq \omega_1(s)$. At time $t = 2$, all payoffs are realized. The firm's final value v_2^b is determined, and the game ends.

This timing convention yields the following Stackelberg's game structure. The **FM** is the leader since she decides which kind of scoring protocol to adopt. In what follows, we refer to either (i) a forward-looking scoring mechanism that assesses the decarbonization progress of a firm; or (ii) a backward looking scoring mechanism that looks at current emission levels. At $t = 0$, the **FM** chooses ω_0 anticipating the **CEO**'s optimal response $I_0^*(\omega_0)$. In addition, the **FM** anticipates that at $t = 1$, after observing the signal s, she may need to revise her allocation subject to adjustment costs.

The **CEO** is the follower. At $t = 0$ ($t = 1$), the **CEO** observes ω_0 (ω_1) and chooses $I_0 \leq \omega_0$. At $t = 1$, the **CEO** observes $\omega_1(s)$ and chooses $I_1 \leq \omega_1(s)$. If the **FM** decides to adopt a forward-looking scoring, the **CEO** has the option to disclose additional

information about her type, i.e., her growth option quality. For the sake of simplicity, in what follows we assume that the **CEO** announces a decarbonization target $\bar{D}$ for t=1. This announcement should be interpreted broadly, meaning that the **CEO** could simply disclose additional data that scoring agencies can then process and turn into a decarbonization potential.

2.2 Firm's type, Technology, and Signals

We find it optimal to describe the key features of the **CEO**'s corporation starting from $t = 2$. Specifically, the firm's value at $t = 2$ is given by the following production function,

$$v_2 \coloneqq v_2\left(I_1, I_0, \tau\right) = I_1^{\gamma} + \lambda D_2 - c|I_1 - I_0|, \tag{1}$$

in which $\gamma \in (0, 1)$ so that v_2 is concave in pre-determined investment I_1, $\lambda > 0$ captures the improved market value of a firm with high decarbonization level at the end of the transition, D_2, and $c \in (0,\ \lambda\tau^b)$ captures a proportional investment adjustment cost to be paid if there is reallocation of resources at time $t = 1$.

The final level of decarbonization is modeled as,

$$D_2 \coloneqq D_2(I_1, \tau^i) = \tau^i I_1, \quad \tau^i \in [\tau^b, \tau^g], \tag{2}$$

implying that it depends on both pre-determined investment, and the quality of the decarbonization technology, τ^i. We assume that $0 < \tau^b < \tau^g$, implying that the green type has a higher value by the end of the transition.

The **CEO** knows the decarbonization type, τ^i, since $t = 0$, but the **FM** does not. At time $t = 1$, the **FM** observes a noisy signal about τ^i because she observes,

$$D_1^i \coloneqq D(I_0, \tau^i) = \tau^i I_0 + \varepsilon^i, \tag{3}$$

where I_0 is the investment on the green technology pre-determined at $t = 0$, and

$$\varepsilon^i \sim \text{Uniform}((1-\eta)\tau^i I_0, (1+\eta)\tau^i I_0). \tag{4}$$

We assume that the variance of ϵ increases proportionally with the scale of the investment so that the **FM** cannot easily learn the **CEO**'s type by investing a lot at time zero. This specification is both convenient and realistic since larger decarbonization projects may be subject to more uncertainty due to their complexity. The **FM** knows the distribution of the noise and hence she knows that the maximum decarbonization realization for a bad type is $(1+\eta)\tau^b I_0$, whereas the minimum decarbonization realization for a good type is $(1-\eta)\tau^g I_0$. In what follows, we assume that

$$(1+\eta)\tau^b \geq (1-\eta)\tau^g \Leftrightarrow \eta \geq \frac{\tau^g - \tau^b}{\tau^g + \tau^b},$$

implying that there is a range of values of the signal D_1 for which it is not possible to identify the CEO's type. As a result, if a traditional scoring method is adopted and firms are ranked according to their realized decarbonization, when $\epsilon \in [(1-\eta)\tau^g, (1+\eta)\tau^b]$ the **FM** cannot learn from the signal and the allocation of capital at $t = 1$ is identical to that at time $t = 0$. Thanks to our uniform distribution assumption, the posterior is just based on the **FM**'s prior across the two types.

If the **FM** decides to adopt a forward-looking scoring protocol, the **CEO** can make an announcement ($\bar{D}$) at time 0 and alter the final equilibrium. We discuss this point after describing the problem of the **FM**.

2.3 Fund Manager

The final payoff of the **FM** at time $t = 2$ depends on the following portfolio allocation,

$$V_2^{\mathbf{FM}} = (\omega_{max} - \omega_1)\, p + (1-\theta) v_2(I_1, I_0, \tau),$$

where ω_1 must be chosen at time $t = 1$ so that $\omega_1 \leq \omega_{max}$, p is the final value of a share of the outside option and it can be interpreted as the market value of an 'already decarbonized' company. The fund manager is assumed to capture a fraction $(1 - \theta)$ of the final value of the CEO's corporation, v_2.

At time $t = 1$, the **FM** observes the signal s and solves the following portfolio problem:

$$V_1^{\mathbf{FM}} := \max_{\omega_1 \in [0, \omega_{max}]} \mathbb{E}_1^{\mathbf{FM}} \left[V_2^{\mathbf{FM}} | s \right], \tag{5}$$

where the expectation is computed over the possible **CEO** types. Specifically, let π_0 be the prior probability assigned to the G type. After observing s, beliefs are updated according to Bayes' rule and $\pi_1(s)$ is formed. In what follows, we assume that

$$p - (1 - \theta)\lambda\tau^g > 0,$$

so that this optimization has always an interior solution.[1]

At time $t = 0$, the **FM** chooses the allocation ω_0 by solving the following problem:

$$V_0^{\mathbf{FM}} = \max_{\omega_0 \in [0, \omega_{max}]} \mathbb{E}_0^{\mathbf{FM}} \left[V_1^{\mathbf{FM}} \right], \tag{6}$$

where the expectation is taken prior to observing the signal s and hence under limited information the probability π_0 is assigned to the G type.

In addition, the **FM** decides whether to use a score based on the **CEO** decarbonization potential. That is, the **FM** decides whether to account for the **CEO**'s announcement about $\overline{D}$ and $s = \{D^i, \overline{D}\}$. Let $V_0^{\mathbf{FM},\bar{D}}$ be the time-0 value function of the **FM** when a forward-looking score is adopted. The **FM** will choose this kind of score when

$$V_0^{\mathbf{FM},\bar{D}} \geq V_0^{\mathbf{FM}}. \tag{7}$$

[1] If this inequality were violated, the marginal value of investing in the brown firm would exceed that of the green benchmark and we would have the corner solution $\omega_1 = \omega_{max}$.

2.4 CEO's Problem

At time $t = 1$, the **CEO** observes the capital allocation ω_1^* set by the **FM** and chooses the investment I_1 to maximize her share θ of the firm's value:

$$V_1^{\mathbf{CEO}}(\omega_1, I_0, \tau) \coloneqq \max_{I_1 \leq \omega_1} \left\{ \theta \, v_2^b(I_1, I_0, \tau) \right\}. \tag{8}$$

Note that the **CEO** knows her type and hence, in contrast to the **FM**, computes no expected value at time $t = 1$.

At time $t = 0$, for given ω_0, the **CEO** then chooses the initial investment I_0 to maximize the following objective function:

$$V_0^{\mathbf{CEO}}(\omega_0, \tau) \coloneqq \max_{I_0 \leq \omega_0} \left\{ \mathbb{E}_0^{\mathbf{CEO}} \left[V_1^{\mathbf{CEO}}(\omega_1, I_0, \tau) \,\middle|\, \tau, s = D^i \right] \right\}, \tag{9}$$

where the expectation is computed across realizations of the signal that can alter the allocation of funds at time $t = 1$. If the **FM** decides to take advantage of a forward looking score, the **CEO** can also decide the optimal value of $\bar{D}$ such that

$$V_0^{\mathbf{CEO}}(\omega_0, \tau) \coloneqq \max_{I_0 \leq \omega_0, \bar{D}} \left\{ \mathbb{E}_0^{\mathbf{CEO}} \left[V_1^{\mathbf{CEO}}(\omega_1, I_0, \tau) \,\middle|\, \tau, s = \{D^i, \bar{D}\} \right] \right\}. \tag{9b}$$

In practice, the **CEO** can disclose information $\overline{D}$ to manage the **FM** beliefs about her type and gather more funds at time $t = 0$.

2.5 Definition of Equilibrium

In what follows, we describe the objects that characterize a Perfect Bayesian Equilibrium (PBE) in this dynamic **CEO** and **FM** game. First of all, we need to specify the **CEO**'s strategy. For each type $\tau \in \{\tau_g, \tau_b\}$, her strategy comprises:

1. an announcement $\bar{D}$ if the **FM** adopts a forward looking score;
2. the initial investment choice $I_0^*(\tau) \in [0, \omega_0]$ taking as given the **FM**'s choice of ω_0;
3. the optimal subsequent investment I_1^* taking as given the new allocation ω_1 chosen by the **FM** at $t = 1$.

The strategy of the **FM** comprises:

1. the decision to account for the **CEO** announcement $\bar{D}$;
2. an initial capital allocation rule $\omega_0^* \in [0, \omega_{\max}]$;
3. a reallocation rule $\omega_1^* \in [0, \omega_{\max}]$ after observing signal $s \in S$.

Given the dynamic of the information set of our agents, both agents satisfy sequential rationality.

2.6 Solution with Backward Looking Signal

Time 1. We start solving the equilibrium from at $t = 1$. At $t = 1$, the signal $s := D^i$ is observed and the **FM** updates her belief $\pi_1(s)$ using Bayes' rule. There are three possible scenarios: (i) the signal is uninformative and the capital allocation remains unchanged; (ii) the signal is extremely positive and it identifies a G type, and (iii) the signal is extremely negative and it identifies B type. In each case, the **CEO** chooses investment $\omega_1^*(s)$ anticipating the **CEO**'s reaction.

Green type. If $s > (1+\eta)\tau^b$, the **FM** knows that the **CEO** type is G and $\pi_1(s) = 1$. According to equations (1)–(2), the **CEO** has a marginal incentive to invest as much as possible since

$$\frac{\partial v_2}{\partial I_1} = \gamma I_1^{\gamma-1} + \lambda\tau - c\mathbf{1}_{\{I_1^* \neq I_0\}} > 0.$$

Hence, the **FM** knows that $I_1 = \omega_1 > I_0$ and the **CEO** just invests the amount chosen by **FM**. Taking this channel into account, the solution of the time-1 **FM** problem detailed in equation (5) is:

$$\omega_1^g = \left(\frac{(1-\theta)\gamma}{p - (1-\theta)(\lambda_g \tau_g - c\mathbf{1}_{\{I_1^* \neq I_0\}})} \right)^{\frac{1}{1-\gamma}}. \tag{10}$$

Brown type. If $s < (1-\eta)\tau^g$, the **FM** knows that the **CEO** type is B and $\pi_1(s) = 0$. The **CEO** objective function is unchanged and hence she has an incentive to invest as much as possible. Absent fixed adjustment costs, the **FM** has an incentive to retrench and set

$$\omega_1^b = \left(\frac{(1-\theta)\gamma}{p - (1-\theta)(\lambda_b \tau_b - c\mathbf{1}_{\{I_1^* \neq I_0\}})} \right)^{\frac{1}{1-\gamma}}. \tag{11}$$

Uninformative signal. If $s \in [(1-\eta)\tau^g, (1+\eta)\tau^b]$, it is impossible to identify the CEO's type. Since the noise is assumed to be uniformly distributed, Bayes rule implies $\pi_1(s) = \pi_0$. The optimal capital allocation under this pooling scenario implies:

$$\omega_1^p = \left(\frac{(1-\theta)\gamma}{p - (1-\theta)(\lambda \mathbb{E}_1^{\mathbf{FM}}[\tau] - c\mathbf{1}_{\{I_1^* \neq I_0\}})} \right)^{\frac{1}{1-\gamma}}, \tag{12}$$

and it depends on the expected decarbonization efficiency,

$$\mathbb{E}_1^{\mathbf{FM}}[\tau] = \pi_0 \, \tau_g + (1-\pi_0) \, \tau_b. \tag{13}$$

Time 0 FM problem. At time $t = 0$, the **FM** knows the distribution of ω_1:

$$\omega_1(s) = \begin{cases} \omega_1^g & p_{FM}(G) = \frac{(1+\eta)\tau^g - (1+\eta)\tau^b}{(1+\eta)\tau^g - (1-\eta)\tau^b} \\ \omega_1^p & p_{FM}(P) = \frac{(1+\eta)\tau^b - (1-\eta)\tau^g}{(1+\eta)\tau^g - (1-\eta)\tau^b} \\ \omega_1^b & p_{FM}(B) = \frac{(1-\eta)\tau^g - (1-\eta)\tau^b}{(1+\eta)\tau^g - (1-\eta)\tau^b} \end{cases}, \tag{14}$$

where the probabilities account for the three regions in which the signal can be materialized. Importantly, when

$$\eta = \eta^* := 1 - \frac{\tau^b}{\tau^g},$$

$p_{FM}(G) = p_{FM}(B) = p_{FM}(P)$, i.e., there is an equal probability of the three scenarios. When $\eta > \eta^*$, the probability of being in a pooling equilibrium dominates that of the other two scenarios. This consideration is important because it proves that ω_1^p is the median value. At time $t = 0$, because of our linear adjustment cost, the optimal allocation prescribes:

$$\omega_0^* = \texttt{median}[\omega_1] = \omega_1^p. \tag{15}$$

For the G CEO, it is clear that her optimal solution implies $I_0^* = \omega_0^*$ because the optimal investment level under perfect information would be higher than ω_1^p. The B CEO faces two options. First, it could invest less than ω_0^* in order to avoid reallocation costs and reveal her type. In this case, she would obtain $v_2(\omega_1^b, \omega_1^b, \tau^b)$ with certainty. Alternatively, the bad type could mimic the good type and invest ω_0^*. If the signal is uninformative, she

would preserve the same investment allocation at time $t = 1$ and obtain a higher payoff. In what follows, we assume a parameterization of the model so that

$$\begin{aligned} E_0^{\text{CEO}}[v_2|\tau^b] &= v_2(\omega_1^p, \omega_1^p, \tau^b)\frac{p_{FM}(P)}{p_{FM}(P)+p_{FM}(B)} + v_2(\omega_1^b, \omega_1^p, \tau^b)\frac{p_{FM}(B)}{p_{FM}(P)+p_{FM}(B)} \\ &\geq v_2(\omega_1^b, \omega_1^b, \tau^b), \end{aligned} \tag{16}$$

that is, the B type always behaves as the G type. Note that the reallocation cost is zero in $v_2(\omega_1^p, \omega_1^p, \tau^b)$ and $v_2(\omega_1^b, \omega_1^b, \tau^b)$. Hence the inequality in (16) can be rewritten as

$$\left(\omega_1^{p\gamma} - \omega_1^{b\gamma} + \lambda\tau^b(\omega_1^p - \omega_1^b)\right)\frac{p_{FM}(P)}{p_{FM}(P)+p_{FM}(B)} \geq c|\omega_1^p - \omega_1^b|\frac{p_{FM}(B)}{p_{FM}(P)+p_{FM}(B)},$$

that is, the expected benefit of pooling (left-hand side) should be higher than the expected reallocation cost (right-hand side).

2.7 Solution with Forward Looking Signal

The **FM** at time $t = 0$ announces that at time $t = 1$ she will focus on the following signal:

$$D^i - \overline{D}^i, \quad i \in \{g, b\}$$

that is, the observed decarbonization at $t = 1$ relative to a target $\overline{D^i}$ controlled by the **CEO** at $t = 0$. In addition, we assume that once a target is announced, missing it brings stigma and therefore we replace (1) with,

$$v_2 \coloneqq v_2\left(I_1, I_0, \tau\right) = I_1^\gamma + \lambda D_2 - c|I_1 - I_0| - \mathbf{1}_{D_2^i < \overline{D}^i} s(\overline{D}^i - D_2^i), \tag{1b}$$

where $s > 0$ determines the intensity of the stigma, $\overline{D}^i - D_2^i$ determines the size of the penalty, and $\mathbf{1}_{D_2^i < \overline{D}^i}$ activates the penalty only if the time-2 emissions are below target. This formulation is isomorphic to postulate that the stigma applies immediately at time-1 and it is then revised at time 2. For the sake of the final valuation, only the final assessment of the stigma matters.

We guess and verify a separating equilibrium. Specifically, the G **CEO** knows that, by announcing an ambitious $\overline{D}^g$, the final stigma of the B **CEO** increases and it can overcome the benefit of mimicking the G type. Under the separating equilibrium, the B **CEO** announces $\overline{D}^b \in \left[0, \tau^b \omega_s^b\right]$, with

$$\omega_s^b := \left(\frac{(1-\theta)\gamma}{p-(1-\theta)\lambda\tau_b}\right)^{\frac{1}{1-\gamma}}, \tag{17}$$

being the optimal investment allocation under full information (s stand for separating equilibrium). In this case, the B **CEO** gets a final payoff,

$$v_{2,s}^b = \omega_s^{b^\gamma} + \lambda\tau^b\omega_s^b. \tag{18}$$

Let ω_p^b be the potential amount of funds that the B type could get in a pooling equilibrium,

$$\omega_p^b = \left(\frac{(1-\theta)\gamma}{p-(1-\theta)\lambda\mathbb{E}_0^{\mathbf{FM}}[\tau]}\right)^{\frac{1}{1-\gamma}}. \tag{19}$$

If the B type announces,

$$\overline{D}^g : s\left(\overline{D}^g - \tau^b\omega_p^b\right) = \left(\omega_p^{b^\gamma} - \omega_s^{b^\gamma} + \tau^b\lambda\left(\omega_p^b - \omega_s^b\right)\right), \tag{20}$$

the B type has no longer an incentive to mimic the G **CEO**.

Let

$$\omega_s^g := \left(\frac{(1-\theta)\gamma}{p-(1-\theta)\lambda\tau_g}\right)^{\frac{1}{1-\gamma}}, \tag{21}$$

be the optimal investment given to the G type under full information. If

$$\tau^g\omega_s^g \geq \overline{D}^g, \tag{22}$$

no stigma is realized at the equilibrium and the **FM** obtains the best possible value.

Assuming that (22) holds with equality and using equation (20), we can recover a

minimum stigma intensity s^* that delivers a separating equilibrium:

$$s^* = \frac{\omega_p^{b^\gamma} - \omega_s^{b^\gamma} + \tau^b \lambda(\omega_p^b - \omega_s^b)}{\tau^g \omega_s^g - \tau^b \omega_p^b}. \tag{23}$$

The numerator of s^* captures the pooling gain of the B type, whereas the denominator refers to the decarbonization advantage of the G type in the separating equilibrium.

2.8 Visualization and Take Aways: in Search of Alpha

In this subsection, we calibrate our model to reveal its key mechanisms through visualization. We set $\omega^{max} = 1$ so that ω can be interpreted as a portfolio share. We normalize the price of the already-green company, i.e., the outside safe option so that $p = 1$. This way, all prices can be interpreted as a deviation from 100%. The **FM** has a diffuse prior across the two types, that is, $\pi_0 = 0.5$.

The **CEO** gets a fraction of the final value of the firm equal to 20%, i.e, $\theta = 0.2$. The weight given to capital in the production function is $\gamma = 0.33$, a standard value in the macro literature. In what follows, we keep the mean of the decarbonization potential constant, that is, $\tau_{\text{mean}} = 0.5$. The good (bad) type has a potential $\tau^g = \tau_{\text{mean}} + \Delta\tau$ ($\tau^b = \tau_{\text{mean}} - \Delta\tau$). Under our benchmark calibration, $2\Delta\tau = .2$, implying $\tau^g = .60$ and $\tau^b = .40$. The following parameters are chosen so that the scale of emissions and their implied market value is well-behaved: $\lambda = 0.5$, $c = 0.8$, and $s = 0.5$.

In figure 2, we depict the element required to obtain the minimum stigma intensity value s^* derived in equation (23). Since s is an intensity parameter difficult to interpret, in figure 3 we plot the minimum total stigma penalty, $s(\overline{D}^g(s^*) - \tau^b \omega_p^b)$ as a fraction of the final value of the B **CEO**, v_2^b. Under our benchmark calibration, $2\Delta\tau = 20\%$ and the implied minimum penalty required to have a separating equilibrium is 1.4%, a very small number. Hence the adoption of a forward-looking signal is optimal for small amounts of stigma. Within industries, the decarboniza tion efficiency gap can be small. When we consider a gap of 10%, the required penalty is even smaller than 1% of the firm valuation. When we consider a huge decarbonization gap of 100% across types, the required penalty

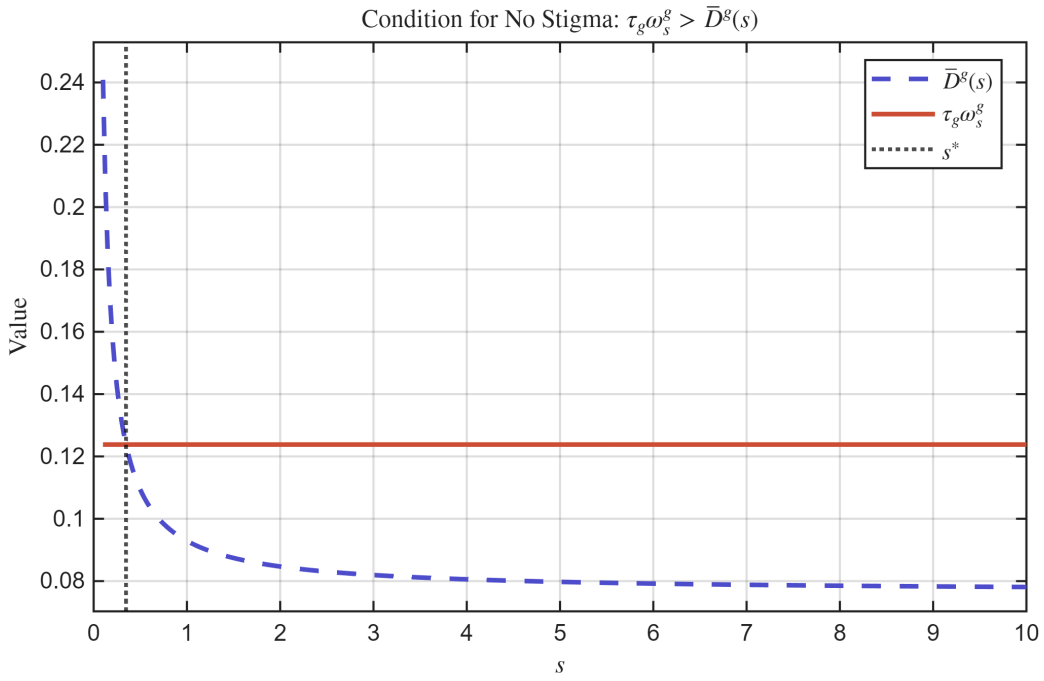


Fig. 2. **Minimum Stigma Intensity.** This figure shows the decarbonization target announced by the G **CEO** as a decreasing function of the stigma intensity s (dashed line). The solid line shows the decarbonization level that the G **CEO** will reach at time 2 under the separating equilibrium. The vertical dotted line shows the value computed in equation (23). When $s > s^*$, the G type pays no stigma penalty at the equilibrium and the B type has no incentive to mimic the G type.

is still smaller than 7%.

In figure 4, we show the ex-ante value of the **FM** under the backward looking signal setting (dotted line), and the forward looking one (dashed line). The solid line shows the value of a **FM** that identifies a G type under the forward-looking signal. We call this value the ex-post valuation, meaning that it considers the gains conditional on the **FM** investing in the G type. Since the total wealth to be invested is normalized to be 1, these numbers can be interpreted as percentage values. For a given $\tau^g - \tau^b$, the vertical distance between these lines can be interpreted as an ex-ante or ex-post alpha.

Under our benchmark calibration, $\tau^g - \tau^b = .2$, and the implied percentage difference in the time-0 ex-ante value of the **FM** is in the order of 4%. That is, a fund manager that embraces the forward looking signal has an alpha, i.e., an investment advantage that prevents costly misallocation of capital.

Under the backward looking setting, as $\tau^g - \tau^b$ increases, the cost associated to the reallocation of capital at time $t = 1$ increases because it is proportional to the size of the

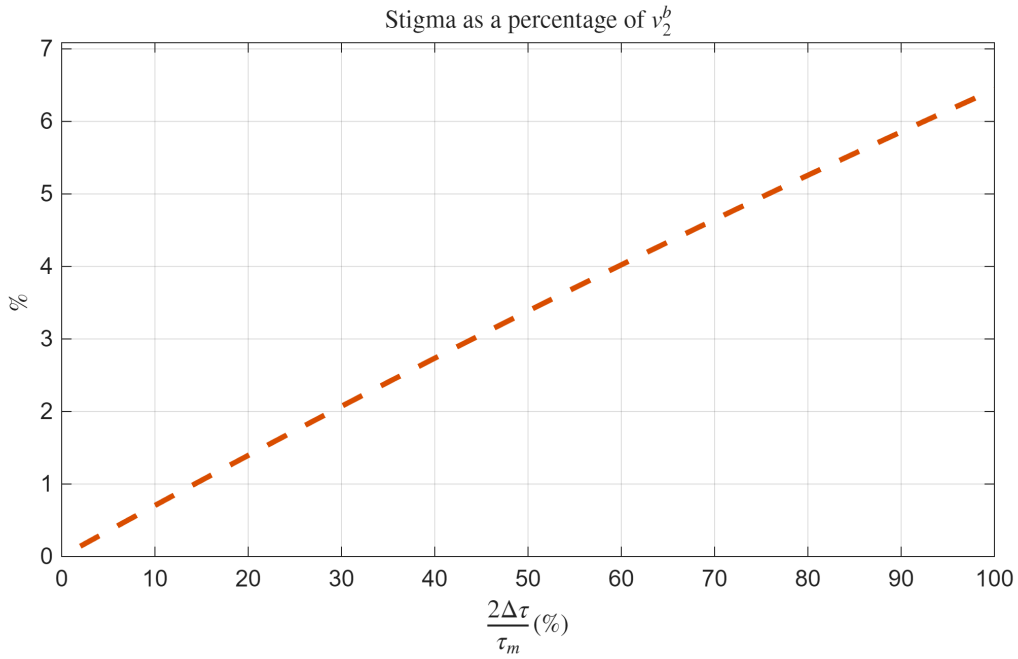


Fig. 3. **Minimum Stigma Intensity.** This figure shows the stigma penalty, $s(\overline{D}^g(s^*) - \tau^b\omega_p^b)$ as a fraction of the final value of the B **CEO**, v_2^b. The equilibrium allocations are computed by varying the decarbonization gap $\Delta\tau$. All figures are multiplied by 100.

reallocation which gets larger with a bigger $\tau^g - \tau^b$. Hence, the ex-ante value of the **FM** declines in $\tau^g - \tau^b$.

Under the forward looking setting, a separating equilibrium is reached and no reallocation cost is paid. Given a prior $\pi_0 = 50\%$ and a mean-preserving variation in $\Delta\tau$ (i.e., across different values of $\Delta\tau$, $E_0^{\mathbf{FM}}[\tau] = \tau_{\text{mean}}$), the ex-ante **FM** valuation remains nearly constant. Ultimately, the **FM** potential alpha increases in scenarios in which $\tau^g - \tau^b$, i.e., when information is very valuable. In the next section, we run time-series tests to assess whether forward looking scores produce an alpha compared to traditional ESG scores.

3 Empirical Investigation

In this section we study investment strategies based on different ESG indicators. In what follows, we briefly describe their methodologies and then we proceed with our time series tests.

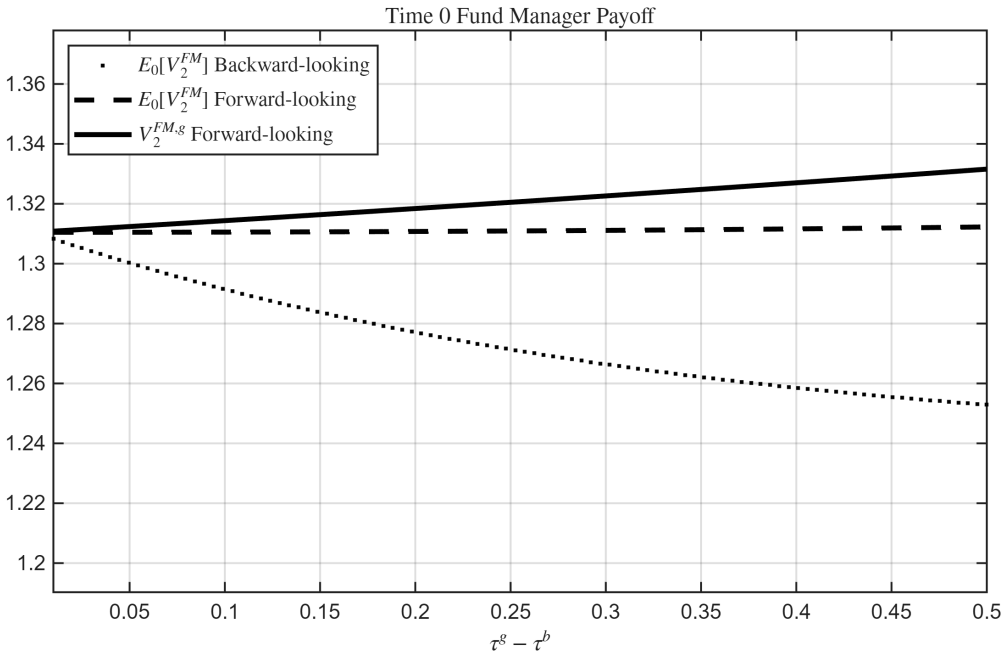


Fig. 4. **Alpha.** This figure shows the ex-ante value of the **FM** under the backward looking signal setting (dotted line), and the forward looking one (dashed line). The solid line shows the value of a **FM** that identifies a G type under the forward-looking signal (ex-post valuation). Since $\omega_{\max} = 1$, these numbers can be interpreted as percentage values. For a given $\tau^g - \tau^b$, the vertical distance between these lines can be interpreted as an ex-ante or ex-post alpha.

MSCI. A standard index to evaluate the 'greenness' of firms is the MSCI ESG index, see MSCI ESG Research LLC (2024). Most of the contributors to the index are related to current environmental data. Only a small portion reflects green opportunities. We think of this popular index as 'backward looking', meaning that it reflects primarily current environmental impact.

ConsciESG. ConsciESG (https://www.consciesg.com/) is a new provider of ESG-related scores. Their methodology differs in at least two key dimensions. First they use AI to extract and analyze numerical data from company reports, as the model is based solely on quantitative information. Second, they explicitly use these data to assess the 'progress to target' of each company. The resulting scores belong to three groups: 'Egressus', i.e., negative progress to target (0-10); 'Ante', i.e., positive progress to target (10-27); and 'Nova', i.e., met or surpassed targets (27+). We refer to this scoring approach as forward looking.

More precisely, ConsciESG's scoring framework relies exclusively on quantitative cor-

porate performance and target data. Targets are either those set by the firm itself or derived from relevant EU regulatory frameworks. "Progress" is defined as the observed rate of movement toward stated targets over time. In addition, the thematic weights used to construct both the granular and aggregate Nova Scores are sector-specific. No qualitative assessments or subjective ratings are included.

Like ConsciESG, Truvalue Labs Truvalue Labs, A FactSet Company (2020) uses AI in order to provide ESG scores for many companies. In contrast to ConsciESG, their indices do not account for distance-to-target.[2]

Portfolio formation. We consider one ESG score at a time and construct a zero-dollar investment strategy that is long in the top 20% and short in the bottom 20% of firms ranked by their ESG score for ConsciESG and by improvements in the ESG score for MSCI. In order to have an implementable strategy, we use pre-determined scores and we form the portfolios once a year. The annualized Sharpe ratio is equal to 0.68 for the ConsciESG sorting and it is equal to -0.46 for the MSCI sorting.

Sample. Due to limited availability of ESG disclosure, the cross section of companies analyzed by both ConsciESG and MSCI is limited. The merged dataset comprises 1329 international companies which we track from 2019 to 2023.

On the positive side, our sample involves a total of 30 countries (see table 1). We have a good coverage of both the US, and the EU-Core+UK economic areas.

In table 2, we report our firms distribution across the FF12 classification. Importantly, both the ConsciESG score and the MSCI ESG score are industry-adjusted. As shown in table A.1 in the Appendix, our cross section spans many industries as defined in Factset. We provide financial statistics in table 3 and we note that our firms tend to be large.

[2]Truevalue states that "The Momentum Score measures the trend of a company's Insight score. It is a unique metric in the industry that gives investors a high-precision view of the trajectory of a company's ESG or SDG performance, relative to peers. It does so by precisely articulating upward or downward movement, relative to that of all others in the universe, making it a measure that enhances quantitative workflows." These assessments are based on published news about the company considered.

Table 1: Geographical Distribution of Companies

Country	Number of Companies
United States	843
Japan	140
United Kingdom	57
Switzerland	41
Canada	32
Italy	28
Australia	24
Germany	23
Spain	20
France	19
Sweden	19
Ireland	12
United Arab Emirates	12
China	10
Bermuda	8
Hong Kong	7
Netherlands	6
Saudi Arabia	5
Mexico	4
Luxembourg	4
Puerto Rico	3
Belgium	2
Singapore	2
Qatar	2
Austria	1
Chile	1
Finland	1
Israel	1
Uruguay	1
Cyprus	1

Notes: This table presents the geographical distribution of companies in the sample by country of headquarters. The United States accounts for the largest share of firms, followed by Japan and the United Kingdom.

Main Results. Our main results are reported in table 4. We run standard no arbitrage-based time series regressions controlling for both the FF5 factors (Fama and French, 2017) and the traditional ESG factor. The traditional ESG factor is contructed by considering the excess return of a zero-dollar investment strategy long (short) in the top-20% (bottom-20%) of firms ranked according to their industry-adjusted MSCI ESG score in levels.

The top panel shows our results when we use the distance-to-target measure of ConsciESG, whereas the bottom panel reports our results when we use the improvement of the MSCI ESG score. In both cases, we control for both the market, the market and a

Table 2: FF12 Industry Classification

Sector	Frequency
Business Equipment	174
Chemicals	42
Durables	54
Energy	49
Health	123
Manufacturing	212
Finance	274
Non-Durables	82
Other	122
Shops	97
Telecommunications	32
Utilities	68

Notes: This table reports the Fama and French 12 industries classification and the number of companies per sector. Frequency represents the count of observations in each industry category.

Table 3: Descriptive Statistics

Variable	N	Mean	Median	Std. Dev.	Pct25	Pct75
Total Assets	6,500	62,297.82	10,776.79	187,229.30	3,305.14	36,223.79
Book Equity	6,500	11,081.46	3,486.42	21,122.19	1,129.26	10,575.88
Sales	6,502	16,911.02	4,953.60	32,762.86	1,600.50	15,876.00
Total Debt	6,500	14,159.78	2,851.28	38,911.48	755.58	9,589.69
Cash	5,782	2,709.50	674.85	5,991.76	197.80	2,213.63
Profitability (ROA)	6,481	4.46	3.76	7.56	1.07	7.59
Market Value	6,461	29,918.46	9,772.02	58,187.84	2,913.98	29,136.94
Book Leverage	6,500	0.30	0.28	0.18	0.16	0.41
Market Leverage	6,447	0.28	0.23	0.22	0.12	0.42
Cash over Assets	5,782	0.13	0.09	0.14	0.03	0.16

Notes: This table reports descriptive statistics for the main variables used in the analysis. **Total Assets** is the book value of total assets. **Book Equity** is shareholders' equity measured at book value. **Sales** represent annual firm revenues. **Total Debt** is the sum of short-term and long-term interest-bearing liabilities. **Cash** denotes cash and cash equivalents. **Profitability (ROA)** is the ratio of net income to total assets, expressed in percentage points. **Market Value** is the market capitalization of equity. **Book Leverage** is total debt divided by total assets. **Market Leverage** is total debt divided by the sum of market value of equity and total debt. **Cash over Assets** is the ratio of cash holdings to total assets. All monetary values are expressed in millions of U.S. dollars. The table reports the number of observations (N), mean, median, standard deviation, and the 25th and 75th percentiles. Variables are winsorized at the 1% level.

traditional ESG factor, as well as the traditional ESG factor plus the FF5 international factors.

Across all specifications, a portfolio based on the improvement of the MSCI ESG score

Table 4: Time Series Test of Progress Portfolios for ConsciESG and MSCI

Panel A	**ConsciESG-based Portfolio**		
	(1)	(2)	(3)
α	0.175**	0.189***	0.153**
	(0.077)	(0.066)	(0.066)
MKT	-0.115***	-0.096***	-0.052
	(0.037)	(0.021)	(0.032)
ESG		0.414***	0.299**
		(0.133)	(0.117)
SMB			-0.098
			(0.108)
HML			-0.277**
			(0.114)
RMW			0.367***
			(0.106)
CMA			0.334
			(0.236)
Panel B	**MSCI-based Portfolio**		
	(1)	(2)	(3)
α	-0.010	-0.010	-0.009
	(0.006)	(0.006)	(0.006)
MKT	0.008	0.009	0.011**
	(0.006)	(0.006)	(0.005)
ESG		0.003	-0.000
		(0.010)	(0.013)
SMB			0.014
			(0.011)
HML			-0.017**
			(0.008)
RMW			0.004
			(0.007)
CMA			0.024***
			(0.008)

Notes: In Panel A (B) the dependent variable is the weekly excess return (multiplied by 100) of a zero-dollar portfolio that goes long (short) the top (bottom) quintile of firms ranked by the ConsciESG (improvements in the MSCI ESG) score. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the ESG factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by MSCI ESG score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

produces no significant additional alpha. In contrast, the investment strategy that uses the forward looking signal of ConsciESG produces a weekly alpha of about 0.18 across specifications. In annualized terms, the alpha is in the order of 9%. Accounting for additional factors increases our point estimate. Importantly, the alpha is never significative

when we use the improvement in the MSCI score. Even after controlling for both the ESG and FF5 factors, the point estimate is small and slightly negative.

Results across geography and industries. In order to understand the deeper origins of these results, we group our firms across three major economic areas, namely, North America, Europe including the UK, and all of the other countries. We repeat our empirical exercise by forming portfolios using firms within each one of these three economic areas and report our results in table 5. The alpha is both statistically significant and sizable in the EU and UK. In contrast, in other regions the alpha continues to have a sizable point estimate, but it is not well identified. This result is interesting because it suggests that the disclosure requirements implemented in Europe might help the identification of strong green growth option.

Table 6 shows that positive and statistically significant alphas are concentrated in Business Equipment and Chemicals, which display large and highly robust alphas across all three asset pricing specifications. Non-Durables also exhibit positive and statistically significant alphas in the first two models, while Manufacturing shows positive alphas that are significant at the 10 percent level in two out of three specifications. These industries are characterized by relatively high abatement potential (see, for example, Walker et al. 2025a and Walker et al. 2025b).

Additional considerations. Our results on the performance of the portfolio based on the forward-looking signals deserve further discussion. More specifically, we anticipate that the magnitude of the alpha will decline over time, as market participants gradually incorporate transition progress into firm valuation. The speed of this process will depend on (i) the adaptation of disclosure practices, and (ii) the speed at which sustainability performance becomes more efficiently priced. In this sense, a reduction in alpha over time does not indicate a deterioration of the signal, or diminished relevance of our results. To the opposite, a reduction in alpha would reflect a successful market adoption of superior forward-looking scoring techniques.

Table 5: Time Series Test: Geographic Breakdown

Panel A: North America	CAPM	CAPM + ESG	FF5 + ESG
α	0.151	0.164*	0.124
	(0.098)	(0.088)	(0.082)
MKT	-0.006	0.012	0.041
	(0.033)	(0.029)	(0.031)
ESG		0.394***	0.268**
		(0.136)	(0.111)
SMB			-0.128
			(0.160)
HML			-0.218*
			(0.115)
RMW			0.469**
			(0.207)
CMA			0.200
			(0.235)
Panel B: Europe + UK	CAPM	CAPM + ESG	FF5 + ESG
α	0.180*	0.190**	0.232***
	(0.097)	(0.091)	(0.080)
MKT	-0.265**	-0.251***	-0.300***
	(0.109)	(0.082)	(0.094)
ESG		0.302	0.191
		(0.228)	(0.164)
SMB			-0.177
			(0.120)
HML			-0.279
			(0.311)
RMW			-0.328
			(0.279)
CMA			0.057
			(0.298)
Panel C: Others	CAPM	CAPM + ESG	FF5 + ESG
α	0.168	0.166	0.123
	(0.129)	(0.129)	(0.113)
MKT	-0.232**	-0.235**	-0.167**
	(0.101)	(0.097)	(0.065)
ESG		-0.054	0.004
		(0.056)	(0.094)
SMB			-0.019
			(0.099)
HML			0.036
			(0.090)
RMW			0.164
			(0.115)
CMA			0.245
			(0.200)

Notes: This table is constructed as Table 4. The dependent variable is the weekly excess return (multiplied by 100) of the long–short ESG portfolio constructed separately for firms whose headquarter is based in North America, Europe + UK, and Other regions. Standard errors are reported in parentheses. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

Table 6: Industry-level alphas

Industry	CAPM	CAPM+ESG	FF5+ESG
Utils	0.157	0.143	0.179
	(0.213)	(0.212)	(0.202)
Telcm	0.095	0.101	0.091
	(0.133)	(0.133)	(0.112)
BusEq	0.409***	0.425***	0.347***
	(0.088)	(0.080)	(0.095)
Manuf	0.127*	0.135*	0.137
	(0.075)	(0.073)	(0.088)
NoDur	0.151**	0.156**	0.125
	(0.064)	(0.065)	(0.087)
Durbl	0.095	0.077	0.109
	(0.215)	(0.223)	(0.259)
Shops	-0.019	-0.026	-0.056
	(0.119)	(0.102)	(0.090)
Hlth	-0.075	-0.040	-0.022
	(0.094)	(0.085)	(0.080)
Enrgy	0.029	0.046	0.033
	(0.131)	(0.138)	(0.124)
Chems	0.322***	0.327***	0.389***
	(0.096)	(0.098)	(0.119)
Money	-0.036	-0.044	-0.037
	(0.057)	(0.058)	(0.038)
Other	-0.183	-0.184	-0.061
	(0.232)	(0.236)	(0.177)

Notes: The table reports portfolio alphas from time-series regressions using weekly excess returns of ConsciESG quintile portfolios. Each raw corresponds to a zero-dollar portfolio formed using only firms belonging to a specific industry. The portfolios long in high-score firms and short in low score firms. Column (1) refers to the CAPM model (MktRF); column (2) adds the ESG factor; column (3) further includes the international SMB, HML, RMW, and CMA. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the ESG factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by MSCI ESG score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

3.1 Addition Analysis

Alternative indices. In this section, we extend our analysis to two additional indices to measure sustainability. Specifically, we consider also the FTSE Russel ESG, and the LSEG Data by Refinitiv.

The FTSE Russell ESG Data Model aims to "[...] assess corporate 'ESG exposure and performance', both in terms of measuring the impact of the scored entity on the external

environment (e.g. through theme and pillar Exposures) and measuring the scored entity's risk exposure or resilience to ESG-related risks (e.g. through pillar and theme Scores). FTSE Russell's ESG Scores and data model allows investors to understand a company's exposure to, and management of, ESG issues in multiple dimensions."

ESG scores from LSEG are designed to "[...] transparently and objectively measure a company's relative ESG performance, commitment and effectiveness, based on company-reported data." This approach focuses on 10 main themes including emissions, environmental product innovation, human rights, shareholders and so on. They also provide an overall ESG combined (ESGC) score, which is discounted for significant ESG controversies impacting the corporations they cover.

We repeat the analysis done with the MSCI ESG score and report our results in tables 7 and 8. Across both indices, we find no significant alpha for the FTSE ESG and the LSEG ESG. Our time series tests simply confirm our benchmark results reported in table 4.

Additional results. In the Appendix, we show that most of the ConsciESG alpha that we document is concentrated in the high portfolio, implying that our results are not driven by potentially costly short positions (see table A.2). In table A.3, we show that our main results reported in table 4 remain unchanged if we only use the E MSCI score to form an E-factor to be added to the international FF5. Using monthly return data, we confirm our benchmark results, which are based on weekly returns (see table A.4). Finally, in table A.5 we confirm the results reported in table 4 using the full ConsciESG universe of firms.

Table 7: Time Series Test of Progress Portfolio for ConsciESG and Refinitiv

Panel A	**ConsciESG-based Portfolio**		
	(1)	(2)	(3)
α	0.160**	0.158**	0.151**
	(0.070)	(0.075)	(0.064)
MKT	-0.086*	-0.079	-0.076
	(0.047)	(0.059)	(0.051)
ESG		0.056	-0.041
		(0.126)	(0.094)
SMB			-0.181
			(0.147)
HML			-0.344***
			(0.084)
RMW			0.265***
			(0.093)
CMA			0.241
			(0.164)
Panel B	**Refinitiv-based Portfolio**		
	(1)	(2)	(3)
α	0.041	0.044	0.046
	(0.057)	(0.057)	(0.051)
MKT	0.011	0.001	0.000
	(0.062)	(0.057)	(0.075)
ESG		-0.073	-0.090
		(0.088)	(0.125)
SMB			-0.090
			(0.116)
HML			-0.091
			(0.141)
RMW			-0.036
			(0.276)
CMA			0.073
			(0.248)

Notes: In Panel A (B), the dependent variable is the weekly excess return (multiplied by 100) of a zero-dollar portfolio that goes long (short) the top (bottom) quintile of firms ranked by the ConsciESG (improvement in the Refinitiv LSEG) score. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the ESG factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by LSEG Refinitiv ESG score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

Table 8: Time-Series Tests of Progress Portfolios for ConsciESG and FTSE

Panel A	**ConsciESG-based Portfolio**		
	(1)	(2)	(3)
α	0.174**	0.174**	0.173**
	(0.080)	(0.084)	(0.074)
MKT	−0.136***	−0.109*	−0.106*
	(0.044)	(0.056)	(0.060)
ESG		0.184	0.120
		(0.123)	(0.112)
SMB			−0.126
			(0.137)
HML			−0.353***
			(0.128)
RMW			0.194*
			(0.101)
CMA			0.254
			(0.194)
Panel B	**FTSE-based Portfolio**		
	(1)	(2)	(3)
α	0.064	0.064	0.111
	(0.091)	(0.091)	(0.081)
MKT	0.079*	0.084**	0.024
	(0.045)	(0.034)	(0.041)
ESG		0.034	0.053
		(0.227)	(0.187)
SMB			0.131
			(0.156)
HML			−0.087
			(0.111)
RMW			−0.004
			(0.138)
CMA			−0.234
			(0.167)

Notes: In Panel A (B) the dependent variable is the weekly excess return (multiplied by 100) of a zero-dollar portfolio that goes long (short) the top (bottom) quintile of firms ranked by the ConsciESG (changes in FTSE ESG) score. The international Fama and French (2017) factors are obtained from Kenneth French's data library. The ESG factor is constructed by going long (short) the top (bottom) 20% of firms based on FTSE ESG scores. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

4 Conclusion

This manuscript studies both empirically and theoretically the practice of assigning scores to firms in a transition phase. Our main application relates to ESG-related scores. We build a model to prove that forward looking scores are better than backward looking scores. Forward looking score are based on the performance of a firm compared to its estimated transition target. Backward looking scores, instead, focus on an historical perspective.

We show that forward looking scores can produce an alpha, i.e., great portfolio performance, for fund managers because these scores help fund managers to identify 'currently-brown' firms that have a large growth opportunity along the green transition. Backward looking scores, i.e., scores based on realized performance over time, facilitate an equilibrium in which it is impossible to distinguish 'good' and 'bad' firms in terms of transition-related growth opportunities. As a result, these scores can force fund managers to implement inefficient capital allocations.

Future research should continue to investigate these empirical findings and their robustness. To the extent to which our model is right, we should expect ESG scores to become forward-looking and fund managers to adopt them systematically. Our documented alpha should decrease due to greater market efficiency as firms and investors adopt sustainability improvements. New scoring technologies and methods may emerge and prove their superiority: our paper sets the stage for a theory-based analysis that should help both scholars and practitioners to rationalize the benefits of this progress. Last but not least, this paper should help regulators to better design disclosure rules.

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Appendix A. Data collection

As shown in table A.1, our sample spans many industries, as identified in FactSet.

TABLE A.1: **Distribution of Companies by Industry**

Industry	N. of Firms
Real Estate Investment Trusts	67
Industrial Machinery	45
Regional Banks	44
Medical Specialties	43
Electric Utilities	41
Major Banks	40
Packaged Software	40
Pharmaceuticals: Major	38
Miscellaneous Commercial Services	33
Semiconductors	33
Chemicals: Specialty	27
Specialty Stores	24
Integrated Oil	22
Information Technology Services	21
Multi-Line Insurance	21
Engineering & Construction	20
Finance/Rental/Leasing	20
Motor Vehicles	19
Electrical Products	19
Investment Banks/Brokers	18
Internet Software/Services	17
Biotechnology	17
Food: Specialty/Candy	16
Wholesale Distributors	16
Investment Managers	15
Household/Personal Care	14
Real Estate Development	14
Auto Parts: OEM	14
Major Telecommunications	14
Steel	13
Aerospace & Defense	13
Data Processing Services	13
Trucks/Construction/Farm Machinery	13
Electronic Production Equipment	13
Gas Distributors	12

Continued on next page

Industry	N. of Firms
Apparel/Footwear	12
Apparel/Footwear Retail	12
Restaurants	12
Agricultural Commodities/Milling	11
Other Metals/Minerals	11
Chemicals: Major Diversified	11
Building Products	10
Air Freight/Couriers	10
Alternative Power Generation	10
Electronic Equipment/Instruments	10
Containers/Packaging	10
Property/Casualty Insurance	10
Wireless Telecommunications	10
Homebuilding	10
Telecommunications Equipment	9
Food: Major Diversified	9
Beverages: Alcoholic	9
Oil & Gas Production	9
Hotels/Resorts/Cruiselines	8
Precious Metals	8
Marine Shipping	8
Recreational Products	8
Internet Retail	8
Personnel Services	8
Life/Health Insurance	8
Casinos/Gaming	7
Airlines	7
Other Consumer Services	7
Financial Conglomerates	7
Medical Distributors	6
Construction Materials	6
Oil Refining/Marketing	6
Railroads	6
Environmental Services	6
Computer Peripherals	6
Managed Health Care	6
Automotive Aftermarket	6
Miscellaneous Manufacturing	6
Food Retail	6
Home Furnishings	6

Continued on next page

Industry	N. of Firms
Food Distributors	5
Savings Banks	5
Electronic Components	5
Movies/Entertainment	5
Oil & Gas Pipelines	5
Electronics/Appliances	5
Water Utilities	5
Pulp & Paper	5
Specialty Telecommunications	5
Trucking	5
Medical/Nursing Services	5
Other Consumer Specialties	5
Office Equipment/Supplies	4
Food: Meat/Fish/Dairy	4
Home Improvement Chains	4
Tools & Hardware	4
Commercial Printing/Forms	4
Chemicals: Agricultural	4
Industrial Specialties	4
Discount Stores	4
Services to the Health Industry	3
Computer Processing Hardware	3
Advertising/Marketing Services	3
Tobacco	3
Contract Drilling	3
Other Transportation	3
Beverages: Non-Alcoholic	3
Oilfield Services/Equipment	3
Aluminum	3
Insurance Brokers/Services	3
Electronics Distributors	3
Department Stores	2
Industrial Conglomerates	2
Hospital/Nursing Management	2
Broadcasting	2
Metal Fabrication	1
Coal	1
Textiles	1
Financial Publishing/Services	1
Investment Trusts/Mutual Funds	1

Continued on next page

Industry	N. of Firms
Electronics/Appliance Stores	1
Specialty Insurance	1
Pharmaceuticals: Generic	1
Cable/Satellite TV	1
Drugstore Chains	1
Forest Products	1
Pharmaceuticals: Other	1

Notes: This table reports the distribution of firms across industry categories. Frequencies represent the number of companies operating in each industry.

Table A.2: Time Series Test: Portfolio Alphas

	(1) CAPM	(2) CAPM + ESG	(3) FF5 + ESG
ptf1 (Low)	-0.021	-0.025	-0.041
	(0.056)	(0.053)	(0.045)
ptf2	0.030	0.029	0.000
	(0.039)	(0.039)	(0.041)
ptf3	-0.009	-0.009	-0.048
	(0.040)	(0.040)	(0.036)
ptf4	-0.009	-0.011	-0.037
	(0.031)	(0.030)	(0.039)
ptf5 (High)	0.154***	0.163***	0.112**
	(0.053)	(0.047)	(0.048)

Notes: The table reports portfolio alphas from time-series regressions using weekly excess returns of ConsciESG quintile portfolios. Column (1) includes the CAPM (MktRF); column (2) adds the ESG factor; column (3) further includes SMB, HML, RMW, and CMA. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the ESG factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by MSCI ESG score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

Table A.2 shows that most of the ConsciESG alpha is concentrated in the long portfolio.

Table A.3: Progress Portfolio for ConsciESG and MSCI (E Factor)

Panel A	**ConsciESG-based Portfolio**	
	(1)	(2)
α	0.159**	0.147**
	(0.074)	(0.069)
MKT	-0.129***	-0.080
	(0.041)	(0.053)
E	0.195*	0.089
	(0.100)	(0.101)
SMB		-0.084
		(0.125)
HML		-0.355***
		(0.097)
RMW		0.357***
		(0.092)
CMA		0.356*
		(0.214)
Panel B	**MSCI-based Portfolio**	
	(1)	(2)
α	-0.011*	-0.011*
	(0.007)	(0.006)
MKT	0.007	0.010**
	(0.005)	(0.005)
E	0.017	0.015
	(0.013)	(0.015)
SMB		0.013
		(0.012)
HML		-0.015***
		(0.005)
RMW		0.001
		(0.008)
CMA		0.024***
		(0.008)

Notes: In Panel A (B) the dependent variable is the weekly excess return (multiplied by 100) of a zero-dollar portfolio that goes long (short) the top (bottom) quintile of firms ranked by the ConsciESG (improvements in MSCI ESG) score. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the E factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by MSCI E score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%,and 10% with ***, **, and *, respectively.

In table A.3, we show that our main results reported in table 4 remain unchanged if we only use the E MSCI score to form an E-factor to be added to the international FF6.

Table A.4: Progress Portfolios for ConsciESG and MSCI (Monthly)

Panel A	**ConsciESG-based Portfolio**		
	(1)	(2)	(3)
α	0.622***	0.679***	0.645**
	(0.234)	(0.216)	(0.309)
MKT	0.025	0.039	0.087
	(0.059)	(0.054)	(0.057)
ESG		0.328**	0.300*
		(0.129)	(0.156)
SMB			0.104
			(0.174)
HML			-0.509***
			(0.111)
RMW			0.276*
			(0.163)
CMA			0.788***
			(0.205)
Panel B	**MSCI-based Portfolio**		
	(1)	(2)	(3)
α	-0.419	-0.361	-0.458
	(0.343)	(0.346)	(0.407)
MKT	-0.100	-0.086	-0.131*
	(0.072)	(0.069)	(0.078)
ESG		0.333***	0.342***
		(0.115)	(0.093)
SMB			-0.067
			(0.176)
HML			0.411*
			(0.240)
RMW			0.188
			(0.283)
CMA			-0.591*
			(0.331)

Notes: In Panel A (B) the dependent variable is the monthly excess return (multiplied by 100) of a zero-dollar portfolio that goes long (short) the top (bottom) quintile of firms ranked by the ConsciESG (changes in MSCI ESG) score. The international Fama and French (2017) factors are obtained from Kenneth French's data library. The ESG factor is constructed by going long (short) the top (bottom) 20% of firms based on MSCI ESG scores. All regressions are estimated using Newey–West standard errors with 12 lags. Significance at the 1%, 5%, and 10% levels is denoted by ***, **, and *, respectively.

In table A.4, we show that our main results reported in table 4 remain unchanged if we use monthly return data.

Table A.5: Time Series Tests for ConsciESG Full Universe

	Long–Short ESG Portfolio		
	(1)	(2)	(3)
α	0.178**	0.192***	0.169**
	(0.079)	(0.066)	(0.068)
MKT	-0.121***	-0.102***	-0.080***
	(0.042)	(0.022)	(0.028)
ESG		0.417***	0.308***
		(0.142)	(0.115)
SMB			-0.154
			(0.103)
HML			-0.246**
			(0.104)
RMW			0.227**
			(0.103)
CMA			0.235
			(0.199)

Notes: The dependent variable is the weekly excess return (multiplied by 100) of a zero-dollar long–short portfolio that goes long (short) firms in the top (bottom) quintile ranked by ConsciESG score. This table is constructed starting from the full sample of ConsciESG which consists of 1550 companies. The international Fama and French (2017) factors are obtained from Kenneth French's data library, while the ESG factor is constructed by going long (short) on the top 20% (bottom 20%) of firms by MSCI ESG score. All coefficients are reported with HAC-adjusted standard error. We denote significant level of 1%, 5%, and 10% with ***, **, and *, respectively.

In Table A.5, we show that our main results reported in table 4 remain unchanged if we use the entire universe of firms provided by ConsciESG.